

PECDC Default Rate Study 2013

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ABOUT PECDC

A cross border initiative to help measure credit risk, PECDC is a non-profit association owned by the banks who share credit data anonymously.

PECDC houses the world's largest LGD/EAD database, with over 50,000 default observations totalling over €100 billion in most non-retail Basel 2 Asset Classes from 38 member banks across Europe, Africa, North America, Asia and Australia.

PECDC also has the world's largest PD database of defaults and PD estimates for large corporates, banks, SMEs and specialised lending.

Created 'by banks, for banks'

CONTACT PECDC

Philip Winckle, Executive Director
Philip.winckle@pecdc.org

Steve Bennett, North America
steve.bennett@pecdc.org

www.pecdc.org

SUMMARY

This report shows an excerpt of the fourth Observed Default Frequency Study run by PECDC using data from 17 of its member banks. The annual study enables participants to benchmark the calibration and performance of their rating systems and their credit portfolios. PECDC members benefit from receiving the detailed data collected in this study and a comprehensive report comparing their data with the total study. In this report we focus primarily on results for the asset class Large Corporates.

The 2013 study uses the portfolio and default observations from 17 banks over 10 years, being 2003 to 2012. It covers most non-retail asset classes: SME, Large Corporates, Banks, Central Banks, Hedge Funds, Pension Funds, Mutual Fund Managers, Financial Market Companies, Aircraft Finance, Shipping Finance, Real Estate Finance, Project Finance, Commodity Finance and Sovereigns. The observations and categorization comply with the definitions of Basel 2.

All banks in this study submitted ratings and PD estimates based on a Through-The-Cycle rating ("TTC") method; i.e. estimates which do not primarily attempt to predict business cycle fluctuations in the default rate and thus are expected to be relatively stable over time.

In **summary**, the study looks at:

- **Default estimates (PD)** over time and in comparison to the observed default frequency. Study participants are able to compare their PD rates for different asset classes and grades to those of other banks and to compare the difference between PD and outcome with that observed at other banks;
- **Actual default frequencies** are observed for Large Corporates. These have been compared to the levels published by Standard and Poor's for the equivalent rating grades in the same years enabling participants to review the use of different external data sets.
- **Discriminatory power** of the banks' PD models is measured through the accuracy ratio. Study participants are able to compare the accuracy ratios of their risk grading systems to their anonymised peers;
- **Empirical asset correlations** are calculated for each bank's data and the combined data set assuming a Vasicek distribution. Study participants can use the inter asset and inter sector correlations as input for internal capital models, as a complement to correlations derived from bonds or equity price movements.

INTRODUCTION

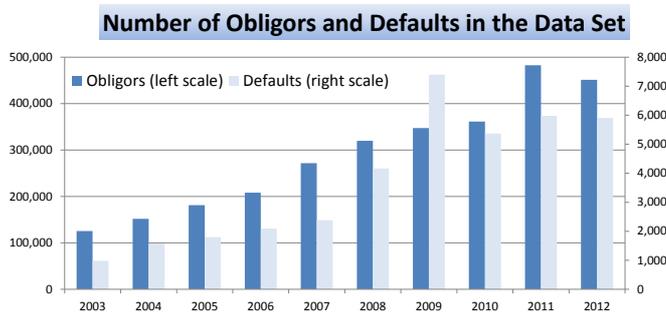
PECDC – established in 2004 – started with the collection of historical LGD and EAD observations. In 2006 the member banks decided on a data template for Observed Default Frequencies (ODF), and the data collections have been carried out regularly since then.

The ODF study compares the number of obligor defaults in a particular year to the total number of obligors on January 1st in that year. Results are grouped by bank internal ratings mapped to the S&P rating scale, bank internal PD estimates, GICS industry codes, country or region and asset class. Definitions used are aligned with Basel 2 definitions.

COMPOSITION OF THE DATABASE

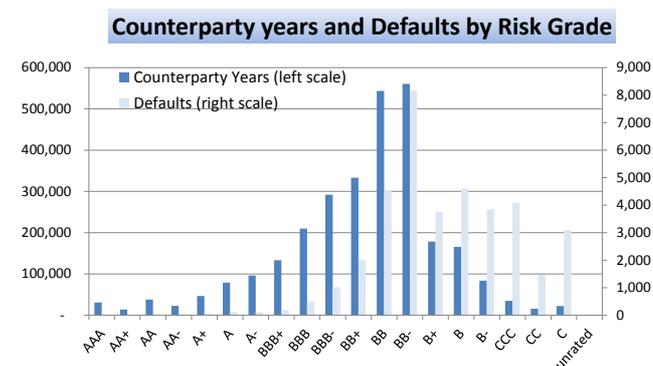
The data contributed by participating banks comprised 37,634 defaults coming from 2.9 million “counterparty years” (i.e. counting a counterparty for each year it is reported). The actual number of unique counterparties is likely to be much smaller as they are counted at January 1st of each year between 2003 and 2012. Apart from the unidentified multiple defaults and the overlap in reporting between banks, the defaults are unique. The data was collected from 17 banks from Europe, Australia, South Africa and North America.

EXHIBIT 1



Note that the number of banks delivering data for each Asset Class and Year varies throughout the study, for example recent years have data from more banks than older years. Therefore the time series for the number of defaults is not completely consistent, although it does show the 2009 downturn experienced by many contributors

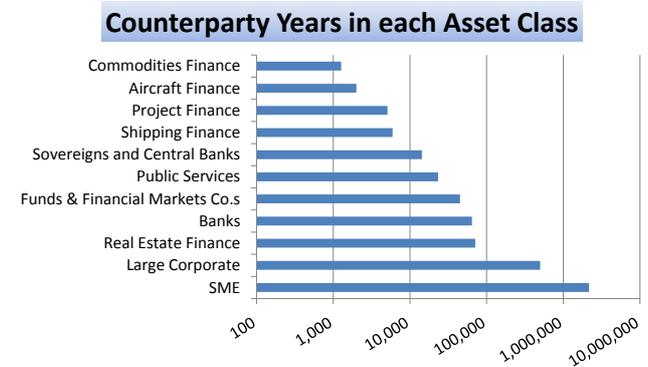
EXHIBIT 2



The data delivered reflects the portfolios of the participating banks, with most of the data below investment grade.

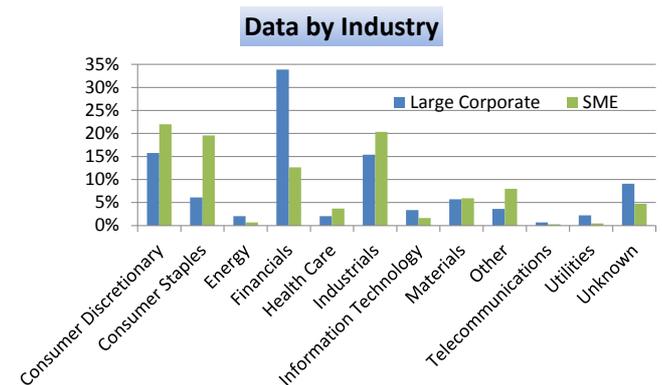
Exhibit 3 shows the volume of data per Asset Class in “counterparty years”, using a log scale. Large Corporates and SME have the most observations allowing stable analyses and a drill-down into regions and industries.

EXHIBIT 3



For asset classes Large Corporate and SME, where distinguishing per industry is most relevant, there are sufficient observations to make such a distinction both possible and meaningful, as shown in exhibit 4.

EXHIBIT 4



Telecom, financials, information technology and utilities are better represented in Large Corporates whereas consumer staples are better represented in SME. We also calculate the ODF and PD per industry for SME and Large Corporates.

The observations made in the remainder of this report focus mainly on the asset class Large Corporate, as this data is comparable globally. SME data is more numerous but due to local variation it is normally studied by participants on a regional or country level.

NOTE ON TERMS USED

PD refers to the forward looking estimate of Probability of Default. PECDC concentrates on the 1 year probability which is valid at any time in a business cycle, termed **TTC** for Through-The-Cycle.

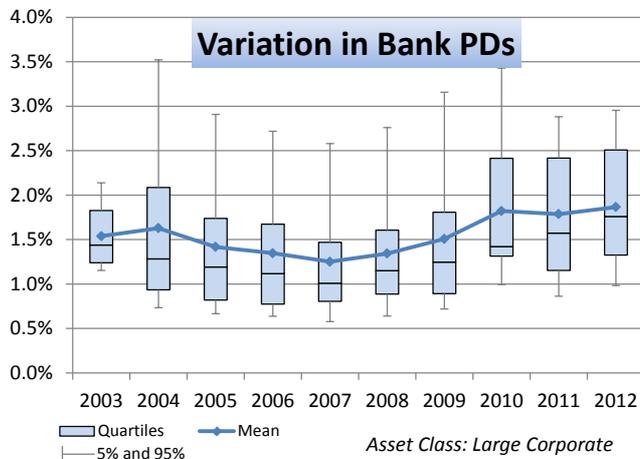
ODF refers to the backward looking rate of default and stands for Observed Default Frequency. Rating Agencies often refer to this as the **Default Rate**.

PD AND DEFAULT VARIATION

RWA is a regulatory approved measure of banks' assets and off-balance sheet exposures, weighted according to risk. Since the introduction of Basel 2, banks have been allowed – under certain approaches – to calculate the key determinants for the measurement of RWA. These determinants are PD, LGD, EAD and Maturity. This study enables banks to compare the variations in their PDs.

Banks have different portfolios, different underwriting policies and different views on the credit risk of individual counterparties and therefore we would expect to see variation in both their PD and ODF.

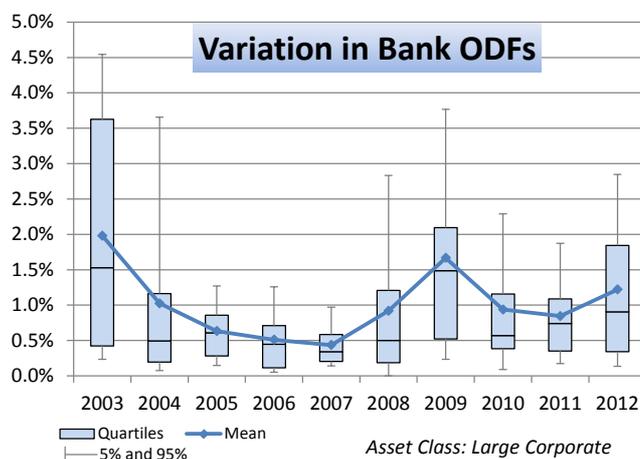
EXHIBIT 5



Uniquely, the ODF Study by PECDC has the data that facilitates the comparison of the variation in PDs and defaults between banks. In Exhibit 5 we show the TTC PD per bank per year in the form of Whisker plots showing percentiles of 5% and 95% and boxes showing 25% and 75%, respectively. In addition, the median is indicated by a line within each box and the average TTC PD of all banks is shown as a continuous line.

The PD differences for the estimates per bank inevitably are a cause of differences in the calculated RWAs. When we look at the same plot but for ODF (Exhibit 6) we also see significant differences between individual banks.

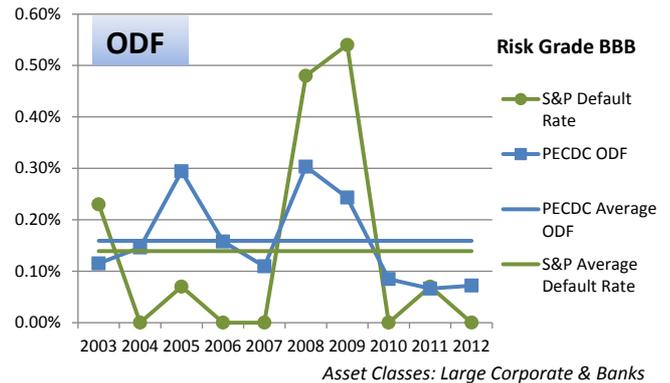
EXHIBIT 6



BANK COUNTERPARTY DEFAULTS VERSUS RATING AGENCY DEFAULTS

Using data made publicly available by Standard and Poor's¹ we are able to compare the ODF of bank loan books to that of a global pool of rated corporate bonds and loans, using the same risk grades. Note that Exhibit 7 covers both asset classes Large Corporate and Banks in order to use the maximum data available from the rating agency.

EXHIBIT 7



The difference in volatility of the portfolios is seen in the example of Risk Grade BBB above, where Standard and Poor's data comes from 1637 issued ratings (including BBB+ and BBB-) as at December 2012 while PECDC data includes more than 10 times that number of obligors. PECDC data had a similar average ODF but much lower volatility.

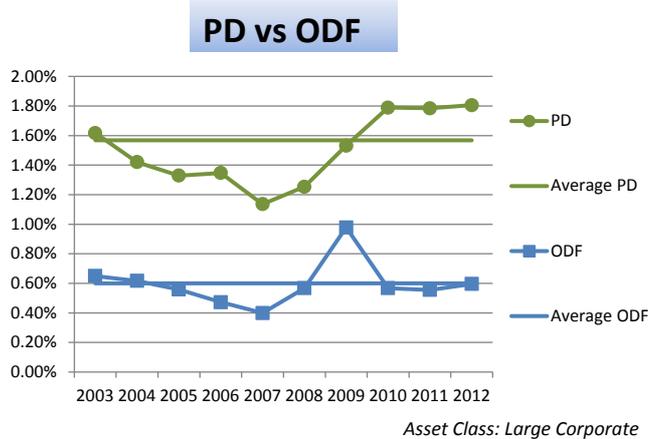
Lower volatility is expected when data volumes are increased, however the difference also points to a fundamental difference between the PECDC data, which is sourced from loans by banks, and rating agency data, which is restricted to externally rated counterparties only and therefore comprises mainly bonds and bond defaults. There is also a difference in the average borrower size, where PECDC data comprises bank loans to large corporates with €50m or greater turnover (Basel definition) while rating agencies generally cover only the larger end of this range.

The comparison is similar for other Risk Grades where pooled bank loan data show lower volatility than rating agency data. PECDC member banks are able to use the pooled data as an alternative benchmark when calibrating their low default portfolios and when looking for a time series of volatility in comparison to macroeconomic events, for example when performing stress tests.

¹2012 Annual Global Corporate Default Study And Rating Transitions. Publication date: 18-Mar-2013 www.standardandpoors.com

PD VERSUS OBSERVED DEFAULTS

In Exhibit 8 we plot the average ODF and PD of all the banks where the averages are obligor weighted and not bank weighted as in exhibit 5 and 6.

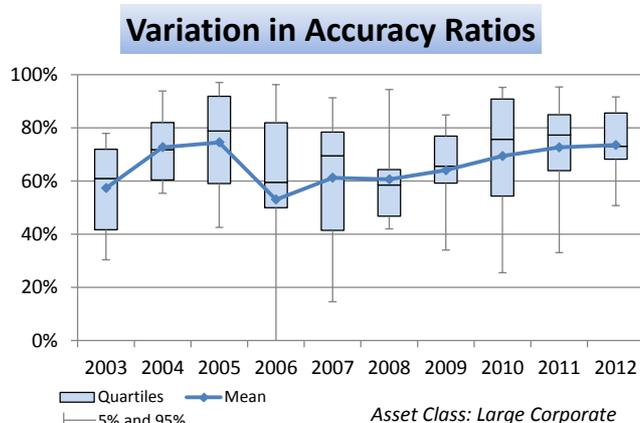
EXHIBIT 8


The banks in this study reported their estimates on the basis of a TTC rating methodology which implies a relatively stable PD. In the economic recession year of 2009 the ODF rises, as does the PD. Until 2009 the PD shows a similar trend to the ODF, but then remains higher and does not level back down in 2010, 2011 and 2012 as the ODF does. The average PD for Large Corporates exceeds the ODF over the whole observation period. It should however be noted by reference to Exhibit 6 that many of the banks incurred ODF levels in 2009 higher than the average PD shown here and indeed higher than their own PD levels.

Study participants are able to use this data to determine the level of conservatism of their own and other banks TTC-rating systems over time periods of economic growth and decline.

COMPARISON OF RATING MODEL ACCURACY

The Whisker plots of the Accuracy Ratio's (AR)² for PD scales from selected banks are displayed in Exhibit 9. A score of 0% means that the model performed equal to a random model. A score of 100% means that all observed defaults occurred in the worst risk rating category; indicating the perfect model.

EXHIBIT 9


Most banks showed Accuracy Ratios of 60% to 80% or above which suggests good to strong discriminatory power. Study participants are able to compare the accuracy ratios of their risk grading systems to anonymised peers.

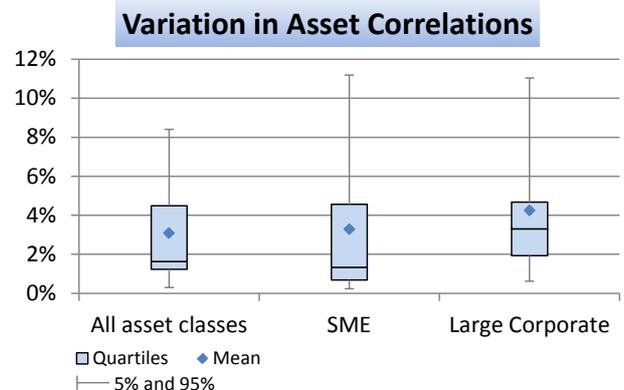
²For the definition of Accuracy Ratio, see "Testing rating Accuracy", Engelmann, Hayden & Tasche, Risk Jan 2003.

ASSET CORRELATION

The Basel II framework for regulatory capital using the Internal Ratings-Based (IRB) approach sets a fixed correlation for each asset class. For corporate portfolios this value is 12% - 24% while for SME it is 8% - 24%, dependent upon annual sales of the borrower group. Rating agencies and others also publish correlation studies based on bond default and equity price data. For example, from US Bank loss data Fitch³ estimates corporate correlation in the range 4.1% - 6.1%.

PECDC's default database is based on the Basel II default definition and therefore we are able to extract asset correlations consistent with the Basel II methodology. PECDC calculates asset correlations at bank level and at asset class level.

Different methods exist to extract the correlation information present in the ODF time series, when assuming a single factor model. We show in Exhibit 10 asset correlations calculated on each contributing bank's data set using the method presented by Fitch³. We have performed this on each bank's total data set, their SME alone and their Large Corporates alone. The whisker plot shows the percentiles of 5% and 95% and boxes show 25% and 75%, respectively. The variation between banks is of interest as are the absolute levels of the calculations. Care should be taken in interpreting such data as it is likely to fluctuate with the time period chosen.

EXHIBIT 10


Study participants are able to see the detail of the correlation data extracted from observed defaults on bank loans and can compare this to the data from methods using equity and bond data as a proxy for loans. They also receive tables of inter sector correlation based on the industries submitted – which can only be obtained from large data sets. Banks can use such correlations in their economic capital and risk models.

³Fitch Ratings, "Basel III Correlations, An Empirical Analysis Reflecting the Financial Crisis", 2 November 2011.

ATTRIBUTION

This document is based on a voluntary inter-bank working group composed of PECDC member banks chaired by Michel van Beest of NIBC Bank N.V..

Working group support and analytics were performed by: Open Source Investor Services

