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ASSESSING PORTFOLIO CREDIT RISK CHANGES IN A SAMPLE OF EU LARGE AND COMPLEX BANKING GROUPS IN REACTION TO MACROECONOMIC SHOCKS

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In 2009 all ECB publications feature a motif taken from the €200 banknote.

CONTENTS

Abstract

In terms of regulatory and economic capital, credit risk is the most significant risk faced by banks. We implement 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. Furthermore, the results show that large negative shocks to real GDP have the largest impact on the credit risk profiles of banks in the sample. Notwithstanding some caveats, the results demonstrate the potential value of this approach for monitoring financial stability.

Key words: Portfolio credit risk measurement; stress testing; macro-economic shock measurement

JEL classification: C02, C19, C52, C61, E32

Non-technical summary

This paper attempts to address the issue of measuring credit risk in the European banking sector using an approach based on publicly available data. For the ECB this is particularly relevant because although it does not have supervisory responsibility for individual institutions and consequently access to supervisory data, it is responsible for contributing to the stability of the European financial system. By linking publicly available bank exposure data to information received from a global marcoeconomic model we are able to simulate the effects of different macroeconomic shocks on corporate sector credit quality/default probabilities. This enables a model based assessment of credit risk in European bank portfolios under different macroeconomic scenarios and provides a tool for financial stability scenario analysis.

To run the credit risk model without any scenario analysis we use bank exposure data, probabilities of default (PD) for each exposure and information on loss given default (LGD). All of them can be related to the following sectors: corporates, financial institution, households and the public sector. Using these inputs, the credit Value at Risk (VaR) for each single bank is calculated. The results show that credit risk varies across banks depending on the business lines pursued as well as their geographical and sector exposures.

The remainder of the paper elaborates on the effects of macroeconomic shocks on Value at Risk (VaR) which are calculated in two steps. First, the impulse responses of the GVAR (Global Vector Autoregression) model to a five standard standard deviation shocks in different macroeconomic variables are calculated. These shocks include real Gross Domestic Product (GDP), real stock prices, inflation, short-term and long-term interest rates and the euro-dollar exchange rate. In the second step, the results of these macroeconomic shocks are regressed on the sector specific PD values. The main results from the macro shocks show that the effect on credit risk of European banks depends on the source of the macroeconomic shock as well as the banks loan exposures. Overall, shocks to real GDP increase the median VaR of banks in the sample the most from the shocks considered in this paper.

1 Introduction

This paper presents a framework that allows for stress-testing large euro area banks' credit risk exposures using publicly available data. In that context, the impact of a range of shocks generated by a macroeconometric model on banks' credit portfolios can be assessed and the relative severity of the shocks can be ranked in terms of credit value-at-risk.

Credit risk is the risk that a borrower may be unable to repay its debt. The art of quantifying this risk has advanced markedly since the late 1990s with the development and dissemination of models for measuring credit risk on a portfolio basis. 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 internal and/or a legal definition, or alternatively, through a credit rating migration approach. In the former, what matters is that the borrower exceeds some 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 paper, portfolio credit risk refers to the credit risk arising from loans and other credit exposures included in the loan items of banks' financial statements. Other exposures such as structured products or over-the-counter (OTC) derivatives are not considered due to the lack of reporting on these type of products. Depending on the size of these exposures and their risk weight the results of the credit risk estimation could change.

Broadly speaking, the increased focus on measuring credit risk can be attributed to the following facts. First, advances in analytical methods for implementing credit risk models. Second, incentives provided for quantifying credit risk accurately in order to allocate capital efficiently within banks. This includes as well better pricing, due to better valuation of financial contracts, and improved fund management, due to better analysis of risk and diversification. Third, regulatory developments such as the Basel II Capital Accord. Similar kinds of models to the one described in this paper also enable a better understanding of the impact of concentration and diversification of banks' overall credit portfolio risk, and consequently can indicate how economic capital requirements vary depending on how the bank's loan portfolio changes.

As credit risk tends to be the largest source of risk for banks (c.f. ECB (2007)), any additional tool that could further aid the assessment of credit risk in EU LCBGs (c.f. ECB (2006))[1] would be a useful addition to the financial stability monitoring tool kit. This is a pertinent issue for central banks - including the ECB - that lack supervisory responsibility and consequently access to supervisory data on individual institutions. Furthermore, the ECB does not have widespread access to data on individual loans which could be provided through sharing of credit register data in the euro area. Notwithstanding these drawbacks, the usefulness of models based on publicly available data as tools for financial stability assessment has been noted previously by the IMF, the Bank of

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[1] For a detailed explanation of the term "LCBG", see Special Feature A in the December 2006 Financial Stability Review of the ECB.

England and Sveriges Riksbank (see for example Riksbank (2006)). The latter have used a similar credit risk framework than presented in this paper to assess the degree of credit risk in four large Swedish banks.[2]

Moreover, credit risk is the most important risk factor facing banks and analyzing changes in banks' loan portfolios as a response to various macro-financial shocks and scenarios is an important part of risk management, both at the individual institution and at the systemic level. In spite of recent methodological advances, stress testing of infrequently traded credit risk still represents a challenge owing to complex modelling and data issues. Although stress in loan portfolios is often caused by macroeconomic shocks, the scale of models available for financial firms which link the macro economy to the loan portfolio level remains limited. In recent years, central banks and supervisory agencies have also built their own stress testing tools in order to assess the stability of financial institutions at the systemic level. One area where research has been carried out is the so-called macro-micro link of credit risk, which bridges the gap between macroeconometric models and credit quality variables (see Sorge (2004) for a comprehensive review of the literature on the methodologies of macro stress-testing). Although it can be argued that – when compared to models for analysing monetary policy – the financial stress testing models still represent more art than science, the current state-of-the art in this field of modelling is nevertheless already rather sophisticated. Plenty of work is ongoing both within the academic community, the financial industry and central banks to further advance the modelling techniques. Recent interest in incorporating financial stability considerations into economic and monetary analysis has further fuelled the research in this field.

Figure 1 summarises a commonly applied approach to stress testing by financial firms and central banks. The design of the macroeconomic stress scenario is the first stage. These scenarios can be simulated using either structural macroeconomic models designed for macroeconomic forecasts and monetary policy analysis, reduced-form VAR models or pure statistical methods that model the multivariate distribution of macro-financial variables using nonlinear dependency structures. In the second stage of the process, macro variables are mapped to microeconomic indicators of banks' credit risk, usually by means of a "satellite" or auxiliary model. Unlike the macroeconomic model, the credit risk satellite model is often estimated on data at individual bank or even individual borrower level. These auxiliary models provide the link between macroeconomic stress scenario conditions and loan performance at the sector or bank level. The macroeconomic model is then used in the next stage to project the time path of macro variables under stress conditions. These estimates, in turn, are fed into the auxiliary credit risk model in order to determine the stressed credit quality indicators (such as provisions or projected default rates in banks' credit portfolios). The final step of the stress testing process is an assessment of whether banks can withstand the assumed shock. Depending on the type of the

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[2] For a detailed overview of work that inspired the analysis presented in this paper, see Riksbank (2006) and Avesani, Liu, Mirestean, and Salvati (2006).

credit risk model used, the final output of the stress testing exercise is typically expressed in terms of a risk metric such as credit value-at-risk.

[Insert here Figure 1: A process for stress testing banks' credit portfolios]

The current paper contributes to this stream of research in several important ways. First, it takes advantage of the recent improvements in banks' financial disclosure, partly driven by the Pillar III recommendations in the new Basel II accord, to use publicly available data on banks' credit risk exposures. This approach is particularly valuable to analysts and authorities who want to assess the credit risk in a given institution but who have no access to detailed supervisory information on bank's loan portfolio composition. To this end, we construct a unique data set on large euro area banks' loan exposures using information from banks' annual reports which is fed into a credit portfolio model at the individual bank level. Second, we combine this work with a framework that takes advantage of recent advances in modelling the link between the global macro-financial environment and micro-level borrower default analysis. Third, we augment the chosen standard credit portfolio risk model (CreditRisk+) in such a way that problems related to limited data availability on bank specific loan portfolios can be mitigated. To this end, we use stochastic loss given default (LGD) values for back testing of the results and perform simulation exercises to address the change in volatility of the underlying systematic risk factor as a response to macroeconomic shocks. The overall system provides a full-fledged framework that can analyse the impact of a wide range of macro-financial shocks to individual banks' balance sheets. To our knowledge, this is the first effort to do such an exercise at the euro area level.

In terms of content, this paper first provides an overview of the main concepts applied 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, CreditRisk+, using publicly available balance sheet information and data on probabilities of default to construct an indicator of credit risk among a sample of EU LCBGs. Afterwards, these results are amended by several stress tests which are conducted using different macroeconomic risk factors. The paper concludes by assessing the usefulness of this framework as a monitoring tool and identifies where additional work could be undertaken to improve it further.

2   Credit Portfolio Modelling: Some General Concepts

Through their function of intermediating credit in the economy, banks may experience losses as a result of borrower 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.

First, 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[3]. 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 may occur and 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 published by the Basel Committee on Banking Supervision (BCBS). Among other goals, the accord 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 a level of losses that would be exceeded at a given probability. Assuming the model used to quantify these losses 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 Figure 2). 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.

[Insert here Figure 2: Stylised loss distribution]

The shaded area in Figure 2 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.[4] Assuming that the EL is covered by adequate risk pricing/impairment charges, the likelihood of a bank's losses exceeding its

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[3] "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.

[4] However, an important drawback of VaR as a single figure in general is that it cannot explain how much will be lost if an unlikely event does occur.

capital (i.e. resulting in its insolvency) over a fixed time horizon is equal to the confidence interval.

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 due to changes in the state of the economy or company-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 (cf. Crosbie and Bohn (2002)). The exposure at default (EAD) 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.

Another concept, worth mentioning but not applied in the current framework, is Expected Shortfall (ES). ES allows creating an average or expected value of all losses greater than the VaR. This can be useful if two portfolios with the same VaR are compared that might have different distributions of their losses beyond the VaR, in the so called tails of the distributions (cf. Frenkel, Hommel, and Rudolf (2005)).

3 Brief Review of Commonly Used Models

There are four main vendor credit portfolio models that have been widely implemented by commercial banks.[5] These models are used to assess banks' credit risk and as input for calculating required regulatory capital standards set down in the Internal Ratings-based Approach (IRB) introduced by the Basel II Capital Accord (see Basel Committee on Banking Supervision (2001)). 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 (one year in most cases).

One model is structural and based on option pricing theory. This approach builds on the asset valuation model originally proposed by Merton (1974) and is commercially distributed as Moody's KMV's Credit Monitor. It is known as a structural model of default as it is based on modelling a firm's value and capital structure. It 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 bound or default threshold.

The next group of models are reduced form models as these do not model firms' assets or capital structure. These models specify that credit events occur owing to some type of exogenous statistical process. Reduced form models

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[5]For a more comprehensive review of the industry models see Gordy (2000) and Crouhy, Galai, and Mark (2000).

can be divided into models that (i) construct credit events as migrations between rating classes (including default) known as credit migration models; and (ii) those that specify the default time known as intensity models. The credit migration approach has been developed by JP Morgan and is commercially implemented as CreditMetrics. 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 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 (see also Wilson (1998)).

Finally, CreditRisk+ (CR+) by Credit Suisse Financial Products (CSFP) uses an actuarial approach, and focuses purely on default. In this model, default rates are not in absolute levels – such as 0.25% for a BBB-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 the CR+ model, the default correlations are not modelled with indicators for regional economic strength or industry-specific weakness but by estimates of the volatility of the default rate. These estimates are produced by using 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 of the long tail in the portfolio loss distribution given that default correlations induced by external factors are difficult to observe and may be unstable over time.

The 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. The main advantage of the CR+ 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. Given that the aim of this paper 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, CreditRisk+ and CreditPortfolioView have an obvious appeal

compared to migration-based models.[6] Since CreditPortfolioView incorporates already macroeconomic variables, which will become relevant for stress testing (see section 7), the current framework will draw on CreditRisk+ to the estimate single bank's portfolio VaR, which is neutral to the state of the economic cycle.

4 Theoretical Aspects Related to Credit Portfolio Modelling in CreditRisk+

The CreditRisk+ model calculates the portfolio losses over a fixed horizon – one year in this case – for a given confidence interval. It does this by using the frequency of defaults and the losses given these defaults related to all exposures in the portfolio as inputs. Since default rates can vary over time, the distribution of defaults is more skewed compared to time-invariant default rates. Moreover, the default rate distribution affects the severity of losses because the amount lost in any default depends on the exposure to any given borrower. Under these conditions, default for individual loans or bonds is assumed to follow an exogenous Poisson process. An assumption underlying the CreditRisk+ model is that the number of defaults occurring in one period is independent of the defaults in other periods.

CreditRisk+ is modelling default risk. Therefore, the two possible end-of-period states for each borrower in the model are default and non-default. In case of a default, a certain part or the entire lender's exposure to the borrower might be lost. CreditRisk+ allows calculating the distribution of portfolio losses in a convenient analytical form, i.e. no Monte Carlo simulations are necessary as in other models of credit risk.

Default correlations in CreditRisk+ are thought of being driven by a vector Q of risk factors $x = (x_1, x_2, ..., x_Q)$. While it is assumed that defaults of individual obligors are independently distributed Bernoulli draws, conditional on x. The conditional probability $p_i(x)$ of having a default for borrower i is a function of the realization of risk factors x, the vector of *factor loadings* $(y_{i1}, ..., y_{iQ})$ and the rating grade $G(i)$ of borrower i. The sensitivity of borrower i to each of the risk factors is measured by the factor loadings (for a more detailed explanation of the theoretical foundations of the rest of the section see Credit Suisse First Boston International (1997) and Grundlach and Lehrbass (2006)).

In CreditRisk+ this function is specified as

$$p_i(x) = \overline{p}_{G(i)} \left(\sum_{q=1}^{Q} x_q y_{iq} \right), \tag{1}$$

where $\overline{p}_{G(i)}$ is the unconditional default probability for a grade G borrower.

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[6] 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 CreditMetrics an alternative methodology to the one used in this study.

All x have a positive value with mean one. They serve as a scaling factor for the unconditional $\overline{p}_G$ while higher x_q (over one) increase the probability of default for each borrower in proportion to the borrower's weight y_{iq} on that risk factor and vice versa. All weights y_{iq} have to sum up to one for each borrower so that $\mathrm{E}[p_i(x)] = \overline{p}_{(i)}$ is guaranteed.

From a conceptual perspective CreditRisk+ is not calculating the distribution of defaults but the probability generating function (PGF) for defaults. We introduce the PGF $\mathrm{F}_q(z)$ of a discrete random variable q as a function of the auxilliary variable z. This allows us to compute the PGF for a single borrower as

$$F_i(z|x) = 1 - p_i(x) + p_i(x)z = 1 + p_i(x)(z-1). \tag{2}$$

By using the the following approximation, $log(1+y) \approx y$ for $y \approx 0$, equation (2) can be rewritten as follows

$$F_i(z|x) = \exp(\log(1 + p_i(x)(z-1))) \approx \exp(p_i(x)(z-1)). \tag{4}$$

This step can be seen as a "Poisson approximation" since the expression on the right-hand side is the PGF for a Poisson distributed random variable $(p_i(x))$.

Default events, conditional on x, are independent across obligors; therefore the PGF of the sum of borrower defaults is the product of the individual PGFs which can be stated as:

$$F(z|x) = \prod_i F_i(z|x) \approx \prod_i \exp(p_i(x)(z-1)) = \exp(\mu(x)(z-1)) \tag{5}$$

where $\mu(x) \equiv \sum_i p_i(x)$.

The unconditional PGF F(z) can be generated by integrating out the x risk factors. Since the risk factors in CreditRisk+ are assumed to be independent gamma-distributed random variables with mean one and variance σ_q^2 it can be shown that

$$F(z) = \prod_{q=1}^{Q} \left(\frac{1-\delta_q}{1-\delta_q z}\right)^{1/\sigma_q^2} \text{ with } \delta_q \equiv \frac{\sigma_q^2 \mu_q}{1+\sigma_q^2 \mu_q} \text{ and } \mu_q = \sum_i y_{iq} \overline{p}_{G(i)}. \tag{6}$$

After this the last calculation step in CreditRisk+ is to create the probability generating function $G(z)$ for losses. The probability generating function for losses on borrower i is denoted by G_i. While in a portfolio, consisting only of borrower i, the probability of a loss of $v(i)$ units must equal the probability that i defaults, having $G_i(z|x) = F_i(z^{v(i)}|x)$. To derive the conditional PGF for losses in the entire portfolio, the conditional independence of the defaults is used as

$$G(z|x) = \prod_i G_i(z|x) = \exp[\sum_{q=1}^{Q} x_q \sum_i \overline{p}_{G(i)} y_{iq} (z^{v(i)} - 1)]. \qquad (7)$$

Again by integrating out x and rearranging we get

$$G(z) = \prod_{q=1}^{Q} \left(\frac{1-\delta_q}{1-\delta_q P_q(z)} \right)^{1/\sigma_q^2} \qquad (8)$$

where $P_q(z) \equiv \frac{1}{\mu_q} \sum_i y_{iq} \overline{p}_{G(i)}^{v(i)}$ and δ_q and μ_q defined as in equation (6).

As an alternative to this closed-form expression for the PGF it is as well possible to derive a recurrence relation for computing the distribution of losses (cf. Credit Suisse First Boston International (1997)).

5   Empirical Implementation Using European Data

Estimating portfolio credit risk models requires various inputs such as historical exposure data, default rates and their volatilities, and finally LGDs. We use a version of CreditRisk+ based on a Matlab code originally written by Michael Gordy from the Federal Reserve Board. Our sample consists of annual data for the period 2004 to 2005 for 16 EU LCBGs. Due to the fact that several EU banks were not reporting explicitly about the country of origin and the industry sector that an exposure relates to we tried to approximate this information on the following basis. We calculated the average percentage of exposure to all world regions and industry sectors that we have specified for this study using 750 country and industry specific exposure information of 16 banks. For aggregate loan exposure figures in annual reports that had neither a specification towards the industry sector nor the country of origin or just one of these two dimensions missing we assume a uniform distribution, i.e. we split the exposures into the available entries for each dimension following the average percentage values that could be calculated from the available data.[7]

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[7] However, this is only the case for three banks in the sample.

A second necessary input for CreditRisk+ is probabilities of default and their volatilities for the various economic sectors. These were calculated based on data provided by Moody's KMV. Time series observations of default probabilities for households were not available. In this case, default probabilities 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. PDs for each of the 14 sectors were calculated as the median EDF value per time period and sector. There are further measures of default rates that could be included in the model. Instead of the Moody's KMV data one could think about using implied default probabilities extracted from CDS prices broken down by industry sectors (see Schneider, Sögner, and Veza (2007)). Since exposure data are generally not harmonised as each bank has its own definition of various types of lending, they were mapped to 14 economic sectors to make the data comparable with the Moody's KMV data.

Furthermore, our 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.[8] A granularity adjustment has already been proposed by the Basel Committee on Banking Supervision (2001). There are several theoretical approaches to do this. Instead of an artificial increase of the number of exposures in our portfolio we could as well first calculate the VaR and afterwards adjust this figure by a so called granularity add-on (cf. Gordy (2003)). The latter is first estimated based on a theoretical model and then added to the ordinary VaR estimate.

There are several ways to include LGDs into the VaR estimation. First, we initially considered exposure specific LGDs based on LGD values from LCBGs' annual reports when available. However, as most institutions in the sample failed to publish the relevant information, we used LGDs based on the Basel II Capital Accord, and also took into account the experience of practitioners in commercial banks. As the majority of LGDs in this study 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 better disclosure of LGD information would be a useful addition to what financial institutions already publish. In this paper, we assume that LGDs stay constant over time and consequently are not influenced by sector or macroeconomic shocks (cf.Avesani, Liu, Mirestean, and Salvati (2006)).

[Insert here Table 1: Stylised credit portfolio example]

Table 1 shows the typical LGDs and default probabilities used in this paper.

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

It can be seen that the exposures and LGDs vary, as do the probabilities of default for corporate and financial institutions sectors. Owing to a lack of data on households, their default probabilities remain constant. 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.

Because of the lack of institution-specific LGD information, we use stochastic LGDs as a robustness check for the VaR estimation.

These are based on the following stochastic beta process

$$y = f(x|a, b) = \frac{1}{B(a,b)} x^{a-1} (1-x)^{b-1} I_{(0,1)}(x) \tag{9}$$

where B(·) is the Beta function. Schuermann (2004) for instance shows that a beta distribution captures the behaviour of LGDs quite well. The beta distribution generates values that are nonzero and in the interval]0 1[as LGD values can vary from 0 to 100 percent. We calibrate the parameter estimates for a and b by using information from other studies on industry sector specific LGDs. These estimates are then used for the calculation of maximum likelihood estimates of a and b. The latter are the basis for the creation of the stochastic beta process that determines the LGD in the VaR estimation. An extention to this approach could be to include information on the state of the credit cycle which would then link the LGDs to economic downturn or boom periods.

6   Estimation Results

The following section provides a detailed overview of the results that are obtained by running the CreditRisk+ framework with the data described in the last section. All estimations are done with either non-random or random LGDs. In the current implementation of the model, we assume one systematic factor. The input for this factor is calculated as the volatility of default rates across all industries and countries for the time period 1992 to 2005. It would be possible and as well make sense to augment the model by other systematic risk factors (e.g. different industry sectors and their volatility), however but due to the lack of good data this has not been done in this paper.

As mentioned earlier, in normal conditions banks expect on average to lose a certain amount (EL) given the composition of their portfolios. Figure 3 shows how EL varies from one LCBG to the next in the sample expressed as a percentage of the overall portfolio size of each bank. From the year 2004 to 2005, EL decreased for all banks except bank 15, even though the size of the loan portfolios had expanded during this period. Default probabilities of corporates and financial institutions have declined by and large over the sample period which is the reason for the reduction in EL. Note that default probabilities of households were kept constant due to the unavailability of data for the sector but these are unlikely to change substantially from year-to-year.

[Insert here Figure 3: Expected loss as a percentage of the overall portfolio size for a sample of large and complex banking groups in the EU]

Figure 4 shows the credit VaR for a sample of EU LCBGs as a percentage of their total loan portfolios, using a 99.9 percent confidence interval. The resulting VaR can be thought of as the capital in excess of the 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. Except for bank 2 and bank 5, VaR as a percentage of their total loan portfolio is less than five percent. From 2004 to 2005 this figure has increased for four banks and decreased for seven out of a sample of 16. Interestingly, in five cases VaR figures move into different directions from one year to another depending on whether LGDs are stochastic or not.

[Insert here Figure 4: Credit VaR as a percentage of the total loan portfolio for a sample of large and complex banking groups in the EU]

To gauge the magnitude of credit risk risk exposures, the credit VaR of each LCBG portfolio is expressed as a percentage of their total regulatory capital for the years 2004 and 2005 in Figure 5. The picture here is mixed. Four banks are indicating a rise with respect to this indicator and five a decline. All remaining banks, except for bank 1, show both directions depending on the type of LGD used for the calculation of the VaR. Two banks, bank 5 and bank 7, indicate that their total regulatory capital was not sufficient to cover the credit risk. However, for bank 5 this result is in line with the market perception. Bank 5 was rated on a "D" level by Fitch Ratings from 2002 to 2003 and had an increase to level "C" for 2004 and 2005 while net income tripled from 2004 to 2005.

[Insert here Figure 5: Credit VaR as a percentage of total regulatory capital for a sample of large and complex banking groups in the EU]

7   Sensitivity Tests

For a financial stability scenario analysis the linkage between different macroeconomic scenarios and the change in credit risk of the banks loans portfolio is crucial. One way to empirically implement this link is via the PD variable $p_i(x)$. This variable should change after a shock to the underlying economic system has occurred, keeping all other input variables constant except for the volatility of the risk factor x. The macroeconometric model used to generate the macroeconomic shocks is based on Dées, di Mauro, Pesaran, and Smith (2007). Linking $p_i(x)$ to future macroeconomic developments is a somewhat difficult exercise. A detailed discussion is included in Castrén, Dées, and Zaher (2008). In short, they construct a linking model called a Satellite model. This model links

the endogenous variables of a Global Vector Auto Regression (GVAR) model to the PDs of sector j.

The simplest form of the Satellite model is given by

$$s_{jt} = b_{j0} + b_{j1}x_t + \varepsilon_t, \text{ for } j = 1, \ldots k, \tag{10}$$

where j is the index for sectors, x_t is the $k \times T$ matrix of explanatory variables that are endogenous to the GVAR, s_{jt} is the $1 \times T$ vector of the dependent variables for sector j, b_{j0} is the intercept for sector j equation, b_{j1} is a $1 \times k$ parameter vector and ε_t is the $1 \times T$ vector of residuals. More clearly, the estimated Satellite model can be written in the following functional form:

$$\begin{aligned} \text{EDF}_t = \alpha &+ \beta_1 \triangle GDP_t + \beta_2 \triangle CPI_t + \beta_3 \triangle EQ_t + \beta_4 \triangle EP_t \\ &+ \beta_5 \triangle IR_t + \beta_6 \triangle LIR_t \end{aligned} \tag{11}$$

where α and β denote the parameters and $\triangle GDP_t$, $\triangle CPI_t$, $\triangle EQ_t$, $\triangle EP_t$, $\triangle IR_t$ and $\triangle LIR_t$ denote the logarithmic difference of euro area real GDP, CPI inflation, real equity prices, real euro/US dollar exchange rate, short-term interest rate and long-term interest rate at time t, respectively (cf. Castrén, Dées, and Zaher (2008) for a more detailed explanation on the selection of macroeconomic factors).

Feeding the "macro stressed" implied $p_i(x)$ into the CreditRisk+ model instead of the regular $p_i(x)$ that are unconditional on macroeconomic developments allows a calculation of VaR under different stress scenarios. The implied $p_i(x)$ are connected to the unconditional median PDs described earlier in section 5 using the following method.

First, we calculate the percentage change of the non-shocked to the shocked implied PD in period one of the impulse response function. Then, we increase the non-shocked PDs by this percentage change (see Table 2 in the Annex for estimation results of the Satellite model). It should be noted that in this context there is still no consensus as to whether the or not the volatility of the PD of the corresponding sector changes also following macroeconomic shock, i.e. whether there is a higher variation in the number of defaults after a shock and therefore higher risk of unexpected losses in the loan portfolio. This issue was recently addressed by Asberg-Sommar and Shahnazarian (2007) who analyzed the volatility (measured in terms of the standard deviation) in Moody's KMV EDF data before and after a macro shock. They use a modification of the Bassett and Koenker (1982) test, originally developed for detecting the presence of heteroskedasticity in data, to derive the volatility of the EDF. Following their study increased EDF do augment the volatility of EDF as well.

In the current model set-up, we assume an increase in the volatility of the systematic factor following a shock, as we are interested in the potentially VaR larger measure that this could generate as opposed to assuming no change. The increase in volatility is computed by extrapolating via a bootstrapping procedure the asymptotic standard deviation of all stressed PDs that are mapped to our artificial EU exposures portfolio. The bootstrapping experiment is constructed

as follows. First the EDF volatility for the whole EDF universe from 1992 to 2005 is calculated. Then, the 'stressed' median EDF values that are mapped by the dimensions sector, sub sector and country to each exposure in the portfolio are taken and resampled 10.000 times to create 10.000 data sets. After that the standard deviation for each shocked dataset is calculated. Calculating the median over these standard deviations gives an asymptotic estimate for the increase in volatility after a macroeconomic shock has occurred. This procedure is then replicated for each type of the six shocks that are analyzed.

Due to the lack of information on recovery rates that are one of the two components of LGDs, there is still a lot of empirical research necessary to figure out what are the right estimates for recovery rates in different industry sectors, countries and over time[9]. We assume in this paper that a negative relationship exists between the default rates and recovery rates along the credit cycle, i.e. in periods of high default recovery rates are low and vice versa (cf. Altmann, Resti, and Sironi (2004)). There are several studies that find that there are no industry-specific LGDs, which means that recovery rates are independent of the industry of the borrower. We assume that LGDs are not time varying given the relatively short time span we use in this paper.

The following describes a simple exercise that was carried out to assess how credit VaR changes in response to a very large 5 standard error negative shock to euro area GDP and equity prices, and a similar positive shock to euro area short- and long-term interest rates, inflation as well as the euro/dollar exchange rate. Figures 6 and 7 show the change in the level of credit VaR as a percentage of total regulatory capital for each LCBG in the years 2004 and 2005 when an extremely large shock to one of the above mentioned macro factors occurs. Overall, the effect of these shocks on the credit VaR is larger in 2004. For some institutions the change was relatively limited or zero, while for others it was more pronounced owing to the composition of their loan portfolios as well as the default probabilities of the borrowers in their portfolios. It is unclear whether this is a result of the structure of the loan portfolio exposure data or the probability of default proxy being adequate enough to capture the effects of the macroeconomic shock that the bank is exposed to. This is left for future research. From 2004 to 2005 the median and interquartile range have decreased significantly in case of a shock to equity prices and the euro. In both years a negative shock to GDP has the largest impact on credit VaR and a shock to the euro exchange rate the lowest. Except for shocks to equity prices and the euro, for both years in the maximum credit VaR is larger than Tier 1 capital.

[Insert here Figures 6 and 7: Change in credit VaR as a percentage of Tier 1 capital following a five standard error negative shock to several macro variables for a sample of large and complex banking groups in the EU (2004, 2005)]

Comparing these results to the method of calculating VaR with stochastic LGDs for the years 2004 and 2005 reveals that again for the year 2004 shocks

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[9]LGD is defined as (exposure * (1 - recovery rate).

are larger (see Figures 8 and 9). In 2004, the maximum VaR for all of the shocks exceeded the Tier 1 capital threshold of one institution; this was related to its weak financial position at the time. In both years 2004 and 2005 negative shocks to GDP and equity prices have the strongest impact on VaR while all other shocks have a similar impact level. However, in the year 2005 the maximum VaR is either equal to Tier 1 capital for the case of negative shock to GDP and equity prices or around 80 percent. Again a negative shock to equity prices seems to have the lowest impact on VaR looking at the median value.

[Insert here Figures 8 and 9: Change in credit VaR as a percentage of Tier 1 capital following a five standard error negative shock to several macro variables for a sample of large and complex banking groups in the EU (2004, 2005; stochastic LGDs)]

Tables 5 to 8 provide descriptive statistics on the results depicted in Figures 6 to 9. An explanation for the reported equality in median VaR figures under different scenarios is that shocks to different macroeconomic factors can result in similar elasticities with regard to sector specific PDs (see Table 2). As a consequence, median VaR estimates can be in a similar range.

[Insert here Tables 5 to 8: VaR changes following different macroeconomic shocks (2004, 2005; non-stochastic and stochastic LGDs)]

Given that relatively conservative assumptions were used for LGDs as well as default probabilities, it is likely that the estimates presented in this paper could overestimate credit risk in these LCBGs' portfolios. On average, the VaR values reacted to some extent to the changes in LGDs but remained in a similar range to non-stochastic LGDs. The variability in credit VaR appeared 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. However, the effects of simultaneous increases in LGDs and PDs have not been explored extensively in the academic literature with the exception of Altman (2006). In the current version of the paper, we have not attempted this exercise.

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 the slight 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 in the institutions published figures, making their figures lower compared to the estimates in this paper. Third, some institutions

supplied figures that included economic capital required for private equity exposures and these figures were not included in the current model to the extent that they were disclosed separately.

8 Information disclosure and the Pillar III of the Basel Capital Accord

A lack of a complete set of information required as data inputs has been a long standing problem in the credit risk modelling of loan portfolios. While banks began to systematically compile information for the development, implementation, and regulatory approval of internal credit risk models several years ago, in practice very little quantitative information is actually disclosed to the public in either annual reports or quarterly earnings reports. There are three main problems for the purposes of this paper. First, the majority of LCBGs do not make a geographical distinction in their loan exposure figures using international statistical classification systems. In some cases, it is difficult to determine the geographical distribution of loan exposures of the same LCBGs. Second, only a minority of banks provide some quantitative information about how they calculate expected and unexpected losses – such as probabilities of default on their internal rating scales – which determines whether impairment charges are made or not as well as overall economic capital estimates. However, most include somewhat vague qualitative descriptions in their financial statements or provide additional information on the sources of credit risk in separate presentations. Third, only a minority of LCBGs in the sample show in their annual reports a breakdown of their overall impairment figures by geographic region and/or business line, indicating where the sources of current credit losses originate from. Notwithstanding the transition to IFRS, as well as Pillar 3 requirements from Basel II, additional quantitative and qualitative information could aid the interpretation of how credit risk is calculated and would prove more useful for assessing the credit quality of euro area LCBGs. More encouragingly, this aspect of euro area LCBGs' financial disclosures may be improved by the implementation of IFRS 7 for 2007 full year financial results that will be published in 2008, as this requires particular disclosures concerning credit risk for loans and other financial instruments incurring credit risk. In particular, IFRS 7 ("Financial instrument disclosures") contains various disclosure requirements for credit and other risks. Among the requirements for credit risk, banks should provide information about their maximum credit risk exposures on the balance sheet, collateral and other credit enhancements, information on assets that are not past due or impaired and various other disclosures – such as vintage and how assets were deemed to be past due and/or impaired.[10]

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[10]See box 12 of the June 2007 ECB Financial Stability Review for more information on credit risk disclosures by euro area LCBGs.

9   Conclusions

This study 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 results given the restricted inputs.

Overall Tier 1 capital provision of EU LCBGs seems to be in the right ballpark. The development from one year to another reveals that LCBGs VaR figures as a percentage of Tier 1 capital change without following a specific pattern. However, there are some differences between VaR figures that are calculated on the basis of stochastic LGDs or sector specific LDGs.

Results from stress testing show shocks to macro factors have had a larger impact in the year 2004 compared to 2005. In both settings, stochastic vs. sector specific LGDs, and years the most pronounced impact on credit VaR is coming from a negative shock to GDP. The interquartile range of the reaction of VaR lies between zero and 40 for all shocks revealing that 75 percent of the banks could probably withstand any of these shocks.

Limitations to the current framework are the out-of-sample operation of the GVAR as well as a potentially non-linear relationship between the EDF and the explanatory variables of the GVAR which is not yet considered in the Satellite model. In addition to that, model uncertainty plays a vital role regarding the interpretation of the results. First, there is uncertainty about the parameters used in the model; second, uncertainty about the serial correlation properties of shocks; and third uncertainty about data quality.

Two additional refinements could probably enhance 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 this models. These improvements may further increase the usefulness of this tool for financial stability monitoring.

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Annex

Figure 1: A process for stress testing banks' credit portfolios

```
                    ┌──────────────────────────┐
                    │     Shock (scenario)      │
                    └──────────────────────────┘
                                 │
                                 ▼
┌─────────────────────────────┐      ┌──────────────────────────────┐
│   Macroeconomic model        │      │ Credit risk "satellite" model │
│                              │      │                               │
│  Links stress event to       │ ───▶ │  Links the macroeconomic      │
│  macroeconomic variables (e.g.│     │  variables to variables       │
│  GDP, interest rates, exchange│     │  measuring banks' asset quality│
│  rate)                       │      │                               │
└─────────────────────────────┘      └──────────────────────────────┘
                                                 │
                                                 ▼
                    ┌──────────────────────────────────────┐
                    │   Impact on banks' balance sheet       │
                    │  In terms of earnings, capital, credit │
                    │  risk metrics                          │
                    └──────────────────────────────────────┘
```
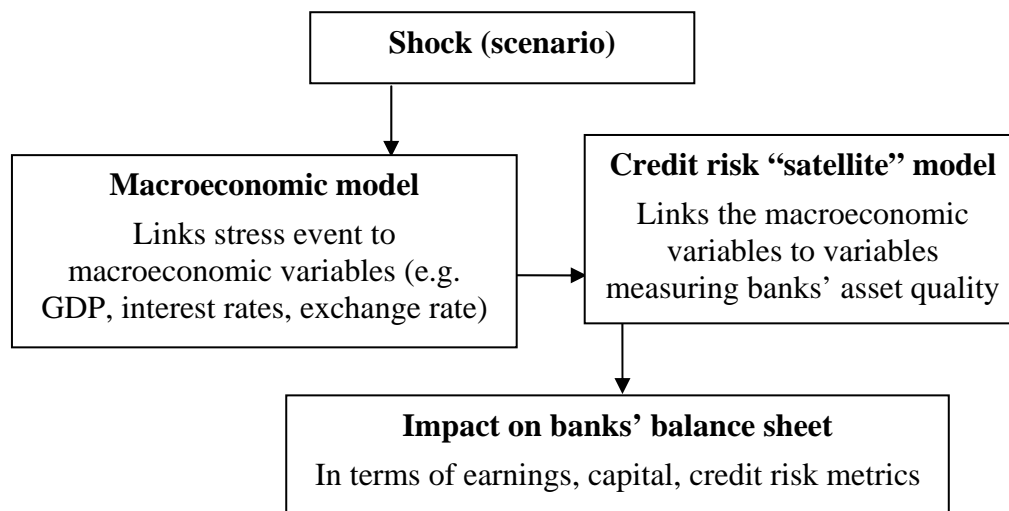
Source: ECB.

Figure 2: Stylised loss distribution
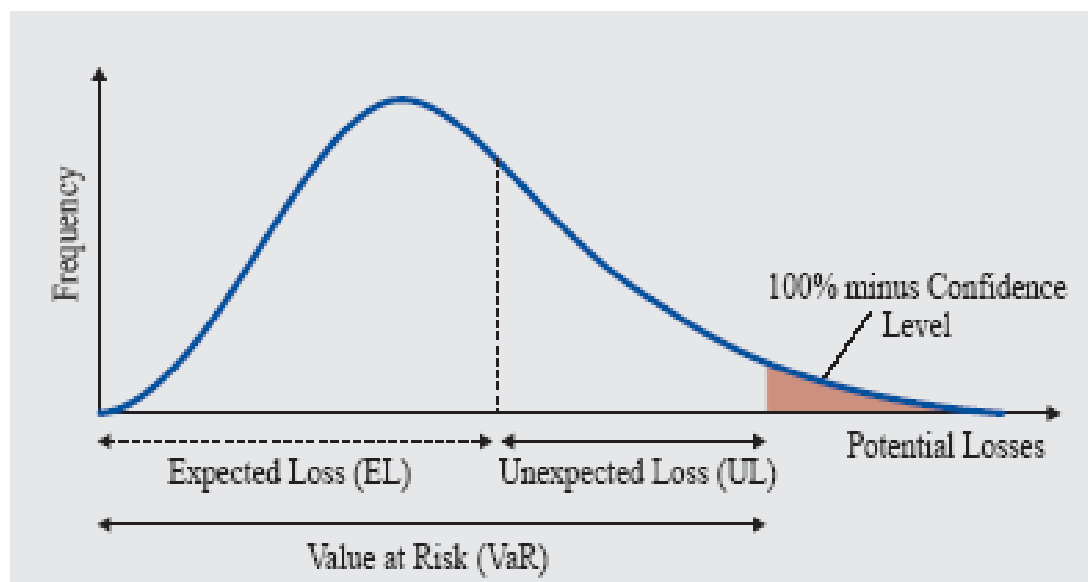
Source: BIS.

Figure 3: Expected loss as a percentage of the overall portfolio size
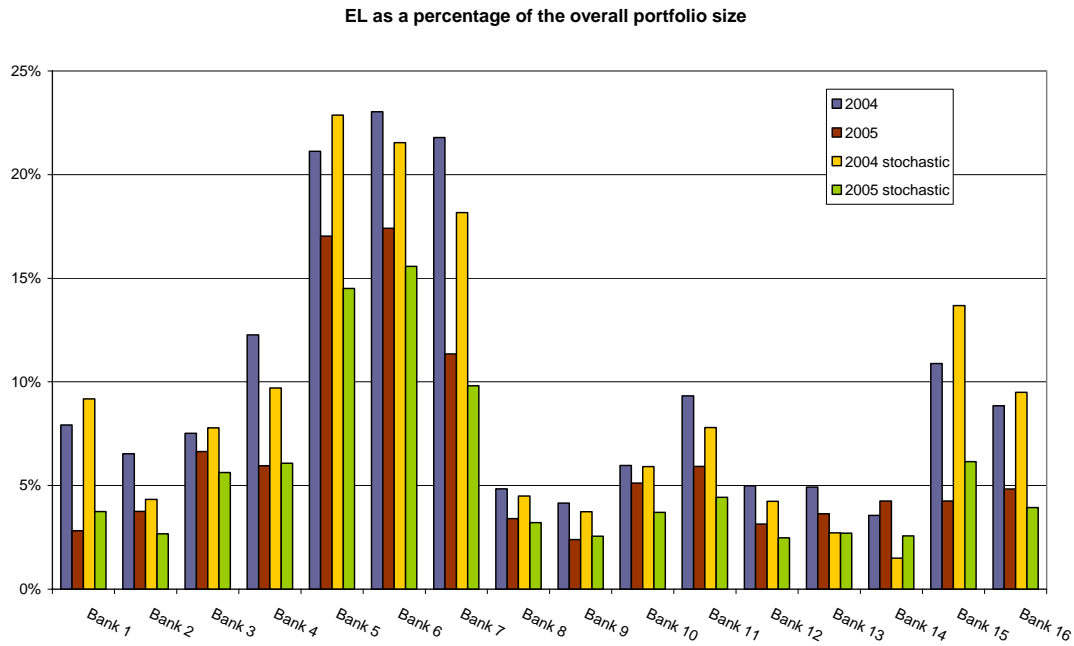
EL as a percentage of the overall portfolio size

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 4: VaR as a percentag of the total loan portfolio
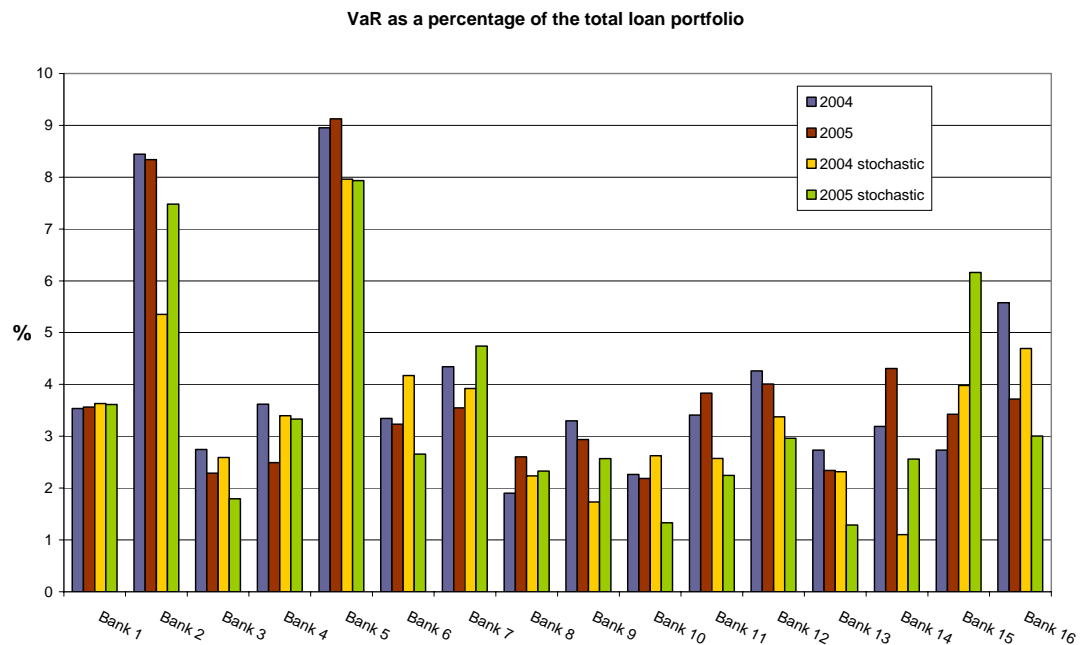
VaR as a percentage of the total loan portfolio

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 5: VaR as a percentage of Tier 1 capital
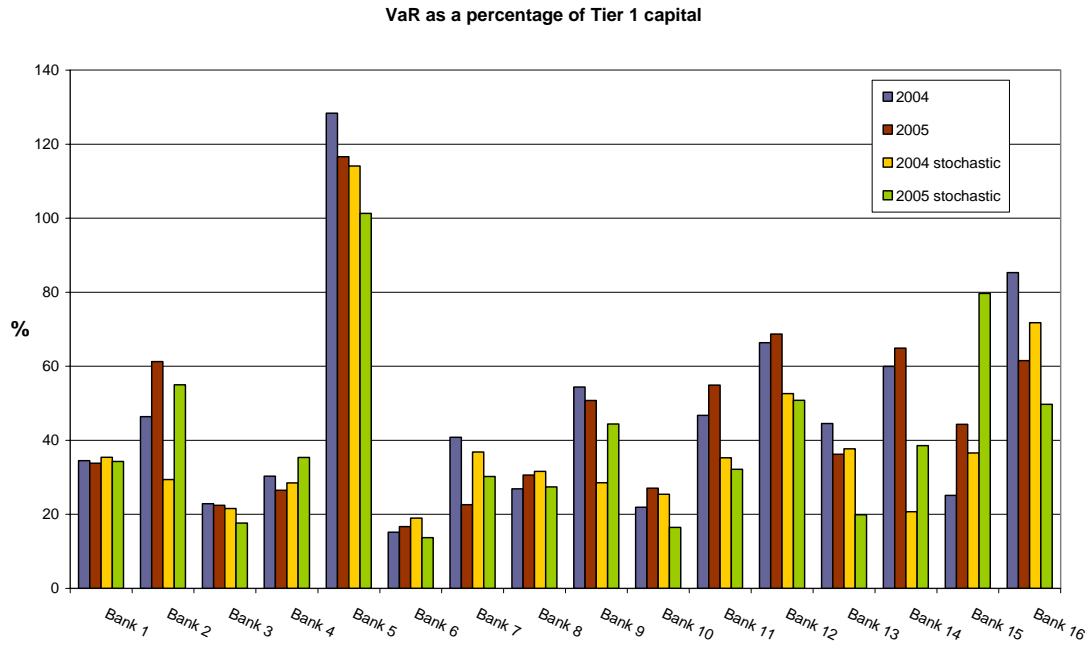
VaR as a percentage of Tier 1 capital

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 6

Change in VaR as a percentage of Tier 1 Capital (2004)
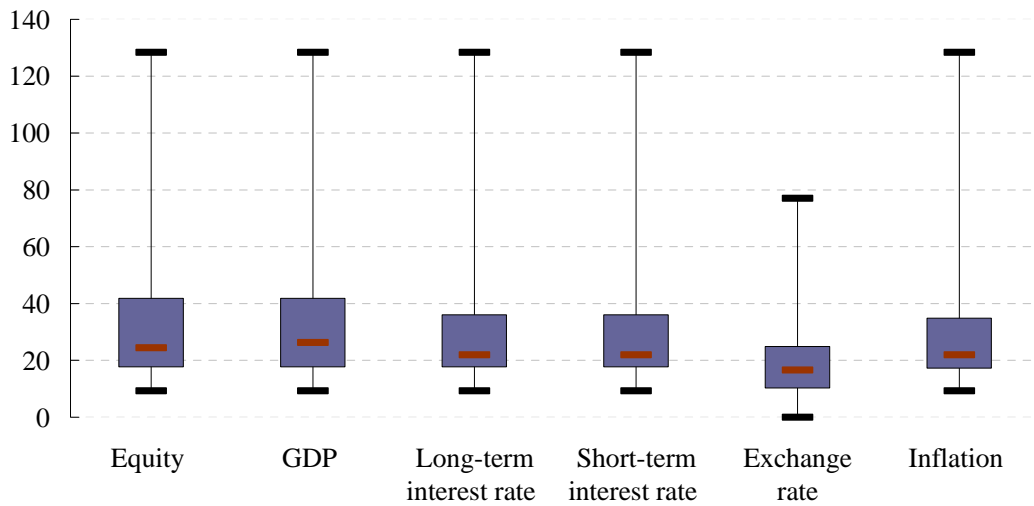
Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 7

Change in VaR as a percentage of Tier 1 Capital (2005)

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 8

Change in VaR as a percentage of Tier 1 Capital (2004, stochastic LGDs)

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.

Figure 9

Change in VaR as a percentage of Tier 1 capital
(2005, stochastic LGDs)

Sources: EU large and complex banking groups' (LCBGs) annual reports and ECB calculations.
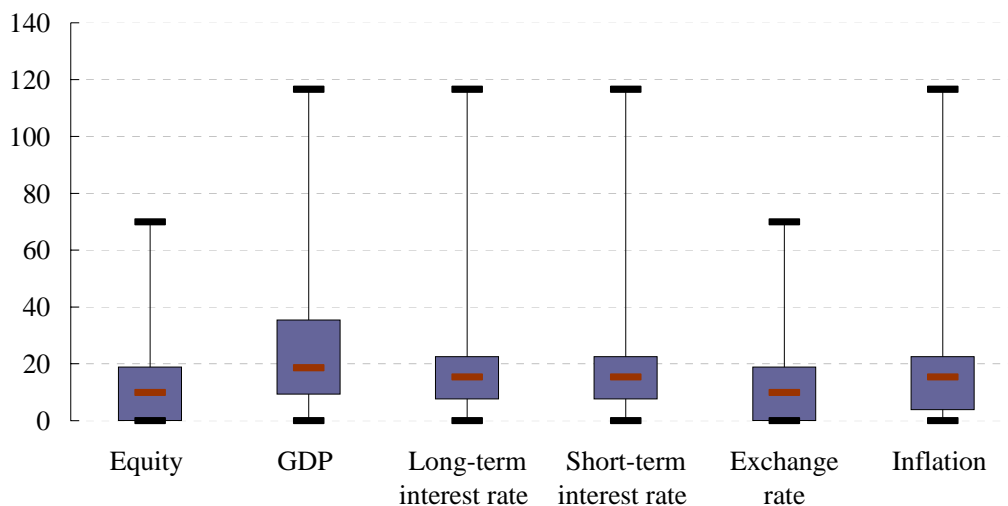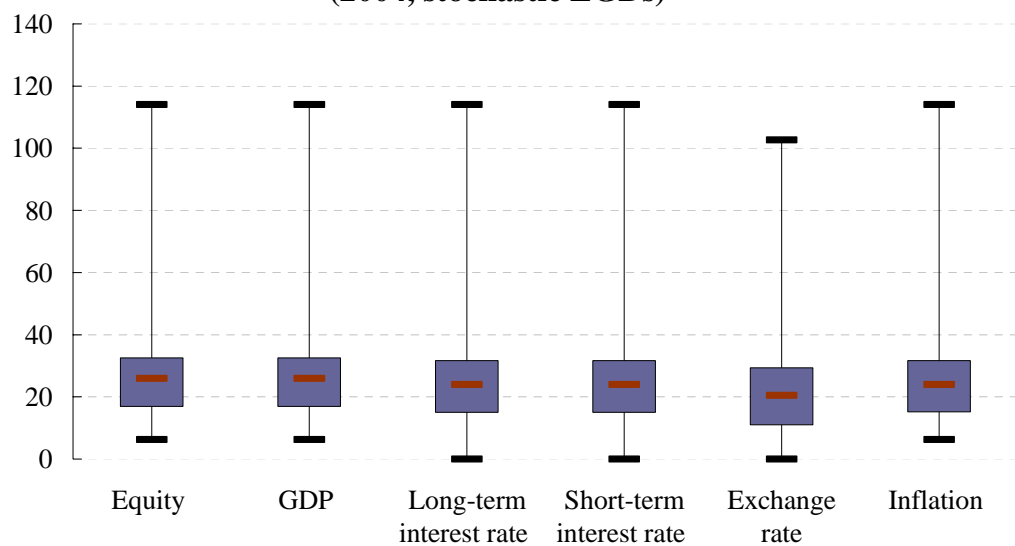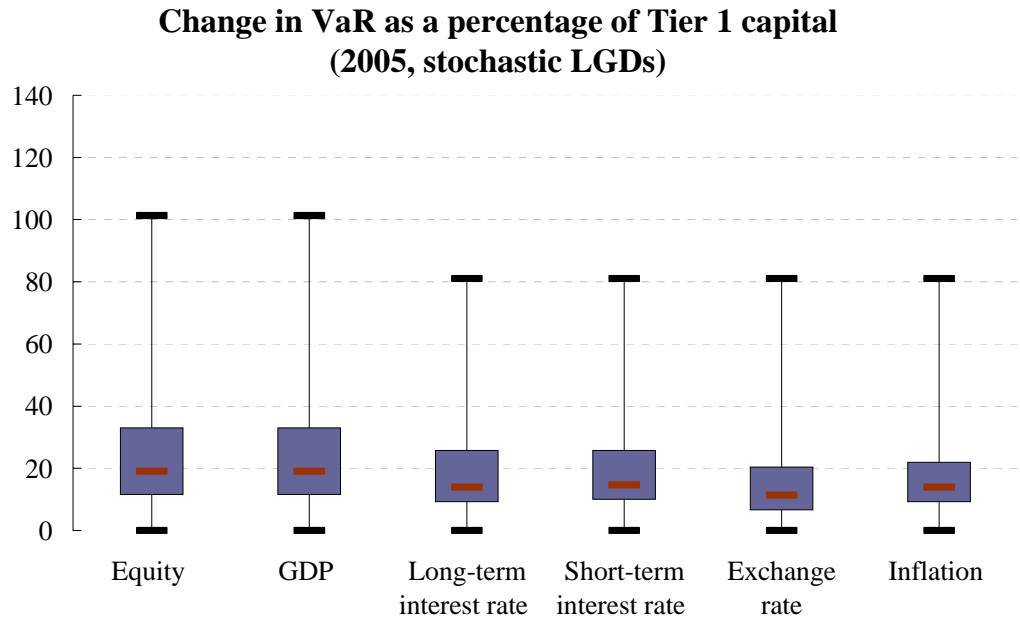
Table 1: Stylised credit portfolio example

Sector	Exposure	LGD	Loss value	Probability of Default	Expected loss
	(EUR millions)	(%)	(EUR millions)	(% probability)	(EUR millions)
Corporate	1062	0.38	404	0.02	8.08
Corporate	4740	0.20	948	0.02	18.96
Corporate	1066	0.27	288	0.02	5.76
Bank	276	0.20	55	0.01	0.55
Household	10598	0.13	1378	0.01	13.78
Household	1776	0.47	835	0.04	33.40
Public	596	0.30	178	0.001	0.17

Source: ECB (2007), "Assessing portfolio credit risk in a sample of EU large and complex banking groups", Special Feature C, Financial Stability Review, June.

Table 2: The Satellite model estimation for median EDFs (1992:Q1-2005:Q4)

	Const	GDP	INFL	EQUITY	EP	IR	Adjusted R-squared
Aggr	0.853	-0.350	-0.054	-0.018	-0.028	-0.010	0.377
P-value	0.000	0.040	0.823	0.020	0.077	0.228	
BaC	0.663	-0.285	0.161	-0.014	-0.012	-0.007	0.470
P-value	0.000	0.006	0.268	0.003	0.198	0.146	
Cap	1.167	-0.465	-0.097	-0.022	-0.034	-0.011	0.371
P-value	0.000	0.030	0.749	0.025	0.089	0.268	
CCY	0.679	-0.266	0.018	-0.015	-0.017	-0.006	0.417
P-value	0.000	0.022	0.915	0.005	0.120	0.270	
CNC	0.520	-0.117	-0.100	-0.010	-0.012	-0.003	0.267
P-value	0.000	0.235	0.485	0.026	0.206	0.558	
ENU	0.160	-0.047	0.031	-0.005	-0.002	0.000	0.406
P-value	0.000	0.080	0.421	0.000	0.332	0.737	
Fin	0.168	-0.030	0.081	-0.003	-0.002	-0.001	0.469
P-value	0.000	0.118	0.005	0.001	0.196	0.404	
TMT	2.385	-1.179	-0.831	-0.062	-0.135	-0.038	0.328
P-value	0.006	0.108	0.433	0.066	0.052	0.272	

Source: Castrén, Dées and Zaher (2008).
Note: EP stands for euro/US dollar real exchange rate and IR for short term interest rate. The parameters are expressed in logs and they can be interpreted as elasticities. The last column presents the adjusted R-squared.

Table 3: Bank specific balance sheet information 2004-2005

Variable	2004					2005				
	Mean	Median	Max	Min	Standard deviation	Mean	Median	Max	Min	Standard deviation
Total Assets	612072.1	639285.5	1062529.0	102819.0	306299.9	754679.5	795122.0	1371988.0	132214.0	362160.6
Deposits and Short Term Funding	436854.9	404284.5	802554.0	73452.0	224103.7	532104.8	493781.5	1002900.0	94116.0	271219.9
Equity	23908.0	18837.0	48111.0	7683.0	13253.2	30144.4	28386.5	55649.0	8417.0	15680.9
Net Income	3349.5	3467.0	7852.0	265.0	1998.5	4236.9	4377.0	8251.0	1271.0	2100.7
Total Capital	11.5	11.6	13.3	9.5	1.2	11.7	11.3	16.3	9.2	1.7
Equity Total Assets	4.3	4.5	7.5	2.3	1.7	4.2	4.0	6.3	2.6	1.2
Net Interest Income	1.3	1.3	2.2	0.5	0.4	1.2	1.2	2.3	0.5	0.4
Return on Average Assets	0.6	0.6	1.1	0.1	0.3	0.7	0.6	1.2	0.3	0.2
Return on Average Equity	14.1	15.8	23.8	2.0	5.7	16.1	15.7	22.6	10.2	3.7
Cost to Income Ratio	63.4	63.4	84.4	41.7	9.9	61.3	59.4	82.8	47.0	8.5
Net Loans to Total Assets	44.3	41.9	64.0	24.4	12.7	43.9	41.3	64.0	23.9	12.7

Sources: Large and complex banking groups' (LCBGs) annual reports and ECB calculations.
Note: Values are expressed in million EUR and ratios in percent.

Table 4: VaR changes following different macroeconomic shocks, 2004

VaR	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	9048	9575	8932	8932	7531	8683
minimum	3621	3621	3621	3621	3018	3621
median	12091	12428	11415	11415	10885	11415
maximum	26914	26914	26914	26914	22579	26914
quartile 3	21343	21343	20570	20570	17362	20570

VaR change as %TIER_1	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	18	18	18	18	10	17
minimum	9	9	9	9	0	9
median	24	26	22	22	17	22
maximum	128	128	128	128	77	128
quartile 3	42	42	36	36	25	35

VaR change as %TOTAL_CAPITAL	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	12	12	11	11	7	11
minimum	7	7	7	7	0	7
median	17	19	15	15	12	15
maximum	76	76	76	76	46	76
quartile 3	24	25	20	20	15	20

Note: All statistics are computed over a sample of 16 LCBGs. The shock size for each macro variable is 5 standard deviations.

Table 5: VaR changes following different macroeconomic shocks, 2005

VaR	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	8345	9020	8379	8379	8345	8379
minimum	4459	4459	4459	4459	4459	4459
median	10749	12519	11789	11789	10749	11789
maximum	23472	42250	30178	30178	23472	30178
quartile 3	21351	25205	24401	24401	21351	24401

VaR change as %TIER_1	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	0	9	8	8	0	4
minimum	0	0	0	0	0	0
median	10	19	15	15	10	15
maximum	70	117	117	117	70	117
quartile 3	19	35	23	23	19	23

VaR change as %TOTAL_CAPITAL	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	0	6	5	5	0	3
minimum	0	0	0	0	0	0
median	7	13	11	11	7	11
maximum	45	75	75	75	45	75
quartile 3	12	24	14	14	12	14

Note: All statistics are computed over a sample of 16 LCBGs. The shock size for each macro variable is 5 standard deviations.

Table 6: VaR changes following different macroeconomic shocks, 2004, stochastic LGDs

VaR	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	8451	8451	8451	8451	8451	8451
minimum	2869	2869	1913	1913	1913	2869
median	12574	12574	11902	11902	11229	11902
maximum	27339	27339	27339	27339	23922	27339
quartile 3	15111	15111	15111	15111	14891	15111

VaR change as %TIER_1	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	17	17	15	15	11	15
minimum	6	6	0	0	0	6
median	26	26	24	24	21	24
maximum	114	114	114	114	103	114
quartile 3	33	33	32	32	29	32

VaR change as %TOTAL_CAPITAL	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	11	11	11	11	8	11
minimum	4	4	0	0	0	4
median	17	17	16	16	15	16
maximum	68	68	68	68	61	68
quartile 3	23	23	22	22	20	22

Note: All statistics are computed over a sample of 16 LCBGs. The shock size for each macro variable is 5 standard deviations.

Table 7: VaR changes following different macroeconomic shocks, 2005, stochastic LGDs

VaR	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	8006	8006	7739	7739	7348	7739
minimum	3999	3999	3999	3999	3999	3999
median	14526	14526	13412	13412	12943	13412
maximum	28679	28679	26289	26289	23899	26289
quartile 3	17773	17773	17662	17662	15599	16958

VaR change as %TIER_1	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	12	12	9	10	7	9
minimum	0	0	0	0	0	0
median	19	19	14	15	11	14
maximum	101	101	81	81	81	81
quartile 3	33	33	26	26	20	22

VaR change as %TOTAL_CAPITAL	Equity	GDP	Long-term interest rate	Short-term interest rate	Exchange rate	Inflation
quartile 1	8	8	6	8	4	6
minimum	0	0	0	0	0	0
median	12	12	10	10	8	9
maximum	65	65	52	52	52	52
quartile 3	24	24	19	19	14	16

Note: All statistics are computed over a sample of 16 LCBGs. The shock size for each macro variable is 5 standard deviations.

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