Point-in-Time PD Curves: IFRS 9 / CECL Applications

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Introduction

Banks and other lenders in particular have a growing need for a Point-in-Time ("PIT") default risk estimates. Current Expected Credit Loss ("CECL") model (under US GAAP) and International Financial Reporting Standard 9 ("IFRS 9") (under IFRS) accounting standards are mandatory for all regulated lenders and require PIT estimates over multiple time horizons[1]. However, there is limited agreement on how these should be constructed, and there are significant methodology variations between various institutions.

See Appendix 1 for a more detailed discussion of the various standards.

This paper is divided into 7 sections:

(1) Illustrates scope for variation in impairment estimates, highlighting the benefit of peer group data for wholesale lenders to assess internal models, and identify where calibrations and methods differ from the peer group.

(2) Introduces credit transition matrices ("CTMs") built from Hybrid Through-the-Cycle ("H-TTC") Consensus estimates.

(3) Illustrates derived Real World cumulative default probability curves. These provide base level estimates that can be converted to PIT estimates calibrated to historic default data and/or the addition of risk premiums.

(4) Reviews long run credit default rate data to

a. demonstrate the typical relationship between H-TTC and PIT estimates.
b. extend CTM calibration to include defaults.

(5) Discusses the specific issue of Real World vs. Risk Neutral PDs.

(6) Uses Sovereign bond and economic data combined with Consensus data to illustrate alternative practical approaches to Risk Premium calibration.

(7) Presents a worked example, combining the various topics discussed in the previous sections.

An Excel workbook is available that illustrates some of the calculations used in this paper. A large and growing set of frequently updated credit transition matrices (listed in Appendix 2) are also available as inputs for this workbook.

[1]Under CECL, a single forecast may be used, however multiple scenarios would assist institutions in conducting sensitivity testing on their models, assumptions and scenario development processes. IFRS 9 requires multiple scenarios to capture a range of economic conditions.

1 Impairment Estimates and the value of Peer Group Benchmarks

Impairment charges or "Expected Credit Losses" (ECL) are defined as the product of Probability of Default ("PD"), Loss Given Default ("LGD"), and Exposure at Default ("EAD"). This note focuses on the use of PDs in the context of PIT, IFRS9 and CECL estimation, applied to loans and debt instruments that are not automatically marked to market.

A lender with access to peer group data is likely to focus on group comparisons such as:

- How do my credit risk estimates compare with the group?
- Are group risk estimates in agreement, or are they dispersed and/or skewed by outliers?
- How do my future economic scenarios compare with the group?
- How does my current scenario compare with the peer group?
- How does my current scenario compare with market prices?
- What weight does the group assign to credit estimates compared with market prices?
- How do my impairment charges compare?
- What is driving differences in impairment charges?

Consensus credit data cannot answer all of these, but it can highlight differences and provide clues to the drivers behind them.

For example, under CECL or IFRS 9 a lender needs to recognize a day one impairment charge through profit and loss based on the Probability of Default of the loan that is not carried at fair value.

CECL calculations are unconditionally based on the loan maturity date; IFRS 9 calculations are based on a "significant increase" in the credit risk of the financial instrument since initial recognition; otherwise, a one-year time horizon is generally[2] used.

The definition of "significant increase" is not defined under IFRS thus it is open to interpretation. What makes it a particular challenge is that the "significant increase" assessment under IFRS 9 must be a relative rather than an absolute comparison of PDs since initial recognition and incorporate forward-looking macro-economic information, which was not required under IAS 39.

[2] As a practical expedient, a 12-month PD can be used if changes in the 12-month PD are a reasonable approximation to changes in the lifetime PD. However, the European Banking Authority guidelines issued in 2017 note that "credit institutions should make limited use of those practical expedients as they have the potential to introduce significant bias and because — given their business — the cost of obtaining the relevant information is not likely to involve 'undue cost or effort'."

The general impairment model does not apply to purchased or originated credit-impaired assets.

The table below (Figure 1) illustrates how an apparently simple impairment calculation for a standard loan can show considerable variations. The estimates depend on the choice of PD projection methods (Hazard vs. Transition) and the relevant accounting regulation (CECL vs. IFRS 9).

Figure 1: Impairment example: $100m BB loan

Loan Maturity	1	2	3	4	5
	Cumulative Default Probabilities				
Cumulative PD (Hazard)	0.50%	1.00%	1.50%	2.00%	2.50%
Cumulative PD (Transition)	0.50%	0.90%	1.35%	1.80%	2.20%
	PD impact on Year 1 Impairment Estimate				
IFRS 9 (No deterioration) $m	0.5	0.5	0.5	0.5	0.5
IFRS 9 (Deterioration, Hazard) $m	0.5	1	1.50	2.00	2.50
IFRS 9 (Deterioration, Transition) $m	0.5	0.9	1.35	1.80	2.20
CECL (Hazard) $m	0.5	1	1.50	2.00	2.50
CECL (Transition) $m	0.5	0.9	1.35	1.80	2.20

The same loan value has an estimated impairment of $0.5m - $2.5m depending on the method used, the loan maturity and credit status, and the applicable regulation.

There is an immediate and obvious value for lenders in comparing their own PD assumptions with those of their peer group. This is particularly the case when it comes to year-end audits where companies are required to support their underlying assumptions and disclosures and comply with the European Banking Authority ("EBA") requirements.[3]

Cumulative Probability of Default ("CPD") term structure curves are the foundation for this comparison, and peer group benchmarks for these can be derived from Credit Transition Matrices ("CTMs") built from Consensus credit data. CTMs and CPDs are discussed in the next two sections.

[3] EBA/GL/2017/06 published 12 May 2017 requires credit institutions to have policies and procedures to "validate models" used to measure expected credit losses. A sound model validation framework must include "a review of the model validation process by independent parties." The credit data must also be "accurate, reliable and complete."

2 Consensus Credit Transition Matrices

Cumulative Probability of Default ("CPD") curves can be derived from credit transition matrices ("CTMs").

CTMs record, for a group of borrowers, the frequency of Consensus changes in 7-category credit notches over a set period (usually one year)[4].

Figure 2 shows the one-year Consensus CTM for Large[5] Corporates (All regions), with a default row and column added. Each row adds to 100%.

Figure 2: Large Corporates One-year CTM (All Regions)

	aaa	aa	a	bbb	bb	b	c	d
aaa	96.535%	1.730%	0.346%	0.346%	0.692%	0.346%	0.000%	0.005%
aa	0.298%	91.288%	6.751%	1.109%	0.379%	0.149%	0.014%	0.014%
a	0.019%	4.009%	87.297%	7.298%	1.185%	0.134%	0.013%	0.045%
bbb	0.018%	0.442%	8.483%	81.708%	8.470%	0.645%	0.059%	0.175%
bb	0.008%	0.110%	0.752%	10.525%	82.494%	4.704%	0.406%	1.000%
b	0.000%	0.129%	0.386%	1.387%	17.929%	72.332%	3.303%	4.535%
c	0.000%	0.000%	0.371%	1.263%	7.873%	12.998%	46.940%	30.556%
d	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	100.000%

This shows, for example, that an estimated 6.8% of the world's Large Corporates changed rating from **aa** to **a** over the past year.

For this example, the default column (red box) is based on average contributed PDs in each category. *See next section for a discussion of default estimates.*

Figure 3 shows the equivalent 3-year matrix, which is derived by "powering up" (the matrix equivalent of raising a number to a power) the one-year matrix.

Figure 3: Large US Corporates Three-year CTM

	aaa	aa	a	bbb	bb	b	c	d
aaa	89.976%	4.631%	1.307%	1.170%	1.948%	0.848%	0.034%	0.087%
aa	0.793%	76.840%	16.473%	3.917%	1.436%	0.405%	0.040%	0.097%
a	0.085%	9.717%	68.881%	16.210%	4.265%	0.559%	0.054%	0.228%
bbb	0.054%	1.917%	18.581%	58.370%	17.880%	2.165%	0.208%	0.825%
bb	0.027%	0.502%	3.970%	21.848%	60.489%	8.847%	0.861%	3.456%
b	0.006%	0.384%	1.575%	7.169%	33.500%	40.644%	3.771%	12.951%
c	0.003%	0.117%	1.093%	4.060%	15.273%	15.024%	11.137%	53.294%
d	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	100.000%

To derive the three-year matrix, the one-year matrix is multiplied by itself and the resulting two-year matrix is post-multiplied by the original one-year to give the three year matrix, which includes the cumulative three year default probability (red box).

For example, the **c** credit category one-year PD of 30.6% becomes 53.3% after three years.

The "powering up" approach assumes that the one-year matrix is valid for future time periods, but in practice the matrix may change through the credit cycle. A major advantage of the Credit Benchmark dataset is that it covers multiple industries and geographies, so it provides a choice of transition matrices at different stages of the credit cycle.

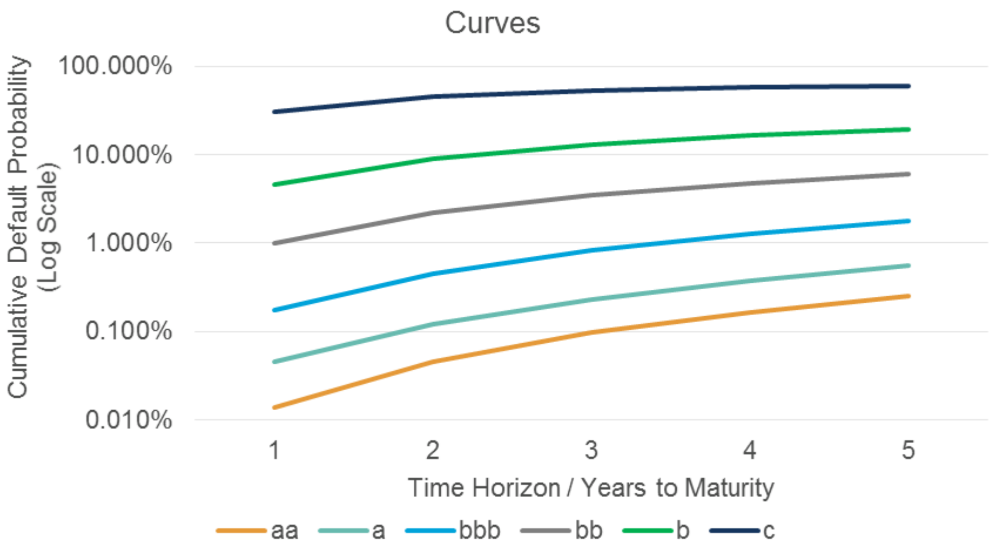
This raises the possibility of chain-linking a set of 1-year matrices which reflect the different stages of the credit cycle.

[4] See Appendix for a list of currently available 7x7 matrices. 21x21 matrices are also available.
[5] "Large" means any borrower with revenues of more than $50m.

3 Derived Cumulative Probability of Default Curves

The CTM shown in the previous section can be powered up to give estimated "Real World" CPD curves for each credit category[6]. These are shown in Figure 4.

Figure 4: Estimated Real World PD curves by credit category (aaa excluded)



Note: Log scale for y-axis.

These curves plot the cumulative default rates (on a log scale) outlined in red in Figures 2 and 3, but extended to all time horizons between 1 and 5 years.

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These represent "Real World" probabilities of default. These can be converted into approximate Point-in-Time curves through the addition of the relevant risk premiums for each maturity. This will be discussed in detail in section 5.

These curves can be used for IFRS 9 and CECL applications, where there is a requirement to calculate impairment charges over the lifetime of the loan. In some cases, the impairment charge may be highly sensitive to the transition matrix assumptions.

It is possible to simulate impairments under various assumptions and plot the resulting distributions. This can be used to establish confidence levels for the different impairment estimates across the loan portfolio.

[6] These exclude **aaa**, which is very close to the **aa** curve.

4 Default Rates

The CTMs in section 2 include a row and column to represent defaults[7]. The column represents all movements from every credit category into default (including multi-notch "jumps to default") over the chosen time period[8].

Default calibration is a broad and heavily debated topic, but it is possible to make some useful generalizations from the long run data. The charts below show the long run corporate default data provided by Moody's and S&P[9].

Figure 4.1 Moody's Long Run Credit Default Rate, Indexed (100 = sample average), Global Corporate Issuers

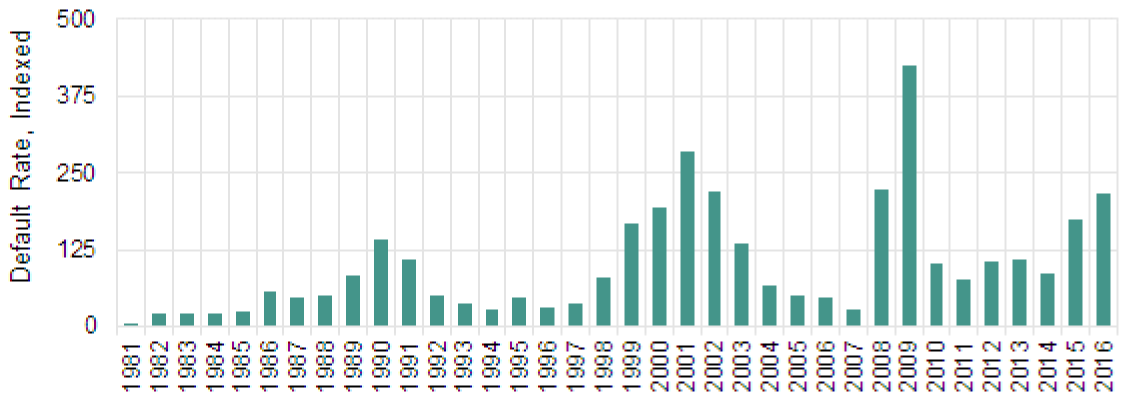
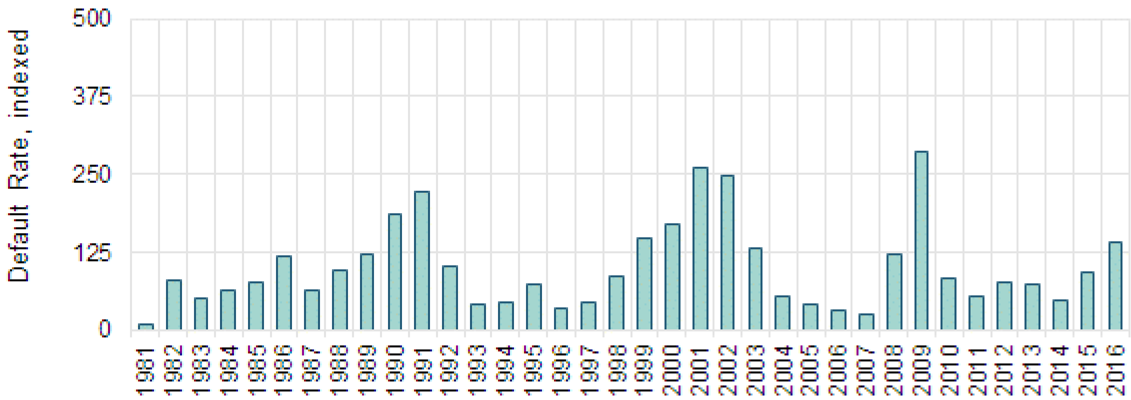


Figure 4.2 S&P Long Run Credit Default Rates, Indexed (100 = Sample average), Global Corporate Issuers



[7] 'Default' is not itself actually defined in IFRS 9/CECL. Banks must instead reach their own definition. For example, an entity shall apply a default definition that is consistent with the definition used for internal credit risk management purposes for the relevant financial instrument and consider qualitative indicators (e.g. financial covenants) when appropriate.
[8] The ***row*** represents recovery from default. These are currently set to zero, so the CTM in section 2 treats default as an "absorbing" state. When companies default, they may change identity before emerging; or (in some rare cases) they may be in technical default for short periods before returning to their previous credit status. Recovery from default is a topic for future research on the Consensus dataset.
[9] Moody's Annual Default Study: Corporate Default and Recovery Rates 1920-2017; S&P 2017 Annual Global Corporate Default Study and Rating Transitions

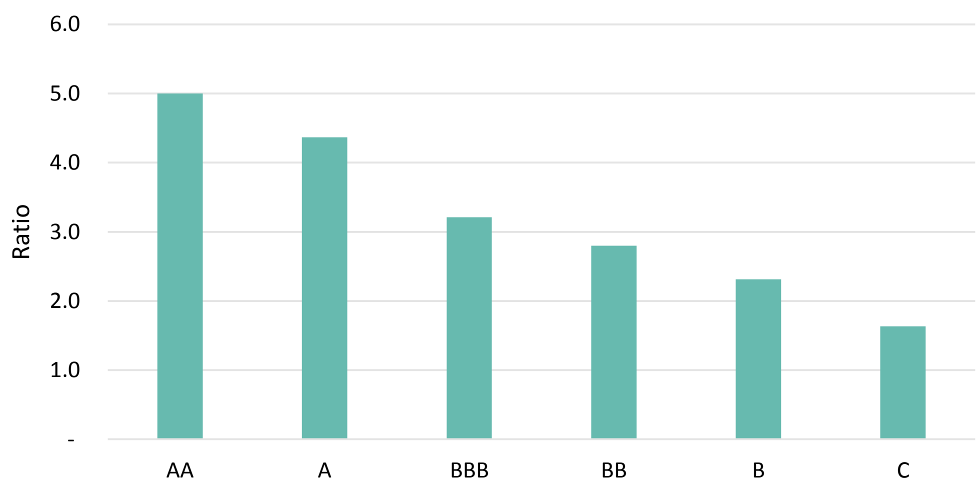
There are three distinct periods where default rates were severely elevated: 1990-91, 2001-2002, and 2008-09. The ratio of average default rates in "High" default years to those in "Low" default years is 2.82 for the S&P data and 2.74 for the Moody's data. The ratio of the average default rates for the whole period (analogous to the H-TTC measure) to the default rate for the low default years is 1.365 for S&P and 1.348 for Moody's. Averaging across both agencies gives values of 2.78 for the "High" / "Low" ratio in default years and 1.36 for the whole period.

A very basic PIT calibration could be based on averaging ratios from the two main agency data series, and assuming two PIT "regimes" – Low Default and High Default:

- For each credit category, assume an H-TTC default rate, D_T.
- Estimate the PIT default rate for the expansionary / low default periods = D_L = D_T / 1.36 = D_T * **0.74**
- Estimate the PIT default rate for the contractionary / high default periods = D_H = D_T /1.36 * 2.78 = D_T * **2.05**

This simple two-state approach can be applied across the credit spectrum, but the calibrations needs some adjustment. Figure 4.3 shows, for each credit category, the ratio of default rates in High default years to the average across all years in the sample. This is the counterpart to the 2.05 adjustment factor in the box above.

Figure 4.3 Ratio of default rates, High years vs. Long Run average, S&P



The ratio declines along with the credit category. Defaults in the upper Investment Grade categories are rare, so the data is also subject to large sampling error. But it seems intuitive that higher credits have a very low base default rate so any increase is proportionately greater. The 2.05 adjustment factor in the box above is closely aligned with the ratio for the B category.

Actual default rates by credit category are a key but controversial element in the calibration process. The table below (Figure 4.4) shows historic and expected default frequencies ("EDF") from a range of data providers, covering various time periods and borrower samples.

Figure 4.4 Historic and Expected Default Rates, various providers, date ranges and borrower samples (Bps)

Bps	Historic								Expected	
Moody's / S&P	Moody's from 1920	Moody's from 1970	Moody's from 1983	S&P from 1987	Consensus 2016-18	Average of Historic	Relative Standard Deviation	Median of Historic	Consensus EDF	Consensus
AAA	0	4	0.0	0.0	0.0	0.8	2.2	0.0	0.6	aaa
Aa/AA	6	6	1.5	1.8	20	7.1	1.1	6.0	2.3	aa
A	8.4	13	5.9	5.8	47	16	1.1	8.4	6.8	a
Bbb/BBB	25.7	47	19	20	54	33	0.5	26	22	bbb
Bb/BB	116.4	240	87	79	72	119	0.6	87	78	bb
B	329.2	749	339	438	268	425	0.5	339	400	b
C	1,474	1,690	1,508	2,570	1,896	1,828	0.2	1690	2500	c

Sources: Moody's, S&P, Credit Benchmark

The Consensus EDF is very closely aligned with the S&P historic rates since 1987. The relative standard deviation is highest for the AAA category and lowest for C (consistent with Figure 4.3).

Across the columns of the table, the default rates for each credit category increase in ratios that vary from about 3 to 4.5. Recalling the Low to High adjustment factor of 2.78 reported previously, leads to a useful summary of how credit changes during a periods when default risk is elevated:

During a High default phase, the entire credit distribution can be viewed as moving to the right; all borrowers are temporarily downgraded, at least by some fraction of a notch; and in some periods by an entire notch or even more.

Some academic work has identified at least two types of credit transition matrices – those that apply in an economic expansion, and those that apply in a contraction. A topic for future research could be the relationship between these two matrices combined with a possible shift to the right of the entire credit distribution during high default phases.

5 Conversion of Hybrid-Through-the-Cycle to Point-in-Time

The previous section discussed possible 2-state and 7-notch adjustment factors that can be applied directly to H-TTC PDs to convert each credit category risk estimate to its High or Low default state PD equivalent. These can be used to establish a basic benchmark for PIT purposes.

But many use cases require detailed and higher frequency calibrations for different geographies, industries, or portfolios. At this more granular level, default data is sparse; but PDs implied by market prices can be modified to provide a high frequency and detailed proxy for Real World default risk.

The challenge with inferring PDs from market prices is that they are subject to a range of distortions. These include compensation for liquidity risk, hedging and stock borrowing costs, and even short term sentiment. Collectively, these "distortions" are usually treated as a composite "Risk Premium".

For the avoidance of doubt, "financial risk premium" is defined as the additional return (vs. the risk-free rate) required by investors for assuming a particular form of risk.

Risk Premiums: The Parable of the Bookmaker

"A bookmaker is taking bets on a two horse race. Choosing to be scientific, he studies the form of both horses over various distances and goings as well as considering such factors as training, diet and choice of jockey. Eventually he correctly calculates that one horse has a 25% chance of winning and the other a 75% chance, Accordingly the odds are set as 3-1 against and 3-1 on respectively.

But there is a degree of popular sentiment reflected in the bets made, adding up to $5000 for the first and $10000 for the second. Were the second horse to win, the bookmaker would make a net profit if $1667, but if the first wins he suffers a loss of $5000. The expected value of his profit is 25% x (-$5000) + 75% x ($1667) = $0, or exactly even. In the long term, over a number of similar but independent races, the law of averages would allow the bookmaker to break even. Until the long term comes, there is a chance of making a large loss.

Suppose however that he had set odds according to the money wagered - that is , not 3-1 but 2-1 against and 2-1 on respectively. Whichever horse wins, the bookmaker exactly breaks even. The outcome is irrelevant.

In practice the bookmaker sells more than 100% of the race and the odds are shortened to allow for profit. However, the same pattern emerges. Using the acual probabilities can lead to long term gain but there is always a chance of a substantial short term loss. For the bookmaker to earn a steady riskless income, he is best advised to assume the horses' probabilties are something different, That done, he is in the surprising position of being disinterested in the outcome of the race, his income being assured." Source: Baxter & Rennie, Financial Calculus, 1996.

Financial risk premium estimation is a controversial topic with a huge associated academic literature, leading some to comment that "the only thing we really know about risk premiums is that they move around a lot".

The table below (Figure 5.1) is taken from Hull et al (2004)[10], analyzing the difference between Real World PDs (based on Moody's cumulative default rates 1970-2003) and Risk Neutral PDs (based on a ML bond universe) and used these to calculate a snapshot of risk premiums for each major credit category.

Figure 5.1 Hull et al. PD and Risk Premium Estimates (US Dollar Corporates, provided by Merrill Lynch)

Hull, Predescu, White 2004	RW PD pa (Moody's 1970-2003)	Expected Loss = spread to comp for RW default	7Y Swap vs US TSY minus 10bps	7Y Bond Yield vs US TSY	Risk Premium(s)
Aaa	4	2	43	83	38
Aa	6	4	43	90	43
A	13	8	43	120	69
Baa	47	28	43	186	115
Ba	240	144	43	347	160
B	749	449	43	585	93
Caa	1690	1014	43	1321	264
Recovery assumed = 40%					

Column 1 is the historic default rate using a subset of the Moody's data reported in Figure 4.4. The Column 2 multiplies this by an assumed LGD of 60% (derived from an assumed recovery rate of 40%). This is an approximation to a corporate bond yield that only compensates for Real World credit default risk. Column 3 is the swap spread vs the US Treasury 7-year bond (less 10 basis points) – this is a proxy for the market risk free rate. Column 4 is the average bond yield in each category. Column 5 is the difference between column 4 and the sum of columns 2 and 3.

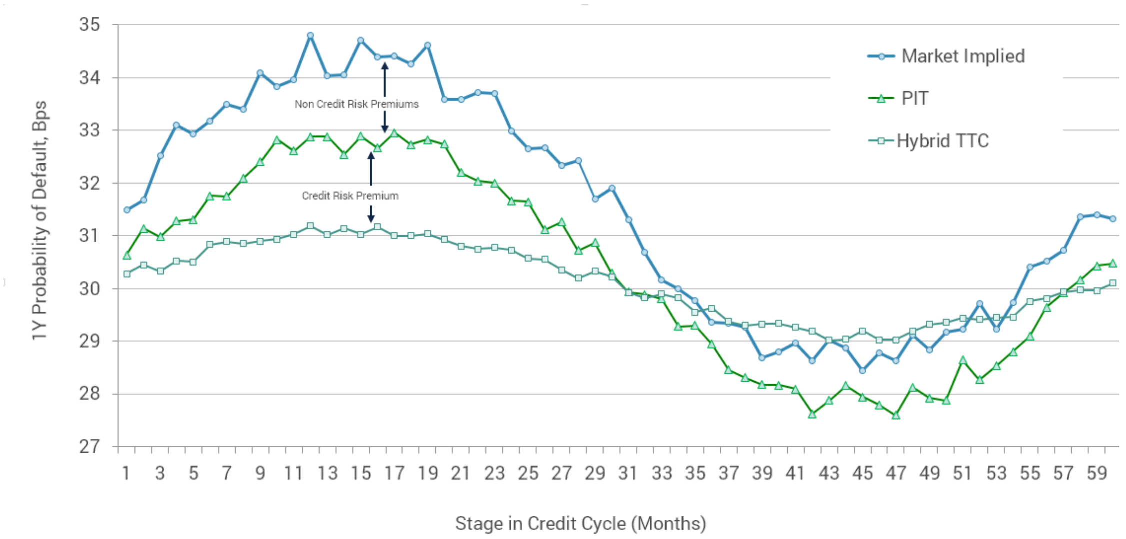
This shows that risk premium varies by credit category but the relationship is far from monotonic. This illustrates the challenge in using this calculation in reverse to estimate market-implied PDs: unless the credit category risk premiums are known, this approach may produce counterintuitive estimates of Real World PDs.

The Hull et al. estimates are a snapshot which they derive to illustrate the differences between Risk Neutral and Real World estimates. Figure 5.1 shows the types of distortions that will be magnified across multiple geographies, industries and maturities. But even without these distortions, there will be differences between H-TTC and PIT that arise because of different stages of the credit cycle in different economies and industries.

[10] Hull, J., M. Predescu, and A. White, 2004 "The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements" *Journal of Banking and Finance* 2004, vol. 28, issue 11, 2789-2811

The chart below (Figure 5.2) shows a hypothetical version of the credit cycle, with plotted lines representing TTC, H-TTC, PIT and Market-implied views of credit risk.

Figure 5.2 The Credit Cycle and Default Risk Estimates: Hypothetical Example



In practice, every cycle is different. But the basic concept is that market-implied PDs show much larger variation than H-TTC PDs, and somewhat larger variation than PIT PDs. More controversially, market-implied PDs are usually higher than Real World PDs (which includes H-TTC and PIT). When non-credit related distortions have been stripped out of market yields, the implied PD may be treated by some analysts as equivalent to a PIT estimate.

Credit Default Risk Premiums: The example of Drexel Burnham and the Junk Bond market

The junk bond market of the late 1980's is a classic risk premium study: when Michael Milken was at now bankrupt bank Drexel Burnham, he observed that while an investor with a well-diversified portfolio of high yield bonds would historically experience a number of defaults, they would still earn an above-average return. At that time, high yield bonds were typically trading at prices which more than compensated for their default risk.

This apparent free lunch was used to kick start the junk bond market – now an established part of the financial landscape. But even today, the junk bond market can appear to offer a free lunch, or at least a free sandwich.

Milken was urging investors to abandon their desire for a ***credit*** risk premium, but investors still (usually) require one. This is mainly because the default and recovery rates are themselves variable and uncertain. But Milken's basic analysis – estimating the credit risk premium by comparing the default rates implied by bond prices with the actual historic default rate – remains valid.

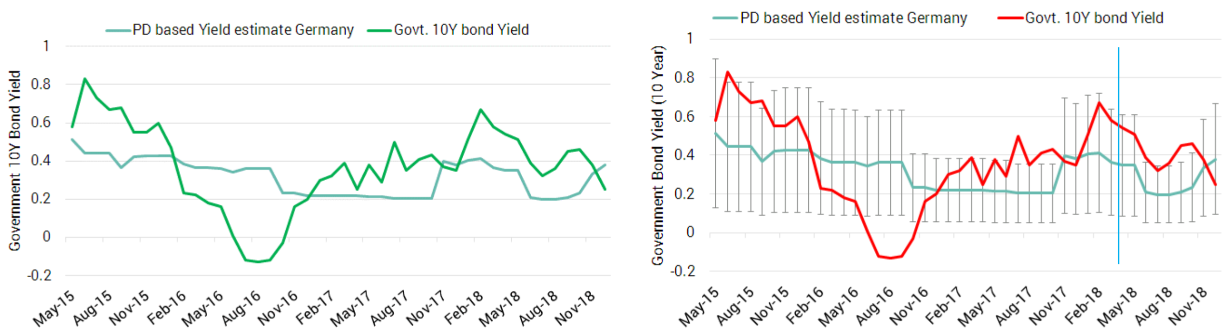
What Milken probably actually achieved was a major reduction in the ***liquidity*** risk premium that often lurks in bond yields. By bringing large numbers of buyers and sellers into the junk bond market, he created liquidity.

6 Risk Premium Calibration

Consensus credit data is published monthly, so it provides an opportunity to plot at least some of the elements of Figure 5.2 with real data. Sovereign risk and 10-year bonds are used to minimize the impact of liquidity, hedging and sentiment effects. Sovereign bond yield levels can be viewed as the sum of the global risk-free rate and risk premiums for inflation and credit. In developed economies, inflation risk changes slowly; so apart from changes in the global risk-free rate, credit default risk should be the main determinant of short-term variation in individual Sovereign yields.

Figure 6.1 plots data for one of these Sovereigns: it shows the actual 10-year Government Bond Yield against the estimated bond yield, fitted to the German Sovereign Consensus PD. The fit is based on the months to the left of the vertical blue line; the "PD-based Yield Estimate" for Germany to the right of the blue line is the out of sample estimate.

Figure 6.1 German Government 10-year bond yield and fitted yield based on Real World PD estimate.



In this case, Real World PD estimates provide a stable series which tracks the more volatile bond yield. If the bond yield is above the fitted PD line, then short term market-implied credit risk is elevated; if it is below, then short term market-implied credit risk is low. With suitable ranges (like those in the right hand chart) an analyst can set trigger points for changing the current PIT estimate to a higher or lower alternative.

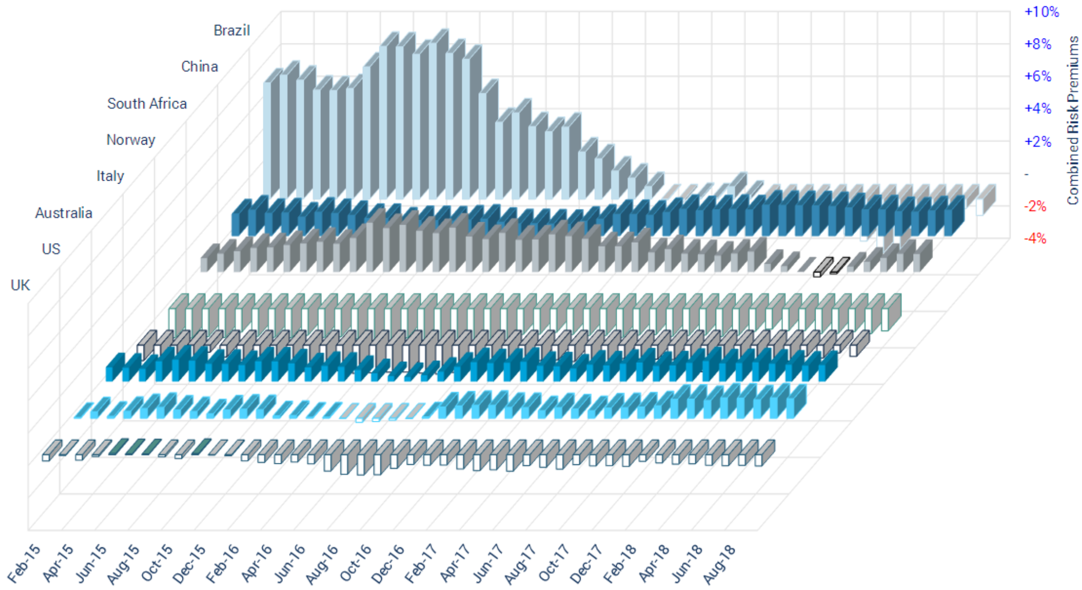
The corollary to this is that the same plotted relationships may be used for making decisions about when to increase or reduce the risk profile of a credit portfolio in line with risk appetite; they may also provide a basis for traders to make buy/sell judgements.

The approach in Figure 6.1 can be expanded to multiple Sovereigns - and making various adjustments for inflation and interest rates[11] – it is possible to estimate the market-implied risk premium over the past few years. Since Sovereign bonds are typically much more liquid than corporates, the short-term risk premium will be dominated by short term variations in the credit risk premium, as well as some variable elements representing inflation and term-related risk premiums.

[11] This is a detailed regression model which pools data across all Sovereigns and time periods where Consensus data is available – documentation pending.

So the regression residuals plotted in Figure 6.2 are a form of composite short term risk premium.

Figure 6.2 Example market-implied composite risk premiums (≈ regression residuals) May 2015 – Nov 2018



These show highly positive autocorrelation: the average one-month autocorrelation coefficient is +0.75. This can be taken as strong evidence of trending (and probably cycles) in the residual short-term risk premiums.

Figure 6.2 shows that risk premiums estimated from corporate bond or CDS data may show very large ranges between peaks and troughs. A recent paper by Berndt et al. (2018)[12] compared median 5-year CDS rates with 5-year expected loss (EDF) estimated by Moody's Analytics, for the period 2002-15. The ratio of CDS to EDF varied between about 1.2 (in 2004) and more than 10x (over 2008/09). Their data shows that since the 2008/09 crisis, the ratio has remained elevated with a range of 2x to 4x.

A number of methods are available to convert observed risk premiums to PIT estimates:

1. Arithmetic differences between current yield and yields estimated from H-TTC estimates (as in Figure 5.1). This has the disadvantage of treating the composite risk premium as being the same as the credit risk premium. In practice some allowance for liquidity and other elements will be needed.
2. Ratios of current yields to fitted estimates – these remove some of the structural risk premiums, since liquidity (for example) is likely to be stable – the focus is the relative displacement of the current market from the trend. Some adjustments required for negative yields.
3. Measure the cross-sectional volatility of the estimated risk premiums, and use % changes in volatility to scale the H-TTC default rates up or down.

[12] Berndt, Douglas, Duffie, Ferguson "Corporate Credit Risk Premia" Review of Finance, Volume 22, Issue 2, 1 March 2018, Pages 419–454

7 Worked example

This example is taken from the accompanying Excel workbook. A one-year 7x7 credit transition matrix is used (Figure 7.1) that covers All Regions, All Entity Types (Corporates and Financials), All Industries, and Large companies (>$50m revenue). The number of obligors meeting these criteria is 79,265.

In this example, the credit transition matrix uses Consensus data for the credit category transitions and "Consensus EDF" for the default rates.

Figure 7.1 Credit Transition Matrix

August 16 - August 17						
Categories:	Region	Region Group	Entity Type	Industry	Size :	Observations
	All	All	All	All	Large only	79,265

This is one example of the 40+ credit transition matrices calibrated to consensus data available to clients.

	aaa	aa	a	bbb	bb	b	c	d	↓ High Default adjustments for individual credit categories
aaa	78.87%	18.31%	0.70%	1.41%	0.70%	0.00%	0.00%	0.0060%	5.00
aa	0.11%	88.56%	7.74%	2.03%	1.36%	0.14%	0.06%	0.0225%	5.00
a	0.00%	3.01%	88.25%	6.30%	2.12%	0.29%	0.03%	0.0675%	4.20
bbb	0.00%	0.48%	14.21%	73.79%	9.91%	1.38%	0.22%	0.2200%	3.10
bb	0.00%	0.19%	1.38%	13.43%	76.94%	7.41%	0.65%	0.7800%	2.80
b	0.00%	0.05%	0.81%	2.72%	17.18%	75.03%	4.20%	4.0000%	2.20
c	0.00%	0.27%	1.07%	4.14%	7.74%	17.42%	69.36%	25.0000%	1.60
d	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	

Currently treat d as absorbing state

↑ Choose default rates from tab "Default"

Figure 7.2 H-TTC Curves

Cumulative PD Term Structure: Real World H-TTC

	1Y	2Y	3Y	4Y	5Y
aaa	0.01%	0.02%	0.06%	0.12%	0.21%
aa	0.02%	0.08%	0.17%	0.30%	0.46%
a	0.07%	0.17%	0.33%	0.53%	0.79%
bbb	0.22%	0.56%	1.0%	1.5%	2.1%
bb	0.8%	1.8%	3.0%	4.2%	5.5%
b	3.8%	7.6%	10.9%	13.8%	16.3%
c	20.0%	31.7%	38.8%	43.3%	46.2%

Figure 7.3 PIT Curves (PD Adjustment Factor = 2)

Cumulative PD Term Structure: Real World PIT

	1Y	2Y	3Y	4Y	5Y
aaa	0.06%	0.20%	0.44%	0.79%	1.3%
aa	0.22%	0.60%	1.1%	1.8%	2.5%
a	0.56%	1.3%	2.2%	3.3%	4.4%
bbb	1.3%	3.1%	5.2%	7.4%	9.7%
bb	4.2%	8.8%	13.4%	17.7%	21.7%
b	15.0%	26.8%	35.7%	42.4%	47.5%
c	44.4%	63.2%	71.9%	76.3%	78.9%

If the default state is set to "High", the default rates in Figure 7.1 are adjusted by a scale factor of 2x (as calibrated in Section 4) and are further adjusted by the category-specific adjustments shown in Figure 4.3. (These are also shown to the right of the matrix above). The matrix is then raised to the fifth power, and the resulting PIT curve values are shown in Figure 7.3. Figure 7.2 shows the equivalent curves prior to the High Default state adjustments.

This process can be repeated for a range of scenarios. These scenarios could reflect, for example:

1. current market yields compared with their long run averages or a fitted yield, adjusted to reflect a pure credit risk premium.
2. multiple credit transition matrices representing different stages of the business cycle.

A large number of scenarios can be generated, and the resulting curves can be assigned probabilities based on historical experience or forward looking expectations derived from market prices and curves. This gives the probability-weighted set of curves required by various regulations. Each will correspond to a specific impairment estimate under CECL or IFRS 9.

Comparison of current market yields with fitted yields or with long run averages is one way of determining whether the IFRS 9 "material deterioration" in credit has been triggered; but an alternative is to monitor Consensus aggregates to give a purer reading of Real World credit trends.

8 Conclusions

- For various Point-in-Time applications, Hybrid Through-the-Cycle data can be used as a robust base for Credit Transition Matrix calibration where Point-in-Time data is unavailable or too volatile.

- Historic default data shows distinct high- and low- default phases, and the ratio between the two varies with credit category.

- PIT PD term structure scenarios can be estimated by adjusting the default rate column of the H-TTC matrix to reflect historic data.

- Sovereign Consensus credit risk estimates can be combined with Government bond yield data to provide a robust, minimum-error base for Credit Risk Premium calibration.

Consensus CTMs can provide a Real World H-TTC benchmark for Cumulative Probability of Default curves. These can be modified in a number of ways to derive PIT equivalent curves with a range of applications including stress testing, regulatory requirements, pricing and portfolio risk management.

An Excel-based workbook which illustrates some of the calculations is available on request. Appendix 2 shows a full list of CTMs available to clients to populate that workbook.

Appendix 1: IFRS 9 and CECL accounting standards

1. Current Expected Credit Loss (CECL) and International Financial Reporting Standard 9 (IFRS 9) are two new accounting standards that include more robust, **forward looking** requirements for calculating accounting impairments resulting from potential credit losses for a potentially wide range of companies.

   Note that:

   - Certain countries still report under local GAAP and have not adopted IFRS or US GAAP. (e.g. private companies in UK may follow UK GAAP which still permits the application of IAS 39). See:
     - https://www.iasplus.com/en/resources/ifrs-topics/use-of-ifrs
     - https://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/united-states/#extent

   - Not all US companies necessarily use CECL. CECL is only applicable to companies that report under US GAAP. There are number of companies in US that are IFRS reporters.

   - IFRS 9 scope is broader than just banks and lenders. There is a significant impact on insurance companies (many of which deferred IFRS 9 until the effective date of insurance standard IFRS 17, effective 2022).

   - Non-Financial Institutions are also impacted by larger and more volatile bad debt provisions on trade, lease receivables and contract assets, and the impact of expected credit losses on financial investments.

   - Any company with a large investments book that is not carried at Fair Value could be significantly impacted (e.g. those with complex treasury functions with substantial financial assets, or significant long tem receivables)

   - CECL is not effective yet for certain entities. Public business entities that are SEC filers must adopt CECL guidelines for fiscal years beginning after December 15, 2019, but all other public business entities must adopt CECL guidelines for fiscal years beginning after December 15, 2020. There is also an optional temporary exemption from applying IFRS 9 Financial Instruments, granted to insurers (to align with effective date of IFRS 17 which is 2021).

   - There is some debate about the suitability of past default and transition behavior, or market-implied data, as inputs when the requirement is for forward-looking estimates. Hybrid/Through-the-Cycle estimates are explicitly forward-looking, but the models used to generate those estimates will – to varying degrees – be calibrated against historical data and in some cases market data as well. Risk premium assumptions will be critical in establishing a credible link between market data and Real World credit risk estimates.

2. IFRS 9 requires multiple scenarios whereas CECL requires only 1 single forecast. For example, if a bank makes a loan, and the borrower's credit standing deteriorates, then the IFRS 9 impairment allowance is described (without a precise definition) as the "probability-weighted average *[not median]*" of the possible losses. The CECL allowance definition leaves more room for interpretation. (See boxed section on definitions, below).

3. CECL is simpler and more conservative; it calculates the impairment over the lifetime of the asset. Some aspects of IFRS 9 deliberately allow each bank some leeway in the exact application of the standards to reflect their loan book and business models.

   IFRS 9 shortens the 'lifetime' time horizon to 12 months, unless there is a significant deterioration in the credit outlook in which case the full lifetime impairment applies. If the outlook improves, then the time horizon is again reduced to 12 months.

   This approach means that IFRS 9 is likely to lead to more volatility than CECL in the impairment calculation; but it also means that IFRS 9 allowances are likely to be lower.

4. As these changes are implemented, it is critical to note that, from an audit perspective, the data used needs to be verifiable. The EBA issued specific guidance for credit institutions that talks about independent verification.

   See:
   https://eba.europa.eu/documents/10180/1842525/Final+Guidelines+on+Accounting+for+Expected+Credit+Losses+%28EBA-GL-2017-06%29.pdf

IFRS 9 Paragraph 5.5.17:

An entity shall measure expected credit losses of a financial instrument in a way that reflects:

- *An unbiased and probability-weighted amount that is determined by* ***evaluating a range of possible outcomes***
- *The time value of money*
- *Reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions*

IFRS 9 Paragraphs 5.5.18, B5.5.41 and B5.5.42:

*When measuring expected credit losses, an entity need not necessarily identify every possible scenario. However****, it shall consider the risk or probability that a credit loss occurs by reflecting the possibility that a credit loss occurs and the possibility that no credit loss occurs,*** *even if the possibility of a credit loss occurring is very low.*

CECL:

To forecast the CECL over the life of the loan on origination, a bank will need to measure all expected credit losses based on historical experience, current conditions and reasonable and supportable forecasts that incorporate forward-looking information. Where banks are unable to be obtain reasonable and supportable forecasts then CECL requires the bank to revert to ***unadjusted historic credit loss experience*** *but adjusted to current economic conditions.*

Appendix 2: Consensus CTMs

Credit Benchmark now publish 46 CTMs each month. These cover various dimensions:

- Regions & regional groups
- Borrower types & industries
- Size

Figure A1 shows the complete list:

Figure A.1: Current list of Consensus-based Credit Transition Matrices

Region	Region Group	Entity Type	Industry	Size	# Observations
All	All	All	All	Large	76,519
All	All	All	All	All	229,851
All	All	Corporates	All	Large	48,443
All	All	Financials	All	Large	20,371
All	All	Financials	All	All	34,033
All	Developed	All	All	Large	63,555
All	Developed	Corporates	All	Large	40,913
All	Developed	Financials	All	Large	15,818
All	Developed	Financials	All	All	27,532
All	Emerging Markets	Financials	All	All	4,867
Europe	All	All	All	Large	35,022
Europe	All	Corporates	All	Large	22,679
Europe	All	Financials	All	Large	8,547
Europe	All	Financials	All	All	14,092
North America	All	All	All	Large	24,461
North America	All	All	All	All	79,641
North America	All	Corporates	All	Large	15,580
North America	All	Corporates	All	All	24,437
North America	All	Financials	All	Large	6,333
North America	All	Financials	All	All	12,401
All	Developed	Corporates	Basic Materials	Large	3,388
All	All	Corporates	Consumer Goods	Large	6,209
All	Developed	Corporates	Consumer Goods	Large	4,798

Region	Region Group	Entity Type	Industry	Size	# Observations
North America	All	Corporates	Consumer Goods	All	2,981
All	All	Corporates	Consumer Services	Large	10,175
All	Developed	Corporates	Consumer Services	Large	8,840
North America	All	Corporates	Consumer Services	Large	2,929
North America	All	Corporates	Consumer Services	All	5,231
All	All	Corporates	Health Care	Large	2,354
All	All	Corporates	Health Care	All	5,726
All	Developed	Corporates	Health Care	Large	2,274
North America	All	Corporates	Health Care	All	2,114
All	Developed	Corporates	Industrials	Large	11,244
North America	All	Corporates	Industrials	Large	2,997
North America	All	Corporates	Industrials	All	5,409
All	All	Corporates	Oil & Gas	Large	3,093
All	All	Corporates	Oil & Gas	All	4,457
All	Developed	Corporates	Oil & Gas	Large	2,709
All	Developed	Corporates	Oil & Gas	All	3,868
North America	All	Corporates	Oil & Gas	All	2,080
All	All	Corporates	Technology	Large	2,534
All	Developed	Corporates	Technology	Large	2,298
All	All	Corporates	Utilities	Large	2,642
All	All	Corporates	Utilities	All	3,557
All	Developed	Corporates	Utilities	Large	2,228
All	Developed	Corporates	Utilities	All	2,992

The number of observations refers to individual bank views on individual entities. These cross sections are typically very large and robust compared with CTMs published by rating agencies.

*Credit Benchmark publish Consensus credit ratings for more than 27,000 individual borrowers. There are 21 separate rating categories (**aaa,aa+…cc,c**), and 7 summary categories (**aaa,aa…c**). The 27,000 published Consensus ratings are based on a broader database of 750,000 monthly credit updates contributed by 30 major banks. This broader database supports the calculation of aggregates such as credit risk time series, as well as the credit transition matrices. The current history represents nearly 4 years of monthly data.*

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