Credit risk modelling

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LAST AUTUMN the Bank of England and the Financial Services Authority (FSA) hosted a conference to examine developments in credit risk modelling and their regulatory implications. The conference was co-organised by the Federal Reserve Board of Governors, the Federal Reserve Bank of New York and the Bank of Japan, and was attended by central bankers, regulators, academics and senior practitioners working in the field.

The main goal of the conference was to look at evidence on the construction and reliability of credit risk models. This issue has financial stability implications in terms of both the reliance that firms can place on models to improve their credit risk management and the reliance that regulators can place on them to calculate capital requirements for credit risk, which form the main prudential buffer in banks' balance sheets. The Basel Committee on Banking Supervision was actively considering whether models were sufficiently well developed to be used as a regulatory tool in any revision to the credit risk treatment set out in the 1988 Basel Accord.

The 1988 Accord established a common minimum standard for the capital requirements for internationally active banks in the G10, the central element of which were credit risk requirements. In 1996, the Accord was amended to include new risk-based requirements for securities and fx trading books. As part of this risk-based approach, sophisticated firms were given the option of requesting recognition of their in-house value-at-risk (VaR) models to set the capital requirements for their trading books. These VaR models assessed likely losses taking into account the volatility and correlations of the returns on different assets.

Banks are now developing models to enable the calculation of value-at-risk on portfolios of credit exposures. Like market VaR models, these take into account the correlations between returns on different exposures. Banks are starting to use them to allocate economic capital and as a risk management tool. **William McDonough** (Chairman of the Basel Committee on Banking Supervision and President of the Federal Reserve Bank of New York) said in a keynote address to the conference that the development of credit risk modelling would be the catalyst for a major rethinking of the theory and practice of credit risk management over the next few years. Other speakers also applauded their potential use as a risk management tool.

Banks have been pressing for the recognition of models in setting capital for credit books, because of distortions created by the current requirements. The conference started by considering the extent to which strains had developed in applying the current standard and then looked at developments in credit risk modelling. The key issue on which the conference attempted to shed light was the accuracy of the models. Credit risk modelling is at an earlier stage of development than modelling of trading book VaRs and the data problems are more acute, making an assessment of reliability essential. The conference also looked at ways in which the models could be tested and how they might evolve in the future.

Strains in the current system

The 1988 Basel Accord placed exposures in broad risk categories to which capital weights were applied: essentially 0 per cent for OECD government exposures, 20 per cent for interbank, 50 per cent for residential mortgages, and 100 per cent for the remainder (including the full range of corporate exposures). The broad bands, encompassing a wide range of risks, provide incentives for banks to carry out regulatory arbitrage — reducing the regulatory measure of their risk with little or no reduction in their economic risk.

David Jones (Federal Reserve Board) showed how securitisation and other financial innovations had enabled banks to engage in such arbitrage. This had created the danger that reported regulatory capital ratios could mask a deterioration in a bank's true financial condition.

Claes Norgren (Director General, Financial Services Authority, Sweden) discussed more generally the pressures on the current treatment of credit risk. The Accord did not acknowledge risk diversification and gave only limited allowance for risk reduction through collateral, guarantees or netting. Nor did it take account of new instruments or techniques such as credit derivatives.

John Mingo (Federal Reserve Board) looked at the policy implications of regulatory arbitrage. He suggested that it was tempting for regulators to respond by formally forbidding the procedures used by banks to reduce their effective capital requirements. But this would be ill advised, in part because financial innovation would enable banks to find alternative avenues. Perhaps more important, regulatory arbitrage provided a safety valve, mitigating the effects of capital requirements that substantially exceeded an economic assessment of risk. He set out the goals for prudential regulation and supervision and looked at how the Basel Accord could be brought into line with the banks' own assessment of risk. There were two proposals on the table — modification of the Basel risk bucket approach or a full models approach. In his view it was not necessary for Basel to adopt a full models approach — although in theory that would be preferable — but any new risk bucketing system would have to bear some resemblance to banks' own internal rating systems.

Michael Foot (Managing Director, Financial Services Authority, UK), expressed a strong preference for supervisory tools based on methods used by the regulated firms themselves. He hoped that in time it would be possible for supervisors to accommodate credit risk modelling within their own regulatory procedures. But at present the dangers, as well as the rewards, of credit risk models were much greater than those of market risk models. He identified issues that needed to be addressed. These included the scarcity of data, particularly covering more than one business cycle; the scale and sophistication of the banks that would be able to run these models; and the need for more work to be done on operational risk and on the correlations between market, credit and operational risk. He announced that, when UK banks could demonstrate that their credit risk modelling contributed to sound risk management practice, the FSA would take this into account in setting individual risk asset capital ratios for those banks.

Current credit risk modelling and internal grading practice

A survey by the FSA into the use of credit risk modelling techniques in the UK found that major banks, like their continental counterparts, had been working to incorporate within their credit risk management processes models that have been published or sold by third parties. The survey, described in a paper by **Vyvian Bronk** and **Emmanuelle Sebton** (Financial Services Authority, UK), noted that credit

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portfolio modelling was typically confined to certain parts of the asset portfolio. Different techniques were applied to different types of business. For example, "bottom-up" approaches were generally applied to individual large corporate exposures (where information on each corporate was readily available). "Top-down" models tended to be applied to retail credit portfolios, grouping together exposures where there was little information on individual obligors. Models were commonly used to allocate economic capital within business units and as an input to more consistent pricing of certain credit risks. However, the use of models to create an integrated approach to overall credit risk management was rare.

One important issue discussed in the FSA's survey related to the choice of modelling horizon. Longer horizons implied correspondingly larger possible losses. The horizon most commonly chosen was one year — because data on changes in credit quality (default rates and credit rating transition probabilities) were most commonly available at this horizon. This horizon might be suitable for some purposes, but could be too short for others. An important consideration when deciding upon the modelling horizon was whether the portfolio model aimed to capture only the probability of loss due to default (ie a "default mode" model) or whether it was designed also to capture changes in economic value during the planning horizon (a "mark-to-market" model).

The Federal Reserve System has recently published a comparable study which reviews credit risk modelling practice in the US *(Credit Risk Models at Major US Banking Institutions: Current State of the Art and Implications for Assessments of Capital Adequacy, 1998)*. **John Mingo** stated that for several of the major US banks surveyed, credit risks were measured in a crude fashion or not at all for some business activities (eg consumer or small business credit products). In business areas where credit risk measurement was more sophisticated (eg in the trading book and for large and middle market corporate lending) the Federal Reserve study noted significant shortcomings both in model construction features and model validation procedures. These included a lack of stress testing or backtesting.

Bill Treacy and **Mark Carey** (Federal Reserve Board) presented the results of their survey of internal rating systems at large US banks. They noted that as the rating process almost always involved the exercise of human judgement, banks needed to pay careful attention to the internal incentives that could distort rating assignment. Also, rating criteria might be largely a matter of "credit culture" rather than formal written policy, and data might not have been kept in a form that allowed the analysis of the relationship between assigned grades and actual loss experience. While a few US banks were moving towards models as the primary basis for internal ratings, most still believed that properly managed judgemental rating systems delivered more accurate assessments of risk.

Jeremy Gluck (Moody's, New York) described the rating process used by Moody's for collateralised debt obligations (CDOs) — a rapidly-growing class of debt instruments which consisted of securitised pools of bonds or loans. Moody's had attempted to replicate the loss behaviour of the securitised pool of assets by postulating a smaller pool of assets (for each of which Moody's had produced a rating, which could be related to an historical estimate of default probability). For this pool, the loss distribution had the same mean and volatility as the CDO, so that, by simulating various loss scenarios, the expected loss (and hence rating) for each tranche of the CDO could be estimated.

Credit risk models and inputs

A number of the papers at the conference examined the design of credit risk models and problems with the inputs used. Credit risk models must take account of shortcomings in the data, notably the lack of mark-to-market price data on loan books. The different models (see Box 1 for a description of the main model types) tackle this by devising proxies for market prices using other information about the obligor. For example, some employ bond ratings or a bank's own internal counterparty ratings, while others use the equity market capitalisation of obligors.

All credit risk models inevitably depend heavily on the quality of data inputs. For example, it is essential for ratings-based models that ratings are accurate and consistent indications of credit standing. While a rating itself provides information on the current credit standing of an obligor, rating migration patterns indicate how credit standings may change over the modelling horizon.

Gordon Delianedis and **Robert Geske** (UCLA) examined the relationship between default probabilities and credit rating transitions (including default), and demonstrated that rating downgrades may lag behind the deterioration in credit quality. While this characteristic of rating changes was well known, the magnitude of these lags (up to 18 months in some cases) suggested a serious limitation on the usefulness of ratings.

In another study of the reliability of ratings for credit risk purposes, **Pamela Nickell**, **William Perraudin** and **Simone Varotto** (I)(Bank of England) argued that the use of a single rating transition matrix in credit risk models might not be appropriate. A multivariate model, distinguishing obligors by domicile and industrial sectors, and taking account of the business cycle, might provide a more valid summary of migration patterns than the common practice of using simple estimates of transition probabilities based on historical averages. They also questioned whether the use of rating transition models estimated from data on changes in bond ratings was appropriate in credit risk models applied to loan portfolios. Until recently, empirical corporate default rate studies had considered only bonds (whose prices were readily observable), rather than loans. **Edward Altman** and **Heather Suggitt** (Stern School, NYU and Credit Suisse First Boston) presented the first study of default rates and rating changes in the corporate loan market. They found that default behaviour of loans quite closely resembled that of bonds five years after issuance, but was somewhat different for one to three years after issuance. However, these results covered the recent relatively benign credit period in the US (1992-1997).

Evaluating credit risk models

The main issue for regulators contemplating the use of credit risk models to calculate capital requirements is whether they can produce accurate results. In fact, validation is extremely difficult, largely because all credit risk models suffer from lack of data. This hampers both the construction of models and the ability to carry out backtesting. One problem with credit risk is that the loss distribution is heavily skewed. A long time series of data (covering many business cycles) would be necessary to identify the shape of the tail of the distribution. In the absence of these long runs of data, many models assume that the distribution is normal. This simplifying assumption would be likely to create biases in the value-at-risk estimates.

A large number of observations are needed from any model in order to judge whether it is accurate. Since the relevant holding period for credit risk modelling is long (a year is probably the minimum), it is extremely difficult to construct data sets with many observations. In backtesting credit risk models, judging accuracy is made more difficult by the absence of a market price for a loan portfolio, and therefore the absence of a ready measure of the change in the value of the portfolio against which the model's calculated value-at-risk can be compared. A further difficulty is that the proxies for market value employed by the models are not available for many obligors. Many companies do not have an equity market quotation (either because the equity is tightly held and not marketed or because they are privately owned) and most small and medium-sized firms are not rated. Indeed, outside the US even large firms are often not rated.

The conference included presentations of some of the first serious attempts to evaluate model results.

A paper by **Michel Crouhy** and **Robert Mark** (Canadian Imperial Bank of Commerce, Canada) and another by **Michael Gordy** (Federal Reserve Board) compared the values-at-risk and thus capital levels implied by different models at a point in time. Crouhy and Mark applied several models (CreditMetrics, KMV, CreditRisk$^+$ and CIBC's own CreditVar1) to a large diversified benchmark bond portfolio. Their results suggested that (when parametrised in a similar manner) models of apparently different types could yield broadly consistent values-at-risk, although some did differ by as much as 50 per cent. Michael Gordy compared the values-at-risk implied by CreditMetrics and CreditRisk$^+$ using simulated portfolios designed to resemble banks' actual holdings. He found that CreditRisk$^+$ and a restricted version of the CreditMetrics model yielded similar results, although the former was more responsive to the credit quality of the portfolio. He did, however, find that the output of his CreditRisk$^+$ model could be highly

Box 1 Credit risk models

Credit risk models attempt to estimate, for a portfolio of credit exposures, the loss over a particular time horizon which will be exceeded on not more than, say, 0.5 per cent of occasions — in other words, the value-at-risk estimated with 99.5 per cent confidence. Models are designed to estimate the loss either arising from default (default-mode models) or as a result of the change in economic value of the loans because of credit deterioration (mark-to-market models). A number of credit risk models have been developed over the past decade. These include both proprietary applications intended for internal use by financial institutions, and others intended for sale or distribution to third parties. Among the better known publicly available models, there are four main types:

- Merton-based, eg KMV's PortfolioManager
- Ratings-based, eg The RiskMetrics Group's CreditMetrics
- Macroeconomic, eg McKinsey's CreditPortfolioView
- Actuarial, eg CSFP's CreditRisk^{+}

Merton-based models

These are based on the model of a firm's capital structure first proposed by Merton in 1974: a firm is considered to be in default when the value of its assets falls below that of its liabilities. The magnitude of the difference between the assets and liabilities and the volatility of the assets then determine the borrower's default probability. KMV has developed an extensive database to assess the loss distribution related to both default and credit quality migration. KMV's Credit Monitor calculates an expected default frequency (EDF) for each individual borrower as a function of the firm's capital structure, the volatility of its asset returns and its current asset value, using Merton's contingent claim model. KMV's historical data are then used to derive loss estimates.

Ratings-based models

CreditMetrics assumes that changes in a latent variable which drives credit quality are normally distributed. The probability of a borrower's change in credit quality (including default) within a given time horizon can be expressed as the probability of a standard normal variable falling between various critical values. These critical values are calculated using the borrower's current credit rating and historical data on credit rating migrations. They are generally presented in the form of a matrix of probabilities that a borrower with one rating might move into another rating category during a year. For example, for an A-rated credit one row of the matrix shows the probabilities that its rating will change to AAA, AA, BBB, BB, or C, or that the obligor will default; the closer the rating category to the current rating, the higher the probability of a move to that category. Both Merton-based and ratings-based models convert the estimates of losses on individual credits to estimates of loss on whole portfolios by estimating the correlations in changes in credit quality for all pairs of obligors. Both CreditMetrics and KMV's PortfolioManager make the simplifying assumption that a firm's asset returns are generated by a set of common, or systematic, risk factors along with idiosyncratic factors. The idiosyncratic factors may be firm specific, country specific or industry specific.

Macroeconomic models

The most widely used of these, CreditPortfolioView, measures only default risk, and attempts to take into account the link between default probabilities in any period and the macroeconomic climate. It uses Monte Carlo simulation to estimate the joint distribution of default probabilities for individual credits conditional on the value of macroeconomic factors such as the unemployment rate, the growth rate of GDP, the level of long-term interest rates, foreign exchange rates, government expenditure and the aggregate savings rate. Correlations between default rates for different obligors are considered to arise from the covariance structure of the underlying macroeconomic variables.

Actuarial models

Credit Risk^{+} estimates the loss distribution using statistical techniques developed in the insurance industry. Only default risk is considered. Rather than attempting to relate this to the structure of the firm, the model allocates borrowers amongst "sectors", each of which has a mean default rate and a default rate volatility. Default for individual loans is assumed to follow a Poisson process. Although credit migration risk is not explicitly modelled, CreditRisk^{+} assumes that the mean default rate is itself stochastic. This assumption generates a skewed distribution of default events, which is taken to account (if only partially) for migration risk.

sensitive to one particular parameter, which describes the tail thickness of the distribution of the systematic risk factor. The main conclusion of both studies was that models might appear very different in mathematical formulation but supply broadly similar risk measures if parametrised in a consistent fashion.

Comparison of value-at-risk calculations produced by different models on the same portfolios at one point in time (as in the studies by Crouhy and Mark, and by Gordy) may help to show whether the outputs of different models are consistent. However, in order to be confident about the relative performance of various models one would need to test the value-at-risk figures produced by the models against the out-turn over a fairly lengthy period — several business cycles at least. The important question is whether the models would in fact generate more exceptions (periods when the value-at-risk was exceeded by actual losses) than they were built to deliver. A model built to deliver a value-at-risk that was exceeded on only one occasion in a hundred might in practice deliver many more exceptions.

Jose Lopez and **Marc Saidenberg** (Federal Reserve Bank of San Francisco and Federal Reserve Bank of New York) discussed a mixture of time series and cross-sectional testing of credit risk models (although they did not actually run these tests on data). They suggested that models should be evaluated not only on their forecasts over time, but also on their forecasts at a given point in time for simulated credit portfolios. They contended that cross-sectional evaluation of models might permit validation in the absence of long data runs.

Pamela Nickell, **William Perraudin** and **Simone Varotto (II)** presented a paper evaluating two of the most widely applied types of credit risk model on an out-of-sample basis. The models tested were a ratings-based framework resembling CreditMetrics and an equity-based model resembling the approach of the consulting firm KMV. They were tested using an extensive data set of Eurobond prices. The assessment of the models was carried out in a rigorously out-of-sample fashion, comparing the model's one-year holding period value-at-risk estimates with out-turns. This test was conducted on a variety of portfolios over an 11-year period.

They concluded that the two approaches implied similar capital requirements for well diversified portfolios, although significant differences emerged when the models were applied to low-credit quality exposures and less well diversified portfolios. An important finding was that the estimate of value-at-risk was too low. The models were built to deliver a 99 per cent confidence level — in other words, one occasion in a hundred when losses exceeded the value-at-risk estimate. When run on portfolios of US corporate exposures, the losses exceeded the value-at-risk estimate in one year out of the eleven. But when run on portfolios of exposures to non-US borrowers the figure was five times this. There were also a large number of exceptions when the models were used to calculate value-at-risk numbers for portfolios of exposures to financial companies including banks.

A general conclusion that emerges from the few studies of the accuracy of credit risk models so far conducted is that they are not robust to slight changes in the parameters (as demonstrated in particular by Michael Gordy). For each model, several of the more important parameters are hard to pin down convincingly using the data available. This last point had become obvious to Nickell, Perraudin and Varotto in their construction of two models. Each required various assumptions to be made about parameter values. In addition this paper raised questions about whether the value-at-risk figures produced by the models were sufficiently conservative.

Testing methods used in the various papers presented at the conference

Comparison of the anatomy of the models	Gordy Crouhy and Mark
Comparative simulation exercises	Gordy
Comparison of estimates from different models for a single portfolio	Crouhy and Mark Gordy
Development of empirical tests	Lopez and Saidenberg
Comparison of forecasts and out-turns over time	Nickell, Perraudin, Varotto

... There are significant hurdles that will have to be overcome before the models could be used to set regulatory capital requirements. In particular, it is not clear that the output of the models is yet sufficiently transparent and susceptible to backtesting ...

Patricia Jackson (Head of Regulatory Policy, Bank of England) summing up the session on testing methods said that in order to consider a regulatory use of models there needed to be a clear understanding of what the various models delivered — how one type of model compared with another; the weaknesses of the various approaches; whether they supplied unbiased measures of value-at-risk; whether some models worked better for some types of exposure than others; and whether the models could accurately rank credit portfolios according to their relative riskiness. All the papers presented at the conference had focused on models based on publicly available data (ratings/equity prices) for large corporate exposures. Even less was known about the accuracy of models built by the banks for other parts of the book using in-house data.

Overall, the results presented at the conference indicated that significant further work will be necessary before the output of these credit risk models can be regarded as robust and reliable measures of risk. Meanwhile, efforts to develop new models that describe the essential credit risk behaviour of corporate loan portfolios continue: the conference provided an opportunity for several approaches to be discussed.

New techniques

Darrell Duffie (Stanford University) reviewed some methods for simulating correlated defaults for loan portfolios, and compared some of the features of their implied distributions. **Robert Jarrow** and **Stuart Turnbull** (Cornell University and CIBC, Canada) presented a model that (unlike CreditMetrics and KMV) incorporated macroeconomic variables that appeared to influence the aggregate rate of business failures. Correlations in default probabilities were assumed to arise from their common dependence on the same economic factors. As an alternative to the conventional value-at-risk method for determining adequate capital, **Daisuke Nakazato** (Industrial Bank of Japan) proposed a version of a Coherent Pricing Method that used a contingent pricing approach and attempted to capture the diversification effect of the credit portfolio.

Conclusions

Both **Howard Davies** (Chairman, Financial Services Authority, UK) and **Oliver Page** (Director, Financial Services Authority, UK) expressed the widely-held view that credit risk models are a useful addition to the armoury of risk management tools. They stressed the need for regulators to find ways of rewarding good credit risk management. Models could represent sensible and illuminating ways of organising assumptions about the risks involved in credit portfolios. They could help both management and regulators to improve their understanding of institutions' risk taking.

However, the conference highlighted the fact that many issues have not yet been resolved, in particular questions of data availability and model validation. There are therefore significant hurdles that will have to be overcome before the models could be used to set regulatory capital requirements. In particular, it is not clear that the output of the models is yet sufficiently transparent and susceptible to backtesting to allow them to be used in this way. This point was stressed in the report published recently by the Basel Committee on Banking Supervision ("Credit risk modelling: current practices and applications", April 1999).

Alastair Clark (Executive Director, Financial Stability, Bank of England), summing up the conference, emphasised that regulatory progress would be highly dependent on industry progress with data collection and testing, and on further academic advances.

CREDIT RISK MODELLING AND THE REGULATORY IMPLICATIONS

CONFERENCE HELD AT THE BARBICAN, LONDON 21-22 SEPTEMBER 1998

Programme

WELCOMING REMARKS

David Clementi (Bank of England)

INTRODUCTORY ADDRESS

CREDIT RISK AND THE REGULATORS

Howard Davies (Financial Services Authority, UK)

STRAINS IN THE CURRENT SYSTEM

Chairman: Naoki Tabata (Bank of Japan)

OVERVIEW: STRAINS IN THE CURRENT SYSTEM

Claes Norgren (Financial Supervisory Authority, Stockholm)

EMERGING PROBLEMS WITH THE ACCORD: REGULATORY CAPITAL ARBITRAGE AND RELATED ISSUES

David Jones (Federal Reserve Board, Washington)

CURRENT CREDIT RISK MODELLING PRACTICE

Chairman: Michael Foot (Financial Services Authority, UK)

POLICY IMPLICATIONS OF THE FEDERAL RESERVE STUDY OF CREDIT RISK MODELS
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John Mingo (Federal Reserve Board, Washington)

CREDIT RISK MODELLING BY BANKS: A UK PERSPECTIVE

Vyvian Bronk and Emmanuelle Sebton (Financial Services Authority, UK)

INTERNAL CREDIT RISK SCORING SYSTEMS AT LARGE US BANKS

Mark Carey and Bill Treacy(Federal Reserve Board, Washington)

MOODY'S RATINGS OF COLLATERALISED BOND AND LOAN OBLIGATIONS

Jeremy Gluck (Moody's, New York)

CREDIT RISK MODELLING AND CAPITAL: AN OVERVIEW

Michael Foot (Financial Services Authority, UK)

WHAT DO THE MODELS DELIVER?

Chairman: Patricia Jackson (Bank of England)

EVALUATING CREDIT RISK MODELS

Jose Lopez and Marc Saidenberg (Federal Reserve Banks of San Francisco and New York)

Discussant: Anthony Saunders (Stern School, NYU)

A COMPARATIVE ANALYSIS OF CURRENT CREDIT RISK MODELS

Michel Crouhy and Robert Mark (CIBC, Toronto)

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A COMPARATIVE ANATOMY OF CREDIT RISK MODELS

Michael Gordy (Federal Reserve Board, Washington)

Discussant: Christopher Finger (JP Morgan)

RATINGS- VERSUS EQUITY-BASED CREDIT RISK MODELLING; AN EMPIRICAL ANALYSIS OF CREDIT RISK MODELLING TECHNIQUES
Pamela Nickell, William Perraudin and Simone Varotto (Bank of England)
Discussant: John Andrew McQuown (KMV)

CREDIT RISK ISSUES
Chairman: Patrick Parkinson (Federal Reserve Board, Washington)

DEFAULT RATES IN THE SYNDICATED BANK LOAN MARKET; A MORTALITY ANALYSIS
Edward Altman and Heather Suggitt (Stern School, NYU and Credit Suisse First Boston)
Discussant: Stephen Schaeffer (London Business School)

STABILITY OF RATINGS TRANSITIONS
Pamela Nickell, William Perraudin and Simone Varotto (Bank of England)
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CREDIT RISK AND RISK NEUTRAL DEFAULT PROBABILITIES: INFORMATION ABOUT RATING MIGRATIONS AND DEFAULTS
Gordon Delianedis and Robert Geske (UCLA)
Discussant: Anthony Neuberger (London Business School)

THE INTERSECTION OF MARKET AND CREDIT RISK
Robert Jarrow and Stuart Turnbull (Cornell University and CIBC, Toronto)
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SPECIAL ADDRESS
ISSUES FOR THE BASEL ACCORD
William McDonough (Federal Reserve Bank of New York)

NEW TECHNIQUES FOR CREDIT RISK MODELLING
Chairman: Alastair Clark (Bank of England)

SIMULATING CORRELATED DEFAULTS
Darrell Duffie and Kenneth Singleton (Stanford University)

DETERMINATION OF THE ADEQUATE CAPITAL FOR CREDIT DERIVATIVES AS A CONTINGENT CLAIM EVALUATION PROBLEM
Daisuke Nakazato (Industrial Bank of Japan)
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PANEL SESSION: PRACTICAL WAYS FORWARD
Chairman: Oliver Page (Financial Services Authority)

Claes Norgren (Financial Supervisory Authority, Stockholm),
Jochen Sanio (Federal German Supervisory Office), Joe Rickenbacher (UBS)

CLOSING REMARKS
Alastair Clark (Bank of England)

The following summaries of the individual papers were prepared or approved by the speakers. The full versions of most of the papers will be published in a special edition of the *Journal of Banking and Finance* covering the conference.

Emerging problems with the accord: regulatory capital arbitrage and related issues

David Jones, Federal Reserve Board, Washington

THE USEFULNESS of the Basel Accord's risk-based capital (RBC) ratios — as a "trigger" for supervisory interventions, and an important basis for financial disclosures that are scrutinised by bank counterparties — depends on the reliability of total risk-weighted assets as their implicit measure of bank risk taking. Yet, even at the Accord's inception, it was clearly understood that total risk-weighted assets were not a reliable measure of risk. For example, within the banking book, all commercial loans receive the same 100 per cent risk-weight, regardless of the ratings of the borrowers. The measure also ignores critical differences in diversification, hedging, and the quality of risk management.

Such shortcomings, together with recent financial innovations, are undermining the effectiveness of regulatory capital policies by encouraging widespread regulatory capital arbitrage and discouraging effective risk management practices.

Regulatory Capital Arbitrage

Regulatory capital arbitrage is defined as activities that permit a bank to assume greater risk with no increase in its minimum regulatory capital requirement, while at the same time showing no change, or possibly an increase, in its reported capital ratios. Such activities reflect banks' efforts to keep their funding costs, inclusive of equity, as low as possible. In practice, capital arbitrage exploits the large divergences that can arise between a portfolio's true economic risks and the Accord's measure of risk. At present, four major types of capital arbitrage appear to predominate:

1 *Cherry-picking* This is the oldest form of capital arbitrage. Within a particular risk-weight category, cherry-picking is the practice of shifting the portfolio's composition toward lower quality credits, so that the bank's total risk-weighted assets and regulatory capital ratios would appear unchanged, even though its overall riskiness increases.

2 *Securitisation with partial recourse* Securitisation involves the sale of assets to a "special purpose vehicle" (SPV), which finances this purchase through issuance of asset-backed securities (ABSs) to private investors. Often, a bank can treat securitised assets as "true sales" for accounting and regulatory purposes, even though it retains most of the underlying risks through credit enhancements it provides to the ABSs. Under the Accord, when securitised assets have been previously "owned" by a bank, its credit enhancement is treated as "recourse", which normally incurs an effective 100 per cent RBC requirement. This treatment implies that as long as the assets are of sufficiently high quality that the amount of recourse is less than 8 per cent of the securitised pool (termed "partial recourse"), the bank's tier 1 and total RBC ratios will increase, regardless of whether any significant risk has been shifted to the ABSs. In substance, most securitisations with partial recourse amount to sophisticated cherry-picking.

3 *Remote origination* Many banks structure their securitisation programs so that partial credit enhancements are treated as "direct credit substitutes", which incur only an 8 per cent RBC requirement, rather than a complete write-off as with recourse. The SPV, rather than the bank itself, originates the securitised assets — a process termed "remote origination". Even though the bank is exposed to much the same risk as in a traditional securitisation, since the bank never formally *owns* the underlying assets, the credit enhancement is treated as a direct credit substitute.

4 *Indirect credit enhancements* Under the Accord, it is possible to provide the economic equivalent of a credit enhancement in ways that are *not* recognised as instruments subject to any formal capital requirement. Investors are often willing to accept "indirect credit enhancements", such as early amortisation and fast-payout provisions, in lieu of traditional financial guarantees. Their use reduces even further a bank's RBC charges against securitised assets, in some cases to *zero*.

Erosion of effective capital standards

With the proliferation of capital arbitrage techniques, the largest banks now routinely achieve *effective* RBC requirements against certain portfolios that are well below the Accord's *nominal 8 per cent* standard, thus eroding *effective* capital standards.

Under the current Accord, capital arbitrage poses difficult policy tradeoffs. Capital arbitrage fundamentally is driven by large divergences that arise between economic risks and the Accord's total risk-weighted assets measure. Without addressing these fundamental factors, supervisors may have little practical scope for limiting capital arbitrage other than by, in effect, imposing broad restrictions on banks' use of financial engineering technologies.

Such actions, however, would be counterproductive and perhaps untenable. Capital arbitrage often functions as a safety-valve for mitigating the adverse effects of *nominal* capital requirements that, for certain activities, are unreasonably high. By reducing *effective* capital requirements against such activities, capital arbitrage permits banks to compete in relatively safe businesses they would otherwise be forced to abandon, owing to insufficient returns on the regulatory capital needed to support the business. Moreover, as evidenced through their widespread use by non-banks, securitisation, credit derivatives, and other risk unbundling techniques appear to provide significant economic benefits quite apart from their role in capital arbitrage.

Related concern: distorted risk management incentives

The anomalies in the Accord which give rise to capital arbitrage also distort bank risk management practices by discouraging the effective hedging of credit risks. In general, outside the trading account, the Accord provides little or no regulatory capital benefit for (a) increased diversification, (b) improved risk mitigation techniques, such as the use of non-bank collateral and financial guarantees, (c) the shedding of *significant* (albeit partial) credit risk via securitisation and credit derivatives, or (d) the cross-hedging of banking book, trading account, and counterparty credit risk positions. Because such risk reducing actions are costly, they are less likely to be adopted by banks in the absence of regulatory capital benefits. From an overall safety and soundness perspective these risk management distortions may be every bit as important as the problem of regulatory capital arbitrage.

Policy implications of the Federal Reserve study of credit risk models at major US banking institutions

John Mingo, Federal Reserve Board, Washington

THE PAPER concludes that the current Basel Accord is a lose/lose proposition. On the one hand, regulators cannot conclude that a bank with a nominally high regulatory capital ratio has a correspondingly low probability of insolvency. This is because of the "one size fits all" nature of the Accord, in which exceedingly low-risk positions receive the same capital charge as exceedingly high-risk ones. In addition, "regulatory capital arbitrage" (such as through the use of securitisation or credit derivatives) is routinely conducted by the large banks to effectively reduce or eliminate the formal regulatory capital charge on certain types of risk positions.

On the other hand, because the Accord in many cases levies a capital charge out of all proportion to the true economic risk of a position, large banks *must* engage in regulatory arbitrage (or exit their low risk business lines). Since such arbitrage is costly, the capital regulations keep banks from maximising the value of the financial firm.

Three questions need to be answered by regulators in order to craft a rational replacement for the Accord.

1 What are the goals of prudential regulation and supervision?

2 How should "soundness" be defined and how should it be quantified?

3 At what level should a minimum "soundness" standard be set in order to meet the (perhaps conflicting) goals of prudential regulation and supervision?

The paper attempts possible answers to these three questions, then lays out, in broad architecture, the two leading proposals for permitting regulators to verify that banks are indeed meeting a minimum "soundness" standard — a "modified-Basel" (or ratings-based) approach and a "full-models" approach to a revised Accord.

The paper argues that only by using the same analytical framework for regulatory capital requirements as large banks themselves use for calculating internal "economic capital" will both the goals of the regulator and the goals of the shareholder be realised.

Credit risk modelling by banks: a UK perspective

Vyvian Bronk and Emmanuelle Sebton, Financial Services Authority

THE FINANCIAL Services Authority (FSA) has conducted a survey into the use of credit risk modelling techniques by banks in the UK

UK banks' practice

Major banks in the UK, like their continental counterparts, have been working principally to incorporate published/vended models within their credit risk management processes. Amongst the banks surveyed, credit portfolio modelling is typically confined at this stage to parts of the asset portfolio only (such as exposures to large corporates). Different modelling techniques are applied to different types of business (for example, "bottom-up" modelling approaches for large corporates and broader "top-down" models for retail credit portfolios).

Counterparty risk in the trading book is only sparsely covered by models, with coverage typically limited to swaps rather than more complex derivatives.

It is common for model output to be used to allocate economic capital within business units and as an input to more consistent pricing of certain credit risks. However, an integrated approach to credit risk overall is not common, and few banks in the UK use portfolio models for the purpose of actively managing their credit risk portfolio as a whole. Nevertheless, some large banks have re-structured to create a centralised risk management unit responsible for managing a subset of the bank's credit risks actively, and these banks expect re-structuring to have a major impact on their strategic approach to credit risk over time.

Regulatory implications of the development of credit risk modelling

An appropriate supervisory "burden of proof" for credit risk models depends on the regulatory perspective: if the aim is to incorporate credit risk model output into an internationally comparable minimum standard for capital adequacy, then many questions remain to be resolved. However, subject to reassurances on certain technical and implementation issues, Financial Services Authority supervisors may begin soon to take into account the use of credit risk models in their qualitative assessment and comparison of banks' credit risk management functions.

Important benefits may arise from the use of credit risk models in terms of improved measurement of portfolio credit risk and of the effect of risk mitigating actions. Banks have emphasised that benefits could be gained even at the data gathering stage, through the process of estimating the main inputs to the models (size of banks' exposures, default/transition probabilities, loss incurred in default).

There nevertheless remain a number of fundamental implementation issues which the FSA needs to discuss with banks in considering whether a credit risk portfolio model adds value to their credit risk management.

The scarcity of default data may impact on the quality of a model's output and/or its scope. Assumptions on modelling horizons may have a substantial impact on the size of loss, and the FSA would want to discuss the reason for choosing a given modelling horizon and whether this was consistent with the type of model, the portfolio being modelled and the purposes for which the model output was being used in decision-making.

Finally, the bank would need to demonstrate that the model had been tested. Among other things, the FSA would expect banks to have assessed the sensitivity of model output to the various modelling assumptions made and to perform stress testing regularly.

Next steps

The FSA will be undertaking further work in the following areas, in consultation with practitioners:

- a comparative survey of banks' internal loan grading systems and their relationship with default probabilities

- a review of the regulatory treatment of various methods for offsetting credit risk in the light of information gathered through the process of trading book specific risk model recognition, and

- work towards building a credit portfolio review function within the FSA, designed to inform the qualitative assessment of banks' credit risk management functions in the FSA's risk-based approach to supervision ("RATE") and in setting each bank's individual target and trigger ratio above the Basel minimum.

Internal credit risk scoring systems at large US banks

Mark Carey and Bill Treacy, Federal Reserve Board, Washington

CREDIT RATINGS are becoming increasingly important in credit risk management at large US banks. Banks' internal ratings are somewhat like ratings produced by Moody's, Standard & Poor's, and other public rating agencies in that they summarise the risk of loss due to failure by a given borrower to pay as promised. Like the agencies, banks typically produce ratings only for business and institutional loans and counterparties but not for consumer loans. However, banks' rating systems differ significantly from those of the agencies (and from each other) in architecture and operating design as well as in the uses to which ratings are put.

Most large banks use ratings for several purposes, such as guiding the loan origination process, portfolio monitoring and management reporting, analysis of the adequacy of loan loss reserves or capital, profitability and loan pricing analysis, and formal risk management models. Understanding how rating systems are conceptualised, designed, operated, and used in risk management is thus essential to understanding how banks perform their business lending function and how they choose to control risk exposures.

The specifics of internal rating system architecture and operation differ substantially across banks. The number of grades and the risk associated with each grade vary across institutions, as do decisions about who assigns ratings and about the manner in which rating assignments are reviewed. To a considerable extent, variations across banks are an example of form following function. There does not appear to be one "correct" rating system. Instead, "correctness" depends on how the system is used. In general, in designing rating systems, bank management must weigh numerous considerations, including cost, efficiency of information gathering, consistency of ratings produced, incentives, the nature of the bank's business, and the uses to be made of internal ratings.

As with banks' decisions to extend credit, the rating process almost always involves the exercise of human judgement because the factors considered in assigning a rating and the weight given to each factor can differ significantly across borrowers. Moreover, the operational definition of each grade is largely an element of credit culture that is communicated informally rather than being written in detail. Given the substantial role of judgement, banks must pay careful attention to the internal incentives they create or biased rating assignments may result. Such biases tend to be related to the functions that ratings are asked to perform in the bank's risk management process. For example, at banks that use ratings in computing internal profitability measures, establishing pricing guidelines, or setting loan size limits, some staff members may be tempted to assign ratings that are more favourable than warranted. Rating assignments at banks at which all ratings are assigned by independent credit staff are less subject to bias, but the important role of medium-size and smaller loans in most banks' portfolios often makes rating assignment by relationship managers cost-effective. Review activities, especially those conducted by loan review units, are crucial to limiting biases in rating assignments and to maintaining common understanding and discipline.

Although form generally follows function in assigning ratings to business loans, our impression is that in some cases the two are not closely aligned. For example, because of the rapid pace of change in the risk management practices, large banks' rating systems are increasingly being used for purposes for which they were not designed. When a bank introduces a new function that uses ratings, such as risk-sensitive analysis of business line profitability, the existing ratings and rating system are often used as-is. It may become clear only over time that the new function has imposed new stresses on the rating system and that changes in the system are needed.

Several conditions appear to magnify such stresses. The conceptual meaning of ratings may be somewhat unclear, rating criteria may be largely or wholly maintained as a matter of culture rather than formal written policy, and corporate databases may not support analysis of the relationship between grade assignments and historical loss experience. Such circumstances make ratings more difficult to assign, use, review and audit.

Points of external comparison, such as public rating agency grades or results of statistical models of borrower default probability, can aid internal rating assignment and review. A few banks are moving toward models as the primary basis for internal ratings. Such an operating design largely removes the problems of culture maintenance and conflicting incentives that make management of judgemental rating systems challenging, but most banks believe that the limitations of statistical models are such that properly managed judgemental rating systems deliver more accurate assessments of risk.

It is likely that both regulators and rating agencies will come to depend more upon banks' internal ratings as time passes. Use of internal ratings by such external entities has the potential to introduce qualitatively different stresses on banks' rating systems in which incentive conflicts are not purely internal but which potentially pit banks' interests against those of the external entities. If this occurs, some degree of external validation of internal rating systems would probably be necessary. In our view, while such validation is probably feasible, careful development of a new body of practice will be required. We expect that such developments would emerge from a dialogue among the interested parties.

This summary is based on a review of approaches taken by the fifty largest US bank holding companies: this review included interviews at institutions which covered the spectrum of size and practice among those fifty banks, but a disproportionate share of which had relatively advanced internal rating systems.

Moody's ratings of collateralised bond and loan obligations

Jeremy Gluck, Moody's, New York

THE MARKET for collateralised debt obligations (CDOs) has grown rapidly over the last three years, both in volume and in the range of transaction type. Since Moody's began rating CDOs a decade ago, we have rated more than 250 of these transactions.

In a typical CDO, a pool of bonds or loans is securitised by selling the assets to a special purpose vehicle (SPV), which finances the purchase by issuing two or more tranches of debt. The junior tranche absorbs the initial defaults within the collateral pool, thus insulating the senior tranche from losses. Excess spread (of the coupon payments received on the collateral over the coupons paid on the liabilities) also provides credit enhancement.

This structure may be adopted for either cash-flow or market-value transactions. In the former case, the analytical focus is on the sufficiency of cash flows generated by the collateral pool to meet the interest and principal payable on the SPV's liabilities. In the market-value context, the focus is instead on the liquidation value of the assets in comparison to the principal and accrued interest due on the liabilities. Since 80-90 per cent of CDOs have been of the cash-flow variety, we devote the bulk of our discussion to these structures.

Recently, a number of bank-sponsored transactions have instead hedged exposures within the loan or derivatives portfolio by issuing "synthetic" notes. In these structures, debt is issued by the SPV and invested in highly creditworthy instruments. At the same time, the SPV enters into a credit swap in which it pays the return on the investment pool in return for cash flows sufficient to pay the interest on the rated debt. Should defaults occur within a reference pool of credits, a portion of the invested funds will be liquidated and paid to the bank, reducing the principal available to the investors. These "synthetic" structures allow banks the flexibility to create assets with

Chart 1: Typical CDO Structure

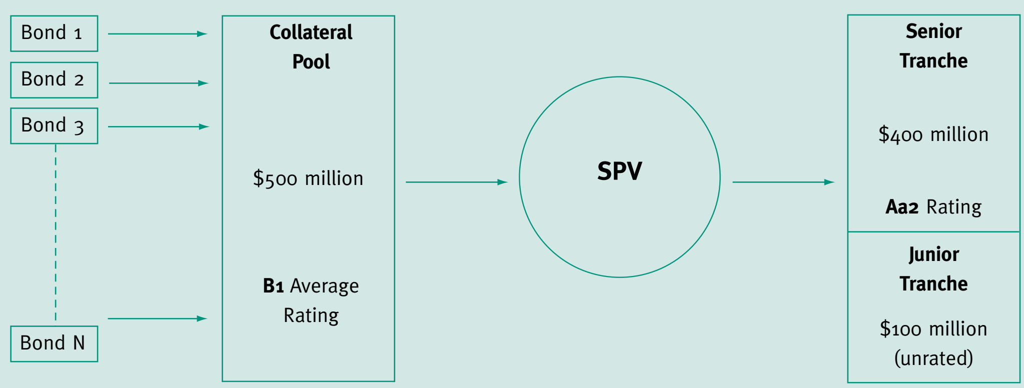
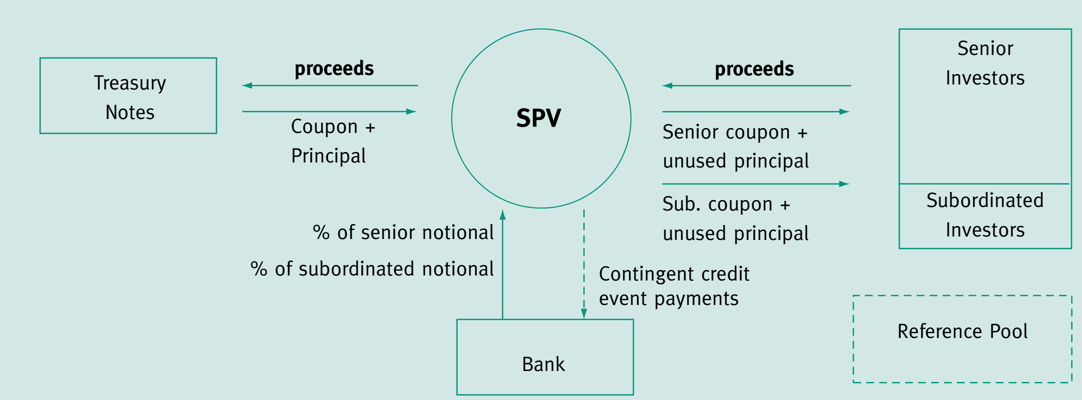


Chart 2: A Potential "Synthetic" CLO Structure



such properties as they require in terms of maturity, coupon etc.

Moody's rates these transactions on the basis of expected loss measured relative to the *promise* made by the issuer. Models of the transactions are used to generate ratings of CDOs that reflect (1) a judgement as to the expected loss for each tranche within the CDO and (2) a comparison of that loss with historical losses on conventional bonds for each rating category.

Moody's generally use an analytical technique — the Binomial Expansion Technique (BET) — to estimate expected losses, rather than Monte Carlo simulation, which is computationally burdensome. BET is less accurate and flexible than simulation methods, but is fast, reliable and easily understood.

The method entails reducing the portfolio to a set of independent bonds with the same loss, or return, distribution as the original portfolio, and considering various loss scenarios. The expected loss is the weighted average of the losses (relative to whatever was promised) across all the scenarios:

$$\text{Expected loss} = \sum P_s L_s$$

where L_s is the loss experienced by the investor under scenario $_s$ (under which s defaults occur) and P_s is the probability that the scenario will occur.

The probability of each scenario is given by the probability of j defaults using a modified binomial formula

$$P_j = \frac{D!}{j!(D-j)!}(\lambda p)^j(1-\lambda p)^{D-j}$$

where p is the probability of default for any one of the identical assets, λ is a stressing factor, and D is a "*diversity score*" — the number of independent, identically sized bonds that mimic the return distribution of the portfolio being modelled. D is intended to reflect the correlations in default rates, the distribution of default probabilities, and the distribution of asset sizes within the actual portfolio.

Current practice is to calculate the diversity score by grouping assets into industries and/or regions and attributing relatively high correlation to those credits that share the same industry or region. The correlation in defaults across different industries/regions is addressed by stressing default rates (using stressing factor λ) to account for the variation in such rates over time. Moody's are evaluating alternative sources of default correlations such as stock price movements (filtered to remove the correlations that are unrelated to default behaviour) or factor analysis applied to Moody's own historical ratings transition database.

Given a full set of default correlations, a diversity score can be calculated by matching the first two moments of the return distribution of the actual portfolio: this gives

$$D = \frac{(\sum_{i=1}^{n} p_i F_i)(\sum q_i F)_i}{\sum\sum \rho_{ij}\sqrt{p_i q_i p_j q_j}\, F_i F_j}$$

where p_i is the default probability for bond i that is implied by its rating (as derived from Moody's historical default studies), q_i is $1\text{-}p_i$, ρ_{ij} is the default correlation between assets i and j and F_i is the face value of bond i.

Experimentation with a variety of portfolios suggests that the homogeneous portfolio consisting of D assets adequately approximates the tail of the return distribution.

The computation of L_j must be based on a model that reflects the appropriate cash flow availability and distribution under each of the D possible default scenarios of the ideal pool, and that reflects accurately the priority of payments and the payment of all the fees involved in the transaction. Also, the analyst must make a reasonable assumption in terms of the timing of defaults and the timing of recoveries, and the model must take account of the fact that some average parameters of the ideal pool will vary with time. Coverage tests *(overcollateralisation* and *interest coverage tests)* are aimed at protecting the integrity of the CDO transaction. Important structural issues which must be considered include a changing diversity score (this may decrease as assets amortise), a "ramp-up period" (if the collateral pool is not fully in place before the closing date), liquidation of collateral, contingent equity structures, frequency of payment, and guarantees from insurers.

Evaluating credit risk models

Jose Lopez and Marc Saidenberg, Federal Reserve Bank of San Francisco and Federal Reserve Bank of New York

AN IMPORTANT question for both the users of credit risk models and for their regulators is whether we can evaluate, or backtest as it is popularly known, these models.

A major impediment to backtesting credit risk models is the small number of forecasts available with which to evaluate a model's accuracy. Whereas value-at-risk (VaR) models for daily market risk calculations generate about 250 forecasts in one year, credit risk models can generally produce only one forecast because of their longer planning horizon. Also, only a limited amount of historical data on credit losses is available — probably not enough to span several macroeconomic or credit cycles. These data limitations create serious difficulties for users' own validation of credit risk models and for validations by third-parties, such as external auditors or bank regulators.

We propose a method for backtesting credit risk models based on cross-sectional simulation. Specifically, models are evaluated not only on their forecasts over time, but also on their forecasts at a given point in time for simulated credit portfolios. Once the credit loss forecasts corresponding to these portfolios are generated, the underlying model can be evaluated using statistical tests commonly used for VaR models: these are relatively simple, are well known in the forecast evaluation and risk management literatures, and are general enough to be used on any type of credit risk model.

Although our approach cannot avoid the limited amount of yearly data available on credit defaults and rating migrations, it provides quantifiable measures of forecast accuracy that can be used for model validation, both for a given model and across models.

Backtesting simulated credit portfolios

The data limitations for evaluating credit risk models are considerable. In terms of a panel dataset, credit data is generally plentiful in the cross-sectional dimension, but scarce in the time dimension. This limitation has led the users of credit risk models to construct alternative methods, such as "stress testing", for validating these models. However, as per the evaluation of VaR models, the ability to compare a credit-risk model's forecasts to actually-observed outcomes is more desirable. In this paper, we present evaluation methods that specifically focus on quantitative comparisons of this type.

Methods commonly used for forecast evaluation in time-series analysis can be adapted for use with panel-data analysis, such as credit-risk modelling. The intuition behind such forecast evaluation is to test whether a series of out-of-sample forecasts exhibit properties characteristic of accurate forecasts. This idea can be extended to the cross-sectional element of panel data analysis. In any given year, out-of-sample predictions for cross-sectional observations not used to estimate the model can be used to evaluate its accuracy. As long as these additional out-of-sample observations are drawn independently from the sample population, the observed prediction errors should be independent. Standard tests for the properties of optimal predictions can be then used to test the cross-sectional model's accuracy.

For evaluating credit risk models, we propose to use simulation methods to generate the additional credit loss observations needed for model evaluation. The models in question can be used to forecast the loss distributions corresponding to the simulated portfolios, and these forecasts and the corresponding observed losses can then be used to evaluate the accuracy of the models. The simulation method used here to generate these additional credit portfolios is simply resampling with replacement from the original panel dataset of credits.

Consider a credit dataset that spans T years of data for N assets, where N > T. In any given year t, let $\rho \in (0,1)$ denote the percentage of credits to be included in the resampled portfolios. We can construct a resampled portfolio by generating N independent draws from the uniform distribution over the interval [0,1]. For each draw above ρ, the associated credit is assigned a weight of zero and is not included in the resampled portfolio. For each draw below ρ, the associated credit is assigned a weight of one and is included in the resampled portfolio.We would expect the resampled portfolio to contain ρ*N credits, on average.

Let ΔP_{it+1} denote the change in value of resampled portfolio i over a one-year horizon. Credit model m can be used to generate the corresponding loss distribution forecast $\hat{F}_m(\Delta P_{it+1})$. For each of the T years, we resample with replacement R times (ie, i = 1,...,R), where R is a large number (say, 1,000). Doing so, we have (T * R) forecasted loss distributions with which to evaluate the accuracy and performance of model m, as opposed to just T forecasts based on the original credit portfolio. We can then use a variety of statistical tests to evaluate the accuracy of these model forecasts, such as the binomial test commonly used to backtest VaR models.

Given the data limitations discussed, the T available years of credit data for model evaluation may not span a macroeconomic or a credit cycle, not to mention the larger number of such cycles that would be ideally available. Although the proposed simulation method makes the most use of the data available, evaluation results based on just one or a few years of data must be interpreted with care since they reflect the macroeconomic conditions prevalent at that time. As more years of data become available, the resampling of credit portfolios under different economic conditions provides for a sterner and more extensive evaluation of a credit model's forecast accuracy.

A comparative analysis of current credit risk models

Michel Crouhy and Robert Mark, Canadian Imperial Bank of Commerce

IN THIS PAPER we first review the new 1998 BIS Accord and CAD II for the bank's overall regulatory capital requirement. Under the new regime the trading book (on- and off-balance sheet) is subject to market risk capital charge only. But market risk encompasses two components: *general market risk* which relates to the change in market value resulting from broad market movements, and *specific risk* which relates to adverse price movements due to idiosyncratic factors related to individual issuers. Specific risk for fixed income securities is nothing else than *credit risk*. With the new 1998 BIS Accord banks have the choice between the standardised and the internal models approaches to measure both general market risk and credit risk. Contrary to the standardised approach, internal models are designed to capture portfolio diversification and concentration effects and, therefore, may provide opportunities for capital reduction through a better risk assessment. Numerical examples illustrate why the standardised approach is flawed. It can lead to a misallocation of capital that may trigger regulatory arbitrages.[1] Examples of such arbitrage opportunities are discussed.

The second part of the paper gives an overview of the current proposed industry sponsored methodologies for measuring credit risk:

1 *The credit migration approach* as proposed by CreditMetrics from the RiskMetrics Group, CreditVaR from CIBC and CreditPortfolioView from McKinsey. The first two are unconditional credit risk models, while the last one is a conditional credit risk model where default probabilities are functionally related to macroeconomic variables which are the key drivers of the credit cycle.

2 *The option pricing approach* as proposed by KMV. KMV challenges the assumption that all firms within the same credit class have the same default rate, which, in addition, is assumed to be constant and set to some historical average. Instead, KMV estimates the actual probability of default, the EDF, for each obligor based on a Merton (1974) type model of the firm. The probability of default is a function of the firm's capital structure, the volatility of the asset returns and the current asset value. The EDF is thus firm specific and keeps varying over time.

3 *The actuarial approach* as proposed by Credit Suisse Financial Products (CSFP) with CreditRisk$^+$. CreditRisk$^+$ applies an actuarial science framework to the derivation of the loss distribution of a bond/loan portfolio. Only default is modelled, not downgrade risk. Contrary to KMV, default risk is not related to the capital structure of the firm. In CreditRisk$^+$ no assumption is made about the causes of default. CreditRisk$^+$ proposes an elegant and computationally fast analytic expression for the loss distribution.

Credit risk models aim to capture spread risk, default risk as well as downgrade risk, recovery rate risk and concentration risk (portfolio diversification and correlation risk). These models generate either the loss distribution, as in KMV (analytic model) and CreditRisk$^+$, or the entire distribution of the portfolio value at the risk horizon, say one year, as in Monte-Carlo based models such as CreditMetrics, CreditVaR and KMV (simulation model). Table 1 provides a comparative summary of the main features of the credit risk models.

The key input parameters common to all models are the exposures, recovery rates (or equivalently the loss given default), and default correlations, which are derived from asset correlations. The current state of the art does not yet allow for the full integration of market and credit risk. Market risk models assume no credit risk, and credit risk models assume away market risk and consider exposures as exogenously determined. The next generation of credit models should remedy this schizophrenia.

In the third part of the paper we compare the various credit risk models by applying them to the same large diversified benchmark bond portfolio. Consistent assumptions are made to ensure comparability of the models. Results show that models of apparently different types produce similar values at risk.

The asset return correlation model appears to be a critical factor in CreditMetrics, CreditVaR and KMV. Values at risk when correlations are forced to one are approximately 10 times greater than when correlations are assumed to be zero.

For credit migration based models, results are also shown to be quite sensitive to the initial rating of the obligors. Values at risk for speculative portfolios are five to six times greater than for investment grade portfolios. Results for CreditRisk$^+$ are also very sensitive to default correlations as well as the standard deviation of the default rate.

Table 1: Comparison of Models

	CreditMetrics CreditVar	**CreditPortfolioView**	**KMV**	**CreditRisk$^+$**
Definition of risk	Δ Market Value	Δ Market Value	Default losses	Default losses
Credit events	Downgrade/Default	Downgrade/ Default	Continuous default probabilities	Default
Risk drivers	Asset values	Macro factors	Asset values	Expected default rates
Transition probabilities	Constant	Driven by Macro factors	Driven by: individual term structure of EDF; asset value process	N/A
Correlation of credit events	Standard multivariate normal equity returns	Factor loading: correlation of residual risks	Standard multivariate normal asset returns (sophisticated factor model)	Correlated default processes
Recovery rates	Random (Beta distribution)	Random	Random (Beta distribution)	Loss given default
Numerical approach	Simulation/ Analytic	Simulation	Analytic/Simulation	Analytic
Return measurement	N/A	N/A	RAROC	N/A

The study concludes that all these models are reasonable frameworks to capture credit risk for vanilla bonds and loans portfolios. For derivative instruments, like swaps or loan commitments, with contingent exposures, these models should be extended to allow for stochastic interest rates. The incorporation of credit derivatives in these models creates another level of complexity, since the portfolio distribution is based on actual probabilities of default while the pricing of the derivatives relies on risk neutral probabilities. The next generation of credit risk models should address these challenging issues.

Notes

1 For a detailed discussion see "The New 1998 Regulatory Framework for Capital Adequacy" by M Crouhy , D Galai and R Mark in *Risk Management and Analysis*, ch. 1, Editor: Carol Alexander (Wiley).

A comparative anatomy of credit risk models

Michael Gordy, Federal Reserve Board, Washington

OVER THE past decade, financial institutions have developed and implemented a variety of sophisticated models of value-at-risk for market risk in trading portfolios. Much more recently, important advances have been made in modelling credit risk in lending portfolios. The new models are designed to quantify credit risk on a portfolio basis, and thus have application in control of risk concentration, evaluation of return on capital at the customer level, and more active management of credit portfolios. Future generations of today's models may one day become the foundation for measurement of regulatory capital adequacy.

Two of the models, the RiskMetrics Group's CreditMetrics and Credit Suisse Financial Product's CreditRisk$^+$, have been released freely to the public since 1997 and have quickly become influential benchmarks. Practitioners and policy makers have invested in implementing and exploring each of the models individually, but have made less progress with comparative analyses. The two models are intended to measure the same risks, but impose different restrictions and distributional assumptions, and suggest different techniques for calibration and solution. Thus, given the same portfolio of credit exposures, the two models will, in general, yield differing evaluations of credit risk. Determining which features of the models account for differences in output would allow us a better understanding of the sensitivity of the models to the particular assumptions they employ.

Direct comparison of the models has so far been limited, in large part, because the two models are presented within rather different mathematical frameworks. The CreditMetrics model is familiar to econometricians as an ordered probit model. Credit events are driven by movements in underlying unobserved latent variables. The latent variables are assumed to depend on external "risk factors." Common dependence on the same risk factors gives rise to correlations in credit events across obligors. The CreditRisk$^+$ model is based instead on insurance industry models of event risk. Instead of a latent variable, each obligor has a default probability. The default probabilities are not constant over time, but rather increase or decrease in response to background macroeconomic factors. To the extent that two obligors are sensitive to the same set of background factors, their default probabilities will move together. These co-movements in probability give rise to correlations in defaults. CreditMetrics and CreditRisk$^+$ may serve essentially the same function, but they appear to be constructed quite differently.

This paper offers a comparative anatomy of CreditMetrics and CreditRisk$^+$. We show that, despite differences in mathematical language, the underlying probabilistic structures are similar. If we consider a somewhat restricted form of CreditMetrics, then each model can be mapped into the mathematical framework of the other. This exercise allows us to describe quite precisely where the models differ in functional form, distributional assumptions, and reliance on approximation formulae.

Simulations are constructed for a wide range of plausible loan portfolios and correlation parameters. The results suggest a number of general conclusions. First, the two models perform very similarly on an average quality commercial loan portfolio when the CreditRisk$^+$ volatility parameter σ is given a low value. Both models demand higher capital on lower quality portfolios, but CreditRisk$^+$ is somewhat more sensitive to credit quality than the two-state version of CreditMetrics. It should be emphasised, however, that the full implementation of CreditMetrics encompasses a broader notion of credit risk, and is likely to produce somewhat larger tail percentiles than our restricted version.

Second, results do not depend very strongly on the distribution of loan sizes within the portfolio, at least within the range of size concentration normally observed in bank portfolios. The discretisation of loan sizes in CreditRisk+ has negligible impact.

Third, both models are highly sensitive to the volatility of default probabilities, or, equivalently, to the average default correlations in the portfolio. When the standard deviation of the default probabilities is doubled, required capital increases by two to three times.

Finally, the models are highly sensitive to the shape of the implied distribution for the systematic risk factors. CreditMetrics, which implies a relatively thin-tailed distribution, reports relatively low tail percentile values for portfolio loss. The tail of CreditRisk+ depends strongly on the parameter σ, which determines the kurtosis (but not the mean or variance) of the distribution of portfolio loss. Choosing less kurtotic alternatives for the gamma distribution used in CreditRisk+ sharply reduces its tail percentile values for loss without affecting the mean and variance.

This sensitivity ought to be of primary concern to practitioners. It is difficult enough to measure expected default probabilities and their volatility. Capital decisions, however, depend on extreme tail percentile values of the loss distribution, which in turn depend on higher moments of the distribution of the systematic risk factors. These higher moments cannot be estimated with any precision given available data. Thus, the models are more likely to provide reliable measures for comparing the relative levels of risk in two portfolios than to establish authoritatively absolute levels of capital required for any given portfolio.

Ratings- versus equity-based credit risk modelling: an empirical analysis of credit risk modelling techniques

Pamela Nickell, William Perraudin and Simone Varotto, Bank of England

IN THIS study we consider how well credit risk models track the risks they claim to measure, and how well they might serve as a means of calculating appropriate regulatory capital for the credit exposure associated with portfolios of defaultible assets.

A fundamental difficulty in assessing credit risk is that most credit exposures have no easily observable market price. The two main methodologies adopt different solutions to this.

1 Ratings-based methods (eg Creditmetrics) use proxy data. A rating is attributed to each credit exposure, and historical rating transition probabilities and historical average spreads are used to estimate the mean and volatility of returns for each exposure. The VaR can be estimated by using estimated correlations and assuming joint normality, or by using Monte Carlo methods. (These estimated correlations are based on an ordered probit model of ratings transitions, using equity value correlations derived from a weighted average of industry and country indices, with an idiosyncratic noise term.)

2 Equity-price-based methods (eg KMV) regard a firm's equity, under limited liability, as a call option on the underlying asset value, with strike price equal to the debt level, and invert this to infer the firm's asset value. The distance of the asset value from the insolvency trigger level indicates the likelihood of default. Estimated asset values and their correlations are used to derive the value of the loan exposure portfolio.

Our study involved a direct comparison — a "horse race" — of representative ratings-based and equity-price-based methodologies when applied to large portfolios of credit exposures.

Our data requirements were substantial. Our database comprised ratings histories, price histories and cash flows for 5,546 Eurobonds, along with default-free yield curves. For the ratings-based method, we also required ratings transition matrices, default spreads, equity indices, sector classifications for the obligors, and idiosyncratic risk weightings. For the equity-price-based method, we needed liability data and equity market capitalisations for the obligors.

We focussed on the 1,430 dollar-denominated bonds over the period 1988 to 1997 (our "total sample"), and created several sub-portfolios.

The paper presented preliminary results comparing the two methodologies and found that they did not perform identically in all circumstances; differences were sometimes marked.

We also compared ratings-based VaRs for various sub-portfolios, including 4 randomly selected "quartile" samples, all US-domiciled and all non-US-domiciled bonds in the total sample, and all bank and all non-bank bonds in our total sample. The non-US obligors appeared to be the main contributors to incidences of the VaR implied by the model being exceeded in fact (an "exception" in Basel terms).

In addition to conducting empirical comparisons, if these two broad approaches to credit risk modelling are to be evaluated fully, it is important to assess the sensitivities of estimates to the various assumptions made.

With respect to ratings-based models, several questions require consideration. First, how much can forecasts of ratings transitions be improved by conditioning on, say, the level of interest rates, or the stage of the business cycle? How stable is the relationship between ratings and bond spreads? How important is the lag between changes in ratings and changes in credit spreads? For equity-price-based methods, it is important to establish how sensitive the results are to assumptions about the trigger level for insolvency. For example, should this vary across countries, depending upon insolvency legislation, and the scope for out-of-bankruptcy workouts?

Beyond these empirical investigations, there remain questions on the use of credit risk models in capital requirement calculations, regarding issues such as the interaction of credit risk and trading risks such as interest and foreign exchange risk, and the potential for back-testing of the kind performed on VaR models.

Default rates in the syndicated bank loan market: a mortality analysis

Edward Altman and Heather Suggitt, Stern School, NYU and Credit Suisse First Boston

THE MOST fundamental aspect of many credit risk models is the rating of the underlying assets and the associated expected and unexpected migration patterns. The most important negative migration is to default. While default rate empirical studies of corporate bonds are now commonplace, and recovery analysis on both bonds and bank loans is increasingly available, there has never been a study on default rates in the corporate bank loan market.

This paper assesses, for the first time, the default rate experience on large, syndicated bank loans. The results are stratified by original loan rating using a mortality rate framework for the 1991-1996 period. Ratings on large bank loans have been assigned by the major ratings agencies only since 1995. For the years 1991-1994, we assign "shadow ratings" to our bank loan sample based on the public bond ratings of the same company. Our sample includes 4,069 loan facilities from 2,184 different borrowers over the six-year issuing period. Loans are all at least $100 million with aggregate facilities in our sample of $2.4 trillion.

We find that the mortality rates on bank loans are remarkably similar to those on corporate bonds. Table 1 compares marginal and cumulative mortality rates on syndicated bank loans with those on corporate bonds for the sample period. Although not identical, these comparative rates are quite similar. For example, the five-year B-rated cumulative default rate was 9.97 per cent for bank loans and 9.24 per cent for bonds.

We also assess the bias in the magnitude of our findings given that the study period covered a benign credit cycle in the United States. When we compared five-year cumulative mortality rates for corporate bonds in the 1991-1996 and 1971-1996 periods (Table 2), the results indicated that the longer period's rates, for lower rated bonds, were two to three times greater than those for the more recent shorter period covered in our bank loan default rate analysis.

Our results provide important new information for assessing the risk of corporate loans not only for bankers but also for mutual fund investors and analysts of structured financial products, credit derivatives and credit insurance. Finally, regulators will also be interested for their assessment of bank soundness and adequate reserves.

Table 1	Comparison of Syndicated Bank Loan versus Corporate Bond Mortality Rates Based on Original Issuance Principal Amounts (1991-1996)										
		1 year		2 years		3 years		4 years		5 years	
		Bank	Bond	Bank	Bond	Bank	Bond	Bank	Bond	Bank	Bond
Aaa	Marginal	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Cumulative	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
A	Marginal	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Cumulative	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
A	Marginal	0.00%	0.00%	0.12%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.05%
	Cumulative	0.00%	0.00%	0.12%	0.00%	0.12%	0.00%	0.12%	0.00%	0.12%	0.05%
Baa	Marginal	0.04%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.54%	0.00%	0.00%
	Cumulative	0.04%	0.00%	0.04%	0.00%	0.04%	0.00%	0.04%	0.54%	0.04%	0.54%
Ba	Marginal	0.17%	0.00%	0.60%	0.38%	0.60%	2.30%	0.97%	1.80%	4.89%	0.00%
	Cumulative	0.17%	0.00%	0.77%	0.38%	1.36%	2.67%	2.32%	4.42%	7.10%	4.42%
B	Marginal	2.30%	0.81%	1.88%	1.97%	2.59%	4.99%	1.78%	1.76%	1.86%	0.00%
	Cumulative	2.30%	0.81%	4.11%	2.76%	6.60%	7.61%	8.27%	9.21%	9.97%	9.24%
Caa	Marginal	15.24%	2.65%	7.44%	3.09%	13.03%	4.55%	0.00%	21.72%	0.00%	0.00%
	Cumulative	15.24%	2.65%	21.55%	5.66%	31.77%	9.85%	31.77%	29.51%	31.77%	29.51%

Table 2	Cumulative Bond Mortality Rates for 1991-1996 vs 1971-1996									
Original	1 year		2 years		3 years		4 years		5 years	
Rating	1991-96	1971-96	1991-96	1971-96	1991-96	1971-96	1991-96	1971-96	1991-96	1971-96
AAA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.19	0.05	0.27
BBB	0.00	0.03	0.00	0.42	0.00	0.82	0.54	1.49	0.54	1.88
BB	0.00	0.44	0.38	1.41	2.67	4.77	4.42	6.47	4.42	9.09
B	0.81	1.41	2.76	5.65	7.61	12.51	9.24	18.58	9.24	24.33
CCC	2.65	2.46	5.66	18.62	9.95	33.02	29.51	41.17	29.51	43.82

Stability of ratings transitions

Pamela Nickell, William Perraudin and Simone Varotto, Bank of England

THIS PAPER describes a study of the distribution of rating transitions using the universe of Moody's long-term corporate and sovereign bond ratings in the period 1970 to 1997. This provides 50,831 issuer-years of histories for notional senior unsecured ratings created by Moody's for all obligors who possess Moody's rated long bonds at a given moment in time.

The geographical and business sector composition of this data set has evolved over the period. Coverage has diversified from an overwhelming bias towards US-domiciled obligors to a more even geographical spread. The industrial composition has seen a marked decline in public utility obligors and an increase in banks. It is well known that rating transitions probabilities vary across time and different issuer types. Given these changes in composition, transition matrices estimated unconditionally based on all the entities rated at a given time would change even if the underlying approach taken by Moody's is constant.

Before applying multivariate models to the data, we computed transition matrices for various sub-samples. First, we compared banks and industrials. The volatility of ratings transitions was higher for banks than for industrials, but large movements in ratings were just as likely for industrials as for banks. Many transition probabilities for banks differed from the sample average, but industrials were more similar to the sample as a whole.

Secondly, we compared obligor domiciles. Matrices for the US and UK were similar to those for the sample as a whole, while for Japanese obligors, low ratings were less volatile than for US obligors but high ratings were more volatile.

Thirdly, we compared stages of the business cycle. Default probabilities appeared to be particularly sensitive to these. For highly rated bonds, volatility fell in business cycle peaks and rose in troughs.

In calculating these transition matrices, though, we had compared the effects of various factors in a "univariate" manner (for example, comparing results for two different industries without holding constant other factors) — as had previous authors. However, for an analyst designing or using a credit risk model, what is needed is the **incremental** or *ceteris paribus* impact of the various conditioning variables upon ratings transitions. In order to evaluate these, we applied an **ordered probit model**, in which transitions were driven by realisations of a latent variable which incorporated a series of dummies for obligor type and business cycle state. From the results of this model we then generated the implied one-year transition matrices. These demonstrated:

Industry effects

Relative to industrials, it appeared that bank ratings might be thought of as reverting to some low investment-grade mean in that highly rated banks were consistently more subject to downgrades than industrials, while low-rated banks were relatively more subject to upgrades. For highly rated US-domiciled obligors, in a trough, banks were much more subject to downgrades than industrials.

Country effects

Cross-country differences were evident for high-rated obligors but appeared less important for non-investment grade issuers. Low-rated Japanese and UK obligors were more likely to experience upgrades than US obligors. For Aaa-rated banks, UK obligors were less prone to downgrades than US obligors.

Business cycle effects

Business cycle effects make an important difference especially for low-rated issuers. For investment-grade but non-Aaa-rated obligors, downgrades seemed to be just as likely in normal times as in troughs, but in both cases were clearly higher than in peak years. For sub-investment grade obligors, trough years were associated with large downgrade probabilities.

We then considered multi-period ratings transitions. By assuming that changes in the business cycle were themselves driven by a temporally independent Markov chain, we were able to calculate default rates at various time horizons. As expected, we found that differences in default probabilities between, say, banks and industrials, diminished as the horizon increased.

The interpretation of models of ratings transitions is complicated by the dispersion of data, with its geographical bias, and the paucity of information on UK and Japanese defaults. A more fundamental question is the extent to which ratings measure obligor credit standing as opposed to the assessment and processes of a rating agency. However, an understanding of the behaviour of ratings is an essential ingredient in credit risk modelling. Our study has allowed the influence upon rating transition probabilities of the type of obligor and stage of the business cycle to be both identified and quantified.

Credit risk and risk neutral default probabilities: information about rating migrations and defaults

Gordon Delianedis and Robert Geske, UCLA

DEFAULT PROBABILITIES are important to the credit markets. Changes in default probabilities may forecast either credit migrations or default. Such changes can affect the firm's cost of capital, credit spreads, bond returns, and the prices and hedge ratios of credit derivatives. While ratings agencies such as Moody's and Standard and Poor's compute historical default frequencies, option models can also be used to calculate forward looking or expected default frequencies. In this paper, we compute risk neutral default probabilities using the diffusion option models of Merton (1974) and Geske (1977). It is shown that the Geske model produces a term structure of default probabilities. Thus, a forward default probability is also computed. While this default term structure can be as complex as defaulting on each scheduled payment, in this study it only includes default on the short and the long term liabilities on the corporation's balance sheet. In an event study we show that these risk neutral default probabilities from both the Merton and Geske models possess significant information about credit rating migrations and default, often more than a year before the event. While the sample of firms that actually default is small, changes in the Geske short term default probabilities appear to detect impending migrations to default most significantly. This may indicate that the short term default probability can detect impending cash flow problems caused by the significance of current liabilities. This is consistent with an inverted term structure of default probabilities, where prior to an impending default, the short term default probability can be higher than the forward default probability. Finally, since rating migration and default events are not a surprise, it appears that the diffusion approach to credit migrations and default may be as or more appropriate than the Poisson approach.

The intersection of market and credit risk

Robert Jarrow and Stuart Turnbull, Cornell University and CIBC, Toronto

ECONOMIC THEORY tells us that market risk and credit risk are intrinsically related to each other and are not separable. For risk management, this implies that we must simultaneously address market and credit risk. We start by describing the two main approaches to pricing credit risky instruments: the structural approach and the reduced form approach. We then review the standard approaches to credit risk management — CreditMetrics, CreditRisk$^+$ and KMV. These approaches are of limited value, if applied to portfolios of interest rate sensitive instruments.

Empirically it is observed that returns on high yield bonds have a higher correlation with the return on an equity index and a lower correlation with the return on a Treasury bond index than do low yield bonds — see Duffee (1998) and Shane (1994). The KMV and CreditMetrics methodologies cannot reproduce these empirical observations given their assumptions of constant interest rates. Altman (1983) and Wilson (1997) have shown that macro economic variables appear to influence the aggregate rate of business failures. We show how to incorporate these empirical observations into the reduced form Jarrow-Turnbull (1995) model. The volatility of the credit spread can be used to determine the sensitivities of the credit spread to the different factors. Correlation plays an important role in existing methodologies. Here default probabilities are correlated due to their common dependence on the same economic factors. We discuss the implications for pricing, given different assumptions about a bond holder's claim in the event of default. We compare the Duffie-Singleton (1997) assumption to the legal claim approach, where a bond holder's claim is assumed to be accrued interest plus capital. Default risk and the uncertainty associated with the recovery rate may not be the sole determinants of the credit spread. We show how to incorporate a convenience yield as one of the determinants of the credit spread. Incorporating market and credit risk implies that it is necessary to use the martingale probability distribution for pricing and the natural probability distribution to describe the value of the portfolio in order to calculate the value-at-risk. We show how to generalise the CreditMetrics methodology in order to incorporate stochastic interest rates.

Simulating correlated defaults

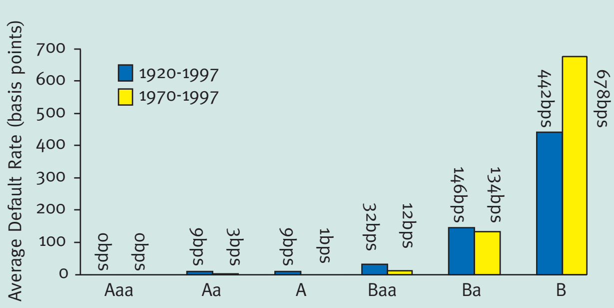
Darrell Duffie and Kenneth Singleton, Stanford University

COMPUTATIONALLY EFFICIENT methods for simulating default times for positions with numerous counterparties are central to the credit risk-management and derivative-pricing systems of major financial institutions. The likelihood of default of a given counterparty or borrower in a given time period is typically small. Computing the distribution of default times or losses on a large portfolio to reasonable accuracy may therefore require a significant number of simulated scenarios. Our paper describes several computationally efficient frameworks for simulating default times for portfolios of loans and OTC derivatives, and compares some of the features of their implied distributions of default times.

Our focus is on the simulation of correlated credit-event times, which we can treat for concreteness as the default times of a given list of entities, such as corporations, private borrowers, or sovereign borrowers.

To put the computational burden of a typical risk-management problem in perspective, consider a hypothetical portfolio consisting of 1,000 randomly-selected firms rated Baa by Moody's, and suppose the risk manager is interested in 10-year scenarios. As indicated by the average default rates for 1970-97 in Chart 1, Baa firms experienced default at a rate of 0.12 per cent per year on average, over this period. Our sample portfolio of 1,000 Baa firms would thus have experienced an expected total of approximately 12 defaults over this 10 period. A "brute-force" simulation of default times for the portfolio using, say, daily survival-default

Chart 1: One year, weighted-average default rates by Moody's rating



Source: Moody's 1998

simulation would call for 10 x 365 x 1,000 = 3.65 million survive-or-default draws per 10-year scenario for this portfolio.

Given random variation in exposures at default, we find that estimation of "long-tail" confidence levels on total default losses for this sort of portfolio would require simulation of roughly 10,000 scenarios, calling for billions of survive-or-default random draws. (Variance-reduction or importance-sampling methods would probably reduce the computational burden.)

Fortunately such computationally intensive algorithms are unnecessary for many risk-management and pricing applications. Instead, one can use a variant of the following basic *recursive event-time* simulation algorithm for generating random multi-year scenarios for default times on a portfolio:

1 Given the simulated history to the last default time T_k, simulate the next time T_{k+1} of default of any entity. If T_{k+1} is after the lifetime of the portfolio, stop.

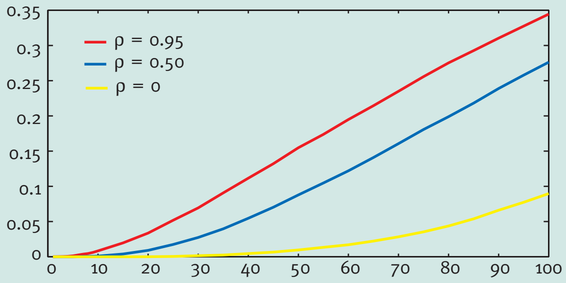
2 Otherwise, simulate the identities of any entities defaulting at T_{k+1}, as well as any other variables necessary to update the simulation model for the next default time.

3 Replace k with k+1, and go back to Step 1.

Algorithms based on recursive event-time simulation are relatively efficient for large portfolios of moderate or low credit risk. For our hypothetical portfolio of 1,000 Baa counterparties, ignoring migration of credit quality for the moment, the recursive event-time algorithm would call for an average of about 120 random inter-default-time draws per 10-year scenario.

We present several frameworks that allow for random variation in an entity's credit-quality over time, while still allowing for the basic efficiency of the recursive event-time simulation algorithm. Moreover, recursive event-time simulation accommodates correlation among default times, including correlations caused by credit events that induce simultaneous jumps in the expected arrival rates of default of different counterparties.

Chart 2: Probability of an m-day period within 10 years having 4 or more defaults (1,000 entities, intensity exponential Ornstein-Uhlenbeck, parameters $\theta = \ln(0.0017)$, $\sigma = 1$, $\kappa = 0.5$, pair-wise shock correlation ρ)



For bank-wide risk management decisions, one may be interested in the likelihood that there will exist *some* interval of a given length, say 10 days, within the given multi-year planning horizon, during which default losses exceed a given amount of a bank's capital. This could be useful information, for example, in setting the bank's capital, structuring its portfolio for liquidity, or setting up provisional lines of credit. For accuracy in this calculation, it would be necessary to simulate the default times of the different entities to within relatively fine time slots, say daily.

Under the obvious proviso that the underlying probabilistic model of correlated default times is appropriate, we show that the recursive event-time algorithm is also well suited for this task, as it generates the precise default times implied by the model, scenario by scenario. When implemented for some hypothetical portfolios, we find that such measures as the distribution of losses for the "worst two weeks within 10 years" are particularly sensitive to one's assumption about correlation among entities.

For example, suppose default arrival rate "intensity" processes for each of 1,000 entities are log-normal[1], with a volatility of 100 per cent, a rate of mean reversion of 50 per cent per year, and an initial default arrival intensity of 17 basis points.

Chart 2 illustrates the role of correlation among intensity processes. Chart 2 shows the probability that there exists some *m*-day period (from a portfolio horizon of 10 years) during which there are at least 4 defaults out of an original portfolio of 1,000 counterparties. The cases shown are for various levels, 0, 0.5, and 0.95, for the pair-wise correlation ρ of the Brownian motions driving individual intensities. For example, with uncorrelated intensities (ρ=0), the probability that there is some 50 day period within 10 years with at least 4 defaults is under 1 percent. At a correlation of ρ=0.5, this probability climbs to almost 9 per cent.

The working paper provides these and other results for alternative intensity and correlation models. We focus particularly on the implications for portfolio default losses of credit events that cause major and simultaneous shocks to the default intensities of a potentially large set of entities. The results illustrated in Chart 2 for a log-normal model are shown to be easily magnified by injecting correlation into the joint-credit event timing, holding individual entity default risk constant.

Notes

1 To be precise, we suppose that the logarithm of each intensity is an Ornstein-Uhlenbeck process driven by Brownian motion. The underlying Ornstein-Uhlenbeck processes were initialised at their long-run mean level.

Determination of the adequate capital for credit derivatives as a contingent claim evaluation problem

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THE PURPOSE of the paper is to provide a practical solution to the problem of determining the adequate level of capital for complex credit derivatives. A rational computational methodology alternative to the value-at-risk (Quantile) method is introduced. This "Coherent Pricing Method" is based on the coherent analytical evaluation of the protection required against the excess default loss over and above the coverage provided by the collateral. As an example, the paper focuses on determining the capital required for default protection when both a bond and a credit default option on that bond have been purchased.

The conventional method for determining adequate capital is the VaR or Quantile method. The collateral required is set at the required confidence level (quantile) from the plot on the probability distribution for the present value of loss. This probability distribution is usually generated by the

Monte Carlo technique. This method has potentially two problems:

1 Monte Carlo simulation can be time consuming, and

2 the resulting adequate capital measure may not capture the diversification effect of the credit portfolio.

In other words, the required capital may be unreasonably high for the aggregate portfolio compared to the sum of each capital requirement in the portfolio. This problem was originally addressed by Artzner, Delbaen, Eber and Heath (1997). They applied the term Coherent Risk Measure to those risk measures where the capital required to protect a portfolio of two positions is not greater than the sum of the capital required for each position. In addition, they postulated that any methodology that calculated the required capital, whilst conforming to the Coherent Risk Measurement definition, would solve the economic problem. Artzner et al provided a coherent methodology based on a modified VaR calculation. The Coherent Pricing Method also conforms to the Coherent Risk Measurement definition, but differs from the Artzner et al solution in that it addresses both the economic and computational timing problems. Instead of using a modified VaR calculation, it focuses on pricing the contingent claim. In practice, the use of pricing methods is not new, but these have not proved to be coherent.

Pricing methods consider the pricing of a contingent claim, which covers the difference (excess loss) between the total loss incurred and the collateral allocated at the time of default. The key to pricing the contingent claim is the insurance premium necessary to cover the total loss incurred at default when the collateral is zero. The Coherent Pricing Method adjusts the required collateral until the price of the contingent claim is sufficiently small when compared to the insurance premium.

The model for pricing a contingent claim was developed by Nakazato (1997). Almost the same model was independently developed by Lando (1994). Both models are a special case of the generalised Duffie-Singleton (1997) credit model, which simultaneously captures both the interest rate risk and the credit risk. When calculating capital adequacy, it is essential to consider both the credit risk and the market risk simultaneously. In our example of the purchase of a bond and a credit default option on that bond, there are several credit risks to consider. There is a risk of credit rating changes, default of the bond, and the risk that the writer of the option (known as the protector), may default on his obligation. The Nakazato model in particular was developed to cope with the credit risk due to default from multiple parties and the risk of credit rating changes.

A notable advantage of the Nakazato pricing model is that the necessary data to evaluate the model are readily available from the market and the rating agencies. Data requirements include the current credit risk-free (Treasury) yield curve, its volatility curve, the current spread curves for each credit class, their volatility curves and the historical credit transition matrix.

Using the Nakazato pricing model, the price of the contingent claim, which covers the excess loss over the collateral, is determined analytically. The analytical solution is not trivial; in fact, the final expression is six pages long even for the simple case of default protection. However, history has repeatedly demonstrated that a model, which has an analytical solution, always provides an efficient numerical/algorithmic solution. In the case of the Nakazato pricing model, the Hull-White (1990) trinomial tree can be used to evaluate the problem efficiently, assuming a single factor. This numerical evaluation takes a fraction of a second on a standard PC. In the case of multi-factor evaluation, an efficient high dimensional lattice generation technique must be used.

The example given in the paper concerns default protection which is the most common use of credit derivatives. This contingent claim is sufficiently complex to demonstrate the flexibility of the approach, since the price depends not only on the market but also on the credit ratings and default risk of both the protector and the issuer of the protected bond. In addition, numerical examples are given to demonstrate some aspects of flexibility of the pricing model, which is essential to determine the capital adequacy of a wide variety of credit linked derivatives.

The advantage of any coherent approach is that the risk measurement captures the diversification effect. This is the essence of credit business and credit risk management.