A Guide to Modelling Counterparty Credit Risk

What are the steps involved in calculating credit exposure? What are the differences between counterparty and contract-level exposure? How can margin agreements be used to reduce counterparty credit risk? What is credit value adjustment and how can it be measured? **Michael Pykhtin** and **Steven Zhu** offer a blueprint for modelling credit exposure and pricing counterparty risk.

Counterparty credit risk is the risk that the counterparty to a financial contract will default prior to the expiration of the contract and will not make all the payments required by the contract. Only the contracts privately negotiated between counterparties — over-the-counter (OTC) derivatives and security financing transactions (SFT) — are subject to counterparty risk. Exchange-traded derivatives are not affected by counterparty risk, because the exchange guarantees the cash flows promised by the derivative to the counterparties.[1]

Counterparty risk is similar to other forms of credit risk in that the cause of economic loss is obligor's default. There are, however, two features that set counterparty risk apart from more traditional forms of credit risk: the uncertainty of exposure and bilateral nature of credit risk. (Canabarro and Duffie [2003] provide an excellent introduction to the subject.)

In this article, we will focus on two main issues: modelling credit exposure and pricing counterparty risk. In the part devoted to credit exposure, we will define credit exposure at contract and counterparty levels, introduce netting and margin agreements as risk management tools for reducing counterparty-level exposure and present a framework for modelling credit exposure. In the part devoted to pricing, we will define credit value adjustment (CVA) as the price of counterparty credit risk and discuss approaches to its calculation.

Contract-Level Exposure

If a counterparty in a derivative contract defaults, the bank must close out its position with the defaulting counterparty. To determine the loss arising from the counterparty's default, it is convenient to assume that the bank enters into a similar contract with another counterparty in order to maintain its market position.[2] Since the bank's market position is unchanged after replacing the contract, the loss is determined by the contract's replacement cost at the time of default.

If the contract value is negative for the bank at the time of default, the bank

- closes out the position by paying the defaulting counterparty the market value of the contract;
- enters into a similar contract with another counterparty and receives the market value of the contract; and
- has a net loss of zero.

If the contract value is positive for the bank at the time of default, the bank

- closes out the position, but receives nothing from the defaulting counterparty;
- enters into a similar contract with another counterparty and pays the market value of the contract; and
- has a net loss equal to the contract's market value.

Thus, the credit exposure of a bank that has a single derivative contract with a counterparty is the maximum of the contract's market value and zero. Denoting the value of contract i at time t as $V_i(t)$, the contract-level exposure is given by

$$E_i(t) = \max\{V_i(t), 0\} \tag{1}$$

Since the contract value changes unpredictably over time as the market moves, only the current exposure is known with certainty, while the future exposure is uncertain. Moreover, since the derivative contract can be either an asset or a liability to the bank, counterparty risk is bilateral between the bank and its counterparty.

Counterparty-Level Exposure

In general, if there is more than one trade with a defaulted counterparty and counterparty risk is not mitigated in any way, the maximum loss for the bank is equal to the sum of the contract-level credit exposures:

$$E(t) = \sum_i E_i(t) = \sum_i \max\{V_i(t), 0\} \tag{2}$$

This exposure can be greatly reduced by the means of netting agreements. A netting agreement is a legally binding contract between two counterparties that, in the event of default, allows aggregation of transactions between two counterparties – i.e., transactions with negative value can be used to offset the ones with positive value and only the net positive value represents credit exposure at the time of default. Thus, the total credit exposure created by all transactions in a netting set (i.e., those under the jurisdiction of the netting agreement) is reduced to the maximum of the net portfolio value and zero:

$$E(t) = \max\left\{\sum_i V_i(t),\ 0\right\} \tag{3}$$

More generally, there can be several netting agreements with one counterparty. There may also be trades that are not covered by any netting agreement. Let us denote the k th netting agreement with a counterparty as NA_k. Then, the counterparty-level exposure is given by

$$E(t) = \sum_k \max\left[\sum_{i \in \mathrm{NA}_k} V_i(t),\ 0\right] + \sum_{i \notin \{\mathrm{NA}\}} \max\left[V_i(t), 0\right] \tag{4}$$

The inner sum in the first term sums values of all trades covered only by the k th netting agreement (hence, the $i \in \mathrm{NA}_k$ notation), while the outer one sums exposures over all netting agreements. The second term in Equation 4 is simply the sum of contract-level exposures of all trades that do not belong to any netting agreement (hence, the $i \notin \{\mathrm{NA}\}$ notation).

Modelling Credit Exposure

In this section, we describe a general framework for calculating the potential future exposure on the OTC derivative products. Such a framework is necessary for banks to compare exposure against limits, to price and hedge counterparty credit risk and to calculate economic and regulatory capital.[3] These calculations may lead to different characteristics of the exposure distribution — such as expectation, standard deviation and percentile statistics. The exposure framework outlined herein is universal because it allows one to calculate the entire exposure distribution at any future date. (For more details, see De Prisco and Rosen [2005] and Pykhtin and Zhu [2006].)

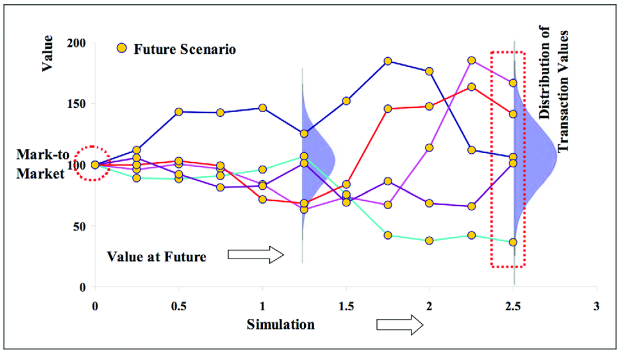
There are three main components in calculating the distribution of counterparty-level credit exposure:

1. Scenario Generation. Future market scenarios are simulated for a fixed set of simulation dates using evolution models of the risk factors.
2. Instrument Valuation. For each simulation date and for each realization of the underlying market risk factors, instrument valuation is performed for each trade in the counterparty portfolio.
3. Portfolio Aggregation. For each simulation date and for each realization of the underlying market risk factors, counterparty-level exposure is obtained according to Equation 4 by applying necessary netting rules.

The outcome of this process is a set of realizations of counterparty-level exposure (each realization corresponds to one market scenario) at each simulation date, as schematically illustrated in Figure 1, next page.

Because of the computational intensity required to calculate counterparty exposures — especially for a bank with a large portfolio — compromises are usually made with regard to the number of simulation dates and/or the number of market scenarios. For example, the number of market scenarios is limited to a few thousand and the simulation dates (also called "time buckets") used by most banks to calculate credit exposure usually comprise daily or weekly intervals up to a month, then monthly up to a year and yearly up to five years, etc.

Figure 1: Simulation Framework for Credit Exposure



Scenario Generation

The first step in calculating credit exposure is to generate potential market scenarios at a fixed set of simulation dates $\{t_k\}_{k=1}^{N}$ in the future. Each market scenario is a realization of a set of *price factors* that affect the values of the trades in the portfolio. Examples of price factors include foreign exchange (FX) rates, interest rates, equity prices, commodity prices and credit spreads.

There are two ways that we can generate possible future values of the price factors. The first is to generate a "path" of the market factors through time, so that each simulation describes a possible trajectory from time t=0 to the longest simulation date, t=T. The other method is to simulate directly from time t=0 to the relevant simulation date t.

We will refer to the first method as "Path-Dependent Simulation (PDS)" and to the second method as "Direct Jump to Simulation Date (DJS)." Figure 2A (across, top) illustrates a sample path for $X(t_i)$, while Figure 2B (across, bottom) illustrates a direct jump to a simulation date.

Figure 2 (A and B): Two Ways of Generating Market Scenarios >>

The scenarios are usually specified via stochastic differential equations (SDE). Typically, these SDEs describe Markovian processes and are solvable in closed form. For example, a popular choice for modelling FX rates and stock indices is the generalized geometric Brownian motion given by

$$dX(t) = \mu(t)X(t)dt + \sigma(t)X(t)dw_t \qquad (5)$$

where $\mu(t)$ is time-dependent drift and $\sigma(t)$ is time-dependent deterministic volatility. From the known solution of this SDE, we can construct either the PDS model:

$$X(t_k) = X(t_{k-1})\exp\left([\bar{\mu}_{k-1,k} - \tfrac{1}{2}\bar{\sigma}^2_{k-1,k}](t_k - t_{k-1}) + \bar{\sigma}_{k-1,k}\sqrt{t_k - t_{k-1}}\,Z\right) \qquad (6)$$

or the DJS model:

$$X(t_k) = X(0)\exp\left([\bar{\mu}_{0,k} - \tfrac{1}{2}\bar{\sigma}^2_{0,k}]t_k + \bar{\sigma}_{0,k}\sqrt{t_k}\,Z\right) \qquad (7)$$

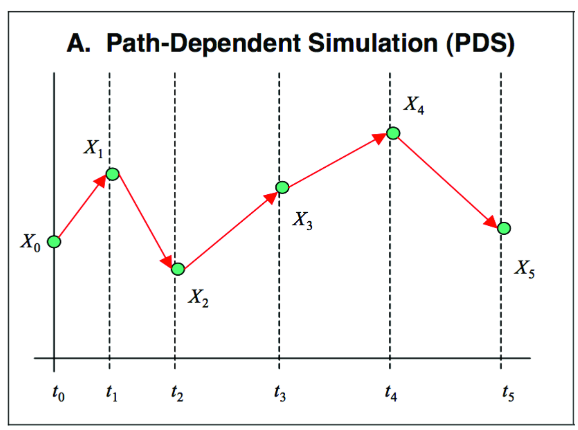
where is a standard normal variable and

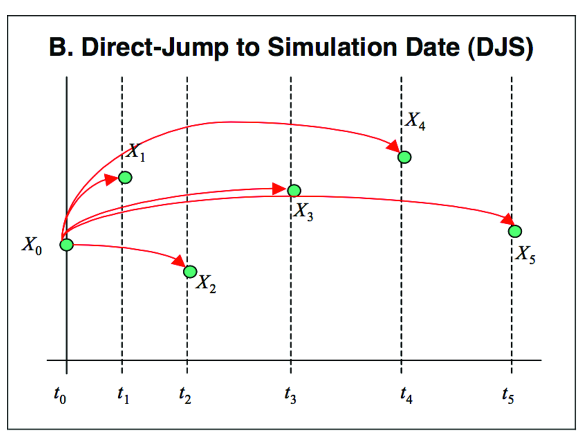
$$\bar{\mu}_{j,k} = \frac{1}{t_k - t_j}\int_{t_j}^{t_k}\mu(s)ds\,, \qquad \bar{\sigma}^2_{j,k} = \frac{1}{t_k - t_j}\int_{t_j}^{t_k}\sigma^2(s)ds \qquad (8)$$

The price factor distribution at a given simulation date obtained using either PDS or DJS is identical. However, a PDS method may be more suitable for path-dependent, American/Bermudan and asset-settled derivatives.

Scenarios can be generated either under the real probability measure or under the risk-neutral probability measure. Under the real measure, both drifts and volatilities are calibrated to the historical data of price factors. Under the risk-neutral measure, drifts must be calibrated to ensure there is no arbitrage of traded securities on the price factors. Additionally, volatilities must be calibrated to match market-implied volatilities of options on the price factors.

For example, the risk-neutral drift of an FX spot rate is simply given by the interest rate difference between domestic and foreign currencies, and the volatility should be equal to





the FX option implied volatility. Traditionally, the real measure has been used in risk management modelling of future events. However, such applications as pricing counterparty risk may require modelling scenarios under the risk-neutral measure.

Instrument Valuation

The second step in credit exposure calculation is to value the instrument at different future times using the simulated scenarios. The valuation models used to calculate exposure could be very different from the front-office pricing models. Typically, analytical approximations or simplified valuation models are used.

While the front office can afford to spend several minutes or even hours for a trade valuation, valuations in the credit exposure framework must be done much faster, because each instrument in the portfolio must be valued at many simulation dates for a few thousand market risk scenarios. Therefore, valuation models such as those that involve Monte Carlo simulations or numerical solutions of partial differential equations do not satisfy the requirements on computation time.

Path-dependent, American/Bermudan and asset-settled derivatives present additional difficulty for valuation that precludes direct application of front-office models. The value of these instruments may depend on either some event that happened at an earlier time (e.g., exercising an option) or on the entire path leading to the valuation date (e.g., barrier or Asian options). This does not present a problem for front-office valuation, which is always done at the *present* time when the entire path prior to the valuation date is known. For example, front-office systems always know at the valuation time whether an option has been exercised or a barrier has been hit.

In contrast, risk management valuation is done at a discrete set of *future* simulation dates, while the value of an instrument may depend on the full continuous path prior to the simulation date or on a discrete set of dates different from the given set of simulation dates. For example, at a future simulation date, it is often not known with certainty whether a barrier option is alive or dead or whether a Bermudan swaption has been exercised.

This problem presents an even greater challenge for the DJS approach, where scenarios at previous simulation dates are completely unrelated to scenarios at the current simulation date. As a solution to this problem, Lomibao and Zhu (2005) proposed the notion of "conditional valuation," which is a probabilistic technique that "adjusts" the mark-to-market valuation model to account for the events that could happen between the simulation dates.

Let us assume that we know how to price a derivative when all information about the past is known. We will denote this mark-to-market (MTM) value at simulation date t_k by $V_{\text{MTM}}(t_k,\{X(t)\}_{t\le t_k})$, where $X(t)$ is the market price factor that affects the value of the derivative contract. However, the complete path of the price factor is not known at t_k. Under a PDS approach, the risk factor is only known at a discrete set of simulation dates, while under a DJS approach, the risk factor is not known at all between today (t=0) and the simulation date (t=t_k).

The idea behind conditional valuation is to average future MTM values over all continuous paths of price factors consistent with a given simulation scenario. Mathematically, we set the value of a derivative contract at a future simulation date equal to the expectation of the MTM value, conditional on all the information available between today and the simulation date. Under the PDS approach, the scenario is given by the set of price factor values x_j at all simulation dates t_j, such that $j \le k$. The conditional valuation is given by

$$V_{\text{PDS}}\left(t_k,\{X(t_j)\}_{j=1}^{k}\right) = \mathrm{E}\left[V_{\text{MTM}}\left(t_k,\{X(t)\}_{t\le t_k}\right)\middle|\{X(t_j)=x_j\}_{j=1}^{k}\right] \quad (9)$$

Under the DJS approach, the scenario is given by a single price factor value x_k at the current simulation date t_k. The conditional valuation is given by

$$V_{\text{DJS}}\left(t_k,X(t_k)\right) = \mathrm{E}\left[V_{\text{MTM}}\left(t_k,\{X(t)\}_{t\le t_k}\right)\middle|X(t_k)=x_k\right] \quad (10)$$

Lomibao and Zhu (2005) have shown that these conditional expectations can be computed in closed form for such instruments as barrier options, average options and physically settled swaptions. The conditional valuation approach described by Equations 9 and 10 provides a consistent framework within which the transactions of various types can be aggregated to recognize the benefits of the netting rule across multiple price factors.

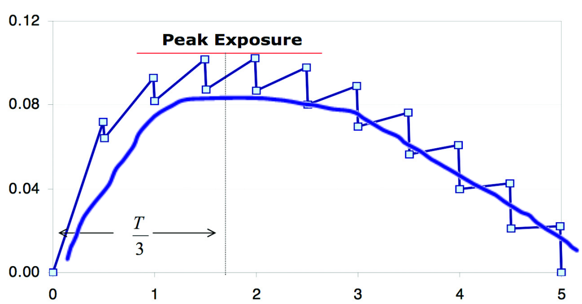
Exposure Profiles

Uncertain future exposure can be visualized by means of exposure profiles. These profiles are obtained by calculating certain statistics of the exposure distribution at each simulation date. For example, the expected exposure profile is obtained by computing the expectation of exposure at each simulation date, while a potential future exposure profile (such profiles are popular for measuring exposure against credit limits) is obtained by computing a high-level (e.g., 95%) percentile of exposure at each simulation date. Though profiles obtained from different exposure measures have different magnitude, they normally have similar shapes.

There are two main effects that determine the credit exposure over time for a single transaction or for a portfolio of transactions with the same counterparty: diffusion and amortization. As time passes, the "diffusion effect" tends to increase the exposure, since there is greater variability and, hence, greater potential for market price factors (such as the FX or interest rates) to move significantly away from current levels; the "amortization effect," in contrast, tends to decrease the exposure over time, because it reduces the remaining cash flows that are exposed to default.

These two effects act in opposite directions — the diffusion effect increases the credit exposure and the amortization effect decreases it over time. For single cash flow products, such as FX forwards, the potential exposure peaks at the maturity of the transaction, because it is driven purely by diffusion effect.[4] On the other hand, for products with multiple cash flows, such as interest-rate swaps, the potential exposure usually peaks at one-third to one-half of the way into the life of the transaction, as shown in the following exhibit:

Figure 3: Exposure Profile of Interest-Rate Swap



Different types of instruments can generate very different credit exposure profiles, and the exposure profile of the same instruments may also vary under different market conditions. When the yield curve is upward sloping, the exposure is greater for a payer swap than the same receiver swap, because the fixed payments in early periods are greater than the floating payments, resulting in positive forward values on the payer swap. The opposite is true if the yield curve is downward sloping.

However, for a humped yield curve, it is not clear which swap carries more risk, because the forward value on a payer swap is initially positive and then becomes negative (and vice versa for a receiver swap). The overall effect implies that both are almost "equally risky" — i.e., the exposure is roughly the same between a payer swap and a receiver swap. Counterparty-level exposure profiles usually have a less intuitive shape than simple trade-level profiles. These profiles are very useful in comparing credit exposure against credit limits and calculating economic and regulatory capital, as well as in pricing and hedging counterparty risk.

Collateral Modelling for Margined Portfolios

Banks that are active in OTC derivative markets are increasingly using margin agreements to reduce counterparty credit risk. A margin agreement is a legally binding contract that requires one or both counterparties to post collateral when the uncollateralized exposure exceeds a threshold and to post additional collateral if this excess grows larger. If this excess of uncollateralized exposure over the threshold declines, part of the posted collateral (if there is any) is returned to bring the difference back to the threshold. To reduce the frequency of collateral exchanges, a minimum transfer amount (MTA) is specified; this ensures that no transfer of collateral occurs unless the required transfer amount exceeds the MTA.

The following time periods are essential for margin agreements:

- Call Period. The period that defines the frequency at which collateral is monitored and called for (typically, one day).
- Cure Period. The time interval necessary to close out the counterparty and re-hedge the resulting market risk.
- Margin Period of Risk. The time interval from the last exchange of collateral until the defaulting counterparty is closed out and the resulting market risk is re-hedged; it is usually assumed to be the sum of call period and cure period.

While margin agreements can reduce the counterparty exposure, they pose a challenge in modelling collateralized exposure. Below, we briefly outline a common procedure that has been used by many banks to model the effect of margin call and collateral requirements.

First, the collateral amount $C(t)$ at a given simulation date t is determined by comparing the uncollateralized exposure at time $t - s$ against the threshold value H

$$C(t) = \max\{E(t-s) - H, 0\} \tag{11}$$

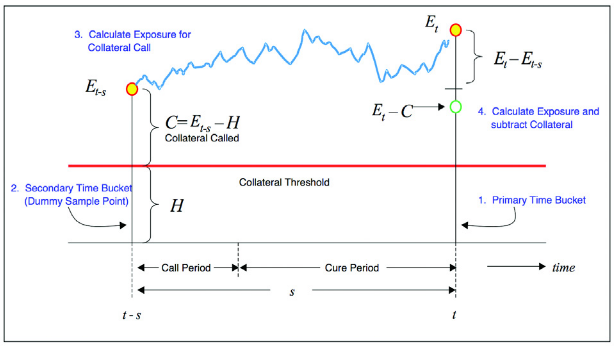
where s is the margin period of risk, and collateral is set to zero if it is less than the MTA. Subsequently, the collateralized exposure at the simulation date t is calculated by subtracting the collateral $C(t)$ from the uncollateralized exposure

$$E_C(t) = \max\{E(t) - C(t), 0\} \tag{12}$$

To compute exposure at time $t - s$, additional simulation dates (secondary time buckets) are placed prior to the main simulation dates. Since the margin period of risk can be different for different margin agreements, secondary time buckets are not fixed. This process is schematically illustrated in Figure 4, next page.

Collateral calculation requires the knowledge of exposure at the secondary time bucket. The obvious approach is calculating this exposure by the Monte-Carlo simulation. This, however, would result in doubling the computation time for margined counterparties. In 2006 (see references), we proposed a simplified approach to modelling the collateral. We used the concept of the conditional valuation approach of Lomibao and Zhu (2005) and calculated the exposure value at the secondary time bucket $t - s$ for each scenario as the expectation conditional on simulated exposure value at the primary simulation date(s).

Figure 4: Treatment of Collateral at Secondary Time Bucket



Credit Value Adjustment

For years, the standard practice in the industry was to mark derivatives portfolios to market without taking the counterparty credit quality into account. All cash flows were discounted by the LIBOR curve, and the resulting values were often referred to as risk-free values.[5] However, the true portfolio value must incorporate the possibility of losses due to counterparty default. Credit value adjustment (CVA) is by definition the difference between the risk-free portfolio value and the true portfolio value that takes into account the possibility of a counterparty's default. In other words, CVA is the market value of counterparty credit risk.

How do we calculate CVA? Let us assume that a bank has a portfolio of derivative contracts with a counterparty. We will denote the bank's exposure to the counterparty at any future time t by $E(t)$. This exposure takes into account all netting and margin agreements between the bank and the counterparty. If the counterparty defaults, the bank will be able to recover a constant fraction of exposure that we will denote by R. Denoting the time of counterparty default by τ, we can write the discounted loss as

$$L^* = 1_{\{\tau \le T\}}(1-R)\frac{B_0}{B_\tau}E(\tau) \quad (13)$$

where T is the maturity of the longest transaction in the portfolio, B_t is the future value of one unit of the base currency invested today at the prevailing interest rate for maturity t. and $1_{\{.\}}$ is the indicator function that takes value one if the argument is true (and zero otherwise).

Unilateral CVA is given by the risk-neutral expectation of the discounted loss. The risk-neutral expectation of of Equation 13 can be written as

$$\mathrm{CVA} = \mathrm{E}^Q[L^*] = (1-R)\int_0^T \mathrm{E}^Q\left[\frac{B_0}{B_t}E(t)\middle|\tau = t\right] d\mathrm{PD}(0,t) \quad (14)$$

where $\mathrm{PD}(s,t)$ is the risk neutral probability of counterparty default between times s and t. These probabilities can be obtained from the term structure of credit-default swap (CDS) spreads.

We would like to emphasize that the expectation of the discounted exposure at time t in Equation 14 is conditional on counterparty default occurring at time t. This conditioning is material when there is a significant dependence between the exposure and counterparty credit quality. This dependence is known as right/wrong-way risk.

The risk is wrong way if exposure tends to increase when counterparty credit quality worsens. Typical examples of wrong-way risk include (1) a bank that enters a swap with an oil producer where the bank receives fixed and pays the floating crude oil price (lower oil prices simultaneously worsen credit quality of an oil producer and increase the value of the swap to the bank); and (2) a bank that buys credit protection on an underlying reference entity whose credit quality is positively correlated with that of the counterparty to the trade. As the credit quality of the counterparty worsens, it is likely that the credit quality of the reference name will also worsen, which leads to an increase in value of the credit protection purchased by the bank.

The risk is right way if exposure tends to decrease when counterparty credit quality worsens. Typical examples of right-way risk include (1) a bank that enters a swap with an oil producer where the bank pays fixed and receives the floating crude oil price; and (2) a bank that sells credit protection on an underlying reference entity whose credit quality is positively correlated with that of the counterparty to the trade.

While right/wrong-way risk may be important for commodity, credit and equity derivatives, it is less significant for FX and interest rate contracts. Since the bulk of banks' counterparty credit risk has originated from interest-rate derivative transactions, most banks are comfortable to assume independence between exposure and counterparty credit quality.

Exposure, Independent of Counterparty Default

Assuming independence between exposure and counterparty's credit quality greatly simplifies the analysis. Under this assumption, Equation 14 simplifies to

$$\mathrm{CVA} = (1-R)\int_0^T \mathrm{EE}^*(t)\, d\mathrm{PD}(0,t) \quad (15)$$

where $\mathrm{EE}^*(t)$ is the risk-neutral discounted expected exposure (EE) given by

$$\mathrm{EE}^*(t) = \mathrm{E}^Q\left[\frac{B_0}{B_t}E(t)\right] \quad (16)$$

which is now independent of counterparty default event.

Discounted EE can be computed analytically only at the contract level for several simple cases. For example, exposure of a single European option is $E(t)=V_{EO}(t)$, because European option value $V_{EO}(t)$ is always positive. Since there are no cash flows between today and option maturity, substitution of this exposure into Equation 16 yields a flat discounted EE profile at the current option value: $EE^*_{EO}(t)=V_{EO}(0)$.

However, calculating discounted EE at the counterparty level requires simulations. These simulations can be performed according to the exposure modelling framework described in the previous section. According to this framework, exposure is simulated at a fixed set of simulation dates $\{t_k\}_{k=1}^{N}$. Therefore, the integral in Equation 15 has to be approximated by the sum:

$$\text{CVA} = (1-R)\sum_{i=1}^{N} \text{EE}^*(t_k)\,\text{PD}(t_{k-1},t_k) \quad (17)$$

Since expectation in Equation 16 is risk neutral, scenario models for all price factors should be arbitrage free. This is achieved by appropriate calibration of drifts and volatilities specified in the price-factor evolution model. Drift calibration depends on the choice of numeraire and probability measure, while volatilities should be calibrated to the available prices of options on the price factor.

For PDS scenarios, the same probability measure should be used across all simulation dates (i.e., the use of spot risk-neutral measure is appropriate). In contrast, the DJS approach does not require the same probability measure, because scenarios at different simulation dates are not directly connected. A very convenient choice of measure under the DJS approach is to model exposure under the forward to simulation date probability measure P_t, which makes it possible to use today's zero coupon bond prices $B(0,t)$ for discounting exposure:

$$\text{EE}^*(t) = B(0,t)\,\text{E}^{P_t}[E(t)] \quad (18)$$

In principle, Equation 18 is equivalent to Equation 16 and, if properly calibrated, they should generate the same result.

Parting Thoughts

Any firm participating in the OTC derivatives market is exposed to counterparty credit risk. This risk is especially important for banks that have large derivatives portfolios. Banks manage counterparty credit risk by setting credit limits at counterparty level, by pricing and hedging counterparty risk and by calculating and allocating economic capital.

Modelling counterparty risk is more difficult than modelling lending risk, because of the uncertainty of future credit exposure. In this article, we have discussed two modelling issues: modelling credit exposure and calculating CVA. Modelling credit exposure is vital for any risk management application, while modelling CVA is a necessary step for pricing and hedging counterparty credit risk. ■

FOOTNOTES

1. There is a much more remote risk of loss if the exchange itself fails with insufficient collateral in hand to cover all its obligations.
2. In reality, the bank may or may not replace the contract, but the loss can always be determined under the replacement assumption. The loss is, of course, independent of the strategy the bank chooses after the counterparty's default.
3. Economic and regulatory capital are out of scope of this article because of space limitation. Economic capital for counterparty risk is covered in Picoult (2004). For regulatory capital, see Fleck and Schmidt (2005).
4. Currency swaps are also an exception to this amortization effect since most (although not all) of the potential value arises from exchange-rate movements that affect the value of the final payment.
5. This description is not entirely accurate, because LIBOR rates roughly correspond to AA risk rating and incorporate typical credit risk of large banks.

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