Credit Benchmark®

Whitepaper // No.5

Ex Ante PD and LGD estimates: Analysis and summary of IRB bank contributions

With reference to the request for submissions by the Basel Committee on Banking Supervision March 2016 Consultation document "Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches"

June 2016

Executive Summary

This paper has been guided by discussions with IRB banks, regulators and industry bodies and draws on the Credit Benchmark contributed dataset (“CB data”). This data shows the position and shape of Ex Ante PD and LGD distributions from IRB models.

Credit Benchmark®

Key points:

1. **Variation:** The range of PD and LGD estimates is proportionately lower for the highest quality obligors. The variation in risk estimates across contributors for the same obligor is lower in 2016 than in 2011.
2. **CRA Ratings:** IRB banks are conservative with respect to rating agencies, especially in the systemically important Sovereign and Bank obligor credit categories. Banks are required to model a very large number of obligors for which no ratings exist, including around 100,000 corporates. Changes in pooled credit views tend to be smoother than CRA based changes.
3. **Market-derived estimates:** These are distorted by a time varying risk premium when compared with bank estimates. For this reason, market derived estimates are more volatile than internal model estimates. Banks are required to model a large number of obligors for which no market-derived estimates exist, especially in the SME and fund obligor categories.
4. **Floors and Adverse Risk Selection:** IRB banks are generally conservative with respect to standardized LGD floors. However, the contributed data shows that the use of LGD and PD floors will increase capital requirements for some categories of funds. The contributed data further shows that there are some asset classes where the floors may be below the current level of risk estimates. Such anomalies increase the possibility of adverse risk selection.
5. **Visibility:** Contributor banks intend to continue to estimate Ex Ante PD and LGD values for economic capital management and stress testing, and see a growing role for contributed datasets, subject to suitable governance. The distributions and summaries in this paper offer frequent visibility to banks and regulators and allow both groups to monitor current risk assessments compared with their own risk appetites.

About Credit Benchmark

Credit Benchmark is a financial data analytics company offering an entirely new source of credit risk data: the crowdsourced internal views of the world's leading IRB banks. Credit Benchmark collects monthly Ex Ante Probability of Default ("PD") and Loss Given Default ("LGD") estimates on Sovereign, corporate, bank, and non-bank financial entities. These are aggregated and anonymized and published back to the contributing banks.

Where there are at least 3 separate banks providing estimates for the same obligor, Credit Benchmark calculate and publish simple average PD and LGD estimates back to contributor banks. PD estimates are also mapped to a 21 category scale called the Credit Benchmark Consensus ("CBC") which provides a benchmark for CRA credit ratings.

The Credit Benchmark dataset

The Credit Benchmark dataset has the ability to flag significant variance in PD and LGD estimates by collecting monthly Ex Ante estimates of PD and LGD across the entire wholesale bank loan book. This gives a large crowdsourced[1] dataset which draws on the work of thousands of credit analysts across the banking sector. This can be used to validate models and provide early warning of potential downgrades, as well as trends towards default. This dataset provides comprehensive, frequent, stable, systemically diverse and unbiased benchmarks for credit risk. The analysis of 'Big Data' is becoming a key component of modern business planning in most large corporates. The banking industry has tended to be a late adopter of these techniques, especially in the analysis of Wholesale risks.

[1] Crowdsourcing is the popular version of the Diversity Prediction Theorem which can be stated as: "The squared error of the collective prediction equals the average squared error minus the predictive diversity" - implying that if the diversity in a group is large, the error of the crowd is small. This is the formalization of the Francis Galton observation of the 'Wisdom of Crowds'.

Introduction

This paper uses the Credit Benchmark dataset in an analysis of some of the issues raised by the Basel Committee final consultation report on proposed changes to the IRB regulatory capital framework issued in March 2016. Since 2012, the Basel committee (with G20 endorsement) has focused on addressing **excessive variability in RWA calculations**. It is our understanding that the objectives are to:

- Improve consistency and comparability in bank capital ratios.
- Restore confidence in the regulatory framework following the financial crisis of 2008.
- Fulfil a commitment to complete the work by the end of 2016.

This paper will focus on the current IRB model data contributed to Credit Benchmark where this has a direct bearing on the specific proposals to restrict the use of internal models in the calculation of regulatory capital requirement for credit risk. In particular, it will focus on the following proposals set out in 2.1 Summary of proposals (P.1 of the Basel document):

1. To remove the IRB approaches for the following portfolios, which as a result will be subject to the standardized approach to credit risk:
    - Banks, and other financial institutions
    - Large corporates (defined as corporates belonging to consolidated groups with total assets exceeding €50bn)
2. To remove the option to use the A-IRB approach for exposures to corporates that are part of consolidated groups that have annual revenues greater than €200m.
3. The outcome of the treatment of sovereign exposures when the review is complete also remains central to understanding how best to manage risk across the global banking sector.

It also appears that part of the rationale for these proposals is largely derived from the July 2013 analysis of RWA variability for banks that adopted the IRB approach. This study suggested that the capital impact of the diversity in risk weights is typically in the range +/- 1 percentage points (of capital). However, this variation could cause outlier bank capital ratios to vary by as much as 2 percentage points from the benchmark.

BCBS Assumptions

The Committee state that the case for further constraints on the use of internal models arises because the July 2013 study: "Revealed notable dispersion in the levels of estimated risk as expressed in the probability of default (PD) and loss given default (LGD) that banks assign to the same exposures. The low default nature of the assessed portfolios, and the consequent lack of appropriate data for risk parameter estimation, was likely one of the key factors leading to differences across banks…"

This paragraph reflects some of the key assumptions that the BCBS has made with regards to managing credit risk. Pooled data from banks can provide key evidence to support or challenge these assumptions:

1. Dispersion in risk estimates

There are numerous examples in this report, which illustrates how banks and regulators alike can leverage high frequency, crowdsourced data to assess changes in the level and diversity of risk appetites across the financial system. Pooled datasets provide the opportunity to observe the extent of this dispersion.

2. Emphasis on historical data

Although credit-worthy obligors are more difficult to calibrate due to lower historical defaults, this modelling work leverages the internal "information capital" generated by each lending institution and can effectively supplement the estimation of credit risk. Pooled datasets record the outputs of the broad, deep and diverse modelling effort within IRB banks.

3. Uncertainty within different portfolios

The BCBS identify scope to reduce the uncertainty when calibrating low default portfolios by making better use of market derived data and credit ratings information. Pooled datasets provide a crucial additional source of credit risk information, especially when ratings or market implied estimates are unavailable.

Key Data Observations

1) Variability

- Changes in variability of estimates over time: Where there are at least 3 estimates on an individual obligor, it is possible to calculate an average PD and LGD. CB also publish the standard deviation of the estimates provided by each contributor. Exhibits 1.1 and 1.2 show that the average PD across a portfolio of 62 global banks has almost doubled between December 2011 and February 2016. However, the normalized variability[2] of those estimates is lower. The data shows that the variance of opinion has reduced since the Basel Committee initially ran its own analysis on PD estimates.

Global bank portfolio metrics, Dec 2011 – Feb 2016

Exhibit 1.1 Average PD (Bps)

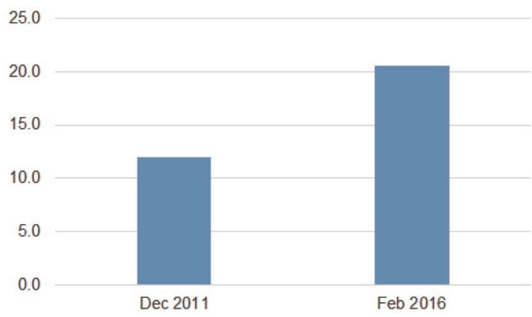
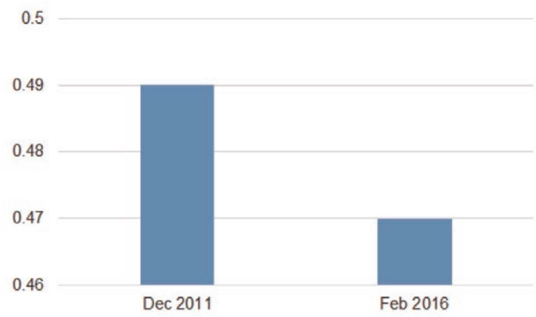


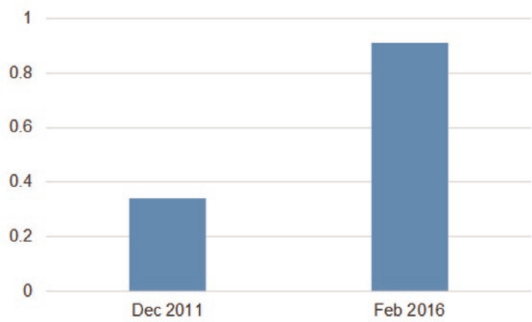
Exhibit 1.2 Relative Standard Deviation



Reduced variance may raise a concern about mean reversion across banks, implying more limited diversity of opinion and increased systemic risk.

Exhibit 1.3 shows that skewness has increased for the same global bank portfolio between 2011 and 2016 despite the fall in variance. The increase in skewness suggests that although the variance in estimates has fallen, the diversity of opinion within these bands has increased.

Exhibit 1.3: Skewness of global bank portfolio, Dec 2011 – Feb 2016



Such diversity of opinion is not only the case for corporates where there is limited information but also for large corporates that might fall under the new standardized approach. For example, Apple is rated AA+ by S&P, whereas IRB banks have a more diverse and more conservative outlook.

[2] Measured by the Coefficient of Variation.

Exhibit 1.4 shows the relationship between PD and Standard Deviation for 4000 quorate obligors. This shows that there is a clear, positive relationship and implies that there is more uncertainty about credit risk in lower quality names. Exhibit 1.5 further shows that this uncertainty is proportionately somewhat higher in the lower quality names.

Exhibit 1.4 Average PD vs Std. Deviation

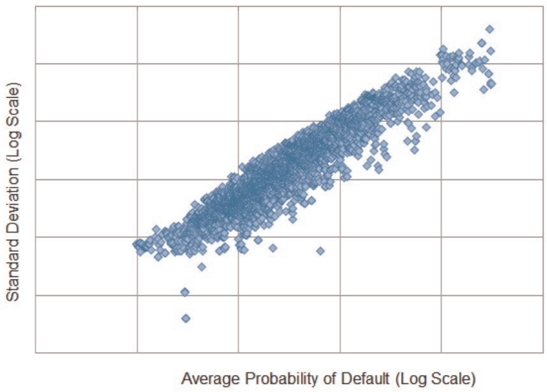
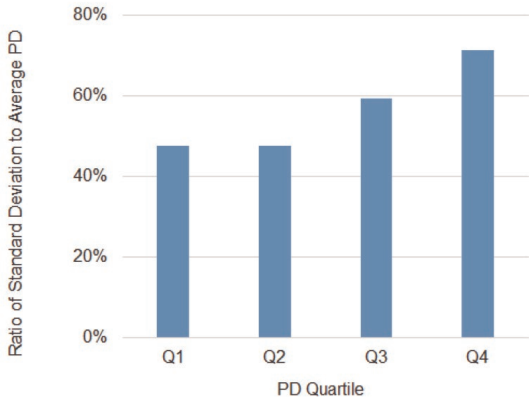


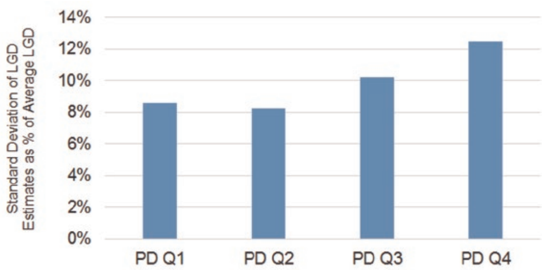
Exhibit 1.5 Ratio of Std. Deviation to Avg. PD



Some banks have commented that the proportionately lower range of PD estimates for the higher quality names raises some questions about the BCBS view that the range of credit risk estimates for Large Corporates is particularly high due to the lack of historical default data. It depends, in part, on the congruence between Large Corporations and low PD names; and it is possible that the BCBS view is that the ranges shown here are still too high given the amount of public data which is available on these names. Exhibits 1.4 and 1.5 do allow this discussion to be quantified.

Exhibit 1.6 shows the same analysis for Senior Unsecured Corporate LGD estimates, again grouped by PD quartile as in Exhibit 1.5. This shows that the proportionate standard deviation of LGD estimates is lower for the highest quality obligors. To the extent that the largest corporates are also the highest quality corporates, this suggests that the uncertainty over losses/recovery rates is also lower as a % of the assumed loss / recovery level.

Exhibit 1.6: Ratio of Std. Deviation to Average for Senior Unsecured LGD



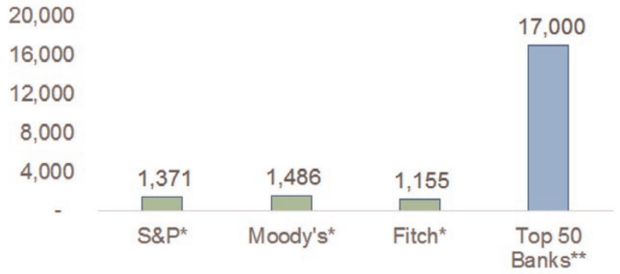
However, the majority of banks and non-bank financials do not have ratings or liquid secondary market credit signals.[3]

[3] The Bankscope database of global banks contains fundamentals on 32,000 for which there are around 5,000 unique ratings http://www.bvdinfo.com/en- gb/about-us/brochure-library/brochures/bankscope The universe of single name CDS is only 2,600 http://www.markit.com/Product/Pricing-Data-CDS-End- Of-Day

2) Credit Rating Agency ("CRA") ratings

- Exhibit 2.1 shows estimates of the number of full time credit analysts in the main rating agencies and the Top 50 banks. This implies that consensus estimates of credit risk sourced from banks are drawing on four times the number of analysts. This is mainly due to the much larger number of obligors that need to be assessed by banks but it demonstrates the depth of analysis which is embodied in crowd sourced credit views.

Exhibit 2.1 Comparison of credit analysis resources



- *Source: SEC Annual Report on NRSROs, 2015
- ** Source: Bank disclosures & Credit Benchmark estimates

Credit Benchmark receives more than 500,000 obligor observations, updated each month. Most of these are unique, and many of them cover the SME and investment fund sectors.

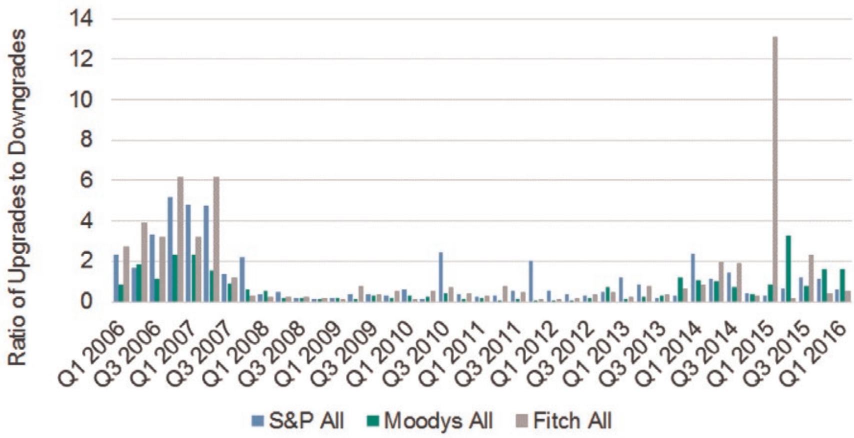
These can be mapped to a very large range of summary groups for portfolio benchmarking purposes. Beyond SMEs and Funds, the mapped universe of more than 130,000 obligors covers Sovereigns, Financials and Corporates.

The quorate universe of single obligors covers more than 4000 names and around 50% of those are not covered by S&P. The semi-quorate universe (where one more contributing bank would result in a quorate estimate) is close to 8000 obligors. This means that the single name quorate universe will soon be larger than that of the main CRAs.

Where credit ratings do exist (which as highlighted above is a small percentage of the overall wholesale book), the ratings themselves tend to show reasonable stability punctuated by dramatic shifts in upgrades or downgrades; these probably correspond to adjustments to ratings models, leading to sudden changes in perceived credit risk.

Exhibits 2.2 to 2.5 show these patterns for the 3 main rating agencies.

Exhibit 2.2: Variation in CRA opinions over time: ratio of downgrades to upgrades



When comparing the upgrade / downgrade ratio for European Financials since Q1 2014, we find that even during this short period of time there is a great deal of volatility in upgrades and downgrades.

However, Exhibit 2.6 shows that the internal PD estimates from IRB banks show much less variability, and, critically, also demonstrates a trend in credit quality.

Ratio of CRA downgrades to upgrades compared with Credit Benchmark PD estimates

Exhibit 2.3 S&P

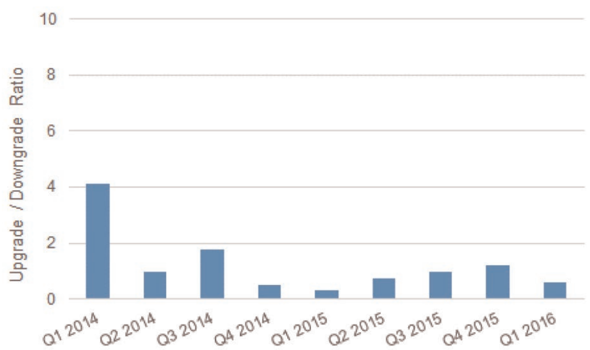


Exhibit 2.4 Moody's

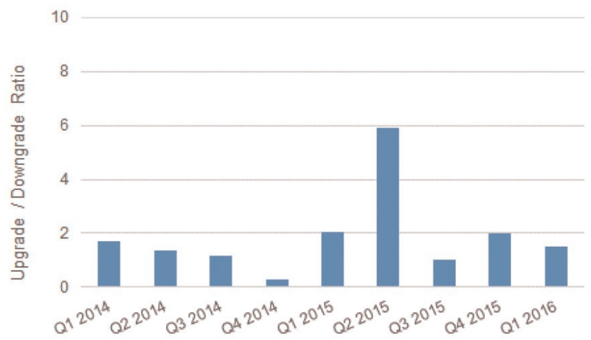


Exhibit 2.5 Fitch

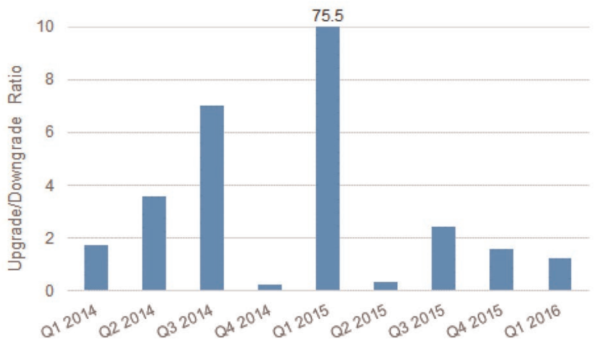


Exhibit 2.6 Credit Benchmark PD trend

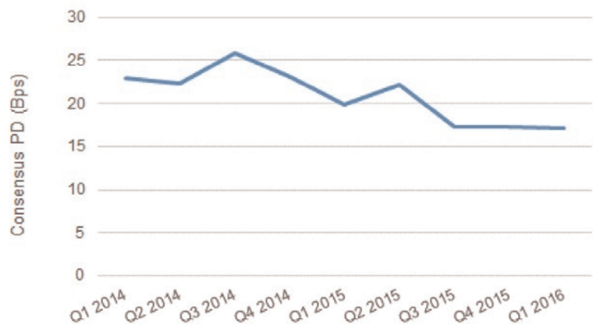
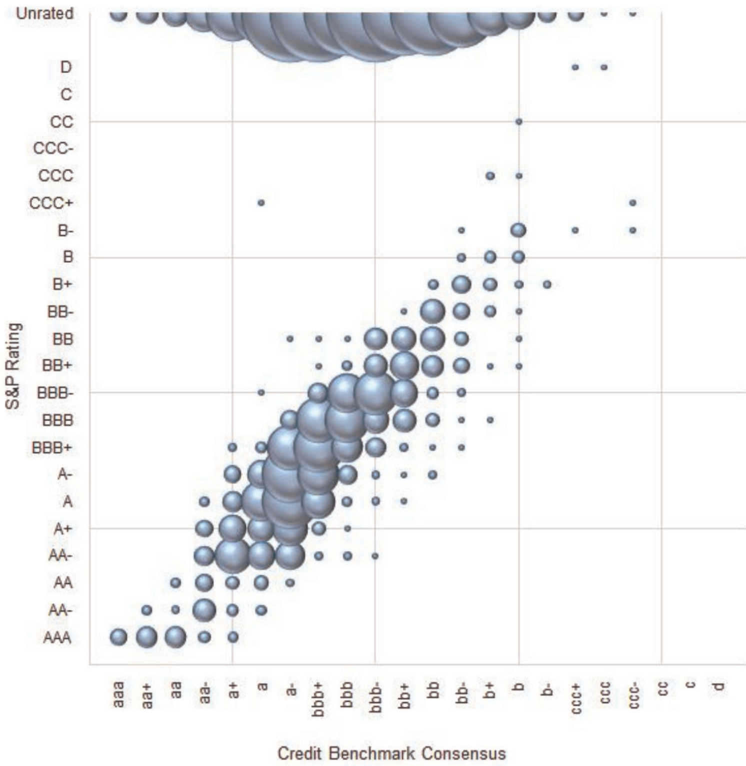


Exhibit 2.7 shows the relationship between the CBC[4] vs S&P for the quorate[5] names. Each point represents names in each CBC or S&P category, with the size of the bubbles representing the number of entities in each category. This shows a relationship that is very close to a 45-degree line, but the outliers tend to be below and to the right of this line. This suggests that contributors are more cautious than rating agencies when assessing credit risk on a like for like name basis. The bubbles at the top of the chart actually show the names that are not rated by S&P. This shows that the unrated names cover most of the credit risk spectrum.

Exhibit 2.7: Comparison of Credit Benchmark Consensus and S&P Long Term ratings



[4] The Credit Benchmark Consensus ("CBC") is a 21-category scale. Each category represents a PD range so any calculated PD can be translated into a credit category.

[5] Quorate names are single obligors where at least 3 banks have contributed current PD estimates.

Exhibit 2.8 shows a comparison of CBC and S&P for the main obligor types in European developed economies. This shows that for key sectors – Sovereigns and Banks – the opinion of IRB banks tends to be more conservative by up to a full notch than the S&P equivalent. In essence the variability in risk weights in the instance of systemically important asset classes is in fact more conservative than the standardized approach.

The analysis also shows that European corporates are rated slightly higher than S&P, although the differences are less than a full notch. Increasing risk weights in this asset class may result in a higher cost of funding for some corporates, even though corporates are less of a contributor to systemic risk than banks and sovereigns.

Exhibit 2.8: Comparison of main quorate obligor types by rating

Europe	CBC	S&P
Corporate	bbb+/bbb	BBB+/BBB
Bank	a-/bbb+	A/A-
Sovereign	aa/aa-	AA+/AA

Exhibits 2.9 and 2.10 shows a CBC /S&P comparison of the major developed economy Sovereigns. This shows that the conservative stance noted in Exhibit 2.7 is observed across the entire credit spectrum.

Exhibit 2.9: Sovereign Comparisons by Rating - 1

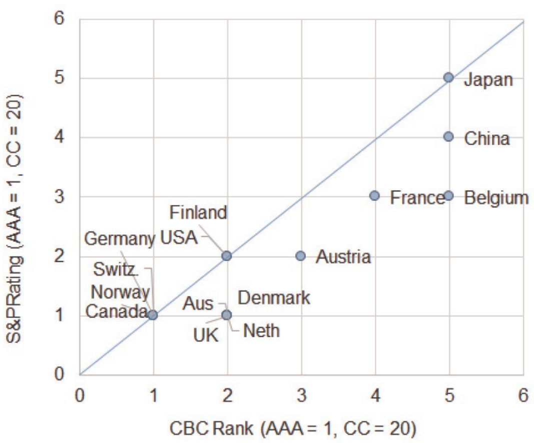
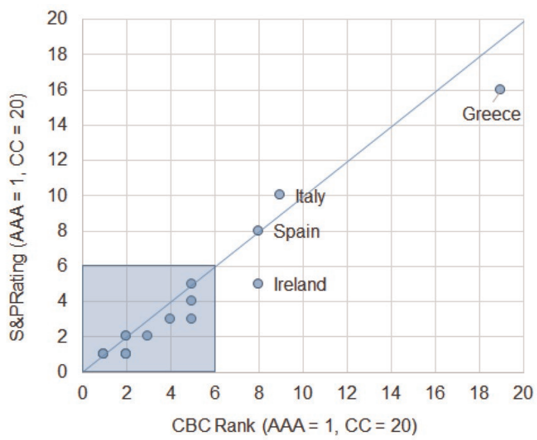


Exhibit 2.10: Sovereign Comparisons by Rating - 2



3) Market Derived

- The issues with market-implied measures are similar to those with credit ratings: it assumes that secondary market data is available, and that the assessments of credit risk implied by the secondary market are always correct. As a counter-example, the implied volatility 'smile' which is now a standard feature of option pricing only came into existence after the 1987 equity market crash.

There is evidence[6] that credit markets tend to underestimate risk of banks and sovereigns during credit booms. To maximize the resilience of the financial system, capital requirements need to be based on opinions that include additional qualitative information and analyze credit risk through an entire cycle.

Exhibits 3.1 and 3.2 show that CDS prices contain a significant risk premium, and Exhibit 3.3 shows that this risk premium varies over time. It is possible to correct for this distortion, but to do so requires robust 'real world' PD estimates source from IRB banks. This type of analysis provides a link between market derived and fundamental estimates of credit risk, and access to this helps banks to improve their mark-to-market counterparty credit risk exposure. Regularly updated sets of risk premiums can also facilitate the calibration of recognizing losses as part of the new IFRS 9 rules.

Exhibit 3.1 Sovereign Comparisons by CDS

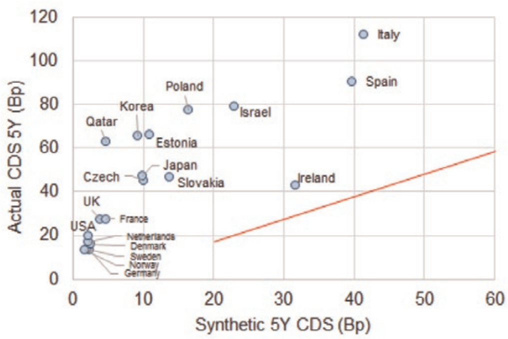


Exhibit 3.2 GSIB Comparisons by CDS

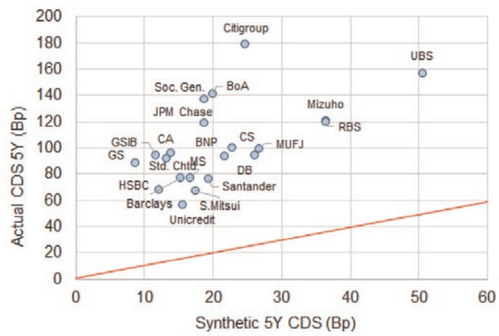
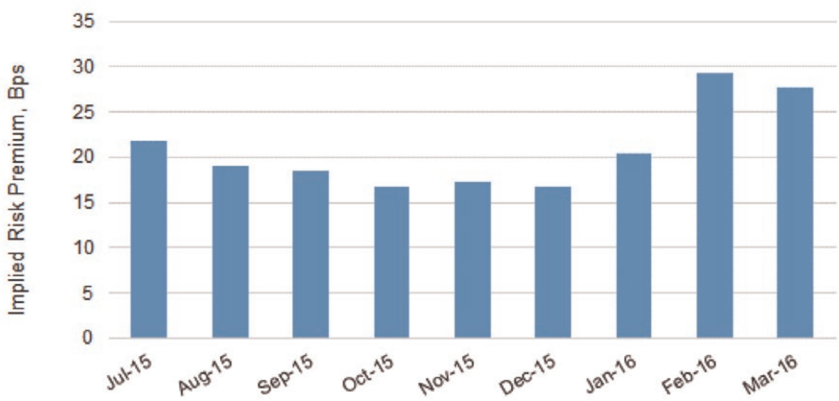


Exhibit 3.3 Sovereign Risk Premium time series (Median of 17[7] IG Sovereign CDS)



[6] See, for example, Profiting from Monetary Policy (Thomas Aubrey) 2012, P10 for a comparison of Greek and German CDS in July 2007.

[7] Australia, Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK, USA. This list is based on IG Sovereigns where a full time series is available for CDS, PD and LGD values.

4) Scope for Adverse Risk Selection and Impact of Floors

The standardized approach has the advantage of providing Regulators with clear comparisons between banks, but has the disadvantage that it standardizes the bank view of risk with respect to Regulatory Capital. The aim of the current proposals is to only use internal models where each bank has an information advantage.

If this results in adverse risk selection through crowding into high quality exposures then the resulting 'Regulatory Capital Premium' is likely to distort the flow of funds and pricing in other segments. Such distortions have occurred before (e.g. 2008) and may add to systemic risk.

Large Corporates and Banks – Imposing the standardized approach on a broader range of banks and asset classes may have some impact on the effective functioning of any market relies on a diversity of opinion. Such diversity is possible even with the same information – for example, large financial institutions take very different views of Apple Inc., depending on whether they focus on its cash rich balance sheet or its innovation driven business model. There are around 28,000 unrated banks (including unrated subsidiaries of rated banks) and the use of rated proxies or market derived data may lead to some distortions.

Sovereigns – depending on the final outcome of the measured and cautious discussions in this area, it is possible that standardization will work better for some countries than for others depending on their short term market funding needs as well as their outstanding stock of Government bonds. Some regional banks may need to concentrate collateral holdings in the bonds of their own Government.

Funds – Some banks, especially those involved in trust banking and custody, differentiate between funds according to their risk characteristics in a way that the BCBS proposals do not. Broadly, the banks assign higher risk to leveraged funds (such as hedge funds, investment trusts with gearing, and sophisticated UCITS funds); and within the unleveraged category they differentiate between funds with variable liabilities (such as pension funds) and those without (such as the majority of mutual funds). They also distinguish between the fund management company and the fund itself.

Exhibits 4.1 and 4.2 show the distribution of Senior Unsecured Ex Ante LGD for Pension Funds and Mutual Funds respectively. This shows that the banks are conservative with respect to mutual funds but that there are some pension funds where standardized risk weights would imply a significant increase in LGD and capital requirements.

Exhibit 4.1 All Pension Funds (Non Quorate)

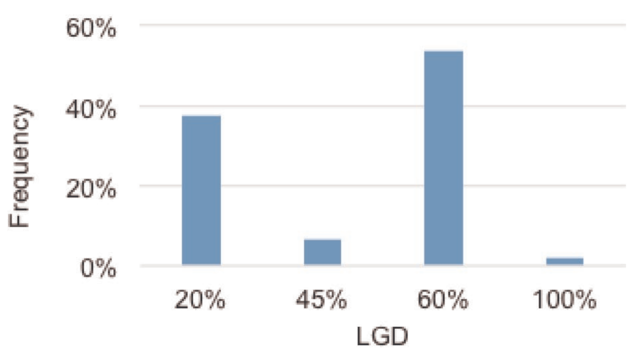
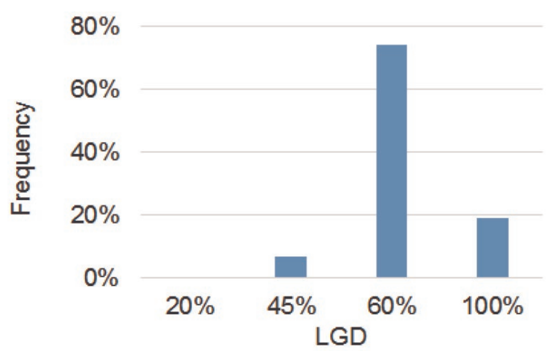


Exhibit 4.2 All Mutual Funds (Non Quorate)



This shows that the bank estimates of LGDs recognize these differences. Depending on how the BCBS proposals are applied in this area – treating funds as financial institutions or corporates – the capital requirements in this sector may increase dramatically; especially if all funds are treated as Financial Institutions. Some banks see a potential increase in the cost of pension products with implications for the savings ratio and/or the risk and asset allocation of savings.

For Corporates, there is a proposal to apply floors to PD (5bp) and LGD (25%, Senior unsecured) values. Exhibits 4.3 and 4.4 show the distribution of 140,000 contributed observations across the PD range for funds and corporates respectively.

Exhibit 4.3 Distribution of Fund PDs

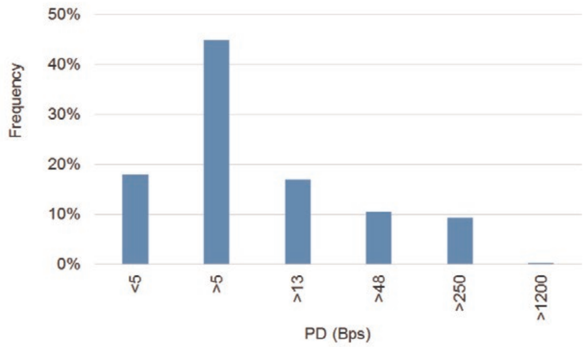


Exhibit 4.4 Distribution of Corporate PDs

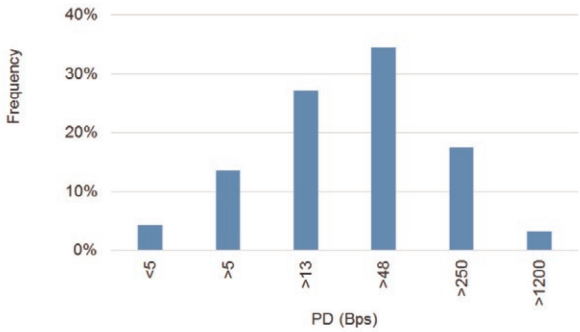


Exhibit 4.3 shows that some funds (mainly pension and mutual funds) will be affected significantly by these proposals – 18% (out of 28,000 observations) have PDs of less than 5 Bps. This appears to be an anomaly, since there are very few instances of default in these asset types. As Exhibit 4.1.1 shows, this impact will be particularly concentrated in pension funds.

Exhibit 4.4 shows that the impact on corporates will be limited, with just 4% (out of 75,000 observations) have PDs of less than 5 Bps.

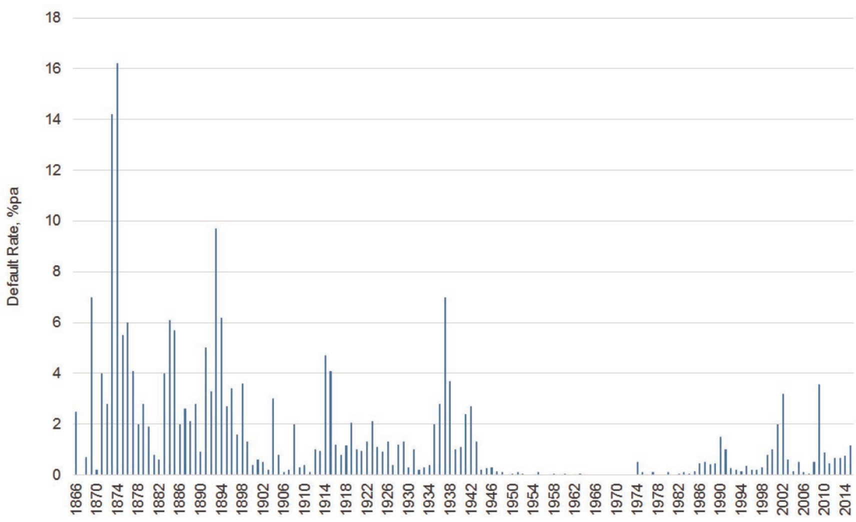
The impact of the LGD floor is also more limited – based on 96,000 observations, just 3% of the fund estimates and 1% of the corporate estimates were less than 25%.

SMEs – Although these are eligible for IRB under the new proposals, Credit Benchmark see wide support from the banking community to develop a pooled database of SME indices / portfolios for benchmarking and risk analysis. The approach is likely to use clustering based on a very large range of sub sectors and business descriptors. This suggests that banks see significant value in benchmarking to an expert peer group rather than only relying on their individual view for IRB model validation.

Under the new proposals, PD models will need to be consistent with default histories, using a minimum 7- year historical period. Although the default history for SMEs will show some different characteristics compared with large corporates, it is useful to understand the dynamics of default histories in general.

Exhibit 4.5 shows the estimated annual default rate in US Corporate bonds (all credit classes) over the past 150 years. This shows the importance of long run structural changes in economies, in funding sources, and in levels of Government support. It also shows that defaults tend to occur in clusters in time.

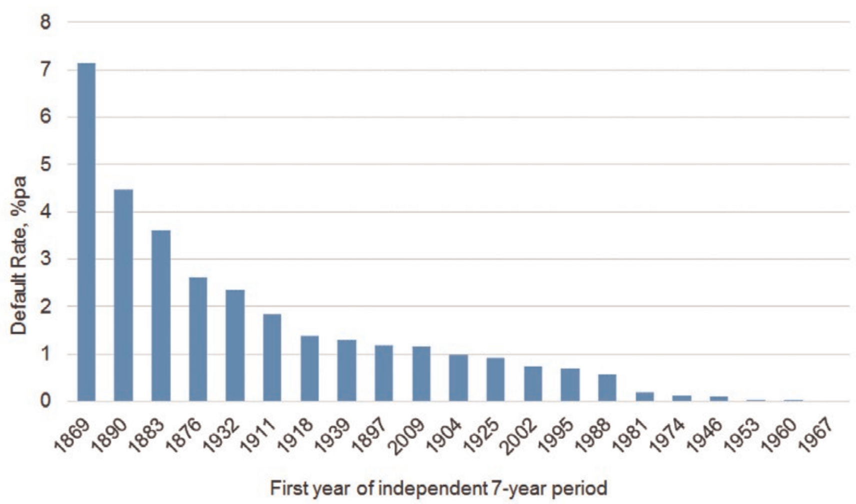
Exhibit 4.5 Annual default rates, US Corporate Bonds, All Credit Classes, 1866-2015



› Sources: NBER, Moody's, Bank of America, J.P. Morgan, S&P, Fitch. Estimates from multiple sources have been pooled for the period 2008-2015; data prior to 2008 is from the NBER study[8]. Estimates for 2008-2015 are provisional and subject to revision.

Exhibit 4.6 shows the same data divided into independent 7-year periods. This shows the considerable variation in average default rates depending on the period chosen – anything from close to zero up to 7%.

Exhibit 4.6 Annual default rates, averaged over independent 7-year periods



It is also worth noting that, as shown by the performance of sub-prime loans during the financial crisis, sole dependence on historical data can lead to persistent underestimation of credit risk. Furthermore, while the historical instances of bank defaults in Europe appears to be low, this is mainly due to the high rate of bank failures followed by subsequent government bailouts.[9]

[8] CORPORATE BOND DEFAULT RISK: A 150-YEAR PERSPECTIVE. (NBER) Kay Giesecke, Francis A. Longstaff, Stephen Schaefer, Ilya Strebulaev Working Paper 15848 http://www.nber.org/papers/w15848

[9] According to Fitch the bank default rate is 1.15% versus a 6.95% failure rate https://www.euroclear.com/dam/Brochures/About/Fitch-sovereign-support-for- banks.pdf

Appendix 1: Comparison to standardized approach of distribution of Ex Ante LGDs, by asset class

Credit Benchmark receive Ex Ante, Senior Unsecured Loss given Default estimates. Detailed distributions of the most recent set of quorate (smaller sample of multi-banked obligors) and non-quorate (larger sample of single bank obligors) estimates (February 2016) for Sovereign, Financial and Corporate obligors are shown in Exhibits A.1 – A.6 below.

Senior Unsecured LGD Estimate Distributions

Exhibit A.1.1: Sovereigns (Quorate)

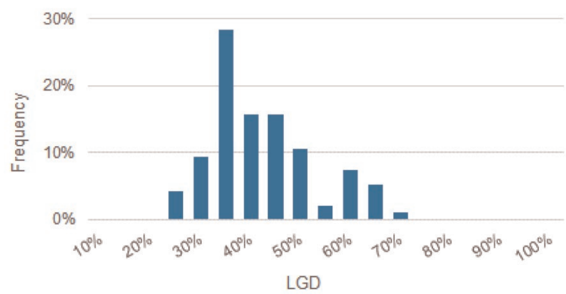


Exhibit A.1.2: Sovereigns (Non Quorate)

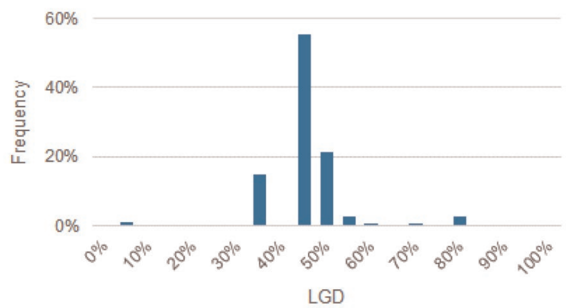


Exhibit A.1.3: Financials (Quorate)

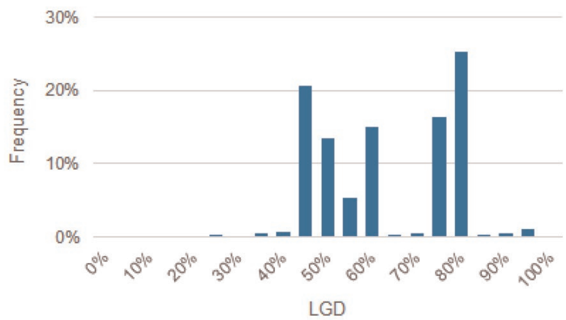


Exhibit A.1.4: Financials (Non Quorate)

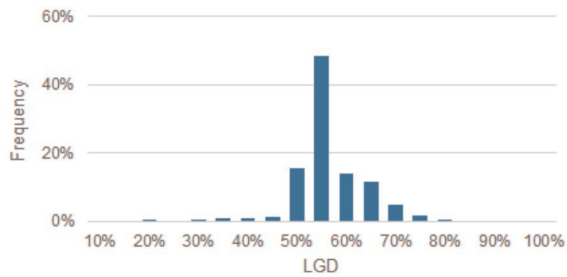


Exhibit A.1.5: Corporates (Quorate)

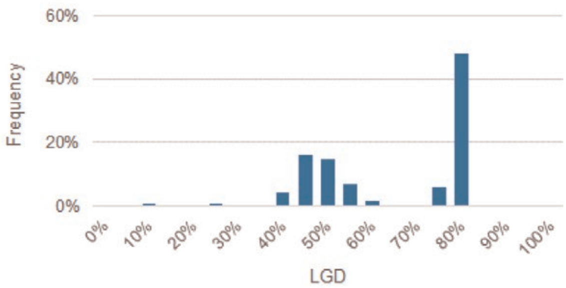
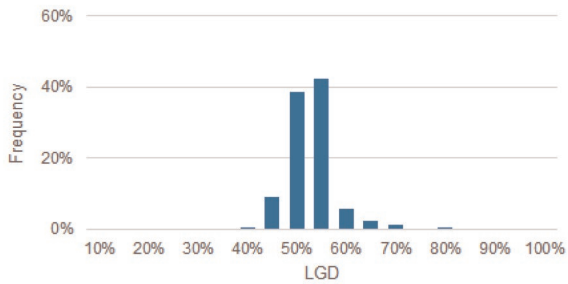


Exhibit A.1.6: Corporates (Non Quorate)

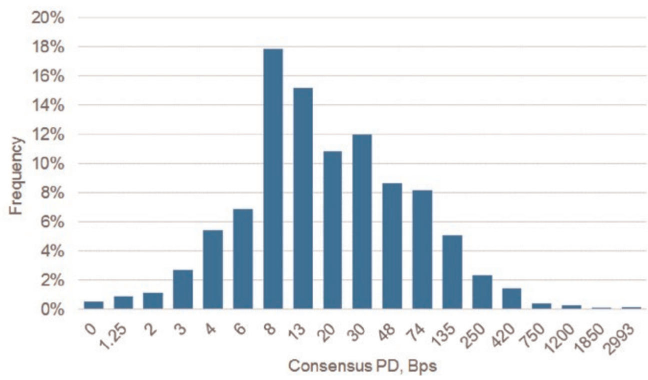


The Credit Benchmark analysis shows the considerable current extent of prudent risk management within IRB banks. For LGDs, IRB banks demonstrate a clear risk differentiation between obligors, with the "majority of obligors" above the standardized levels of 45% in financial institutions and corporates. The data also shows that for sovereigns, LGDs are on the whole at or lower than the 45% level.

Appendix 2: Distribution of Ex Ante Probabilities of Default

Exhibit A.2.1 shows the distribution of quorate PDs in March 2016. This shows a familiar, single peaked but skewed shape. It shows that the majority of obligors have PDs in the range 8Bps – 30 Bps (i.e. investment grade) and number of exposures drops off rapidly beyond 74 Bps. The Credit Benchmark Methodology Committee currently use an Investment Grade / Non-Investment Grade threshold of 48Bps.

Exhibit A.2.1 Distribution of quorate PDs, all asset types, March 2016



Appendix 3: Leverage Ratio: long term dynamics

Exhibit A3.1 shows Figure 5.1 taken from Profiting from Monetary Policy (Thomas Aubrey). This is an example of the dynamic and nonlinear nature of the way in which credit impacts the economy. It shows the relationship through time of the US consumer leverage ratio (debt to income ratio) versus the Wicksellian Differential (Return on capital – cost of capital).

Exhibit A3.1 Consumer Leverage Ratio and Wicksellian differential, Annual 1985 - 2010

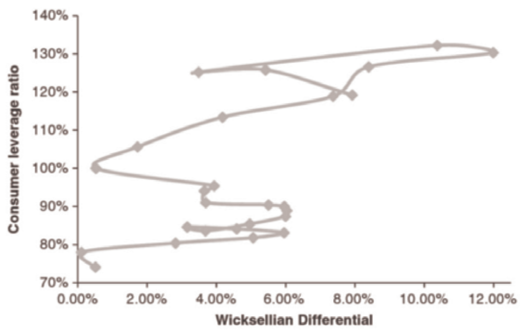


Figure 5.1 US consumer leverage ratio vs Wicksellian Differential
Source: Thomson Reuters Datastream, Credit Capital Advisory.

The chart shows that while there are periods when the consumer leverage ratio increases in line with the Wicksellian Differential, but it also shows periods of asymmetry where deleveraging coincides with a falling Wicksellian Differential. The relationship is also punctuated by periods when other factors have had a far greater impact on the behaviour of economic agents. In general, for each potential value of the Wicksellian Differential, there are multiple solutions through time. This illustrates the challenge of attempting to use historical averages, given that the underlying structure of the economy is in constant flux and this will have a significant impact on individual appetites for debt.

Conclusion

1. **Variation:** The range of PD and LGD estimates is proportionately lower for the highest quality obligors. The variation in risk estimates across contributors for the same obligor is lower in 2016 than in 2011.

2. **CRA Ratings:** IRB banks are conservative with respect to rating agencies, especially in the systemically important Sovereign and Bank obligor credit categories. Banks are required to model a very large number of obligors for which no ratings exist, including around 100,000 corporates.

3. **Market-derived estimates:** These are distorted by a time varying risk premium when compared with bank estimates. For this reason, market derived estimates are more volatile than internal model estimates. Banks are required to model a large number of obligors for which no market-derived estimates exist, especially in the SME and fund obligor categories.

4. **Floors:** IRB banks are generally conservative with respect to standardized LGD floors. However, the contributed data shows that the use of LGD and PD floors will increase capital requirements for some categories of funds. Conversely, the contributed data further shows that there are some asset classes where the floors may be below the current level of risk estimates. Such anomalies increase the possibility of adverse risk selection.

5. **Visibility:** Contributor banks intend to continue to estimate Ex Ante PD and LGD values for economic capital management and stress testing, and see a growing role for contributed datasets, subject to suitable governance. The distributions and summaries in this paper offer frequent visibility to banks and regulators and allow both groups to monitor current risk assessments compared with their own risk appetites.

Credit Benchmark®

Collective Intelligence
for Global Finance

Credit Benchmark is an entirely new source of data in credit risk. We pool PD and LGD estimates from IRB banks, allowing them to unlock the value of internal ratings efforts and view their own estimates in the context of a robust and incentive-aligned industry consensus. The resultant data supports banks' credit risk management activities at portfolio and individual entity level, as well as informing model validation and calibration. The Credit Benchmark model offers full coverage of the entities that matter to banks, extending beyond Sovereigns, banks and corporates into funds, Emerging markets and SMEs.

Thomas Aubrey
Credit Risk Advisor
thomas.aubrey@creditbenchmark.com

David Carruthers
Head of Research
david.carruthers@creditbenchmark.com

Credit Benchmark

www.creditbenchmark.com
info@creditbenchmark.com
twitter: @Creditbenchmark

UK Office (London):
Eagle House, 167 City Road
London, EC1V 1AW
+44 (0)20 7099 4322

US Office (New York):
12 East 49th Street, 11th Floor
New York, NY 10017
+1 646 661 3383