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## Criteria

### CDO Evaluator Version 3.0: Technical Document

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Standard & Poor's Ratings Service's CDO Evaluator is a portfolio credit risk model for analysis of CDO transactions. This document describes the theory, assumptions, and computational methods used by CDO Evaluator version 3.0 to simulate the portfolio loss distribution, which allows determination of the various portfolio risk measures we use in the CDO rating process. The application of the CDO Evaluator to different types of CDO transactions is also discussed.

## Section 1: Introduction

### 1.1 CDO market developments

CDOs are financial instruments that transfer the risk associated with a portfolio of assets to one or more investors. The first CDOs were issued as funded ("cash") investments by an SPE, collateralized by portfolios of bonds and loans. Over the past decade, the unfunded ("synthetic") CDO market has grown rapidly, especially in Europe. Instead of purchasing a debt instrument of a given entity, the SPE enters into a CDS that references the entity. This use of credit derivatives technology has greatly simplified the execution of CDO transactions, and has led to a market dominated by so-called "single-tranche" CDOs, bilateral contracts between a buyer and seller of default protection on a portfolio of entities. These can either take the form of a portfolio CDS between two counterparties or a credit-linked note (CLN).

While the rise of the synthetic CDO market has led to a simplification of the debt issuance, the composition of the asset portfolio has become more complex. In addition to corporate bonds and loans, CDO portfolios now routinely include sovereign bonds, loans to SMEs, ABS, and other CDOs. More recently, equity default swaps (EDSs) and commodity options have also been included. The CDO risk transfer mechanism has also increased in complexity. In addition to referencing a single portfolio, a CDO transaction can also reference a number of bespoke CDO tranches, each of which in turn references a single portfolio. This leveraging creates an investment that is more isolated from small numbers of credit events within the underlying portfolio, but is also more likely to suffer large losses once its credit protection is eroded. So-called "CDO squared" transactions dominated synthetic CDO issuance in 2004 and early 2005, partly due to the tightening of CDS spreads.<sup>1</sup>

In recent years, the synthetic CDO market has witnessed the proliferation of many innovative structures, including CDOs with short CDS positions, forward starting CDOs, *n*th-to-default baskets, leveraged super senior structures, and constant proportion portfolio insurance (CPPI) structures. These innovations typically arise from a variety of different incentives expressed by market participants: from the search by investors for yield in a tight spread environment to the need for investment diversification, from the quest for arbitrage to structures that can be used to express a view on either the credit cycle or idiosyncratic credit risk.

<sup>1</sup> These transactions often include a large proportion of ABS in addition to bespoke CDOs, and are therefore often referred to as "CDO of ABS" transactions.

### 1.2 Portfolio credit risk models

Models for CDO risk analysis are generally based on the estimation of transition/default probabilities and recoveries, and the linkage of these through a dependency model, which specifies the joint transition/default behavior. This allows simulation of the full loss distribution at maturity of a portfolio of assets. This loss distribution can then be used to determine a number of useful measures of portfolio risk.

Many portfolio credit risk models fall into the category of “structural” models, which assume that the default behavior of a firm can be determined from knowledge of the firm’s assets and liabilities. These are based largely on a model originally proposed by Merton (1974), in which the asset value of a firm is assumed to follow a Geometric Brownian Motion characterized by the asset volatility. Default of the firm occurs when the asset value falls below a certain threshold.<sup>2</sup> Within this framework, the default correlation between pairs of firms will depend both on the correlation of asset value and the default threshold for each firm. For an excellent review of structural models, see deServigny and Renault (2004).

In common with many other structural models, CDO Evaluator assumes that the transition/default probabilities, recoveries, and asset value correlations of all assets in the portfolio are exogenous variables, driven either by firm-specific (i.e., idiosyncratic) or systematic effects.<sup>3</sup> However, rather than using *market* data to estimate these parameters for each firm, we estimate these parameters from *historical* data.

For example, in the case of rated firms, we make use of our global CreditPro® database<sup>4</sup> of rating transitions and defaults over the period 1981-2003. This method assumes that the rating on a firm is a good proxy for the likelihood of the firm defaulting over a given horizon, when this firm is part of a portfolio.<sup>5</sup>

### 1.3 Technical document outline

The remainder of this document is divided into five sections. In section 2, the underlying mathematical model for CDO Evaluator Version 3.0 is outlined, along with the assumptions required by the model for computation of the portfolio loss distribution. Sections 3 to 5 outline the data and methods used to estimate these assumptions, which are the main inputs required by CDO Evaluator. Section 6 describes the different CDO risk measures computed by CDO Evaluator, and the application of CDO Evaluator to the risk assessment of various CDO transactions in the marketplace. Many of the detailed assumptions within CDO Evaluator are contained within the Appendices.

While this document addresses all of the technical aspects of the CDO Evaluator model and assumptions, it does not necessarily cover each and every aspect in full, as the purpose of this document is to provide a complete picture of CDO Evaluator to a wide range of market participants. Those readers interested in drilling down to a deeper technical or theoretical level should consult the references provided within the document.

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<sup>2</sup> In the Merton framework, this threshold is related to the value of the liabilities of the firm, and hence more highly leveraged firms will generally possess higher probabilities of default, assuming similar asset volatilities.

<sup>3</sup> Other models focus instead on the instantaneous default probability (also known as the “hazard rate” or “default intensity”), which is itself treated as a stochastic process.

<sup>4</sup> For details, visit [www.standardandpoors.com](http://www.standardandpoors.com), run a search using “CreditPro”, and scroll down to Products & Services.

<sup>5</sup> It is important that this method is used only for portfolios, not single firms. Given that ratings are ordinal measures of creditworthiness, a single rating cannot be uniquely linked to a default probability.

## Section 2: The CDO Evaluator Model

The main purpose of the CDO Evaluator model is the computation of the loss distribution of a portfolio of  $N$  assets. This is carried out by first simulating the *default time* of each asset. If the default occurs before the maturity of the CDO transaction, an asset-specific recovery is also computed. If the exposure to each asset at the time of default is known, then the complete distribution of portfolio losses can be computed.

In addition to modeling the individual (or *univariate*) default and recovery of each asset in the portfolio, the *dependency* between defaults of different assets must also be modeled. The standard dependency model in the marketplace is the *Gaussian copula* model, originally proposed by Li (2000). In this approach, a term structure of survival probabilities  $S^i(t)$  is assumed for the  $i$ th asset. These survival probabilities can be obtained from the cumulative default probabilities for each asset, which we refer to as the *credit curves*. Dependency is then introduced via the Gaussian copula function  $C(u_1, \dots, u_N) = \Phi_{\Sigma}(y_1, \dots, y_N)$ , where  $\Sigma$  denotes the correlation matrix,  $\Phi$  the univariate standard normal cumulative distribution function, and  $\Phi_{\Sigma}$  the multivariate standard normal distribution function with correlation matrix  $\Sigma$ . The copula function therefore links together the standard normal variables  $y_i$  to create a multivariate distribution of uniform random variables  $u_i$ . The standard normal variables  $y_i$  are often referred to as *latent variables* (analogous to asset values in the Merton model).

Correlated default times can therefore be simulated in the following order:

- Simulate a vector of  $N$  standard normal random variables  $y_i$  for each asset<sup>6</sup>;
- Impose a given correlation matrix  $\Sigma$  on the above vector<sup>7</sup>;
- Calculate  $u_i = \Phi(y_i)$ .
- Calculate a default time  $\tau_i = S^{-1}(u_i)$  for each asset. An example is shown in chart 1 for a 'BBB' rated asset.<sup>8</sup>

If  $\tau_i$  is less than the maturity  $T$  of the CDO transaction, the loss  $L_i$  is determined as  $L_i = E_i \times (1 - \delta_i)$ , where  $E_i$  and  $\delta_i$  are the exposure-at-default and recovery<sup>9</sup> respectively for the  $i$ th asset. We can therefore write the portfolio loss up to time  $t$ ,  $L(t)$ , as:

$$L(t) = \sum_i E_i \times (1 - \delta_i) \times 1_{\{\tau_i \leq t\}},$$

where  $1_{\{\tau_i \leq t\}}$  is the default indicator for the  $i$ th asset.<sup>10</sup>

<sup>6</sup> Standard normal random numbers are computed using the well-known Mersenne Twister algorithm. For details see Matsumoto and Nishimura (1998).

<sup>7</sup> This is performed using *Cholesky factorisation*. See for example Glasserman (2004), pp. 72-73.

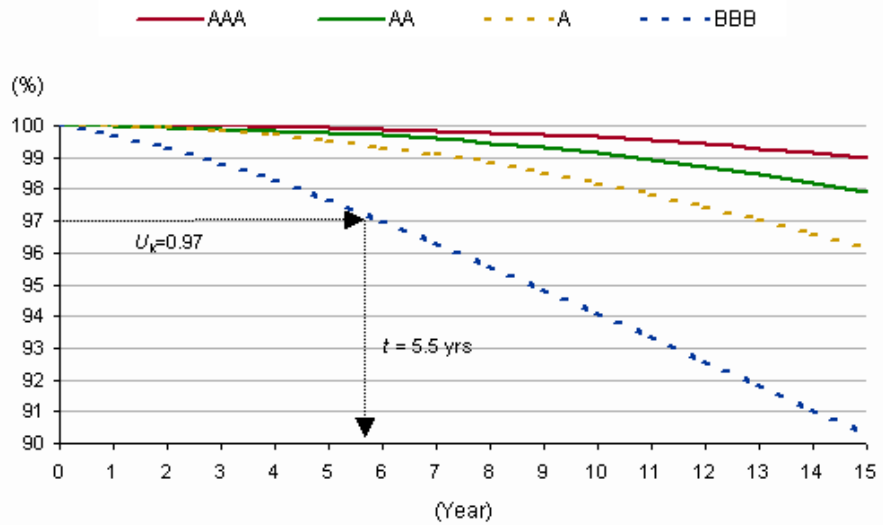
<sup>8</sup>  $S^{-1}$  is used to denote the quasi-inverse of the survival function.

<sup>9</sup> The recovery can either be assumed to be constant, or drawn from a distribution.

<sup>10</sup> The default indicator equals 1 if the expression within parentheses is true, and 0 if it is false.

Chart 1

**An Example Of The Use Of A [0,1] Uniform Variable To Determine A Default Time From S&P's Credit Curves**



**Simulation Procedure**

There are two aspects of the simulation procedure worth discussing in more detail in order to understand the impact of different ratings, maturities, and correlation assumptions on the portfolio loss distribution.

**Individual asset default behavior**

When assets are uncorrelated, the default time for each asset  $i$  is simply obtained by comparing a uniform random variable  $u_i$  with the credit curve for the asset, as shown in chart 1 for a 'BBB' rated asset. If the default time occurs before the asset maturity, a default is recorded. For example, if the 'BBB' rated asset in chart 1 has a maturity of seven years, a default is recorded halfway through year five. For the same rating, it is clear that high values of  $u_i$  will result in lower default times, whereas low values will result in higher default times. Also, for the same value of  $u_i$  it is clear that higher ratings will experience higher default times.

**Joint default behavior**

When assets are correlated, the uniform random numbers for these assets are first correlated to the required level, as described above. For any pair of correlated assets, this produces values of  $u_i$  that tend to move together, i.e., are "clustered" around high or low values. As a result, the default times of the two assets will also move together, leading to more cases in which the assets survive or default together before their maturity.

Using the above Monte Carlo simulation procedure, the distribution of portfolio losses can be determined to a high level of accuracy by generating a sufficient number of default times to achieve satisfactory convergence, which depends on the shape of the credit curves and the degree of asset correlation. For example, highly rated assets will rarely generate low default times, requiring a larger number of simulation trials to generate a significant number of default events before maturity. For most portfolios, 500,000 simulation trials are sufficient to obtain satisfactory convergence.

For a CDO linked to a single portfolio of assets, the portfolio loss distribution contains all of the information required to determine the performance of each CDO tranche. When a synthetic CDO references other synthetic CDOs, the model uses a "drill-down" approach to simulate the default times of the assets underlying each CDO. The drill-down approach is outlined in "Section 6.4".<sup>11</sup>

<sup>11</sup> See also "Drill-Down Approach for Synthetic CDO Squared Transactions", Standard & Poor's Special Report, Dec. 10, 2003, available to subscribers of RatingsDirect, our Web-based credit analysis system, at [www.ratingsdirect.com](http://www.ratingsdirect.com). The criteria can also be found on our Web site at [www.standardandpoors.com](http://www.standardandpoors.com).

## Section 3. Transition And Default Probabilities

### 3.1 Rated companies

For rated companies, we make use of our global CreditPro® database of rating transitions and defaults over the period 1981-2003, which contains a ratings history of 9,740 companies from Jan. 1, 1981 to Dec. 31, 2003, including 1,386 default events. The method used by Standard & Poor's to estimate credit curves involves two stages. The first stage is the estimation of the probabilities of transitions between different ratings – the *transition matrix*. The second stage is the repeated application of this matrix to determine the credit curves.<sup>12</sup> In both cases, rating transitions are assumed to follow a *Markov process*, in which transition probabilities are constant over time, and do not depend on the previous rating on the firm, e.g., whether the firm was recently upgraded or downgraded.<sup>13</sup>

A straightforward method for estimating a discrete transition matrix from empirical data involves observing the transition of cohorts of firms with the same initial rating. Indeed, our annual transition study<sup>14</sup> is based on this cohort analysis. We denote the total number of firms in class  $k$  at time  $t$  by  $n_k(t)$ , and the total number of observed transitions from class  $k$  at time  $t$  to class  $l$  at time  $T$  by  $n_{kl}(t, T)$ . Assuming rating transitions follow a Markov process, the maximum-likelihood estimator of the corresponding transition

probability,  $\hat{q}_{kl}(t, T)$ , is  $\hat{q}_{kl}(t, T) = \frac{n_{kl}(t, T)}{n_k(t)}$ , for all  $k \neq l$ . Denoting the average

annual transition matrix by  $\bar{Q}$ , a  $T$ -period matrix  $\bar{Q}(T)$  is obtained under the Markov assumption using  $\bar{Q}(T) = \bar{Q}^T$ . Credit curves can be directly extracted from this matrix.

An alternative to the cohort method – which compares the initial and final rating over a certain period – is the *duration* method, which takes into consideration the exact points in time at which rating transitions take place, using the instantaneous probability of transition, the *transition intensity*. We directly estimate transition intensities via the generator matrix  $\hat{\Lambda}$  of the (time-homogenous) Markov chain. The off-diagonal transition intensities  $\hat{\lambda}_{kl}$  are given by:

$$\hat{\lambda}_{kl}(t, T) = \frac{m_{kl}(t, T)}{\int_t^T n_k(s) ds}, \text{ for all } k \neq l,$$

where  $m_{kl}(t, T)$  is the total number of transitions from class  $k$  to class  $l$  ( $k \neq l$ ) over the interval  $[t, T]$ . The denominator is the total time (in firm-years) firms spend in rating class  $k$  over the whole sample period. A  $T$ -year transition matrix is then calculated from the

generator matrix (with diagonal elements  $\lambda_{ll} = -\sum_{k \neq l} \lambda_{kl}$ ) using

$$\bar{Q}(T) = \exp\{T \cdot \hat{\Lambda}\}.$$
<sup>15</sup>

By comparing the results of the two methods, and making certain qualitative adjustments<sup>16</sup>, we have derived a single one-year transition matrix that, in our view,

<sup>12</sup> If only default probabilities are required, it is tempting to try to estimate cumulative default probabilities directly from the data. However, given the paucity of historical default data – especially for highly rated firms and/or long time horizons – this method can give unreliable results.

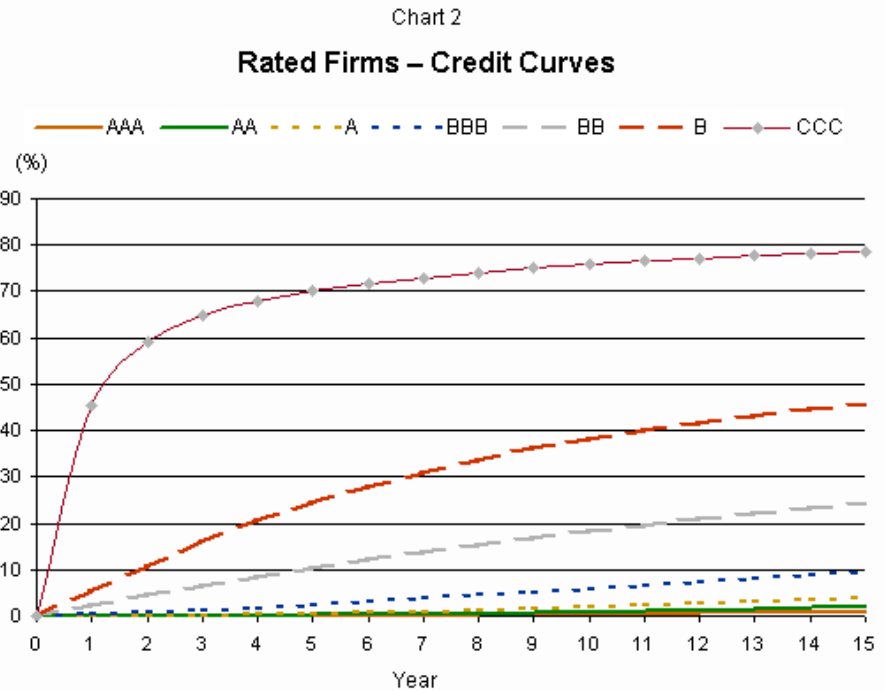
<sup>13</sup> While empirical data suggests that these assumptions do not always hold, they are nonetheless a very useful starting point for estimation purposes.

<sup>14</sup> See for example “*Annual Global Corporate Default Study: Corporate Defaults Poised to Rise in 2005*”, Standard & Poor's, Jan. 31, 2005.

<sup>15</sup> Further details can be found in Jobst N. and Gilkes K. (2003).

<sup>16</sup> For example, we adjust for certain “ratings momentum” effects reported in the literature. For details, see Fledelius et al (2004).

produces the best agreement with the average long-term historical default behavior of rated firms. The full matrix is provided in "Appendix I". The one-year transition matrix is then used to determine the long-term credit curves for each rating category.<sup>17</sup> These are shown in chart 2 for the major rating categories. The full table of credit curves is also provided in "Appendix I".



### 3.2 Asset-backed securities

Given that structured finance securities themselves are often included in CDO portfolios, their transition and default behavior also needs to be estimated. On average, these securities have exhibited considerable ratings stability over the past two decades, and as a result there have been very few cases of default.<sup>18</sup> Given the relative paucity of default data, we have so far adopted a conservative treatment of these securities by using corporate default rates as proxies for their long-term default behavior.

In CDO Evaluator Version 3.0, ABS default rates are determined using a transition matrix that is based on the average historical ABS transition matrix, with certain qualitative adjustments. These adjustments result in long-term ABS default rates that are approximately 55% and 75% of the corresponding default rates for rated firms at investment-grade and non-investment-grade, respectively (for maturities between five and seven years). The ABS credit curves are provided in "Appendix I". Note that ABS maturities are capped at seven years for modeling purposes, as we consider that the probability of default of an ABS asset — conditional upon survival for seven years — is negligible.

### 3.3 Sovereign securities

Given that transition and default data for sovereign debt securities are relatively sparse in comparison with rated firms, the credit curves used for rated firms are currently used as conservative proxies for sovereign default behavior.

### 3.4 Small- to mid-sized enterprises (SMEs)

The wealth of financial information obtained by Standard & Poor's Risk Solutions Group on SMEs has been used to create advanced "credit scoring" models for SME default prediction. For example, in Europe the Credit Risk Tracker (CRT) product can be used to

<sup>17</sup> This is done by raising the matrix to higher powers, and extracting the "default" column of each  $N$ -year matrix ( $N = 1$  to 30).

<sup>18</sup> See for example "Global Structured Securities Rating Performance: 1978-2004", Standard & Poor's, March 24, 2005.

obtain one-year default probability forecasts for more than 1 million SMEs across France, Germany, Italy, Spain, and the U.K. These models have also been used to analyze the historical volatility of default probabilities, in order to create “rating estimates” that combine one-year default probabilities and annualized default volatilities.<sup>19</sup> By analyzing the transition behavior across different rating categories, we have created a one-year SME transition matrix, and used it to create credit curves for SMEs. The credit curves are provided in "Appendix I". Note that while the rating identifiers are written in the same way as those for traditional Standard & Poor's ratings, they are not obtained through the normal rating analysis conducted by our analysts. It is therefore not possible to make direct comparisons between the credit curves for SMEs and those for other rated entities.

### *3.5 Equity default swaps*

An EDS is similar to a CDS, in that a protection seller agrees to pay the protection buyer if the contract is triggered. However, as opposed to a credit event, an EDS is linked to the drop of the equity price of the reference entity below a certain barrier, typically 30% of the initial price. As a result of extensive analysis of historical equity price data from our Compustat® database, capturing approximately 12,000 companies trading in the U.S. or Canada between 1962 and 2003, we have developed new criteria for estimating the probability of an EDS contract triggering over a given time horizon. Using scoring techniques similar to those described in "Section 3.4", we have identified five variables that are very informative:

- The credit rating;
- The historical equity volatility;
- The market capitalization;
- The historical equity return; and
- The general level of the equity market measured by the current value of the S&P500 compared with the highest value of the previous 10 years.

The resulting EDS scoring models are used to derive a risk score between one and five for each EDS. These scores can then be mapped to an EDS default curve, i.e., the cumulative probability of the EDS contract breaching its price barrier.<sup>20</sup> Further technical details can be found in de Servigny and Jobst (2005). An overview of our criteria for CDOs containing EDS can be found in a forthcoming criteria article, and "Appendix I" contains further details of the EDS default curves.

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<sup>19</sup> For example, in the case of two SMEs with low one-year default probabilities but very different volatilities, the one with the lower volatility is likely to be assigned a higher rating.

<sup>20</sup> We can provide these scoring models upon request.

## Section 4: Recoveries

In general, the level of recovery achieved following a default is uncertain, or *stochastic*. For a debt instrument, such as a bond or loan, recovery depends on a number of factors, for instance the seniority of the instrument and the economic environment in which the default occurred. However, in the context of synthetic CDOs recovery can be determined in different ways, including the specification of a fixed level that does not depend on these factors.

In order to properly model the different types of recovery mechanisms included in CDOs, CDO Evaluator treats recoveries in two ways – *fixed* and *variable*. This section outlines the two different methods, both in terms of the rationale for using each method, and the underlying data used to estimate recoveries in each case.

### 4.1 Fixed recoveries

Although recoveries are usually uncertain, there are two main reasons for using fixed recovery assumptions. The first is that recovery can in certain transactions be set at a fixed percentage of the amount at risk, e.g., 50%.<sup>21</sup> The second is that historical data is not always sufficient to allow precise determination of the degree of variability in recoveries. For this reason, a fixed recovery that incorporates some degree of conservatism can be the best compromise. As this clearly involves some level of qualitative judgment, these assumptions are normally determined through a committee process.

### 4.2 Variable recoveries

In some cases, sufficient historical data exists to allow the degree of variability in recoveries to be explicitly modeled. For example, our LossStats® database<sup>22</sup> contains recovery information for more than 500 non-financial public and private U.S. companies that have defaulted since 1988. It contains information on more than 2,000 defaulted bank loans and high-yield bonds, and other debt instruments. This extensive data has allowed us to create recovery distributions for certain types of assets, based on the *beta* distribution, a well-known two-parameter distribution. Specification of the mean and standard deviation of the beta distribution is sufficient for CDO Evaluator Version 3.0 to simulate the full range of potential recoveries for each type of asset. These assumptions are provided in "Appendix II".

## Section 5: Correlation

In addition to specifying the univariate default probabilities and recovery assumptions for each asset in the portfolio, the correlation between pairs of assets must also be specified. As explained in "Section 2", this is assumed to be the *asset value* correlation between each pair of assets, which is not directly observable in the market. In principle, there are several ways to estimate asset value correlation:

- Regression analysis of equity returns within a factor model;
- Using equity return correlations as proxies for asset value correlation;
- Using credit spread correlations as proxies for asset value correlation;
- Inferring asset value correlations from rating migrations; and
- Estimating asset value correlations from empirical default observations.

We have chosen to use empirical default observations to estimate the correlation assumptions within CDO Evaluator, as this estimation method is likely to be less prone to the “noise” within equity return data, and the limited time period of credit spread data. In addition, unlike rating migrations it can be used consistently for a wide range of different rated and non-rated assets, such as corporates, ABS, SMEs, and EDS. In order to determine correlation assumptions for rated firms and EDSs, we have undertaken an extensive analysis of historical data, making use of the CreditPro® and Compustat® databases mentioned in "Section 3.1" and "Section 3.5", respectively. For SMEs, the CRT database mentioned in "Section 3.4" has been used.

We consider several statistical techniques which ensures a good degree of stability, ranging from maximum likelihood methods and factor models, to simple methods based

<sup>21</sup> This is the recovery level typically used for EDSs.

<sup>22</sup> For details, visit [www.standardandpoors.com](http://www.standardandpoors.com), run a search using “LossStats”, and scroll down to Products & Services.

on empirical joint default events. While a detailed overview of these techniques for corporate defaults and EDS can be found in Jobst and de Servigny (2005), the latter approach – frequently referred to as *joint default probability* (JDP) method – is outlined below given the significance of correlation estimates for CDO risk analysis.

The JDP method involves two stages. The first is the estimation of the JDP  $P_{ij}(t)$  between pairs of companies, either in the same industry or different industries. If pairs of companies are drawn (with replacement) from the database, an estimate of the JDP within an industry is given by:  $P_{ij}^c(t) = \frac{(D_t^c)^2}{(N_t^c)^2}$ , and between industries by:  $P_{ij}^{cd}(t) = \frac{D_t^c D_t^d}{N_t^c N_t^d}$ .

In these expressions,  $D_t^c$ ,  $D_t^d$  and  $N_t^c$ ,  $N_t^d$  are the number of defaulted companies and total number of companies in industries  $c$  and  $d$  respectively observed over a time period  $t$ . The empirical *default correlation*  $\rho^{cd}$  can easily be obtained from the standard correlation equation:

$$\rho^{cd} = \frac{\overline{P}^{cd} - \overline{P}^c \overline{P}^d}{\sqrt{\overline{P}^c (1 - \overline{P}^c)} \sqrt{\overline{P}^d (1 - \overline{P}^d)}}.$$

In this formula,  $\overline{P}^k$  denotes the average default probability of companies in industry  $k$ .

The second stage of the JDP method is the calculation of the implied asset correlation from the JDPs. This is done using the Gaussian copula model described in "Section 2", by calculating the asset correlation required to recover the empirically observed JDPs. For two companies, the JDP  $P_{ij}$  is given within the model by  $P_{ij} = \Phi(Z_i, Z_j, \rho_{ij})$ , where  $Z_i = \Phi^{-1}(P_i)$  and  $Z_j = \Phi^{-1}(P_j)$  are "z-scores" indicating the default threshold for each company. This means that the implied asset correlation  $\rho_{ij}$  can be determined by solving  $\rho_{ij} = \Phi^{-1}(Z_i, Z_j, P_{ij})$ .<sup>23</sup> In all cases, correlations were estimated within and between different industry sectors. The average intra-industry and inter-industry correlations across the entire datasets were then used to create the assumptions used in CDO Evaluator. These assumptions are contained in "Appendix III".

<sup>23</sup> For further details, see Jobst and de Servigny (2005).

## Section 6. CDO Risk Analysis

This section describes how CDO Evaluator can be applied to different CDO transactions, in order to analyze the risk exposure of each CDO tranche. First, we discuss the different risk measures that can be computed for each CDO transaction, and then go on to show how the model is used in the risk analysis and rating of different CDO transactions. The emphasis here is on synthetic CDO transactions, as these can be completely analyzed by CDO Evaluator, whereas cash CDO transactions require some additional steps, such as modeling the impact of interest rate and currency risk on the interest payments made to each CDO tranche.

### 6.1 Scenario loss rate

The primary risk measure used in our analysis of CDO transactions is the scenario loss rate (SLR), which is a quantile of the portfolio loss distribution consistent with a given rating and maturity.<sup>24</sup> For example, if the rating quantile corresponding to a certain rating and maturity is 0.5%, the required percentile of the loss distribution will be 99.5%. It is important to note that the rating quantiles have been developed specifically for CDO tranches, and are not identical to the corporate credit curves as in previous versions of CDO Evaluator. This is mainly due to the fact that both the corporate credit curves and CDO rating quantiles were highly “idealized” in previous versions, due to a lack of historical data. As described in “Section 3.1”, the corporate credit curves are now based on a more extensive analysis of historical corporate transition and default data, and have therefore been de-linked from the CDO rating quantiles.

Given that there is much less historical performance data for CDOs than the underlying corporates, the CDO rating quantiles have not been determined purely from historical data. In this case, we have used a number of quantitative and qualitative considerations, including the avoidance of potential instability in high investment-grade SLRs when very low CDO quantiles are imposed, and the observation that high degrees of leverage in CDO tranches tend to result in higher average rating volatility than investment-grade corporates. As a result, the CDO rating quantiles are higher than the corporate credit curves at investment grade rating levels, and converge to the corporate credit curves at low, speculative-grade rating levels. The CDO rating quantiles are provided in “Appendix I”.

For a synthetic CDO, the SLR is equivalent to the *attachment point* (or credit enhancement) required for a tranche with the relevant rating and maturity. For cash CDOs, the credit enhancement is determined through a cash flow modeling exercise, in which the default times of the asset portfolio are combined with interest rates and currency exchange rates (if required) to determine the overall credit performance of each rated CDO tranche.

### 6.2 Rated overcollateralization

Once a CDO transaction has been structured, it is possible to determine the extent to which available credit enhancement exceeds the required level. This can be done either for a cash or synthetic tranche. In the latter case, the SROC (synthetic rated overcollateralization) is given simply by:

$$\text{SROC} = \frac{\text{PortfolioNotional} - \text{SLR}}{\text{PortfolioNotional} - \text{CreditEnhancement}}$$

In the case of cash CDO tranches, the value of any excess spread must also be included, which requires the additional modeling of the transaction cash flows.

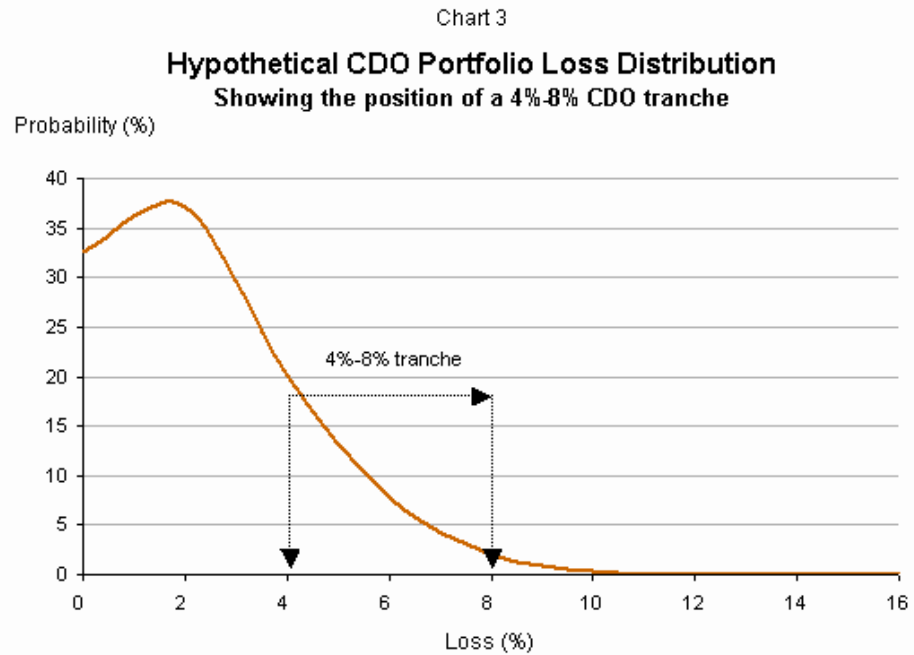
### 6.3 Synthetic CDO tranche risk measures

The SLR is a *portfolio* risk measure. There are also several useful CDO *tranche* risk measures, such as the tranche default probability, expected loss, and the loss-given-default.<sup>25</sup> For a synthetic CDO tranche, these can all be computed by “overlying” the

<sup>24</sup> The mean and standard deviation of the loss distribution are also computed by the CDO Evaluator.

<sup>25</sup> Clearly these measures also exist for cash CDO tranches. However, their determination requires the additional step of modelling time-dependent cash flows.

tranche on the portfolio loss distribution, as shown schematically in chart 3. Here, the tranche has an attachment point equal to 4% of the total notional amount of the portfolio, and a thickness also equal to 4%. This means that the tranche will no longer suffer losses above 8% of the portfolio notional amount, and for this reason this upper loss level is referred to as the *detachment point* of the tranche.



### 6.3.1 Tranche default probability

Given an attachment point  $A$  and detachment point  $D$  (i.e., a tranche thickness equal to  $D - A$ ), the tranche default probability is the probability that portfolio losses at maturity  $T$  exceed  $A$ . This is given by:  $PD^{Tranche} = P(L(T) \geq A) = E[1_{\{L(T) \geq A\}}]$ , where  $L(t)$  is the portfolio loss up to time  $t$  (see "Section 2"),  $1_{\{\cdot\}}$  is the indicator function<sup>26</sup>, and  $E[\cdot]$  denotes the expectation. This forms the basis for assigning a rating to a synthetic CDO tranche.

In the above expression for the tranche default probability, we assumed that the attachment point  $A$  is constant over time. This can easily be generalized to cases where the attachment point is a function of time  $t$ , so that the above expression becomes

$$PD^{Tranche} = P(L(t) \geq A(t)) = E[1_{\{L(t) \geq A(t)\}}].$$

In this case, we evaluate the loss distribution at all points in time at which the attachment point changes. As an example, consider a hypothetical seven-year synthetic CDO transaction. If the attachment point is initially set at 3% of the portfolio notional balance, but then increases to 5% after three years and remains at this level until maturity, we need to evaluate the loss distribution at years three and seven. The cumulative default probability of the tranche is therefore the probability that losses exceed 3% by year three, plus the probability that losses exceed 5% by year seven, *conditional* upon losses not exceeding 3% by year three.

Finally, the time dependency of the attachment point can even be made conditional upon certain levels of loss being reached within the portfolio. For example, it is possible to model transactions in which the attachment point "resets" according to the cumulative loss experienced by the portfolio by a certain date. This dynamic behavior is easily modeled by keeping track of the portfolio loss paths during simulation.

<sup>26</sup> This equals 1 if the expression within parentheses is true, and 0 if it is false.

### 6.3.2 Expected tranche loss

The cumulative loss on the tranche at time  $t$ ,  $M(t)$ , is given by:

$M(t) = (L(t) - A)1_{\{A \leq L(t) \leq D\}} + (D - A)1_{\{L(t) \geq D\}}$ . The expected tranche loss is therefore given by  $E[M(t)] = E[(L(t) - A)1_{\{A \leq L(t) \leq D\}} + (D - A)1_{\{L(t) \geq D\}}]$ .

### 6.3.3 Tranche loss-given-default

The tranche loss-given-default is given simply by:  $LGD^{Tranche} = \frac{E(M(t))}{PD^{Tranche}}$ .

### 6.3.4 Other tranche risk measures

The tranche leverage ( $Leverage^{Tranche} = \frac{E(M(t))}{E(L(t))}$ ) and hedge ratio

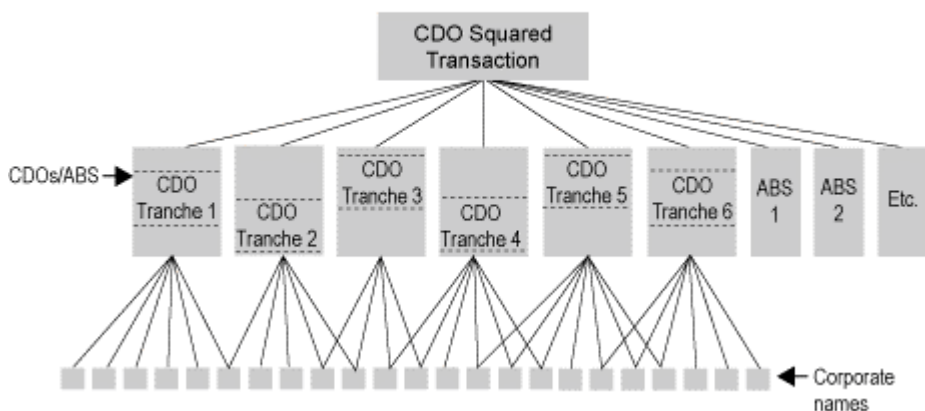
( $HR^{Tranche} = \frac{Leverage^{Tranche}}{TrancheNotional}$ ) are also useful in quantifying implied tranche performance.

### 6.4 Synthetic CDO squared transactions

Synthetic CDO squared transactions have now become an established feature of the global CDO marketplace. Rather than referencing secondary market CDO tranches, these transactions typically use portfolio CDSs to create so-called “bespoke” CDO tranches, each referencing a single underlying corporate portfolio. In this way, additional leverage is created above and beyond the leverage already present in each bespoke CDO, resulting in a yield pickup of these structures relative to similarly rated synthetic CDOs.

While some CDO squared transactions reference only CDOs, many recent CDO squared transactions have referenced portfolios containing a mixture of CDO and ABS tranches, where the proportion of ABS is typically in the range of 70% to 90% by reference notional amount. The ABS component normally consists of funded tranches that exist in the secondary market, while the CDO tranches are often tailor-made for the CDO squared investor. A CDO squared typically references between five and 15 different bespoke CDOs, each of which may reference between 100 and 200 corporate names. At first sight, this might suggest that the underlying corporate reference portfolio could be as large as 3,000 names! However, this is not the case, given that the liquid corporate names in the CDS market number between 400 and 600. For this reason, there is normally significant overlap between the reference portfolios of different bespoke CDOs, ranging from 20% to 30% in most cases. The basic structure of a typical CDO squared transaction is shown schematically in chart 4.

**Chart 4**  
**Structure of a Typical CDO Squared Transaction**



Should a credit event occur on an underlying corporate name, a bidding process is used to establish a recovery, and the resulting loss is allocated to each bespoke CDO that references this name. The overall impact of the credit event will therefore clearly depend on the overlap among the underlying CDO tranches. When the loss allocated to a bespoke CDO exceeds the attachment point of the CDO tranche, the loss is passed through to the

CDO squared transaction. Bespoke CDOs therefore act as “loss filters” between the underlying corporate assets and the CDO squared. This is very different to the ABS tranches, where a credit event in general triggers a bidding process, the ABS tranche is removed from the CDO squared reference portfolio, and the resulting loss is allocated to the CDO squared transaction.

While each bespoke CDO tranche can be analyzed using the approach described in "Section 6.3", CDO squared transactions require additional modeling, such as the ability to “drill down” to the corporate names underlying each CDO tranche included within the CDO squared portfolio. In this way, losses are modeled “from bottom to top”, flowing through each bespoke CDO before being allocated to the CDO squared tranche. This allows the overlap between pairs of bespoke CDO tranches to be explicitly modeled, in addition to their individual default and loss-given-default characteristics.<sup>27</sup>

### *6.5 Cross-subordination*

One of the innovations in the CDO squared market has been the introduction of so-called “cross-subordination”. This mechanism allows different bespoke CDOs to share the total subordination provided by all bespoke CDOs. For example, eight CDOs with attachment points and thicknesses of €10 million would create a total cross-subordination of €80 million. During the life of the transaction, if any CDO experiences losses greater than €10 million, these losses are not passed through to the CDO squared until the total aggregate losses exceed €80 million. In this way, the CDO squared investor is protected from the risk of a small number of CDOs experiencing losses, but is exposed to the risk that a large number of CDOs experience losses.<sup>28</sup>

This is easily modeled within CDO Evaluator by “tracking” the losses experienced by each bespoke CDO in each simulation step, and only passing through the aggregate loss if it exceeds the total available subordination. This can also be extended to cases in which the subordination is only “partially” cross-subordinated (e.g., the CDO squared transaction is insulated from only 75% of the total aggregate subordination of the bespoke CDOs).

Consider a hypothetical CDO squared with the following characteristics:

- The CDO squared references a portfolio containing eight bespoke CDO tranches and 50 'AAA' rated ABS tranches, with an average asset correlation of 10%.
- Each bespoke CDO tranche references a portfolio of approximately 100 'A' rated names with 5% average asset correlation, equal reference notional amounts of €10 million, and assumed recoveries of 35%.
- Each bespoke CDO tranche has an attachment point of €40 million (consistent with a CDO rating at the 'A' rating level) and a detachment point of €50 million, i.e., a tranche thickness of €10 million.
- The average overlap between pairs of bespoke CDOs is 33%.
- Each ABS tranche has a reference notional amount of €10 million, and an assumed recovery of 90%.
- The CDO squared has a maturity of five years.

The CDO squared portfolio therefore has a total reference notional amount of €80 million. Of this amount, the ABS portion makes up 86%, and the bespoke CDOs 14%.

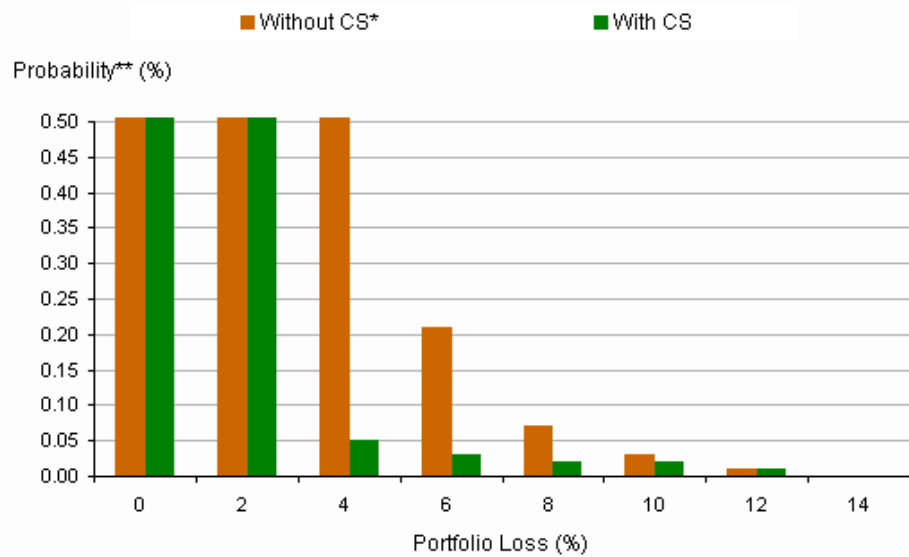
Chart 5 shows the loss distribution of the CDO squared portfolio. In one case, the CDOs are assumed to contribute losses to the CDO squared without cross-subordination, as described in "Section 6.4". In the other case, all eight bespoke CDOs are assumed to be cross-subordinated, as described above. In both cases, the probability of zero or small losses is very high, while there is a “tail” of higher losses. However, in the case of the cross-subordinated transaction, the probability of zero/small losses increases significantly, with a corresponding decrease in the probability of larger losses. This means that a senior CDO squared tranche with a relatively high attachment point has a lower probability of default in the case of cross-subordination, as the total area of the distribution above 6% loss is lower. However, this tranche is likely to exhibit a higher loss-given-default.

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<sup>27</sup> See “Drill-Down Approach for Synthetic CDO Squared Transactions”, Standard & Poor’s Special Report, Dec. 10, 2003.

<sup>28</sup> Another way of stating this is that cross-subordination reduces the idiosyncratic risk specific to each CDO, but increases the systematic risk common to all CDOs.

Chart 5  
**Loss Distribution For Two Hypothetical CDO Squared Transactions**



\*CS - cross-subordination.

\*\*When portfolio loss is assumed to be 0%, those transactions without CS, probability is 86.0%, those with CS, is 88.9%. When portfolio loss is assumed to be 2% probability is 13.0% for those without CS and 10.9% for those with CS. When portfolio loss is assumed to be 4% probability is 0.69% for those without CS and 0.05% for those with CS.

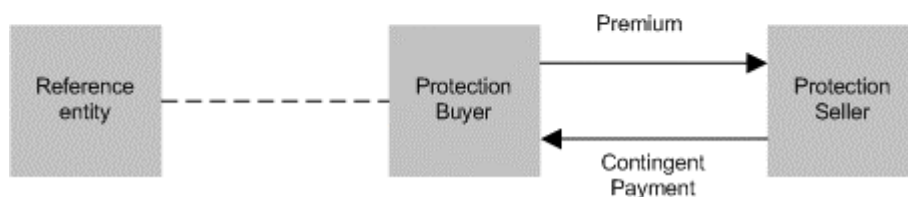
### 6.6 Long/short CDS

CDSs behave in a similar fashion to bilateral insurance contracts. One party (the protection seller) agrees to pay another party (the protection buyer) an amount equal to the reference notional amount of the contract minus a recovery amount in the event of a default of a given reference entity on one or more of its obligations. The recovery amount is normally determined either by physical delivery of a specified obligation, or by cash settlement. The details of allowable obligations and settlement procedures are not discussed in any detail here.

In exchange for this contingent payment, the protection buyer pays the protection seller a premium. A CDS therefore consists of two cash flows, the premium flow and the contingent payment. The “fair value” of the CDS is that which makes the net present value (NPV) of the premium flow exactly equal to the NPV of the contingent payment. Chart 6 illustrates the CDS payment mechanics.

When an entity sells protection in CDS form it is said to take a “long” position, as it receives the same economic loss/benefit as owning a bond issued by the reference entity. Conversely, when an entity buys protection it takes a “short” position. CDO Evaluator models a short CDS simply by reversing the sign of the loss (i.e., making it a gain) in the event of default of the reference name, *conditional upon the survival of the protection seller*. This is one example of the way in which CDO Evaluator treats counterparty risk, which requires additional information on the CDS counterparty when short CDSs are included within the portfolio.

## Chart 6 CDS Payment Mechanics



### 6.7 Long/short CDO tranches

Using CDS technology, it is also possible to take a short position on an underlying CDO tranche within a CDO squared transaction. In this case, the CDO squared buys protection on an underlying CDO tranche, so that if losses exceed the attachment point of the tranche the CDO squared receives a payment equal to the difference between the net portfolio loss and the tranche attachment point, up to a maximum of the size of the tranche.

### 6.8 Nth-to-default baskets

The mechanics of these transactions are similar to those of a CDS (see chart 6), except that the reference entity is replaced by a basket of reference entities, and the seller of protection is exposed to the risk of the  $n$ th default within the basket. An  $n$ th-to-default basket can be treated as a special case of a synthetic CDO containing a small number of equal exposures (typically three to five). As described in "Section 6.3.1", the tranche default probability is the probability that portfolio losses at maturity  $T$  exceed the attachment point  $A$ . For an  $n$ th-to-default basket with a fixed recovery  $\delta$ , the attachment point is clearly equal to  $(n-1)\delta$ .

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# APPENDIX I

## Transition Matrices And Credit Curves For CDO Evaluator Assets

### Rated Firms – One-Year Transition Matrix

(%)	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	D
AAA	83.32	8.92	5.20	1.01	0.53	0.25	0.38	0.09	0.17	0.02	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA+	1.06	78.41	13.10	4.72	1.06	0.84	0.25	0.14	0.20	0.10	0.09	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	0.58	0.56	77.07	13.10	4.26	2.68	0.68	0.54	0.31	0.03	0.01	0.04	0.04	0.01	0.01	0.03	0.00	0.03	0.00	0.01
AA-	0.09	0.22	1.28	75.53	13.57	6.78	1.31	0.44	0.26	0.15	0.09	0.06	0.02	0.05	0.12	0.01	0.00	0.00	0.00	0.01
A+	0.02	0.10	0.57	2.46	76.39	13.05	4.74	1.25	0.69	0.20	0.07	0.14	0.08	0.08	0.12	0.01	0.01	0.00	0.00	0.02
A	0.07	0.09	0.49	0.87	2.13	79.20	11.75	3.17	1.20	0.35	0.19	0.20	0.13	0.08	0.04	0.01	0.00	0.00	0.01	0.02
A-	0.14	0.05	0.21	0.39	1.17	2.81	77.11	13.52	3.21	0.75	0.20	0.15	0.06	0.11	0.03	0.03	0.00	0.00	0.00	0.03
BBB+	0.09	0.08	0.12	0.26	1.01	3.37	2.64	75.69	14.09	1.56	0.36	0.28	0.08	0.08	0.05	0.02	0.00	0.01	0.00	0.20
BBB	0.04	0.03	0.19	0.22	0.62	1.50	2.92	8.87	71.49	11.42	1.08	0.72	0.22	0.17	0.15	0.03	0.01	0.02	0.00	0.29
BBB-	0.12	0.01	0.12	0.28	0.38	1.01	1.30	3.87	12.81	64.39	4.87	5.67	2.26	1.15	0.45	0.37	0.09	0.05	0.02	0.81
BB+	0.19	0.01	0.02	0.20	0.17	0.47	1.00	1.16	4.83	11.79	68.09	8.24	1.24	0.64	0.27	0.13	0.03	0.03	0.01	1.48
BB	0.01	0.04	0.09	0.06	0.03	0.32	0.24	0.51	1.41	3.96	13.35	69.32	6.02	1.48	0.47	0.21	0.09	0.08	0.02	2.30
BB-	0.00	0.01	0.01	0.06	0.12	0.20	0.35	0.49	1.01	1.60	4.85	12.37	66.63	7.08	1.08	0.38	0.16	0.10	0.04	3.46
B+	0.00	0.07	0.02	0.13	0.06	0.11	0.31	0.41	0.24	0.42	0.93	3.40	14.42	68.09	5.66	0.92	0.35	0.24	0.10	4.10
B	0.01	0.00	0.13	0.02	0.06	0.36	0.37	0.30	0.28	0.16	0.71	1.49	3.58	16.42	63.13	5.08	1.44	0.79	0.36	5.29
B-	0.02	0.00	0.01	0.01	0.19	0.18	0.19	0.36	0.22	0.17	0.40	0.59	1.32	6.81	15.08	58.99	4.60	2.00	0.72	8.14
CCC+	0.02	0.00	0.01	0.02	0.86	0.09	0.08	0.62	0.35	0.05	0.17	0.19	1.20	3.64	7.00	15.58	40.65	4.20	1.70	23.58
CCC	0.36	0.01	0.01	0.01	0.04	0.38	0.39	0.73	0.43	0.12	1.06	1.09	0.68	2.09	8.08	6.87	12.57	17.02	2.51	45.56
CCC-	0.01	0.00	0.00	0.00	0.01	0.02	0.02	0.04	0.04	0.06	0.71	0.20	2.08	2.36	1.79	2.71	1.72	12.48	9.34	66.41
D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00

### Rated firms – credit curves

(%)	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	AAA
Year																				
1	0.0002	0.001	0.008	0.014	0.018	0.022	0.033	0.195	0.294	0.806	1.484	2.296	3.457	4.100	5.295	8.138	23.582	45.560	66.413	
2	0.005	0.009	0.039	0.048	0.064	0.080	0.121	0.427	0.684	1.805	2.915	4.506	6.624	8.124	10.833	16.559	38.046	59.087	79.205	
3	0.016	0.027	0.085	0.102	0.138	0.172	0.262	0.701	1.162	2.899	4.312	6.597	9.516	11.903	15.940	23.729	46.605	64.704	82.840	
4	0.034	0.056	0.144	0.178	0.240	0.298	0.451	1.023	1.713	4.034	5.681	8.567	12.164	15.388	20.479	29.578	52.040	67.875	84.478	
5	0.061	0.098	0.219	0.276	0.371	0.459	0.686	1.391	2.323	5.179	7.020	10.424	14.595	18.571	24.463	34.333	55.809	70.042	85.513	
6	0.097	0.153	0.310	0.397	0.531	0.655	0.966	1.805	2.980	6.316	8.327	12.175	16.832	21.462	27.947	38.234	58.626	71.685	86.285	
7	0.144	0.224	0.420	0.543	0.719	0.887	1.287	2.261	3.672	7.434	9.598	13.826	18.895	24.083	30.999	41.476	60.850	73.005	86.907	
8	0.204	0.311	0.549	0.713	0.937	1.152	1.648	2.756	4.390	8.529	10.831	15.387	20.800	26.457	33.680	44.209	62.672	74.105	87.429	
9	0.276	0.414	0.700	0.909	1.184	1.451	2.047	3.284	5.127	9.598	12.025	16.862	22.563	28.610	36.046	46.543	64.204	75.041	87.877	
10	0.362	0.536	0.872	1.130	1.458	1.782	2.479	3.842	5.876	10.637	13.179	18.258	24.197	30.565	38.145	48.559	65.517	75.853	88.268	
11	0.463	0.678	1.066	1.377	1.761	2.143	2.943	4.425	6.634	11.649	14.295	19.580	25.717	32.346	40.016	50.320	66.657	76.565	88.614	
12	0.581	0.839	1.284	1.650	2.092	2.534	3.434	5.029	7.396	12.631	15.371	20.834	27.132	33.973	41.694	51.871	67.659	77.197	88.921	
13	0.715	1.020	1.525	1.947	2.448	2.952	3.952	5.651	8.160	13.587	16.410	22.025	28.453	35.463	43.206	53.248	68.548	77.762	89.197	
14	0.867	1.223	1.790	2.270	2.830	3.396	4.491	6.287	8.923	14.515	17.414	23.157	29.689	36.832	44.575	54.481	69.343	78.271	89.447	
15	1.037	1.447	2.078	2.617	3.237	3.864	5.051	6.936	9.684	15.418	18.383	24.234	30.849	38.096	45.822	55.592	70.060	78.732	89.674	
16	1.225	1.693	2.389	2.988	3.666	4.353	5.628	7.593	10.441	16.296	19.320	25.262	31.940	39.265	46.962	56.599	70.710	79.154	89.882	
17	1.433	1.961	2.724	3.382	4.117	4.862	6.221	8.258	11.193	17.152	20.226	26.243	32.969	40.351	48.009	57.517	71.304	79.541	90.074	
18	1.661	2.250	3.080	3.798	4.588	5.390	6.826	8.928	11.940	17.985	21.103	27.181	33.941	41.363	48.976	58.359	71.848	79.898	90.250	
19	1.908	2.561	3.458	4.234	5.078	5.934	7.442	9.602	12.680	18.798	21.952	28.081	34.862	42.310	49.872	59.134	72.350	80.229	90.414	
20	2.175	2.893	3.858	4.690	5.586	6.493	8.068	10.279	13.414	19.591	22.777	28.944	35.737	43.198	50.706	59.851	72.816	80.538	90.568	
21	2.462	3.246	4.277	5.165	6.110	7.065	8.701	10.957	14.142	20.365	23.577	29.773	36.570	44.034	51.486	60.517	73.249	80.827	90.711	
22	2.769	3.619	4.715	5.657	6.648	7.648	9.340	11.636	14.862	21.123	24.355	30.572	37.365	44.824	52.216	61.140	73.654	81.099	90.845	
23	3.095	4.012	5.171	6.164	7.200	8.241	9.985	12.314	15.575	21.863	25.112	31.343	38.126	45.571	52.904	61.723	74.035	81.355	90.973	
24	3.440	4.423	5.644	6.687	7.763	8.844	10.633	12.991	16.281	22.589	25.850	32.087	38.855	46.281	53.554	62.271	74.394	81.598	91.093	
25	3.804	4.853	6.133	7.223	8.337	9.454	11.284	13.667	16.980	23.300	26.570	32.808	39.556	46.958	54.169	62.789	74.733	81.828	91.207	
26	4.187	5.300	6.638	7.772	8.921	10.070	11.937	14.340	17.671	23.997	27.272	33.506	40.230	47.604	54.754	63.280	75.055	82.048	91.316	
27	4.586	5.763	7.156	8.331	9.513	10.692	12.591	15.010	18.356	24.682	27.959	34.184	40.881	48.222	55.311	63.746	75.362	82.258	91.419	
28	5.003	6.241	7.686	8.901	10.112	11.318	13.245	15.678	19.033	25.354	28.630	34.842	41.510	48.815	55.844	64.190	75.655	82.459	91.519	
29	5.436	6.735	8.229	9.480	10.718	11.947	13.900	16.342	19.704	26.015	29.288	35.483	42.118	49.386	56.355	64.615	75.935	82.653	91.614	
30	5.885	7.241	8.781	10.066	11.329	12.580	14.553	17.003	20.367	26.665	29.933	36.108	42.709	49.936	56.845	65.022	76.205	82.839	91.706	

*ABS – credit curves*

Year	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-
1	0.000	0.001	0.004	0.008	0.010	0.012	0.018	0.107	0.162	0.443	1.113	1.722	2.593	3.075	3.971	6.104	17.687	34.170	49.810
2	0.003	0.005	0.021	0.026	0.035	0.044	0.067	0.235	0.376	0.993	2.186	3.380	4.968	6.093	8.125	12.419	28.535	44.315	59.404
3	0.009	0.015	0.047	0.056	0.076	0.094	0.144	0.386	0.639	1.595	3.234	4.948	7.137	8.927	11.955	17.797	34.954	48.528	62.130
4	0.019	0.031	0.079	0.098	0.132	0.164	0.248	0.562	0.942	2.219	4.261	6.426	9.123	11.541	15.359	22.184	39.030	50.906	63.359
5	0.033	0.054	0.120	0.152	0.204	0.252	0.377	0.765	1.278	2.848	5.265	7.818	10.946	13.928	18.347	25.750	41.857	52.532	64.135
6	0.053	0.084	0.171	0.219	0.292	0.360	0.531	0.993	1.639	3.474	6.245	9.131	12.624	16.097	20.960	28.676	43.970	53.764	64.714
7	0.079	0.123	0.231	0.299	0.396	0.488	0.708	1.243	2.020	4.089	7.198	10.370	14.171	18.062	23.249	31.107	45.638	54.754	65.180

*SMEs – credit curves*

(%)	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-
Year															
1	0.049	0.067	0.110	0.196	0.238	0.441	0.442	1.020	1.711	2.980	8.495	12.138	31.592	31.592	31.592
2	0.130	0.184	0.276	0.459	0.596	0.953	1.038	2.150	3.486	6.077	15.082	22.373	46.180	46.180	46.180
3	0.244	0.345	0.497	0.786	1.039	1.546	1.756	3.351	5.277	9.048	20.311	29.758	54.423	54.423	54.423
4	0.393	0.551	0.772	1.174	1.552	2.209	2.572	4.592	7.043	11.802	24.508	35.127	59.634	59.634	59.634
5	0.578	0.799	1.096	1.618	2.123	2.928	3.462	5.852	8.758	14.318	27.929	39.162	63.185	63.185	63.185
6	0.800	1.088	1.466	2.112	2.742	3.690	4.407	7.115	10.406	16.603	30.770	42.301	65.747	65.747	65.747
7	1.059	1.416	1.877	2.651	3.401	4.486	5.391	8.367	11.979	18.679	33.171	44.821	67.684	67.684	67.684
8	1.354	1.782	2.327	3.230	4.092	5.306	6.401	9.602	13.478	20.571	35.237	46.900	69.205	69.205	69.205
9	1.685	2.182	2.812	3.842	4.811	6.145	7.425	10.814	14.906	22.303	37.042	48.655	70.440	70.440	70.440
10	2.049	2.615	3.328	4.484	5.550	6.995	8.456	11.998	16.265	23.896	38.640	50.168	71.470	71.470	71.470
11	2.446	3.078	3.872	5.151	6.306	7.854	9.487	13.155	17.561	25.369	40.072	51.493	72.348	72.348	72.348
12	2.874	3.570	4.441	5.839	7.075	8.716	10.512	14.282	18.799	26.739	41.369	52.670	73.111	73.111	73.111
13	3.330	4.088	5.033	6.545	7.855	9.580	11.528	15.380	19.984	28.020	42.555	53.729	73.785	73.785	73.785
14	3.814	4.629	5.645	7.264	8.641	10.444	12.533	16.450	21.121	29.223	43.648	54.692	74.388	74.388	74.388
15	4.323	5.193	6.275	7.996	9.433	11.304	13.524	17.491	22.213	30.358	44.663	55.576	74.934	74.934	74.934
16	4.855	5.776	6.920	8.737	10.227	12.160	14.500	18.506	23.264	31.433	45.610	56.393	75.434	75.434	75.434
17	5.410	6.377	7.580	9.485	11.023	13.011	15.461	19.495	24.278	32.456	46.501	57.154	75.894	75.894	75.894
18	5.983	6.995	8.251	10.238	11.819	13.856	16.405	20.459	25.258	33.431	47.341	57.867	76.322	76.322	76.322
19	6.575	7.628	8.932	10.996	12.614	14.695	17.333	21.399	26.206	34.365	48.138	58.539	76.722	76.722	76.722
20	7.184	8.273	9.623	11.756	13.408	15.526	18.245	22.317	27.126	35.261	48.896	59.175	77.098	77.098	77.098

**EDSs**

Barrier (10%)					
(%)	EDS score				
	1	2	3	4	5
0	0.000	0.000	0.000	0.000	0.000
1	0.008	0.018	0.056	0.154	1.721
2	0.028	0.059	0.238	0.717	4.477
3	0.070	0.117	0.428	1.469	7.114
4	0.124	0.196	0.694	2.317	9.180
5	0.177	0.316	1.049	3.131	11.463
6	0.266	0.480	1.390	3.981	13.096
7	0.358	0.696	1.558	4.901	13.896
8	0.400	0.838	1.836	5.463	14.656
9	0.572	0.992	1.989	6.142	15.340
10	0.828	1.105	2.383	6.554	16.089

Barrier (20%)					
(%)	EDS score				
	1	2	3	4	5
0	0.000	0.000	0.000	0.000	0.000
1	0.011	0.037	0.141	0.693	4.532
2	0.035	0.120	0.413	2.044	9.830
3	0.088	0.386	0.888	3.608	14.278
4	0.177	0.584	1.621	5.168	17.766
5	0.354	0.905	2.615	6.564	20.725
6	0.443	1.356	3.296	8.129	22.636
7	0.535	1.788	3.759	9.510	24.283
8	0.732	2.071	4.592	10.296	25.802
9	0.947	2.432	5.308	11.408	27.048
10	1.203	2.770	5.759	12.300	28.273

Barrier (30%)					
(%)	EDS score				
	1	2	3	4	5
0	0.000	0.000	0.000	0.000	0.000
1	0.026	0.146	0.395	1.463	8.484
2	0.088	0.452	1.423	4.588	16.460
3	0.265	1.152	2.435	7.264	21.918
4	0.531	1.745	3.868	9.807	26.184
5	0.885	2.147	5.608	11.824	29.463
6	1.242	2.885	6.441	13.747	31.614
7	1.516	3.964	7.155	15.333	33.685
8	2.010	4.483	8.313	16.568	35.638
9	2.332	5.153	9.234	18.050	36.945
10	2.715	5.773	9.853	18.942	38.239

*CDO tranches - credit curves and rating quantiles*

(%)	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-
1	0.0004	0.002	0.013	0.024	0.027	0.033	0.049	0.234	0.353	0.967	1.632	2.525	3.803	4.510	5.824	8.138	23.582	45.560	66.413
2	0.009	0.017	0.062	0.078	0.097	0.121	0.185	0.514	0.825	2.142	3.211	4.946	7.260	8.885	11.751	16.674	38.104	59.145	79.233
3	0.030	0.050	0.135	0.166	0.212	0.263	0.396	0.850	1.405	3.415	4.758	7.230	10.401	12.960	17.152	24.004	46.752	64.835	82.905
4	0.065	0.104	0.232	0.290	0.372	0.459	0.676	1.246	2.073	4.728	6.276	9.380	13.265	16.694	21.921	30.025	52.288	68.078	84.581
5	0.118	0.182	0.356	0.452	0.578	0.709	1.020	1.704	2.812	6.046	7.763	11.403	15.886	20.087	26.089	34.945	56.158	70.313	85.650
6	0.190	0.287	0.512	0.654	0.830	1.013	1.424	2.221	3.607	7.352	9.216	13.310	18.291	23.156	29.725	38.996	59.071	72.019	86.454
7	0.285	0.420	0.701	0.897	1.128	1.368	1.883	2.792	4.443	8.635	10.632	15.110	20.503	25.929	32.903	42.374	61.383	73.396	87.105
8	0.405	0.584	0.927	1.182	1.472	1.774	2.395	3.413	5.310	9.891	12.007	16.810	22.544	28.435	35.692	45.227	63.284	74.546	87.653
9	0.552	0.781	1.191	1.509	1.859	2.226	2.954	4.076	6.198	11.116	13.340	18.418	24.432	30.702	38.151	47.666	64.886	75.529	88.124
10	0.728	1.013	1.493	1.876	2.290	2.724	3.557	4.777	7.103	12.309	14.631	19.941	26.182	32.760	40.331	49.776	66.261	76.383	88.535
11	0.934	1.280	1.833	2.285	2.762	3.263	4.198	5.510	8.017	13.471	15.881	21.386	27.809	34.633	42.275	51.620	67.459	77.133	88.899
12	1.173	1.583	2.213	2.733	3.273	3.841	4.873	6.269	8.937	14.602	17.091	22.758	29.326	36.343	44.018	53.245	68.512	77.799	89.223
13	1.445	1.923	2.631	3.219	3.822	4.454	5.578	7.050	9.860	15.704	18.261	24.064	30.744	37.910	45.589	54.691	69.448	78.396	89.515
14	1.750	2.300	3.086	3.742	4.404	5.099	6.309	7.850	10.783	16.776	19.394	25.307	32.073	39.353	47.014	55.985	70.287	78.935	89.779
15	2.089	2.712	3.577	4.299	5.018	5.773	7.063	8.664	11.704	17.822	20.491	26.494	33.323	40.685	48.313	57.154	71.045	79.426	90.020
16	2.463	3.160	4.102	4.887	5.662	6.473	7.836	9.490	12.621	18.841	21.555	27.629	34.501	41.920	49.504	58.214	71.733	79.875	90.241
17	2.870	3.643	4.659	5.506	6.332	7.195	8.624	10.325	13.534	19.836	22.587	28.716	35.614	43.070	50.600	59.183	72.363	80.288	90.445
18	3.311	4.158	5.247	6.152	7.026	7.937	9.426	11.167	14.441	20.808	23.589	29.759	36.670	44.145	51.614	60.073	72.943	80.671	90.634
19	3.784	4.704	5.863	6.823	7.741	8.696	10.238	12.013	15.342	21.757	24.563	30.761	37.674	45.153	52.557	60.895	73.479	81.028	90.810
20	4.289	5.281	6.506	7.516	8.475	9.470	11.059	12.862	16.235	22.686	25.510	31.727	38.630	46.102	53.438	61.658	73.978	81.362	90.974
21	4.823	5.885	7.172	8.229	9.225	10.256	11.886	13.713	17.121	23.596	26.434	32.658	39.545	46.998	54.263	62.370	74.445	81.675	91.129
22	5.386	6.514	7.860	8.961	9.989	11.053	12.718	14.563	17.999	24.487	27.334	33.558	40.420	47.848	55.040	63.036	74.883	81.971	91.275
23	5.975	7.168	8.567	9.707	10.765	11.857	13.552	15.413	18.869	25.361	28.213	34.429	41.261	48.655	55.774	63.663	75.296	82.252	91.413
24	6.590	7.843	9.292	10.468	11.552	12.668	14.389	16.261	19.731	26.218	29.071	35.273	42.070	49.426	56.470	64.256	75.686	82.518	91.544
25	7.229	8.538	10.032	11.240	12.346	13.484	15.226	17.105	20.584	27.060	29.911	36.093	42.851	50.162	57.132	64.817	76.057	82.773	91.670
26	7.889	9.250	10.786	12.022	13.147	14.303	16.062	17.947	21.428	27.887	30.733	36.890	43.605	50.868	57.764	65.351	76.411	83.017	91.789
27	8.568	9.979	11.550	12.811	13.954	15.125	16.897	18.784	22.264	28.700	31.538	37.667	44.335	51.546	58.369	65.860	76.750	83.251	91.904
28	9.266	10.721	12.325	13.608	14.764	15.947	17.729	19.616	23.092	29.499	32.327	38.423	45.043	52.200	58.950	66.348	77.074	83.476	92.015
29	9.980	11.475	13.108	14.409	15.576	16.770	18.559	20.443	23.911	30.286	33.102	39.162	45.731	52.832	59.508	66.816	77.386	83.693	92.121
30	10.708	12.240	13.897	15.213	16.390	17.591	19.385	21.265	24.721	31.061	33.863	39.884	46.400	53.443	60.047	67.266	77.687	83.903	92.224

## APPENDIX II

Recovery Assumptions For CDO Evaluator Assets									
	Corporate						Sovereign		
	Senior secured		Senior unsecured		Subordinate		—		
	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)	
U.S.	50.0	20.0	38.0	20.0	19.8	15.0	25.0	12.0	
Isle of Man	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Liechtenstein	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Canada	50.0	20.0	38.0	20.0	19.8	15.0	25.0	12.0	
Egypt	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Morocco	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Algeria	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Tunisia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Senegal	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Ghana	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Nigeria	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Gabonese Republic	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Barbados	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Botswana	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
South Africa	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Greece	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
The Netherlands	47.0	20.0	31.0	15.0	16.0	12.0	25.0	12.0	
Belgium	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
France	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
Spain	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
Portugal	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
Luxembourg	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
Ireland	60.0	20.0	32.5	15.0	17.0	13.0	25.0	12.0	
Iceland	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Albania	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Malta	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Cyprus	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Finland	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0	
Bulgaria	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Hungary	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Lithuania	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Latvia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Estonia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Moldova	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Monaco	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Ukraine	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Croatia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Slovenia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Bosnia & Herzegovina	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Macedonia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Italy	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0	
Romania	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Switzerland	47.0	20.0	31.0	15.0	16.0	12.0	25.0	12.0	
Czech Republic	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Slovak Republic	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Austria	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0	
U.K.	60.0	20.0	32.5	15.0	17.0	13.0	25.0	12.0	
Bermuda	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Denmark	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0	
Sweden	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0	
Norway	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0	
Grenada	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Poland	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Germany	47.0	20.0	31.0	15.0	16.0	12.0	25.0	12.0	
Belize	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Guatemala	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
El Salvador	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Honduras	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Nicaragua	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Costa Rica	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Panama	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Peru	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Mexico	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Argentina	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Brazil	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Chile	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	
Colombia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0	

	Corporate						Sovereign	
	Senior secured		Senior unsecured		Subordinate		—	
	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)	Mean (%)	Standard deviation (%)
Venezuela	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Bolivia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Ecuador	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Paraguay	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Suriname	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Uruguay	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Malaysia	25.0	15.0	16.2	10.0	8.5	6.0	25.0	12.0
Australia	37.4	20.0	24.3	15.0	12.7	9.0	25.0	12.0
Indonesia	18.0	10.0	11.7	5.0	6.1	3.0	25.0	12.0
Philippines	18.0	10.0	11.7	5.0	6.1	3.0	25.0	12.0
New Zealand	40.0	20.0	29.0	15.0	14.0	11.0	25.0	12.0
Singapore	34.6	20.0	22.5	12.5	11.7	8.0	25.0	12.0
Thailand	25.0	15.0	16.2	10.0	8.5	6.0	25.0	12.0
Papua New Guinea	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Cook Islands	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Russia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Kazakhstan	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Dominican Republic	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Japan	21.0	10.0	13.5	8.0	7.0	5.0	25.0	12.0
South Korea	25.0	15.0	16.2	10.0	8.5	6.0	25.0	12.0
Vietnam	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
North Korea	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Hong Kong	34.6	20.0	22.5	12.5	11.7	8.0	25.0	12.0
China	25.0	15.0	16.2	10.0	8.5	6.0	25.0	12.0
Trinidad & Tobago	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Jamaica	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Taiwan	25.0	15.0	16.2	10.0	8.5	6.0	25.0	12.0
Turkey	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
India	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Pakistan	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Sri Lanka	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Lebanon	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Jordan	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Syrian Arab Republic	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Kuwait	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Saudi Arabia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Oman	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
United Arab Emirates	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Israel	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Bahrain	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Qatar	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0
Mongolia	15.0	8.0	10.0	5.0	5.0	3.0	25.0	12.0

## APPENDIX III

### Correlation Assumptions For CDO Evaluator Assets

#### *Rated securities*

Sovereign vs. Sovereign											
Within region											0.2
Between regions											0.0

Obligor vs. Obligor										
	Between sectors					Within sector				
	Corp	ABS	Muni	SME	Corp	ABS	Muni	CDO	SME	
Within country	0.05	0.10	0.00	0.04	0.15	0.30	0.30	0.15	0.10	
Within region****					*0.00					
	0.05	0.10	—	0.04	**0.15	0.20	0.30	—	0.10	
Between regions****					***0.15					
					*0.00					
	0.00	0.00	—	0.04	**0.00	0.00	0.00	—	0.10	
					***0.15					

*\*Local*  
*\*\*Regional*  
*\*\*\*Global*  
*\*\*\*\*If any correlation is without local, regional, or global classifications, then correlation applies to asset pairs regardless of classifications.*

#### *EDSs*

Barrier	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Within sector	0.27	0.27	0.27	0.27	0.27	0.29	0.33	0.37	0.37	0.37
Between sectors	0.18	0.18	0.18	0.18	0.18	0.2	0.23	0.26	0.26	0.26

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