The Regulatory Capital Treatment of Credit Exposures Arising From Derivative Transactions

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1. Background

Algorithmics was founded in 1989 in response to the complex issues surrounding financial risk management for the enterprise. Today, as a leading provider of enterprise risk management software products, we continue to focus our efforts on creating and implementing enterprise risk management software that meets the evolving needs of our customers. Our software solutions cover all aspects of enterprise risk: market, credit, operational, and liquidity risk, across the trading and banking books. At the heart of our software solutions is the Mark-to-Future™ methodology. Mark-to-Future is a scenario-based methodology for risk and reward that can evolve as "best of breed" risk management practices evolve (www.mark-to-future.com).

Headquartered in Toronto, with 16 offices around the world, Algorithmics serves more than 120 global clients with 150 installations in 26 countries. More than 40 out of the 100 largest financial institutions by asset size are our clients. Note that the following submission reflects the position and opinions of the Algorithmics Group of Companies (and does not necessarily reflect the opinions of its customers or suppliers).

This electronic submission consists of:
1. The Regulatory Capital Treatment of Credit Exposures Arising From Derivative Transactions (this document)
2. Calculating Credit Exposure and Credit Loss: A Case Study (Jeff Aziz and Narat Charaput, September 1998) - available in .pdf format
3. Modeling of Collateral Delivery Lags and Call Frequency - available as a PowerPoint presentation

2. Motivation

We applaud the Committee's efforts to develop a more risk-sensitive framework. This response is focused on the issue of the use of internal models for calculating credit equivalent exposure (CEE) for derivatives transactions, and is motivated by the following (emphasis provided by Algorithmics):

> In terms of own estimates, the Committee is aware that many banks are applying modeling techniques to the estimation of individual and portfolio-based PFEs. In principle, the Committee believes that banks should be allowed to use the output of such models in the advanced EAD approach, subject to compliance with additional **sound practice requirements** and possibly some core supervisory-imposed modeling parameters. The Committee will be undertaking further work in the Consultative Period to evaluate the feasibility of own estimates of PFE, and **the requirements, which would be needed to underpin such an approach** (Basel Committee on Banking Supervision*, Internal Ratings Based Approach – Consultative Document*, 2001, paragraph 117).

Specifically, we would like to comment on four major areas:

- Should the Committee allow simulation-based credit exposure models to be used as an alternative to the current Mark-to-Market plus add-on approach?

- What exposure measures should be used to calculate CEE for both non-collateralized and collateralized counterparties?
- Should permission to use simulation-based credit exposure models be linked to permission to use internal ratings-based models?
- What **sound practice requirements** are needed to underpin the approach?

3. Definition of Key Model types and their relationship

The following model types are defined:

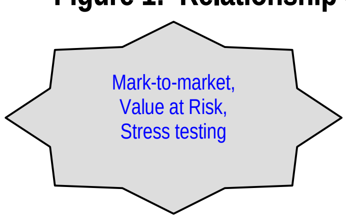
Market risk models calculate value at risk and change in value under stress scenarios accounting for portfolio diversification. The horizon of analysis in market risk models is related to the length of time needed to liquidate or hedge the portfolio. For liquid trading portfolios, the horizon is commonly set at 10 days.

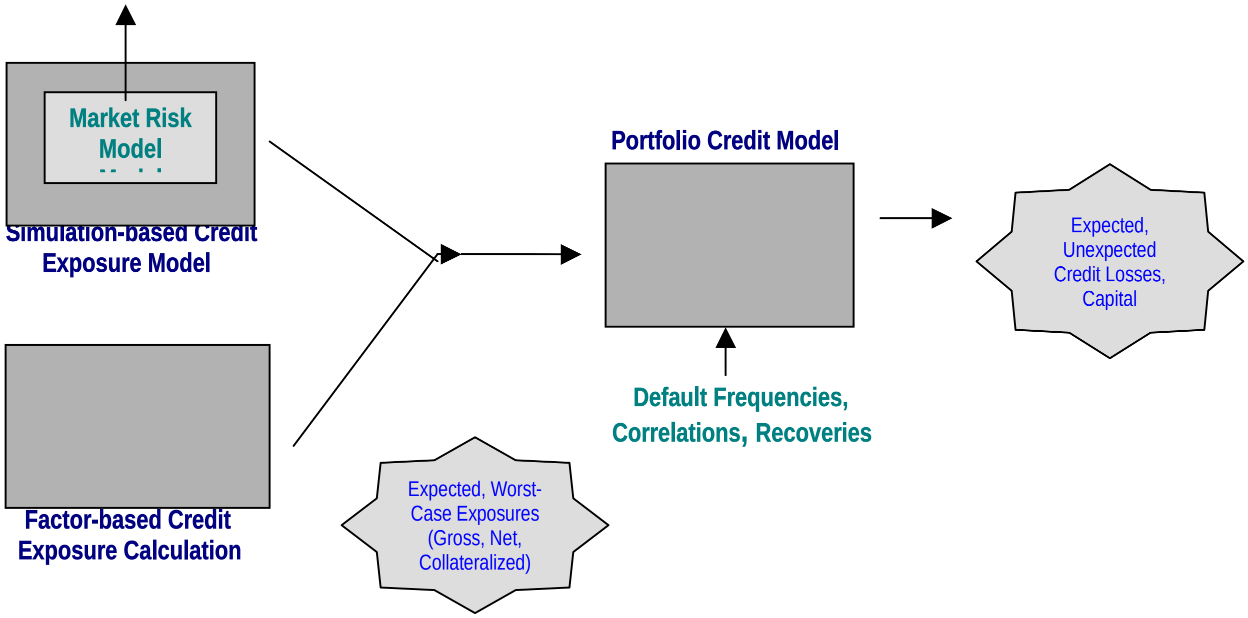
Simulation-based credit exposure models calculate credit exposure - the cost of replacing or hedging a contract at the time of default. This is the maximum value that will be lost if the counterparty to that contract defaults. Since default is an uncertain event that can occur at any time during the life of the contract, the model must consider not only the contract's current credit exposure, but also potential changes in the exposure during the contract's life. This is particularly important for derivative contracts whose values can change substantially over time and according to the state of the market. Outputs from said models include: actual, potential and total exposure (gross, net, and collateralized) at various confidence intervals and under stress scenarios. Outputs do **not** include credit losses and credit capital.

Portfolio credit risk models calculate expected and unexpected credit losses and capital by modeling or taking as inputs default and migration frequencies, correlations, exposures, and recoveries.

The relationship between these three models is illustrated in Figure 1 below. Note that since simulation-based credit exposure models need to calculate changes in value across scenarios and over the life of the contracts, one can consider market risk models to form a subset of simulation-based credit exposure models.

Figure 1: Relationship of Model Types





4. Allowance of Simulation-based Credit Exposure Models

Algorithmics strongly supports the positive tone of the New Accord[1] on the use of models for calculating counterparty exposures arising from derivatives. Algorithmics supportive position is based on four key points.

Point 1 – MtM plus add-on approaches can dramatically understate or overstate true economic exposure, whereas simulation-based credit exposure models more accurately reflect economic exposure, as they easily account for scenario consistency (diversification within a counterparty portfolio), roll-off risk, netting, and collateral.

The limitations of MtM plus add-on approaches are widely recognized by the industry[2] and hence will not be described here in full. The attached paper, "Calculating Credit Exposure and Credit Loss," which forms an integral part of this submission, compares the credit equivalent exposures

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1 Basel Committee on Banking Supervision, 2001, *Internal Ratings Based Approach – Consultative Document*, paragraph 117.

2 For more information, see:
Rowe D., 1995, "Aggregating Credit Exposures: The Primary Risk Source Approach", *Derivative Credit : Advances in Measurement and Management,* London: Risk Publications, p. 13-21.
Lawrence D., 1995, "Aggregating Credit Exposures: The Simulation Approach", *Derivative Credit : Advances in Measurement and Management,* London: Risk Publications, p. 23 – 31.

calculated using Monte Carlo simulation with the BIS methodology. The primary conclusions from this paper, paraphrased and repeated for convenience are:

> CEE calculated under the BIS methodology can be higher or lower than the corresponding simulated CEE, depending on the nature of the contracts with each counterparty. In general it appears that the CEE, calculated under the BIS methodology, is higher when the counterparties' current actual exposure is close to zero and lower when the current actual exposure is high. This is to be expected since the BIS approach applies the same add-on potential exposure regardless of the moneyness of the position.
>
> The BIS approach can overestimate the benefit of netting since it is possible that a portfolio can have exposures that benefit more from netting in the future than today. While a simulation over time captures the changing characteristics of the portfolio and the reduced netting benefits, the static BIS approach does not recognize any changes in the exposure profile over time and can overestimate (or underestimate) the risk reduction due to netting.

Point 2 – Simulation-based credit exposure models do not require additional data over and above the data required for internal market risk models, with the exception of the terms and conditions of netting and collateral agreements, which are readily available.

A common argument used against internal <u>portfolio</u> credit risk models is that key input data – default and migration frequencies, correlations, and recovery rates – are difficult to obtain. This argument does not extend to simulation-based credit exposure models. The input data requirements for simulation-based credit exposure models are in fact much more similar to market risk models than to portfolio credit risk models. In particular, simulation-based credit exposure models do not require difficult-to-obtain default frequencies and correlations data. This is illustrated in Table 1 below. Therefore, one cannot make the argument that simulation-based credit exposure models should be disallowed due to concerns regarding data availability.

Table 1 – Comparison of Input Data Requirements

	Inputs for market risk models	**Inputs for simulation-based credit exposure models**	**Inputs for portfolio credit risk models**
Transaction terms and conditions	Yes	Yes	Yes
Market data	Yes	Yes	Yes

Historical time series of market risk factors used to generate future distributions of risk factors[3]	Yes	Yes	Depends on portfolio model
Netting and collateral agreement terms and conditions	No	Yes	Yes
Default data	No	No	Yes
Correlation on counterparty defaults, migrations	No	No	Yes
Recovery rates	No	No	Yes

Point 3 – Simulation-based credit exposure models can be back-tested

A common argument used against the allowance of portfolio credit risk models is that the models are difficult to back-test due to the infrequency of defaults. This is a legitimate issue for portfolio credit risk models but not for simulation-based credit exposure models. Simulation-based credit exposure models estimate the amount of loss **if** one or more counterparties were to default. Thus, the low frequency of actual defaults that creates difficulties for portfolio models does not matter. Exposure profiles are an observable quantity that can be readily back-tested on a weekly, monthly, or yearly basis.

Point 4 – Simulation-based credit exposure models are practical and achievable using current technology.

As the Committee notes in the aforementioned para 117, "In terms of own estimates, the Committee is aware that many banks are applying modeling techniques to the estimation of individual and portfolio-based PFE's" when managing their economic capital and credit line utilization. We would like to reinforce this point. Many of our banking clients already use simulation-based credit exposure models based on our software. In addition, we are aware of other banks that have developed in-house models or have purchased solutions from other risk management software vendors. In fact, we see allowing internal CEE exposures as key to achieving **two** of the proposed accord's main objectives: encouraging the adoption of best practice risk management processes and aligning economic and regulatory capital.

5. Selection of appropriate risk measures

The current capital calculation is a two-step process:

[3] Note that simulation-based credit exposure models may require a longer time series of market risk factors than is the case for market risk models to calibrate model parameters such as mean reversion.

Step 1 Step 2
Derivative Position -> Credit Equivalent Exposure -> Regulatory Capital

We propose that BIS permit the Credit Equivalent Exposure (CEE) to be calculated using either a simulation-based credit exposure model or the current standard approach.

Simulation-based credit exposure models are generally composed of four logical building blocks:

Scenario generation – Generation of a distribution of multi-step scenarios (paths) through time for all market risk factors that impact portfolio value.
Forward valuation – Valuation of the aged portfolio under all scenarios
Exposure – Transformation of future values to future exposures by incorporating the impact of netting agreements, collateral, and termination clauses.
Risk measures – Post-processing of exposures across scenario and time to compute expected and worst-case exposures.

In simulation-based credit exposure models, the choice of risk measure is decoupled from the underlying scenario generation and valuation analytics. This gives the banks and the Committee considerable flexibility in selecting the appropriate risk measure(s) for measuring and managing risk. For example, a bank may select 95% worst-case gross and collateralized exposure over the entire life of the contracts as the appropriate measures for limits management. On the other hand, in order to treat credit capital for derivatives on an equal footing with loans, the Committee may choose mean exposure over a one-year horizon as the appropriate measure for calculating credit capital. The important point is that both measures can be supported with a common underlying framework, thereby promoting consistency and the alignment of regulatory and economic capital. Moreover, as regulators and banks learn more, the choice of particular risk measures can be changed without costly changes.

It seems overly conservative to use worst-case exposures as the input into Step 2 as it amounts to combining the worst-case exposure with the worst-case credit loss. Overall, mean exposures seem more reasonable. However because of roll-off risks, the wide range of potential future exposures that are possible for many OTC products, and of the potential interaction of market and credit risk, such an approach should be complemented by periodic modeling exercises that test the appropriateness of such an approach. State of the art portfolio models can be designed that take many exposures into account not just mean exposures[4].

6. Independence of Internal Ratings and Simulation-based credit exposure models

The regulatory capital calculation consists of two independent steps. First, credit equivalent exposure (CEE) is calculated. Second, CEE is provided as an input into a second calculation that outputs regulatory capital. One of the key inputs in the second calculation is the credit

[4] Dembo. R.S., A. Aziz, D. Rosen, M. Zerbs, "Step 6: Advanced Mark-to-Future Applications", *Mark to Future: A Framework for Measuring Risk and Reward*, May 2000. (www.mark-to-future.com)

rating of the counterparty. Since the two steps are independent, we believe that the choice to use an internal model for each step should be determined independently. In fact, in many banks these two steps may be computed by completely separate groups with widely different levels of sophistication. By linking the use of models for calculating CEE and IRB, we believe that the Committee is placing an artificial constraint on the move towards internal models and the improved alignment of regulatory and economic capital.

7. Sound practice requirements which would be needed to underpin simulation-based credit exposure models

Based on our experience in developing and supplying enterprise risk software and engaging in joint projects with our clients to establish key modeling parameters for the software, we propose the following sound practice requirements to apply to banks wishing to use simulation-based credit exposure models.

Sound Practice Guideline 1 – Permission to use a simulation-based credit exposure model will be conditional on the satisfaction of minimum qualitative and quantitative standards and will be limited to those banks that have received supervisory recognition for an internal market risk model under the 1996 Market Risk Amendment.

This sound practice guideline is consistent with the Committee's position on the use of internal estimates for haircuts and is appropriate as the market risk model lies at the heart of a simulation-based credit exposure model (see Figure 1).

> Supervisors may permit banks to calculate H using their own internal estimates of market price volatility and foreign exchange volatility. Permission to do so will be conditional on the satisfaction of minimum qualitative and quantitative standards and will be limited to those banks that have received supervisory recognition for an internal market risk model under the 1996 Market Risk Amendment. Banks will be required to calculate a volatility estimate for each category of security (Basel Committee on Banking Supervision*, The New Basel Capital Accord*, paragraph 92).

Sound Practice Guideline 2 – Banks that use the internal models approach for calculating credit equivalent exposure must have in place a rigorous and comprehensive stress testing programme.

The stress testing requirement should be similar in spirit to B.5 Stress Testing, Para 1-8 of the 1996 Market Risk Amendment. We suggest one additional requirement – namely, that banks should stress test market risk factor paths through time in addition to more simple instantaneous shocks to risk factors. This is an important sound practice guideline as some portfolios may have more vulnerability to future changes in market risk factors than to changes in current market risk factors.

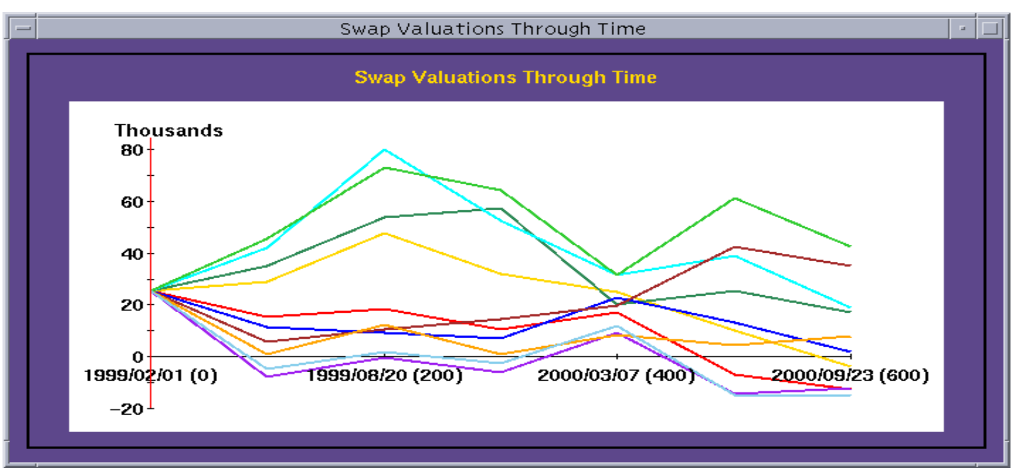
Sound Practice Guideline 3 – Banks that use the internal models approach for calculating credit equivalent exposure must model the path dependency of positions to capture reset risk.

Proper modeling of reset risk is important as it applies to many common OTC products including swaps, FRNs, caps, floors, and swaptions which can form a substantial portion of a bank's holdings. Reset risk occurs when the actual interest rate on a valuation date is different than the expected forward rate that was calculated on the last reset date. From a modeling perspective, capturing reset risk requires that the simulation engine model the risk factors paths through time and understand and keep track of reset rates from one or more previous simulation time steps, as the simulation moves forward in time.

Put another way, the future <u>exposure</u> of a financial instrument at a given time, t_f, in the future is a direct function of the future <u>value</u> at t_f. In turn, the future value of a financial instrument at t_f may not depend just on the state of the market at time t_f but also on the state of the market between today and t_f. This is known as path dependency. For example, the value of an interest rate swap at t_f will depend upon the prevailing level of interest rates at the most recent reset rate, which may have occurred at any time between now and t_f.

To illustrate the importance of path dependency, the graph below shows the valuation of a plain vanilla swap (pay fixed receive floating) across 10 Monte Carlo scenario paths and 6 time steps. The scenarios are generated on the market risk factors (i.e. the interest rate curve underlying the swap) and the swap is revalued at each future point in time, across all scenarios. The swap was reset on day 200.

To illustrate path dependency, we have over-ridden the term structures on day 400 to ensure that in all 10 scenarios, the swap is valued using the same interest rates. The resulting distribution of values on day 400 is then due entirely to the different, floating rates which have been set at previous points in the simulation (day 200) where rates were allowed to differ.



Sound Practice Guideline 4 - Banks that use the internal models approach for calculating credit equivalent exposure must use calibrated long-term evolution processes for the underlying risk factors affecting exposures.

The simulation models should satisfy three criteria:

1) The model should use stable joint processes which properly describes the long term behavior of all the risk factors affecting the prices of the securities. For example, 3 or 4 factors mean reversion processes may be used for interest rates[5] and proper autocorrelations of risk factors accounted for in other economic variables.

2) Robust calibration to historical data. A full business cycle should be used to capture the long term behavior of risk factors.

3) Out of sample testing of the simulation methodology must be performed to demonstrate the suitability of the models. This may be similar in nature to the backtesting methodology currently used for market risk.

Sound Practice Guideline 5 – Before capital relief will be granted to any form of collateral, supervisors will monitor the extent to which banks satisfy the following condition, both at the outset of the collateralized transaction and on an on-going basis:

Banks should conduct regular stress tests to examine the extent to which delivery frequencies, lags, credit rating changes, and correlation between the counterparty portfolio and the collateral portfolio cause the collateralized exposure to exceed the exposure threshold amount specified in the collateral agreement.

This proposed guideline is similar in spirit to the following:

> In order for collateral to provide protection, the credit quality of the obligor and the value of the collateral must not have a material positive correlation. For example, securities issued by the collateral provider – or by any related group entity – would provide little protection and so would be ineligible (Basel Committee on Banking Supervision, *The Standard Approach to Credit Risk*, paragraph 96).

It is our opinion that to properly capture collateral effects, not only is it necessary to capture the correlation of the collateral value with the credit quality of the obligor but also the correlation of market factors influencing the value of both the collateral and the counterparty portfolio. Take for instance a simple example where we have entered into a swap agreement with a counterparty, where the counterparty receives fixed and pays floating. The counterparty has also provided

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[5] Reimers, M., M. Zerbs, "A Multi-factor Statistical Model for Interest Rates", *ARQ*, Volume 2, No.3

collateral in the form of treasury bonds denominated in the same currency as the swap. The collateral posted may seem appropriate as the changing credit quality of our counterparty would certainly have no impact on the valuation of the treasury based collateral. However, assuming treasury rates are highly correlated with interbank rates, a general increase in rates will cause our exposure to the counterparty to rise significantly **at the same time** that our collateral value will fall sharply. This results in much larger swings in collateral payments/receipts and can adversely impact the liquidity position of the bank. Capturing these market-factor based correlations can occur at the scenario level in a simulation based environment where both the counterparty's portfolio and the collateral are valued consistently under each scenario.

Other factors pertaining to collateral also need to be considered in order to fully capture the effects of credit mitigation. First, failure in modeling the payment/delivery lags will miss out on the effect that exposures will be allowed to drift beyond established threshold margins before collateral is received. For instance, establishing an exposure threshold of $35M USD will not necessarily mean the maximum exposure to the counterparty can be assumed to be $35M. Collateral lags could result in the exposure to the counterparty rising well beyond the $35M before the actual collateral is ever received.

Second, failure in modeling the fact that collateral may not be checked daily will also miss out on potential exposure movements beyond established thresholds, as a result of the delay in checking actual collateral levels. For instance, if collateral is only checked weekly, then the exposure to the counterparty can rise well above the threshold level during the week before collateral is checked.

Third, most credit support annex variables (i.e. Thresholds Amounts, Minimum Transfer Amounts, Upfront Amounts etc.) are dynamic in nature. In other words, they are dependent upon both the bank's and counterparty's credit state. For instance, a counterparty's threshold may stay at $35M USD provided the counterparty retains its AA status. A migration to BBB could result in the threshold falling to $10M USD, as the bank is less willing to accept as large an exposure to the counterparty now. Not capturing this dynamic behavior in simulation will result in inaccurate exposure measures. Along this same notion, the own bank's credit rating should be stressed as well, as this may uncover potential liquidity issues (i.e. more collateral needing to be posted) in the event of the bank's downgrade.

The attached PowerPoint presentation illustrates some of these points and gives an indication as to the potential magnitude of the exposure measurement differences.