

Criteria Report

How much Credit in Credit Risk Models?

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■ Executive Summary

This paper addresses the role of credit risk within internal economic capital models in assessing risk appetite and capital adequacy in Fitch's assignment of credit ratings. Other papers addressing related issues such as the role of market, operational risks individually and in combination with credit risk in the context of economic capital models will follow.

Regulatory capital requirements are minimum capital requirements. The amount of capital retained in excess of regulatory requirements will materially influence the credit rating assigned.

This paper outlines characteristics needed in order to place material reliance on their outcome.

Assessment of Credit Portfolio Risk Models in the Ratings Process

Fitch Ratings considers the institutions' own economic capital and regulatory capital models as a factor in its ratings process of banks.

Factors discussed throughout this paper will influence the degree of comfort Fitch will derive from an institution's credit risk model. We will place a higher weight on models with the following characteristics:

Board and Management Oversight of Credit Risk Models

Board and senior management should understand and endorse the use of credit risk models. The Board should ensure that the model is integrated into active management of the company. The outputs and reports of the models should be used to assign and track risk tolerance and associated capital levels. Management should receive regular reports. The Board should require and be apprised of the independent validation of models. Individuals involved in model development should not also be the end users. If this is not possible, an external third party should validate the model.

A High Degree of Transparency to the Agency

The more information provided by the institution (eg detailed documentation of model construction and implementation), the greater the weight Fitch would expect to apply to the institution's own model output. This assumes that models address key credit risks consistently.

Management should be sufficiently well-versed in their models to be able to explain and account for fundamental areas of similarities and differences between model outputs and both accounting and regulatory frameworks.

A Proven Track Record

Models that have been consistently employed to assess risk over a period of time, and where management have a history of decision making and managing their business using the output provided by the models will be assigned higher weights. Credit risk models that are in place but not integrated with the institution's risk management and decision-making framework are, in general, ineffective.

Appropriate Control of the Model

As models can be powerful tools within a bank's business, model controls are important and are a key ingredient of Fitch's assessment. Models should be embedded within the business. Change control and documentation standards should ensure model integrity.

Quality of Model

Models should be chosen that provide a strong fit between their capabilities, assumptions and the properties of the portfolio. Some contemporary credit risk models employ a single-factor model framework and/or assume an infinitely fine-grained portfolio. They are appealing because of their simplicity. Such models may be appropriate for highly diverse portfolios, as found in retail banking or SME divisions, but can only rarely be applied to corporate portfolios. The tractability of credit risk models is lost when less finely-grained portfolios or portfolios which intrinsically depend on a large number of disparate market factors are to be modelled. Thus, it is essential that a suitably sophisticated model be employed.

Models should be updated and shortcomings addressed as the industry continues its enhancements. Appendix 1 provides a brief overview of common credit risk model approaches.

Validation

While validation processes and methodologies are the prime responsibility of the institutions themselves, Fitch will evaluate and assess the process and techniques deployed and attempt to identify best practice amongst institutions.

Ongoing Model Review

Models should be subject to regular periodic audits, continuous testing and benchmarking. Related change control procedures are also important to ensure that only reasonable changes are made without sacrificing model integrity.

■ Introduction

Fitch recognises the advances made by banks in risk management and in particular the increasing use of credit portfolio risk models for the measurement and management of credit risk as part of the overall eco-

nomical capital management framework of these organisations. The growing popularity of these models is only expected to accelerate with the establishment of a new regulatory framework for assessing bank risk-based capital, better known as Basel II. Basel II adapts many of the concepts and techniques used by large financial institutions in their own internal credit risk models for supervisory purposes.

The agency believes that the anticipated convergence between economic capital and regulatory capital frameworks has been a positive impetus to further refine and more broadly spread advanced risk measurement and management practices such as credit portfolio risk modelling.

The assessment of credit risk models and their output represents an important part of Fitch's overall view of an institution's risk appetite and profile within the agency's rating analysis. A number of institutions use standard vendor models available in the market to measure and manage credit risk. There is an increasing trend by many institutions to (1) attempt to separate the conceptual model from its implementation, (2) internally develop credit risk models built to meet their organisation's unique requirements, and (3) access greater diversification benefit through the joint analysis of multiple asset classes.

This report identifies the principal drivers of credit risk models in the measurement of credit risk and the influence of these drivers on the economic capital charge, as well as the impact of these drivers if applicable in determining the capital charges under the new regulatory capital framework (Basel II – internal ratings-based approach). The report uses a sample portfolio of loans as an illustration to compare the influence of these drivers in determining capital charges under economic and regulatory capital frameworks. In addition, the report also outlines the agency's opinion on the use of these credit risk models in the measurement of credit risk and the associated capital charge and how it will factor this into its rating process.

Credit Risk Models and Risk Management

Fitch believes that credit risk models form a very important part of risk management and are a vital input into the pricing of products and services. The understanding of risk on an aggregate basis and an assessment of how these risks associated with single borrowers interact with each other is very difficult to achieve in the absence of some kind of risk model, especially where risks are complex. It is also the agency's opinion that while measuring risks is a necessity, to achieve full economic benefit from the models, their output should be an influencing factor in decision making within an institution.

A credit risk model can be instrumental to an organisation's management: it aggregates individual risks that reside in separate silos and enables an assessment of the overall credit risk faced by an organisation. Credit risk models provide important data and information to aid strategic decision-making. It is critical to understand the prime drivers and how they combine to influence the final output of these models.

Prime Drivers of Credit Portfolio Risk Models

Probability of Default: PD

Most large financial institutions use risk ratings to distinguish among obligors of different credit quality. However, different rating systems accomplish this task in different ways. Rating systems can employ as few as four or five to as many as 30 categories of risk, to classify corporate and individual customers. In general, it is noted that many institutions use rating systems which are characterised by one or more of the following three elements: (i) a traditional method which combines financial and other characteristics of the customer into a relatively subjective approach to determining ratings; (ii) vendor-supplied credit scoring models; or the use of (iii) internally developed credit scoring models. While element (i) is commonly found in rating systems for corporate customers, elements (ii) and (iii) are predominantly found in the rating systems for retail and small and medium-sized enterprise (SME) customers.

In addition, it is necessary to understand the dynamic properties of a rating system (i.e. whether they are designed to capture "through-the-cycle" (TTC) or "point-in-time" (PIT) conditions) and the relationship with default probabilities (PD). Under PIT rating systems, obligors are assigned risk buckets with unique PDs based on best available information about their credit quality and, as this changes, obligors are rapidly transitioned to new risk buckets with differing PDs. By contrast, under TTC systems, obligors are assigned to rating grades and PDs based on evaluations of their abilities to remain solvent through a business cycle which includes a severe stress event. Because of the weight placed on stress conditions rather than current conditions, PDs of TTC ratings tend to change less often than PDs of PIT ratings and therefore tend to be more stable over the business cycle. In practice as it is very difficult to characterise PDs as being pure TTC or PIT and as capital calculations are sensitive to PDs (PIT or TTC) it is critical to understand the process by which PDs are determined.

As PD is the likelihood of a borrower defaulting within a defined time frame, all institutions, irrespective of the rating systems used, will need to

validate their PD estimates using historical default information. The definition of default used by an institution is a critical starting point since the parameter is based on a default event.

Definition of Default

Many unconditional credit risk models assume that obligor default is triggered by a change of the obligor's asset value, ie obligors default if their institution's value falls below a pre-specified threshold point usually taken to be the point at which an institutions asset value equals its liabilities. Obligor's asset values are commonly modelled by a common, standard, normally-distributed factor component and an idiosyncratic standard normal noise or residual component. It should be noted that this definition of default is fundamentally different from the definition used by the accounting framework and an analysis of differences between the two is essential for a proper understanding of how credit risk models work.

From a regulatory perspective, default events arise in general from the non-payment of principal or interest for 90/180 days or when it seems unlikely that obligations will be met. However, an institution may also characterise a loan to be in default where borrowers are either in violation of covenants or are experiencing severe cash-flow problems. As the definition of default can vary across institutions and asset classes, it is critical to understand the rationale behind the default definition adopted by an institution and make an assessment of its application across different asset classes. While estimating PDs, it is also critical to understand the assessment horizon or time-frame taken into consideration.

For example, the use of a one-year PD implies assessment of default over the next 12 months and is strictly related to the rating of the counterparty or a specific deal. This can be contrasted with cumulative or multi-year PDs, where the assessment of default is over a number of years. One common approach to model these PDs is the introduction of a migration or transition matrix to account for the possibility that ratings change over time.

Loss Given Default: LGD

The LGD is a measure of the expected loss that the bank will experience per unit of exposure should its counterparty default, and is expressed as a percentage. Therefore, the definition of default for LGD purposes should be consistent with the definition used for calculating PDs. Although each borrower may have only a single borrower rating – reflected by a single probability of default – different exposures to the same borrower will result in different facility-specific LGD profiles.

The ex ante loss on an exposure if it were to default is a random variable, whose value is unknown until default occurs. Indeed, since the actual net cash-flows on a defaulted loan are not known until a workout is complete, there is uncertainty surrounding the LGD even at the time of default. The expected LGD may be derived from the market price of defaulted debt, from a bank's internal workout and recovery data, or from analysis of consortium-provided workout and recovery data.

Outside the consumer and small business lending areas, there is very limited historical data with which to estimate LGDs. This data problem is further compounded by the fact that LGDs normally will depend on the loan's seniority and collateral (if any), as well as on characteristics of the borrower, such as industrial sector and country.

Where internal workout data is used, recovery cash-flows net of workout costs are discounted at their present value back to the default point. The rate at which these cash-flows are discounted should, in principle, be the rate appropriate for the risk of the defaulted asset. However, this rate is not directly observable, nor is it easy to estimate because data is scarce. Available data for estimation may be influenced by issues such as liquidity. Difficulties also arise in identifying a relevant market for all the various transactions a bank undertakes.

For these reasons a common choice for discounting is the contractual interest rate which has the advantage of being consistent with accounting rules. Although other valid choices exist and are appropriate to use, the relevant interest rate chosen must be justified and the institution must demonstrate that the resultant LGD estimates are reasonable.

The lack of robust data on which to base LGDs across a range of borrower and transaction types is a communal and significant problem in all credit risk analysis. Only a minority of institutions employ historical data spanning more than five years: external sources of these data are growing, but remain not entirely independent from the bank's own unique loss history since they tend to be based on sponsored consortium structures.

Exposure at Default: EAD

Exposure at Default (EAD) is the extent to which a bank is exposed to a credit or counterparty in the event, and at the time, of that counterparty's default.

EAD is a difficult parameter to model for some facility types although conceptually easy to understand. First, there is the question of how one defines exposure: the nominal sum outstanding, the market value of exposure just prior to default, or the market value

of the exposure just prior to default but assuming it were risk-free. Actually, because EAD and LGD are broadly fungible, this issue is often addressed under LGD rather than under EAD, with EAD defined to be outstanding balance sheet exposure.

Second, EAD, in many cases depends on the actions of the counterparty (drawdown when default is imminent) and the bank (withdrawal of limits, tighter covenants). Although there is the possibility that current outstandings may be reduced prior to default, it is reasonable to hold capital against all drawn exposures. In addition, a positive EAD is expected for all un-drawn commitments and advised limits, including unconditionally and immediately cancellable lines of credit.

Third, EAD may be dependent on other factors. For example, in the case of over-the-counter derivatives and securities financing transactions, market rates play a role in determining the market value of the positions today – and at the time of default. While Basel II allows for varying levels of sophistication in treatment of such exposures, internal models are becoming ever more sophisticated, particularly in large institutions.

Maturity: M

The maturity of a derivative, bond or loan is one of the key factors affecting credit risk. All else being equal, the shorter the maturity, the less the core credit risk. Banks can deny credit, raise prices or demand greater protection (in the form of collateral or seniority) in the quest to limit future losses to customers whose financial conditions have deteriorated.

Correlation: ρ

In most banks, the default of a single counterparty is unlikely to be a drain on capital. Rather it is a series or group of defaults that poses a threat. Correlation is the driver that determines the propensity of defaults to group together and hence is an important factor in portfolio analysis. A key differentiator between credit risk models is in the description and calibration of correlations.

Closely related to correlation is the concept of concentration. Generally, credit portfolio risk models are strongly influenced by the property of portfolio invariance. Idiosyncratic risks (associated with individual exposures, and hence the source of concentration) in large portfolios of small exposures tend to cancel one-another out and only systematic risks that affect many exposures have a material effect on portfolio losses.

In many credit risk models, all systematic risks that affect all borrowers to a certain degree (such as in-

dustry or regional risks) are commonly modelled with only one systematic factor. This is the case, for example, in the model underlying the Basel II standards. The single factor needed in the model may be interpreted as reflecting the state of the economy. The degree of the obligor's sensitivity to this systematic risk factor can be expressed by the correlation between the factor and the value of the obligor's assets. So, the correlations could be described as the dependence of a borrower's asset value on the general state of the economy; all borrowers are linked to each other by this single risk factor.

Asset correlations essentially indicate the degree of co-movement between the asset value of one borrower and the asset value of another. Asset correlations also influence the shape of the risk weight formulas. They are asset-class dependent, because different borrowers and/or asset classes show different degrees of dependency on the overall economy. Time series of default frequencies have been used to determine default rates as well as correlations between borrowers. Analysis of these time series reveals two systematic dependencies:

1. Asset correlations decrease with increasing PDs as indicated by both empirical evidence and intuition. Intuitively the higher the PD, the higher the idiosyncratic (individual) risk components of a borrower. The default risk depends less on the overall state of the economy and more on individual risk drivers.
2. Asset correlations increase with firm size, again as indicated by both empirical evidence and intuition. Although empirical evidence in this area is inconclusive, it again appears intuitive that the larger the firm, the higher its dependency upon the overall state of the economy, and vice versa. Smaller firms are more likely to default for idiosyncratic reasons.

Asset correlations are commonly an intermediate step to derive the default correlations that are used in some credit models. Default correlation is a function of: the asset correlation and the PDs of the two obligors that are being correlated. Asset correlation translates into higher default correlations when one (or especially both) obligor PDs are high.

It is also important to recognise that correlation values used in financial institutions in their economic capital models may well differ from those used in regulatory capital models. Typical reasons for the differences include factors such as stated conservatism in the Basel II standards and the use of multi-factor models for economic purposes versus single-factor models for regulatory purposes.

Empirical evidence has so far been contradictory regarding both the relationship between default correlation and PD, and the average level of correlation across geographic regions. Assessing the magnitude of (and reasons for) these correlation differences and patterns will, therefore, be a key consideration for Fitch in the ongoing quest for data transparency and integrity.

Credit Portfolio Risk Models

Credit risk modelling has developed rapidly in the recent past and is now firmly established as a key component of risk management systems in financial institutions. A wide variety of credit risk models have evolved, differing in methodologies and fundamental assumptions. For example, the definition of credit losses (default models define credit losses as loan *defaults*, while mark-to-market or multi-state models define credit losses as ratings *migrations* of any magnitude). In the end, all the identified drivers are combined in a credit risk model to generate a loss distribution, which in turn determines the portfolio capital charge.

Generically, credit risk models can be classified as either conditional or unconditional. Unconditional models do not adjust expectations for cyclical changes in economic conditions, while conditional models adjust explicitly.

All models are conditional to some extent, since all models seek to incorporate some current information about the quality of credit of each borrower and of each credit facility. It is, however, still possible to distinguish between unconditional and conditional models.

In conditional models, explicit adjustments could lag behind the economy by several months due to the time required to procure and process econometric data. However, such models are often favoured by the market for their explicit handling of economic conditions on the basis that ideal credit models should account for *changes* in the economic environment, and not assume constant economic parameters.

The common goal of all credit risk models is to forecast the loss distribution function that may arise from a bank's credit portfolio. Since credit defaults or rating changes are relatively rare events and since debt instruments comprise set payments that limit potential returns, the loss distribution is generally asymmetric, ie skewed towards zero, with a long right-hand tail. Although institutions do not employ the entire loss distribution for capital purposes, different parts of it can be used in support of different decision-making processes (e.g., pricing) so, credit

risk models typically characterise the full distribution.

There are a number of commercial credit risk models in addition to those developed internally. To effectively employ the results in risk practice and other management activities, it is essential for banks to fully understand how these credit models function. Further, it is important for the bank to be able to provide sufficient detail for Fitch to be able to understand, assess and contrast the particular credit risk model being used.

Assessing Quality of Credit Risk Models

Two important components need to be addressed as part of the assessment process, and certainly before credit risk models can be used to determine risk-based capital requirements.

1. **Model input quality.** The need to establish consistent and accurate exposure measurement for the chosen credit rating standard is very important. Much work has been conducted regarding the difficulties involved in creating and maintaining accurate internal ratings systems and although these present challenging issues, they can be addressed by internal and external qualitative monitoring procedures.
2. **Model specification and validation.** The construction of the loss distribution function is possibly the most challenging aspect of credit risk modelling. Changes in credit value are due to several factors, such as correlations between portfolio assets, movements of credit spreads and changes in individual loans' credit status. As a result, a variety of modelling assumptions and parameter values are required for the construction of a credit risk model's forecasted distribution. The lack of sufficient historical performance data, however, limits the testing of the validity of these model components. A relatively large number of observations are required to accurately evaluate any distribution forecast. This issue is of less concern for evaluating distribution forecasts generated by *market* Value at Risk (VaR) models since such models generate daily forecasts of market portfolio changes which can then be evaluated relative to the actual portfolio changes. Whilst some 250 observations (one year of daily trading data) are currently used in the regulatory evaluation of *market* VaR models, it is difficult to gather a large number of observed credit losses with which to evaluate credit risk models since these have much longer forecast horizons – typically one year. As a result, one year generates a single observation of credit losses, so 250 years would be required to

collate an equivalent number of observations as specified for market risk models.

3. **Comprehensiveness.** It is important to the assessment process to clearly identify the risks that are being considered and those that have been ignored by the credit risk model. While there are many potential inclusions and exclusions, two of the most commonly excluded are concentration risk and migration risk. Consider as an example, concentration risk: Name concentration in loan portfolios arises from either a dearth of borrowers or when loan amounts are asymmetrically distributed. The credit portfolio risk model adopted for the Basel II Internal Ratings-Based (IRB) approach does not account for name concentration: it assumes that the bank's portfolio is perfectly fine-grained, meaning that idiosyncratic risk has been fully diversified away, so that economic capital depends only on systematic risk. As a result, each loan constitutes only a small fraction of the total portfolio exposure. True bank loan portfolios are seldom – if ever – perfectly fine-grained. The asymptotic assumption, while approximately valid for large portfolios, may be invalid for portfolios of smaller or more specialised institutions. Where material name concentrations of exposure exist, the residual of undiversified idiosyncratic risk in the portfolio can be significant. Fitch will expect financial institutions to have a process in place to identify, measure, manage and mitigate concentration risk.

Example

Application of Credit Risk Model Methodology to Loan Portfolios

A simple Excel-based single-factor model was constructed to examine how these primary drivers influence model output. The model was also flexed to test sensitivity of model output to changes in values of primary drivers, and to compare it to the regulatory model.

It is important to note that construction of a full-blown credit risk model is not the purpose of this paper. The model employed here (referred to as the "Basic Model") therefore, makes many assumptions about the structure of credit portfolios. It is thus relatively simple, aiming to illustrate the principles on which these models operate rather than focussing on the details.

The data used are hypothetical corporate loan portfolios (which approximate real life bank loan portfolios) and were characterised by the parameters (used as input to the single-factor model) specified below.

Further, the Basic Model assumes that a loan's EAD is simply its current outstanding exposure. In reality, a loan's EAD depends on several factors, e.g., coupon payments, coupon payment frequency, discount rates, and so on – all ignored in the interests of simplicity in this demonstration. Similarly any more complex instruments are ignored in this analysis.

The results are shown in the figures below. Some 20,000 simulations were run for each scenario investigated. This provides a confidence in the results to +/-5%.

Throughout this study, the loans were grouped by PD and LGD classes. For simplicity, both the PDs and LGDs were gross-exposure-weighted within a particular class. “Gross-exposure-weighted” here refers to a scheme which weighs the variable in question by exposure only, not by the product of exposure and LGD (or net exposure). Weighting the PD using the net exposure method would result in mean-invariant portfolio losses, and so is a technique that Fitch understands is widely used in credit portfolio analytics.

Portfolio Results

In addition to a base case, eight scenarios were explored for the portfolio detailed in the table below. Each scenario was designed to investigate the sensitivity of the expected and unexpected losses to changes in the relevant credit risk component (holding other constituents fixed). In each case, all other elements remain the same as for the base scenario apart from the stressed component.

The effect of changing a single parameter in this manner can be important to fundamental analysis, as we provide herein. However, we recommend exercising caution: there are complex interactions between the portfolio content, the assumptions and the confidence level at which the results are measured. The complexity of this interaction means that the

ordering of the significance of the primary drivers should be investigated in the context of a particular portfolio.

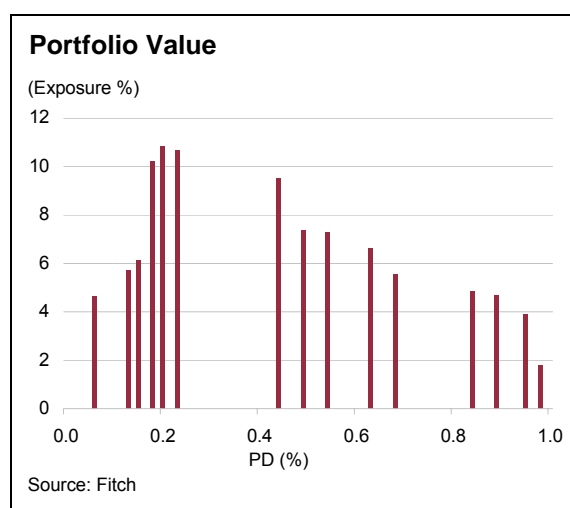
**Portfolio Parameters
(Base Scenario)**

Number of loans	6 000
Total exposure	EUR1.0bn
	Range (%)
PD	PD < 0.2% 38
	0.2% ≤ PD ≤ 0.7% 47
	0.7% < PD ≤ 1.0% 15
LGD (%)	Exposure weighted: 36
Correlation	Basel estimates: 0.12 ≤ ρ ≤ 0.24
Grades	15

Source: Fitch

Base Scenario

The distribution of exposures (as a percentage of EUR1bn total exposure) per PD band is shown in the figure below for the portfolio.



Scenario Tests

Test	Description
1	8 PD grades: The average and standard deviation for each PD band are therefore <i>larger</i> than in the base scenario.
2	22 PD grades: The average and standard deviation for each PD band are therefore <i>smaller</i> than in the base scenario.
3	PDs all up 20%. Standard deviations of PD bands remain the same as the base scenario.
4	PDs all down 20%. Standard deviations of PD bands remain the same as the base scenario.
5	Exposure weighted LGDs all up 20%.
6	Exposure weighted LGDs all down 20%.
7	Correlation up 20%
8	Correlation down 20%

Source: Fitch

PD Bands & Exposure Distribution

PD band	Portfolio	
	Average (%)	% of total exposure
1	0.06	4.64
2	0.13	5.73
3	0.15	6.15
4	0.18	10.24
5	0.20	10.85
6	0.23	10.70
7	0.44	9.54
8	0.49	7.39
9	0.54	7.28
10	0.63	6.65
11	0.68	5.57
12	0.84	4.88
13	0.89	4.67
14	0.95	3.90
15	0.98	1.81

Source: Fitch

Percentage of portfolio exposure by PD band.

The table below shows the average PD and the associated standard deviation of each PD band for the portfolio.

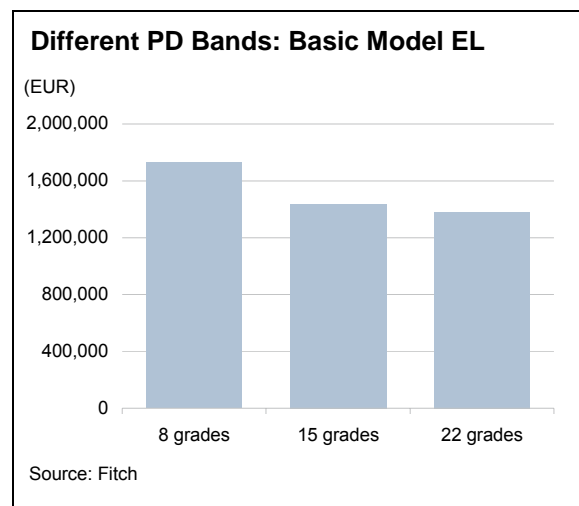
For the base scenario, the results and capital charges were as follows:

Summary of Measures - Base Scenario

Total exposure	EUR1,000,000,000
Expected loss	EUR1,436,692
Unexpected loss @ 99/9%	EUR53,355,699
Capital charge	5.34%

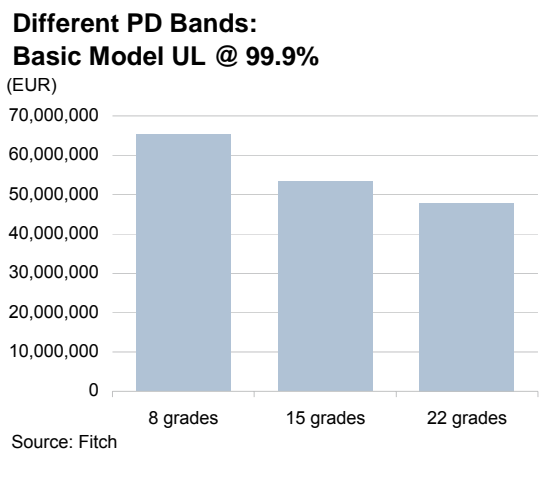
Source: Fitch

The Impact of Change in PD

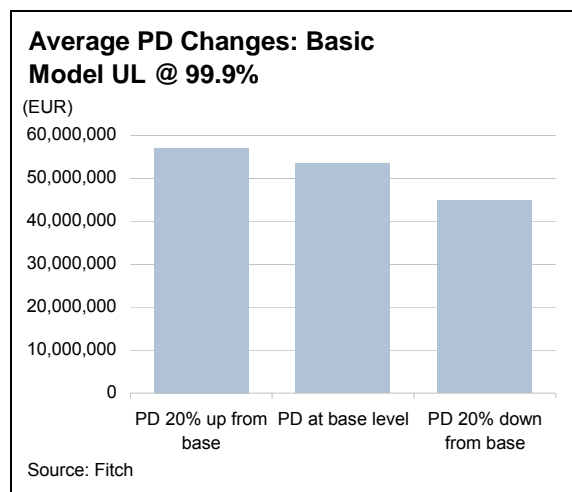


The portfolio was tested at different threshold levels for all PD bands. Higher average PDs increase the UL considerably. This result is not unexpected: lower average PDs result in larger thresholds which must be breached before default (and hence a loss) can occur. Since these thresholds will be more difficult to breach than those for higher average PDs, losses are reduced.

If starting with more than 15, increasing the number of PD buckets used to allocate input data does not have a significant effect on the EL, and the values converge to the base case EL. However, a decreasing number of PD buckets does result in portfolio EL increasing by 20%. Note that if the net exposure weighting method were used here, the portfolio would be mean invariant, so that the number of buckets would have no effect on EL.

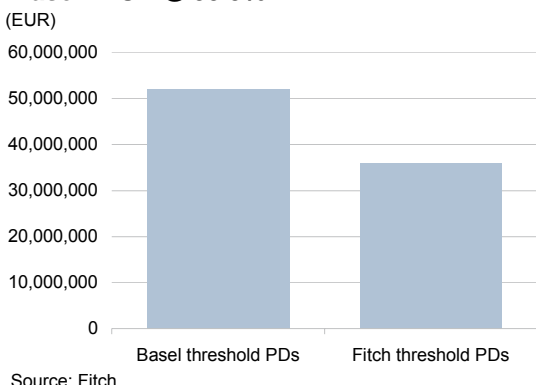


The UL is more sensitive than the EL to the number of PD buckets and increases by 22% when PD buckets are restricted to eight grades. Conversely, when PD buckets increase to 22 grades UL decreases by 10%. When assessing lower-quality portfolios or including migration analysis, the impact of rating scale granularity must be explored in greater depth.



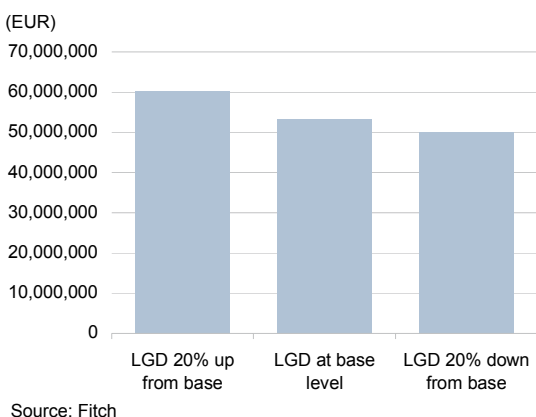
Increasing the average PD of the PD bands increases the UL by 7%. Decreasing the average PD of the PD bands decreases the UL by 17%. This result is sensitive to the interaction between the overall average PD level (i.e., credit quality) and the confidence level.

Different PD Thresholds: Basic Model v. Basel II: UL @ 99.9%



The Impact of Changing LGD

LGD Changes: Basic Model UL @ 99.9%



Increasing the exposure weighted LGDs increases the UL by 13%, while reducing the LGDs decreases the UL by 6%. Note that in this example, UL is less sensitive to changes in LGD than average PDs. This is a common property of models, and direct consequence of the construction of the model, but it can be influenced by assumptions relating to stochastic LGD.

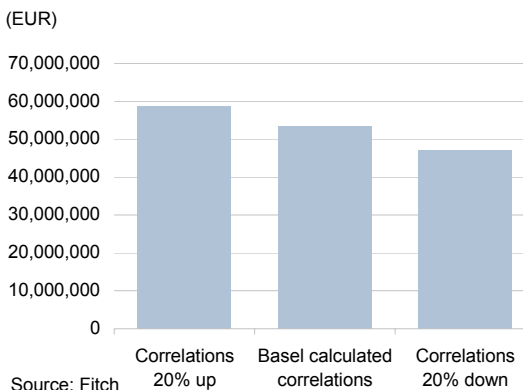
The Impact of Changing Correlation

Increasing the correlation by 20% increased the UL by 10%, while decreasing the correlation decreased the UL by 12%.

In assessing this result, note that a single-factor model assuming infinite granularity has been used to compute results at the 99.9% level. Using a multi-factor model, modelling concentrations, and/or changing the confidence level (esp. to 99.97%) can dramatically increase the impact of correlations on the results. Typically, if concentrations are modelled in portfolios of 6000 large corporate loans (as in this

example), correlation is the dominant driver of results in the tail.

Correlation Changes: Basic Model UL @ 99.9%



Capitalisation Levels

The results in all of the above scenarios were for a bank capitalised at a “AA” level – ie a confidence level of 99.9% (or a probability of default of 0.1%). For illustrative purposes the effect on the UL at various confidence levels and PDs linked to ratings is shown below. It should be noted that institutions may well choose to link their calculations to different parameter values which are equally appropriate

Summary of capital charges

Rating	Bank capitalised at	Capital Charge as a % of exposure
“AAA”	(PD = 0.03%, CI = 99.97%)	7.31
“AA”	(PD = 0.10%, CI = 99.90%)	5.34
“A”	(PD = 0.40%, CI = 99.60%)	3.35
“BBB”	(PD = 1.00%, CI = 99.00%)	2.31
“BB”	(PD = 2.00%, CI = 98.00%)	1.58
“B”	(PD = 4.00%, CI = 96.00%)	1.04
“CCC”	(PD = 8.00%, CI = 92.00%)	0.58

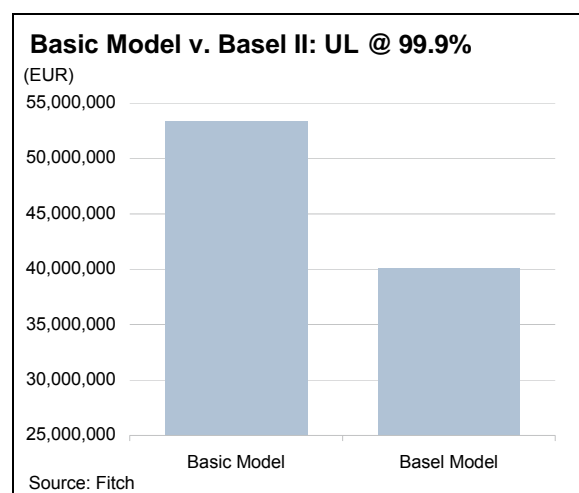
Source: Fitch

Economic Capital vs. Regulatory Capital

Regulatory Capital: Regulatory capital focuses on different “tiers” of capital and relates the level of capital to risk-adjusted assets. Risk is incorporated into the calculation of capital by the assignment of assets into simple discrete risk buckets. Currently risk-weightings are assigned by the regulators and are driven primarily by their view of the amount of capital required within the banking system to protect the stability and soundness of the financial system. Unfortunately, the existing regulatory approach to capital is not risk-sensitive and over time was increasingly seen to be divorced from the underlying risks borne by an institution. This is due to change with the implementation of Basel II, which seeks to align regulatory capital to risk more closely.

Economic Capital: By contrast, from a conceptual point-of-view economic capital is a measure of risk not of capital held. In practice, in most institutions it is considered to be a buffer of capital to guard against unexpected loan losses arising from credit, operational, market and business risks over a one-year horizon and is calculated at a pre-specified confidence level. Fitch believes it is a more forward looking requirement as it is based on an assessment of potential future losses focussing on changes in the true economic value of *assets* (not earnings). Economic capital should provide an indication of the flexibility the bank needs in planning for growth.

Comparison of the Basel-calculated capital charges with those obtained from the Basic Model (also a single-factor credit risk model) showed some difference. However, the results from the Basel Model are also considerably affected by the number of PD grades (with more PD grades giving more consistent results). Recalling the gross-exposure weighted PDs, this result is expected. Other observations are possible with net-exposure methods.



The UL calculated using the Basic Model and the Basel Model exhibit differences which stem from the fact that the Basel equations are closed form and incorporate an intrinsic maturity factor. Model results however, converge for increasing PD grade granularity. EL and UL values increase with increasing PDs, LGDs and correlations in both models.

From Fitch's perspective, the overall aim is clearly to base capital requirements on a true economic capital assessment. However, reliance on a bank's internal economic capital model requires confidence that it produces capital levels commensurate with the risks being run. This is not a straightforward task, and realistically both economic and regulatory capital requirements will need to be considered in Fitch's analysis of a bank's capital adequacy.

Appendix 2 provides more detail concerning the questions Fitch expects to be asking Banks during the review process.

The answers to these questions will provide us with an ability to develop a detailed understanding and level of comfort with a credit risk model. We also expect institutions to perform certain stress tests to key assumptions and provide detailed reports of the results. These reports combined with the model outputs of a sample portfolio from a multitude of rated institutions will enable us to fully understand the models employed and contrast them against benchmarks.

Credit risk modelling continues to evolve, and a lack of practical back-testing alternatives means that the jury is still out regarding their effectiveness over time. Therefore, Fitch's opinion stresses that caution must be exercised when granting credit to credit risk models.

■ Appendix 1

Credit-Worthiness Modelling Approaches

The methodologies underlying contemporary credit risk measurement models can be traced to two different approaches to asset pricing: a structural approach pioneered by Merton in 1974 and a reduced-form approach employing intensity-based models to estimate stochastic hazard rates launched by Jarrow and Turnbull in 1995, further developed by Jarrow, Lando, and Turnbull in 1997 and then by Duffie and Singleton in 1998/1999.

Whilst these two methodologies differ somewhat in their approach, both tackle a central theme common to all credit risk measurement models: the estimation of default probabilities. Commercially available models use at least one of the methodologies referred to above. A discussion of the different approaches is presented below as background.

Structural Approaches

The *structural approach* to credit default models treats a credit-risky bond (or swap) as a credit riskless bond (or swap) minus an option to exchange the bond (or swap) for the debtor's entire portfolio in the event of bankruptcy. Merton modelled a levered firm's equity as a call option on the firm's assets with a strike price equal to the debt repayment amount. If at expiration (coinciding with the maturity of the firm's liabilities, assumed to be comprised of pure discount debt instruments) the market value of the firm's assets exceeds the value of its debt, the firm's shareholders will exercise the option to 'repurchase' the company's assets by repaying the debt. However, if the market value of the firm's assets falls below the value of its debt, the option expires worthless and the firm's shareholders default.

One common model estimates the probability of default¹, the Expected Default Frequency (EDF), for each obligor based on a Merton-type model. The probability of default is thus a function of the firm's capital structure and the credit risk driven by the dynamics of the issuer's asset value (ie the volatility of the asset returns and the current asset value). Given the firm's current capital structure (ie the composition of its liabilities: equity, short-term and long-term debt, convertible bonds, etc.) and having specified the stochastic process which drives the asset value, the probability of default for any time horizon, (one year, two years, etc.) may be calculated. Typically, the EDF is firm-specific and can be mapped into any rating system to derive the equivalent rating of the obligor. EDFs can be viewed as a

¹ This model does not make any explicit reference to transition probabilities, since these are already imbedded in the EDFs. Instead, each value of the EDF is associated with a spread curve and an implied credit rating.

'cardinal ranking' of obligors relative to default risk, instead of the more conventional 'ordinal ranking' used by rating agencies.

This type of model best applies to publicly traded companies for which the value of equity is market-determined. While rooted in a sound theoretical basis, it is only practical for firms with simple capital structures; it is questionable for those with capital structures that are more complex such as financial institutions and international conglomerates.

In addition, Merton's structural model issues early warnings of default by allowing a gradual diffusion of asset values to the default point (equal to the debt level). As a result, this process implies that the PD steadily approaches zero as the time to maturity decreases – a result not observed empirically in the credit spread term structures.

Reduced form Approaches

In contrast to Merton models, credit spreads that are more firmly rooted in practical experience are obtained from *reduced form* or *intensity-based* models. Hence, whilst Merton's structural approach models default as the result of a gradual deterioration in asset values, intensity-based approaches model default as sudden, unexpected events.² These models estimate PDs that are more consistent with empirical observations even though they do not specify the economic process leading to default. Instead, model default is a point process in which defaults occur randomly with a probability determined by the intensity or hazard rate. Intensity-based models decompose observed credit spreads on defaultable debt, or Credit Default Swaps (CDS), to determine the PD (conditional on no default having occurred prior to a specified time) as well as the LGD (given by $1 - R$, where R is the recovery rate).

Intensity-based models are essentially empirical, employing (observable) risky debt prices and credit spreads to measure the stochastic jump process which governs default.

Whilst theoretically pleasing, the model is not without its share of practical problems. The fundamental problem exists that calibration of reduced form models requires the estimation of *two* variables at once: PD and LGD. So observing merely one credit spread is insufficient. Different workarounds have been tried such as observing a term structure of spreads for the firm and assuming one LGD for the whole or pegging PD using the equity price, and then pegging LGD using debt instruments of differing seniority.

² Reduced-form models decompose risky debt prices in order to estimate the random intensity process underlying default, whereas the structural approach models the economic process of default.

■ Appendix 2 - Possible Questions

In order to assess an institution's credit risk model, the starting point for Fitch is a clear understanding of the principles and techniques that the model uses. In order to build up this information, Fitch seeks information on:

High-Level Overview

- Is the credit risk model in use a standard vendor developed model, an in-house model or a combination of both?
- What were the prime factors in determining the vendor credit risk model or the in-house model in use?
- What are the principal assumptions and settings of the model in use (one factor, multi-factor, default definition, mark-to-model)?
- Are the parameters and assumptions appropriate to the institution's portfolio and business models?
- What software tools are used for modelling? How many model assumptions are dictated by the tool?
- What is the probability of survival and time horizon used (eg 99.90% over one year or any other confidence level) by the credit risk model? Does this change with the decision being supported? Where applicable, how does this differ from your current rating (e.g. AA: 99.95%) and the regulatory standards?
- Where appropriate, is the modelling sophistication commensurate with the portfolio holdings?
- Please explain how the outputs from the model feed into the risk management and decision-making process of the bank.

Model Development

- Is the vendor credit risk model in use tailored to meet your in-house requirements or is it implemented with no change?
- If using an in-house model or a tailored vendor model, was model development and changes done in-house or externally by consultants? Or a combination of the two?
- If made or customized in-house, was this driven by a profit centre of the institution or a centralized risk management department?
- Where applicable, is there a separate model for corporate, financial institutions, sovereigns, project finance, mortgages, revolving retail loans and other retail loans?
- Where applicable, do the models differ by country of operation or are they the same across countries?
- What testing was performed on the model prior to implementation? And as ongoing validation?

- Has the model been validated or reviewed by any external agency (eg regulators, consultants)?
- What are the main areas for ongoing and future development?

Inputs of the Model

Fitch does not expect to see every possible feature as part of every model but expects complexity to be commensurate with that of the organisation.

PD

- How are PDs quantified for the following asset classes: corporate, financial institutions, sovereigns, mortgages, revolving retail and other retail loans. (eg historical default experience, statistical model and external mapping approach)?
- How do you set a PD to represent a pool of many similar (homogeneous) obligors (eg retail loans, credit card loans)?
- Can you elaborate on the number of risk buckets (i.e., credit rating grades) used by asset class and the rationale for using these risk buckets in contrast to a higher or lower number of risk buckets (e.g. 8 vs 15 vs 22)?
- Can you also explain:
 - the number of obligors per risk rating bucket?
 - the difference if any between expected and realised PD?
 - the mean and the standard deviation of PDs by risk bucket?
- If your PDs are stressed PDs, explain the difference with unstressed PDs by asset class. If PDs are unstressed, then explain whether they are at all stressed and if so how you factor in stressed PDs.
- What definition of default do you use for PD estimation and loss evaluation? How different is this from the accounting definition of default, and do you reconcile these differences?
- Where applicable, if the model takes into account rating migration, can you provide the default rates observed per rating grade?

LGD

- What is the approach adopted to quantifying LGD for the following asset classes: corporate, financial institutions, sovereigns, mortgages, revolving retail and other retail loans. (eg expert judgement, implied market LGD or discounted cash-flow approach)

- Do you determine LGD values with the help of a grading system? Can you explain in brief how this system works? Where you do not use a grading system, explain how you capture LGD.
- Does the model take into account a stressed LGD for all the asset classes?
- For low default portfolios, how do you estimate LGD values?
- Do you benchmark your LGD values?
- Provide the definition of default used (in internal grading?) and if it is not consistent with the definition used in determining PDs, an explanation as to why.
- In estimating LGD values, do you account for recoveries and costs? Explain briefly how.
- Are collateral values adjusted in arriving at the LGD estimates? Explain briefly what type of collateral and the valuation process for the collateral (eg guarantees, mortgages and receivables).
- Where applicable, if using workout LGD method to calculate LGD values, can you explain the discount rates used?
- If there are significant differences between realised LGD and LGD estimates, can you explain them?

EAD

- How do you incorporate drawn amounts and an estimate of future draw-downs in determining EAD? Explain the method used in estimating future draw-downs.
- Where un-drawn limits are treated as unconditionally cancellable, explain the rationale for doing so (eg credit card limits, interbank lines).

Valuation Methodology

- How is valuation performed? At the loan horizon, or are loan values present values?
- How are coupon frequencies taken into account?
- How is the trading book valued, and why?

Maturity

- Explain how maturity is incorporated in the model for loans with maturity greater than one year (i.e. refers mainly to mortgage and other retail loans).

- Explain how maturity is incorporated in the model for loans with maturity less than one year.
- Where maturity is greater than one year, explain how defaults beyond one year are addressed.

Correlation

- What correlation is measured: asset, default, equity?
- If equity correlation, how is this translated into asset correlation, and from there into default correlation?
- If a single-factor model is used, which economic factor is considered?
- If a multifactor model is used, which factors are considered and how are the correlations obtained?
- How is the level of idiosyncratic risk determined for each obligor or class of obligors?
- What granularity assumptions are made? (Esp. any differences as regards retail, SME and corporates)

Model Output

- What are the key outputs of the model (capital required at what confidence level, capital by business line)?
- What are the primary uses of model outputs? Include both direct and indirect uses (regulators, rating agencies, pricing, performance measurement and others).
- How is diversification taken into account by the model? (eg between risk types and entities)
- What methodology is used to allocate risk back to subsets of the business?

Model Use

- How often is the model used?
- How many iterations does the model employ for the various asset classes?
- If the overall bank credit risk charge is derived from several sub-models, describe how the overall results are aggregated.
- Do the sub-models differ by country?

Model Validation

Validation is a key issue in the use of rating systems. The development of models to effectively and adequately assess obligors' credit risk is severely hampered by limited availability of objective model inputs. Most models in current use measure creditworthiness over a single year or more, but these models require several years' of historical financial data for each borrower.

Large corporate borrowers are replete with reliable and timely financial data. Data for smaller borrowers is uncommon and often unreliable, even less so for

those corporates in financial distress (which are key, after all, to the construction of accurate credit risk models). The highly sporadic nature of default events also results in a scarcity of reliable data required for building credit risk models.

This paucity of data presents challenges in assessing the accuracy and reliability of credit risk models. The Basel Committee has also highlighted the relatively informal nature of credit model validation approaches at many financial institutions in its recent credit risk modelling report. In particular, the Committee has emphasised both “data sufficiency” and “model sensitivity” analysis as significant challenges to the validation process.

For these reasons, it is critical that all inputs to the model, and the main model assumptions be scrutinized in detail. For example, one must assess the validity of the PD models in use. The following section provides an illustration of validation of a risk rating system.

Validating a Risk Ratings System: Input PD
Default risk models, as classification tools, can err in one of two ways. Type I errors result from models which indicate low risk when the risk is high and these correspond to the assignment of high credit quality to issuers who actually do default or approach default. Investors may experience losses on principal and interest, or in the market value of the obligation. Type II errors result from those models assigning low credit quality when the credit quality is high. Losses resulting from these errors include the loss of both return and origination fees when loans are lost by either lender rejection or non-competitive bidding. Minimising one of these errors, however, increases the other. This trade-off gives rise to complex and important issues which are addressed in the validation process.

Validation refers to all activities undertaken to analyse and verify the overall performance of the risk rating system in order to ensure both consistency and accuracy. In general, the validation procedure entails the following activities:

- Confirmation of the conceptual soundness and initial risk quantification of the risk rating system’s design, including the concept, methodology and assumptions
- Confirmation of the operation of the risk rating systems, including the:
 - discriminatory power of the risk rating system;
 - calibration of the risk rating system; and the

- risk homogeneity of the obligors in each of the risk pools.
- Regular examination of overall performance of the risk rating system including back-testing (ie performance assessment of a risk rating system (including PDs, LGDs and EADs) based on historical data. This examination will also compare realised and predicted outcomes and benchmarking (ie the comparison of the performance of two different, but comparable, risk rating systems).
 - Back-testing measures the historical performance relative to some other benchmark model, hence back-testing is merely benchmarking of historical performance.
 - Realised default and migration rates must be checked to ascertain whether they are consistent and are supported by historical evidence from internal data. Systematically high or low PDs must nevertheless maintain the ordinal ranking of the obligors (ie the *relative* riskiness must be preserved) and consequently the calibration of the PD assigned and the actual observed number of defaults requires a quantitative, consistency test.
 - Rigorous statistical testing is required before any conclusions may be drawn about whether assigned PDs are appropriate or not.

Performance statistics for risk rating systems can be highly sensitive to the data sample used for validation. Quantitative models should ultimately aim to avoid this unwanted sample dependency. The banking industry is currently inundated with statistical tests which gauge and rank various aspects of credit model performance. This is the subject of a future Fitch publication and will not be covered exhaustively here. Two simple measures which aim to capture overall model performance or accuracy are the Cumulative Accuracy Profile and the χ^2 -test.

Cumulative Accuracy Profiles (CAPs)
Cumulative Accuracy Profiles or CAPs (also called receiver-operator curves and power curves) allow a visual qualitative assessment to be made of model performance. CAPs refer specifically to cases in which the curve represents the cumulative probability of default over an entire population, ie not only the non-defaulting population.

If a model assigns random risk scores, the fraction of defaulters will be roughly the same as the fraction of total companies, thereby generating a straight line or

Random CAP. A perfect model will produce the Ideal CAP – a straight line capturing 100% of the defaults within a fraction of the population equal to the fraction of defaulters in the sample. Because the fraction of defaulters is usually a small number, the Ideal CAP is steep, as shown in the figure overleaf. A useful property of CAPs is that they reveal information about the discriminatory power of the model over its entire range of risk scores for a particular time horizon.

χ^2 -test

The χ^2 -test is a statistical test, applied to and interpreted using the CAP curve. Under a simple statistical test approach, the null hypothesis is that ratings are no better than random chance. If this were true, then the number of defaults in each rating grade would be the same percentage as for the entire sample. The χ^2 -test algorithm calculates the expected defaults per grade and compares them with actual defaults per grade (by tallying up the individual defaults by grade and total obligors by grade). The χ^2 -probability test measures the statistical significance of the χ^2 - statistic being better than random chance.

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