

C ASSESSING PORTFOLIO CREDIT RISK IN A SAMPLE OF EU LARGE AND COMPLEX BANKING GROUPS

In terms of economic capital, credit risk is the most significant risk faced by banks. This Special Feature implements a credit risk model – based on publicly available information – with the aim of developing a tool to monitor credit risk in a sample of large and complex banking groups (LCBGs) in the EU. The results indicate varying credit risk profiles across these LCBGs and over time. Notwithstanding some caveats, these results demonstrate the potential value of this approach for monitoring financial stability.

INTRODUCTION

The art of quantifying credit risk has advanced markedly since the late 1990s with the development and dissemination of models that permit the quantification of credit risk on a portfolio basis.¹ Broadly speaking, this can be attributed to advances in analytical methods of implementing these models; to the necessity of quantifying credit risk accurately in order to allocate capital efficiently within banks; and to regulatory developments such as the Basel II Capital Accord. As credit risk tends to be the largest source of risk for banks, any additional tool that could further aid the assessment of credit risk in EU LCBGs would be a useful addition to the financial stability monitoring tool kit.

This is particularly relevant for central banks that, like the ECB, lack supervisory responsibility and consequently access to supervisory data. The usefulness of these models as tools for financial sector assessment and financial stability work has been noted previously by the IMF, by the Bank of England and by Sveriges Riksbank. The latter in particular uses a framework of this kind to assess credit risk in the Swedish banking system.²

By way of background, this Special Feature first provides an overview of the main concepts used in credit risk modelling and the main types of

models currently used by banks for assessing loan portfolio credit risk. It then describes the implementation of one of these models, Credit Suisse Financial Products' *CreditRisk+*TM, using publicly available balance sheet information and data on implied probabilities of default to construct an indicator of credit risk among a sample of EU LCBGs.³ It concludes by assessing the usefulness of this model as a monitoring tool, and identifies where additional work could be undertaken to improve it further.

ANALYTICAL CONCEPTS

Through their function of intermediating credit in the economy, banks may experience losses as a result of defaults. These losses can vary over time and in terms of their magnitude, depending on the number of such incidents and their severity. There are two useful ways of analysing the losses incurred by banks on their loan portfolios: firstly, by looking at the overall portfolio; and secondly, by examining the individual components of the portfolio.

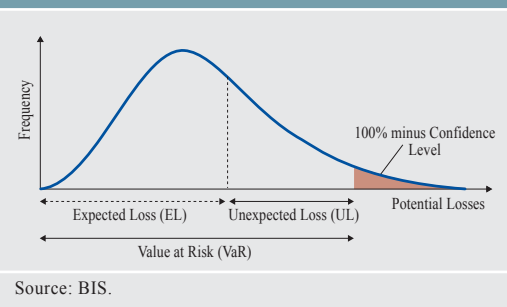
- 1 Credit risk is the risk that a borrower may be unable to repay its debt. Typically, this risk can be calculated on the basis of the probability of default. This can either be based on the fact that a default has occurred (according to the bank's own procedures or national regulations), or a credit rating migration approach. In the former, the only risk that matters is the risk of default and not of a borrower approaching a default threshold. By contrast, the latter approach deals with all mark-to-market gains and losses owing to rating changes, i.e. the migration from one rating level to another. In this Special Feature, portfolio credit risk refers to the credit risk arising from loans and other credit exposures included in the loan items of banks' financial statements, instead of exposures from structured products or from other over-the-counter (OTC) derivatives exposures.
- 2 For a detailed overview of work that inspired the analysis presented in this Special Feature, see Sveriges Riksbank (2006), "Using External Information to Measure Credit Risk", *Financial Stability Report*, 2006/1; and R. Avesani, L. Liu, A. Mirestean and J. Salvati (2006), "Review and Implementation of Credit Risk Models of the Financial Sector Assessment Program", *IMF Working Paper*, No 134.
- 3 Similar kinds of models to the one described in this Special Feature have been implemented internally by LCBGs both in the EU and globally. One benefit of being able to measure credit risk more accurately is that it enables a better understanding of the impact of concentration and diversification on banks' overall credit portfolio risk, and consequently can indicate how economic capital requirements vary depending on how the portfolio changes. For a detailed explanation of the term "LCBG", see ECB (2006), "Identifying large and complex banking groups for financial system stability assessment", *Financial Stability Review*, December.

Looking at the overall portfolios, banks typically expect to lose a certain amount on average – this amount is called expected loss (EL). They cover EL by incorporating a risk premium into the interest rate charged to borrowers and by using loan impairment charges.⁴ Losses that are in excess of expected losses are termed unexpected losses (UL); institutions are aware that such losses will occur, but are uncertain as to when these losses might take place, and as to their magnitude. Therefore, to cover UL, banks have to maintain adequate capital. The amount of capital held is a function of the bank’s management and regulatory requirements, as well as requirements of external parties such as rating agencies, and the investors’ view of the bank’s risk-return profile. However, holding capital in excess of these requirements entails an opportunity cost, as this money could otherwise be used to finance additional lending. For this reason, it is important for banks as well as regulatory authorities to find the right balance regarding the optimal level of capital.

The concepts of EL and UL are utilised in the Basel II Capital Accord, which among other goals seeks to reduce the divergence between the amount of capital that regulators require and the level that banks want to hold. To quantify the ideal size of this capital buffer, a portfolio credit risk model can be used to approximate the level of losses that would be exceeded at a given probability.

Assuming the model adequately represents reality, the required capital value is set in such a way that it ensures that the probability of unexpected losses exceeding this value is extremely low. Typically, the shape of a stylised loss distribution of a risky credit portfolio is skewed and has a relatively fat right tail (see Chart C.1). This distribution indicates that losses less than or around the expected values are most frequent. However, the skew to the right means more extreme outcomes may also occur, and capital must be held to cover this possibility.

Chart C.1 Stylised loss distribution



The shaded area in Chart C.1 depicts the possibility that a bank will not be able to cover these losses with its capital and profits. The Value at Risk (VaR) at the borderline between the shaded and non-shaded area is the threshold value for which banks may incur a loss greater than that figure at a given confidence interval. Required capital can be set according to the difference between the EL and the VaR. Assuming that the EL is covered by adequate risk pricing/impairment charges, the likelihood of a bank’s losses exceeding its capital (i.e. resulting in its insolvency) over a fixed time horizon is equal to the confidence interval.⁵

A second way of understanding losses on a loan portfolio is by looking at its individual components. For example, the expected loss of each loan exposure can be broken down into three components: the probability of default, the exposure at default, and the loss given default. The probability of not repaying the loan is called the probability of default (PD). It is important to note that the average PD of obligors may change over time – e.g. due to changes in the state of the economy or company-

4 “Loan impairment charges” is the term used in the International Reporting Standards (IFRS) for loan loss provisions. Under IFRS, banks incur charges for loans with objective evidence of impairment in their profit and loss account. In practice, banks also tend to set aside impairment charges for loans that are impaired but not recognised on the basis of past experience and internal credit portfolio models. See Box 12 in this Review for more information on loan impairments.

5 However, an important drawback of VaR in general is that it cannot explain how much will be lost if an unlikely event does occur. See Box 13 in this Review for a more in-depth discussion of alternative risk measures.

specific factors. PDs can be inferred from a credit rating, from a bank's internal database on past default history, from a structural model of default, or from a combination of all three.⁶

The exposure amount (E) is the amount outstanding in the event of the borrower's default. In that case, the loss given default (LGD), i.e. the actual loss faced by the bank, depends on how much of the original debt can be recovered through a bankruptcy proceeding and the amount of collateral if available.

BRIEF REVIEW OF THE MAIN CREDIT RISK MODELS

There are four main industry credit models that are widely implemented by banks,⁷ which frequently use them to assess their own credit risk in addition to the Internal Ratings-based Approach (IRB) introduced by the Basel II Capital Accord (which builds on these industry models and sets the regulatory standard for credit risk assessment).⁸ While the various approaches differ, the outputs of these models typically include a probability of default or a loss distribution for a given default horizon (e.g. one year). The first method is a *structural* model based on option pricing theory. This approach builds on the asset valuation model originally proposed by Merton⁹, and is commercially distributed as Moody's KMV's *Credit Monitor*TM. It is known as a *structural model of default* as it is based on modelling a firm's value and capital structure, and links default events to the firm's economic fundamentals (equity and assets). These default events are endogenous and usually occur when the firm's value reaches a certain lower threshold.

The next group of models are *reduced form* models, as these do not model firms' assets or capital structure, but instead specify that credit events occur owing to some exogenous statistical process. Reduced form models can be divided into models that construct credit events as migrations between rating classes (credit migration models) and those that specify

the default time (intensity models). The credit migration approach has been developed by JP Morgan and is implemented as *CreditMetrics*TM. This methodology is based on the probability of moving from one credit quality to another, including default, within a given time horizon. It is based on an ordered probit model, and uses Monte Carlo simulation to create a portfolio loss distribution on the horizon date.

Another way of quantifying credit risk is the *CreditPortfolioView*TM model developed by McKinsey, which uses a discrete time multi-period model in which default probabilities are conditional on the macro variables such as unemployment, the level of interest rates and economic growth – all of which, to a large extent, influence the credit cycle in the economy.

Finally, *CreditRisk+*TM by Credit Suisse Financial Products (CSFP) uses an actuarial approach, and purely focuses on default. In this model, default rates are not in absolute levels – such as 0.25% for a triple B-rated issuer – but are treated as continuous random variables. Given that most banks have large numbers of borrowers, some of these borrowers' default probabilities may be correlated. Moreover, since borrowers may be concentrated in certain economic sectors, it makes sense for a bank to take these factors into account when assessing the overall level of credit risk or potential losses in its loan portfolio.

In *CreditRisk+*TM, default correlations are not modelled with indicators for regional economic strength or industry-specific weakness, but by

6 See the Vasicek-Kealhofer model described in P. J. Crosbie and J. R. Bohn (2002), "Modelling Default Risk", Moody's/KMV.

7 For a more comprehensive review of the industry models see M. B. Gordy (2000), "A Comparative Anatomy of Credit Risk Models", *Journal of Banking and Finance*, 24, 1, 119-149; and M. Crouhy, D. Galai and M. Robert (2000), "A Comparative Analysis of Current Credit Risk Models", *Journal of Banking and Finance*, 24, 1, 59-117.

8 See Basel Committee on Banking Supervision (2001), "The Internal Ratings-based Approach", BIS.

9 R. Merton (1974), "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", *Journal of Finance*, 29, 2, 449-470.

estimates of the volatility of the default rate. These estimates are produced by measuring the standard deviation of the default rate, and are designed to depict the uncertainty that observed default rates for credit ratings vary over time. This feature allows a better capturing of the effect of default correlations, and produces a long tail in the portfolio loss distribution because default correlations induced by external factors are difficult to observe and are unstable over time.

The *CreditRisk+*TM model allows exposures to be allocated to industrial or geographical sectors as well over varying default horizons. As inputs, data similar to those required by Basel II are used, while the effects of concentration are incorporated as credit risk drivers. The main advantage of this model is that it requires a relatively limited amount of data – an important consideration when using publicly available information.

To sum up, each group of models has both advantages and disadvantages, and successful implementation depends on the specific purpose at hand. Given that the aim here is to generate a proxy of overall credit risk for a sample of EU LCBGs, structural models based on their public exposure data, such as Moody's KMV's default model, cannot readily be applied to some of the sectors (i.e. the household sector) in order to calculate default probabilities, as data on equity prices or asset volatilities are not available for this sector. This is a significant drawback, as the household sector is one of the main economic sectors in LCBGs' loan portfolios. Given that the ECB only has access to publicly available data from banks through their quarterly and annual reports, and no rating transition information on individual bank obligors within loan portfolios, the *CreditRisk+*TM model has an obvious appeal compared to some migration-based models.¹⁰

IMPLEMENTATION

The *CreditRisk+*TM model calculates the losses over a fixed horizon – one year in this case – for

a given confidence interval. It does this by determining the frequency of defaults and the losses given these defaults. These two items are then used to calculate the distribution of default losses.¹¹ Since these rates can vary over time, this tends to make the distribution of defaults more skewed compared to time-invariant default rates.¹² Moreover, the default rate distribution affects the severity of losses because the amount lost in any default depends on the exposure to any given obligor. The number of defaults occurring in one period is independent of the defaults in other periods. Under these conditions, default for individual loans or bonds is assumed to follow an exogenous Poisson process.

Estimating portfolio credit risk models requires various inputs such as historical exposure data, default rates and their volatilities, and finally recovery rates. This sample consists of annual data for the period 2003-2005 for nine EU LCBGs including seven of the institutions analysed in Section 4 of this Review.¹³ However, these data are generally not harmonised as each bank has its own definition of various types of lending, and so they were mapped to economic sectors to make the data comparable with the Moody's KMV data.

A second necessary input is expected default rates for the various economic sectors and their volatilities, as provided by Moody's KMV. Time series observations of default probabilities for households and the public sector were not available. In this case, default probabilities

10 However, it should be noted that for corporate sector exposures, an artificial credit rating migration matrix could be constructed using Moody's KMV EDF data, making the *CreditMetrics*TM model an alternative methodology to the one used in this Special Feature.

11 The version of *CreditRisk+*TM that is used in this Special Feature is implemented in Matlab and is based on a code originally written by Michael Gordy from the Federal Reserve Board.

12 Intuitively, this can be thought of as a change in the shape of the loss distribution, resulting in a fatter right tail that reflects a higher probability of more extreme losses. An assumption underlying the *CreditRisk+* model is that the number of defaults occurring in one period is independent of the defaults in other periods.

13 Gathering data on the other EU LCBGs proved to be somewhat problematic as various institutions had changed their reporting breakdowns over the sample period.

were used based on previous work – including work by the Basel Committee and on individual banks’ own estimates of probabilities of default for the household sector.

The portfolio was expanded in order to make it more granular by assuming 80% of the portfolio was of standard credit quality, with the remaining 20% of the portfolio split equally between higher and lower credit quality segments. The default probabilities of the lower and higher credit quality portions of the portfolio were also adjusted to reflect the differing credit qualities.¹⁴

The LGD values from LCBGs’ annual reports were used when available. However, most institutions in the sample failed to publish suitable information. Therefore LGDs based on the Basel II Capital Accord were used, taking into account the experience of practitioners in commercial banks. In addition, information from other studies was used due to the unavailability of recovery rates for each exposure type.¹⁵ As the majority of LGDs in this Special Feature can be classified as stressed or “economic downturn” LGDs according to the fifth Basel II Quantitative Impact Study, the loss distributions for each bank’s portfolio may be more extreme – implying higher VaR estimates – than those obtained using through-the-cycle LGDs. However, publicly available data for LGDs on an industry- and country-specific level are still very limited, and financial institutions need to disclose further information.

Table C.1 Stylised credit portfolio example

Sector	Exposure (EUR millions)	LGD (%)	Loss value (EUR millions)	Probability of default (% probability)	Expected loss (EUR millions)
Corporate	1062	0.38	404	0.02	8.07
Corporate	4740	0.20	948	0.02	18.96
Corporate	1066	0.27	288	0.02	5.75
Bank	276	0.20	55	0.01	0.55
Household	10598	0.13	1378	0.01	13.77
Household	1776	0.47	835	0.04	33.38
Public	596	0.30	178	0.001	0.17

Source: ECB calculations.

Table C.1 shows a stylised version of the typical LGDs and default probabilities used in this Special Feature. It can be seen that the exposures and LGDs vary, as do the probabilities of default for the various economic sectors (for corporate and financial institutions). Owing to a lack of data on households, their default probabilities remain constant (0.01 for mortgage loans and 0.04 for the remaining). A further point to note is that the largest expected loss in this example – household consumer credit – comes from a relatively small exposure caused by a high LGD and a high default probability.

RESULTS

As mentioned earlier, in normal conditions banks expect on average to lose a certain amount (EL) given the composition of their portfolios. Chart C.2 shows how EL varies from one LCBG to the next in the sample. Over the sample period, they tend to decrease slightly owing to a decline in default probabilities, even though the size of their loan portfolios had expanded during the period 2003-2005.¹⁶

In the current implementation of the model, a single systematic risk factor is used. Chart C.3 shows the credit VaR for a sample of EU LCBGs as a percentage of their total loan portfolios, using a 99.9% confidence interval. This resulting VaR can be thought of as the capital in excess of expected loss that these LCBGs need to hold to cover unexpected losses from credit risk. This varies from bank to bank and from year to year.

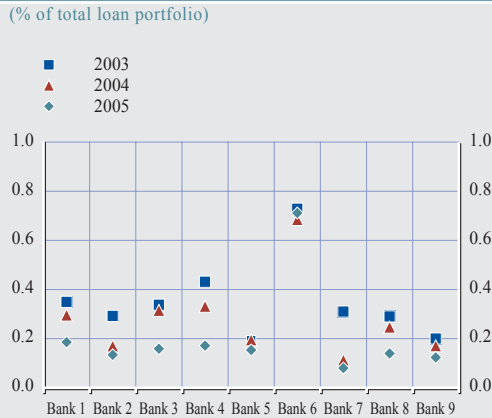
Chart C.4 illustrates the credit VaR of each LCBG portfolio as a percentage of their total regulatory capital for the years 2003, 2004 and 2005. For some banks, a downward trend appears to be visible over time. This is not entirely surprising, as the default probabilities

¹⁴ This increase in granularity of the portfolio is based on best practice results (see also Sveriges Riksbank, op. cit.).

¹⁵ Ibid.

¹⁶ Default probabilities of corporates and financial institutions have declined by and large over the sample period. Default probabilities of households were kept constant due to the unavailability of data for the sector.

Chart C.2 Expected loss for a sample of large and complex banking groups in the EU

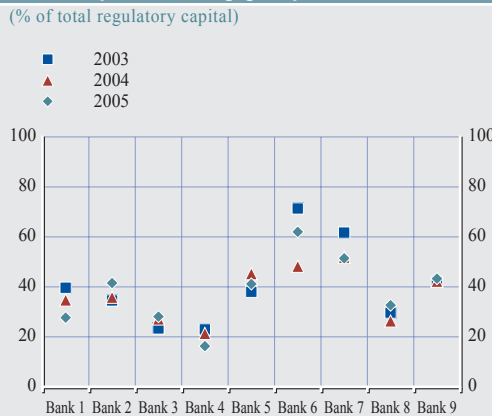


Source: ECB calculations.

of corporate obligors in this sample tended to decline over time.

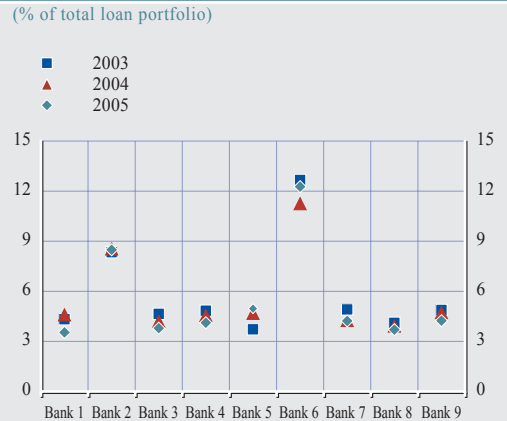
The credit risk profile of other LCBGs remained relatively constant as a percentage of regulatory capital. For one or two, some degree of change was apparent, as acquisitions increased the credit risk profile of the institutions. Overall, the results indicate that over the period 2003-2005, total regulatory capital was more than sufficient to cover credit risk in the sample LCBGs' loan portfolios.

Chart C.4 Credit VaR as a percentage of total regulatory capital for a sample of large and complex banking groups in the EU



Source: ECB calculations.

Chart C.3 Credit VaR as a percentage of total loan portfolios for a sample of large and complex banking groups in the EU

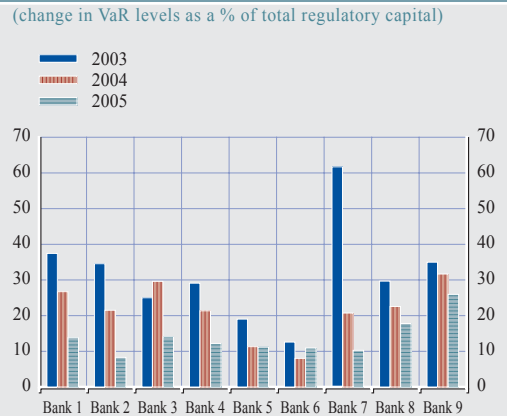


Source: ECB calculations.

A simple exercise was carried out to assess how credit VaR changed in response to a negative shock to real GDP. Changes to the implied default probabilities used in the credit risk model were estimated by applying a one standard deviation shock to real GDP in a Global Vector Auto Regression (GVAR) model.¹⁷ These stressed default probabilities

¹⁷ See Special Feature B in this Review and S. Déès, F. di Mauro, M. H. Pesaran and L. V. Smith (2007), "Exploring the International Linkages of the euro area: A Global VAR Analysis", *Journal of Applied Econometrics*, 22, 1-38.

Chart C.5 Effect of a five standard error negative shock to real GDP on credit VaR levels for a sample of large and complex banking groups in the EU



Source: ECB calculations.

Note: Calculated as the difference between the stressed VaR level and the original VaR level as a % of total regulatory capital.

were then used as inputs to recalculate the credit VaR for each of the three years.

Chart C.5 shows the change in the level of credit VaR as a percentage of total regulatory capital for each LCBG when an extremely large negative global GDP shock occurs (i.e. not a country-specific shock). For some institutions the change was relatively limited, while for others more pronounced owing to the composition of their loan portfolios as well as the default probabilities of the obligors in their portfolios. For one LCBG, the negative shock caused its credit VaR to increase markedly in one year. The main reason for this was that its loan portfolio contained comparatively more exposures to corporate sub-sectors with a higher probability of default under a stress scenario.

Given that relatively conservative assumptions were used for LGDs as well as default probabilities, it is likely that the estimates presented in this Special Feature could overestimate credit risk in these LCBGs' portfolios. Various robustness checks were therefore carried out. To start with, the volatility of the default rates used was varied to ensure that the VaR numbers were not overly sensitive to the chosen volatility. No large change occurred in these values when they were altered. The LGD values were also changed to differing degrees. On average, the VaR values increased somewhat but remained in a similar range to what had been discussed earlier.¹⁸ However, the variability in credit VaR seems to be mainly driven by differences in the distribution of loan exposures across the institutions covered in the current sample of LCBGs and their corresponding PDs.

Finally, an additional plausibility check was carried out by comparing the VaR estimates with the economic capital for credit risk held by those LCBGs that had published such figures. Encouragingly, the estimates using the current model tended to be in a similar range to the institutions' own economic capital figures. Three explanations can be advanced for differences in these estimates from those of the

current model and the institution's estimates. First, better input data were available to the institutions themselves, including information on collateral for their exposures. Second, intra-group diversification effects were taken into account, making their figures lower compared to the estimates in this Special Feature. Third, some institutions supplied figures that included economic capital required for private equity exposures; these figures were not included in the current model.

CONCLUDING REMARKS

This Special Feature has described the analytical concepts underpinning credit risk modelling, and has implemented a credit risk model that seeks to gauge the credit risk profiles of a sample of EU LCBGs. To do so it uses publicly available exposure data from EU LCBGs' annual reports, together with several other inputs. While the sample is comparatively limited, the model nevertheless produces some relatively plausible estimates of the varying credit risk profiles of EU LCBGs, given the limited data inputs.

Two additional refinements would probably improve the results further. First, a more thorough disclosure of exposure information by LCBGs in their annual and quarterly reports would improve the main input and, consequently, the VaR estimates. Second, better information and analysis on LGD values, especially on how they interact with PDs in a downturn, could prove extremely useful in refining the outputs of these models. These improvements may further increase the usefulness of this tool for financial stability monitoring.

¹⁸ The effects of simultaneous increases in LGDs and PDs have not been explored extensively in the academic literature. For a recent contribution, see E. Altman (2006), "Default Recovery Rates and LGD in Credit Risk Modeling and Practice: An Updated Review of the Literature and Empirical Evidence", New York University, mimeo.