the Risk DESK

WWW.SCUDDERPUBLISHING.COM

Volume IV Number 10

SPECIAL REPRINT

## Credit Risk Via EWRM, Part II

### Credit Risk Management for Energy and Commodity Firms in a EWCRM framework

*By Carlos Blanco and Robert Mark*

*This is the second article on an enterprise wide credit risk management (EWCRM) framework. In our first article, we provided an overview of some of the key issues in counterparty risk measurement and management for energy and commodity firms. In this second article, we focus on credit risk potential future exposure (PFE) modeling and the integration of credit risk into both transaction-level pricing and portfolio risk measures.*

**1. Potential Future Exposure Modeling**

Credit risk limits for derivative transactions are typically based on the amount of worst-case exposure. Credit exposure is the amount that would be lost if the counterparty were to default and the transaction were in the money. There is typically an implicit assumption in measuring credit exposure that if the counterparty were to default there would be a zero recovery. The worst-case exposure is the sum of the "current exposure" (CE) plus the "potential future exposure" (PFE). The CE is the current mark–to-market (or mark-to-model) value of the exposure to a counterparty. The PFE is the projected worst-case potential exposure over the life of the transaction with a given degree of statistical confidence[1].

There are several generally accepted versions of a PFE. For example, you can use a "maximum likely potential future exposure" (MLPFE) that is associated with a particular percentile of the PFE distribution through time (e.g. 97.5 percent.). Another PFE measure that can be

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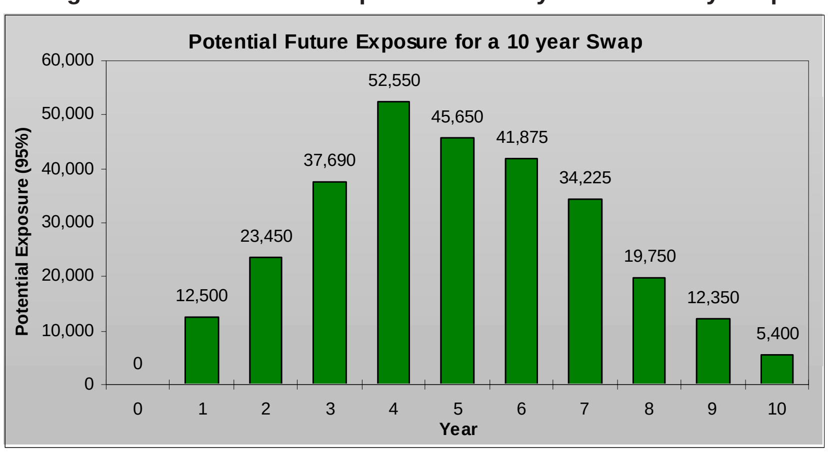
related to the MLPFE is the "average worst-case potential future exposure. "Consistency between exposure measurement and limit design is important. For example, if the firm uses the MLPFE measure of credit risk, then limits should be set in terms of worst-case potential credit risk exposures (in contrast to the average worst-case credit risk exposures). Another measure of PFE is the peak of the PFE through time, which looks at the worst possible scenario and it is referred to as the "maximum potential future exposure" (MPFE).

The "expected future exposure" (EFE) is the average expected exposure over the life of the derivative. The EFE curve is also referred to as the "credit-equivalent" or "loan-equivalent" exposure curve. The EFE is typically used as input to the methodology used for pricing credit charges into deals as well as for calculating economic capital.

The shape of credit exposure profiles is especially important because credit exposures must be viewed over the life of the transaction. Different types of instruments generate different credit exposure profiles because they are impacted by two effects associated with the passage of time: the diffusion effect and the amortization effect. The diffusion effect describes the increasing probability that the value of a position will travel further away from the initial value, thus increasing the amount exposed to default. The amortization effect describes the cash flow from a transacting party to its counterparty over time (e.g. in the form of swap payments), thus reducing the remaining value that is exposed to default. For example, if you are approaching the expiration of a 10-year swap with monthly settlements, the risk of the swap would be relatively low, since most swap payments have already taken place (see Figure 1).

**Figure 1: Potential future exposure for a 10-year commodity swap**

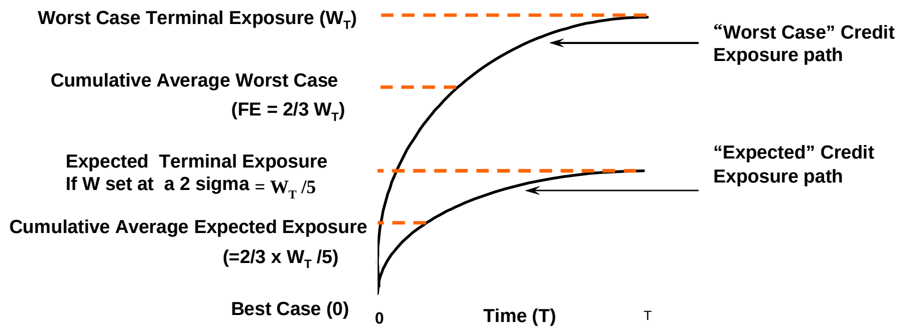



The worst-case credit risk exposure for a typical single cash flow product at time t ($W_t$) grows as a function of time and peaks at the maturity of the transaction. For example, a forward contract with a single payment at the maturity of the instrument would follow this pattern. This is due to the fact that a forward contract contains an embedded option for any of the counterparties to default (see Panel 1, page 7).

Let us define the worst-case credit risk exposure at a K standard deviation level (e.g. if K=2, then we have a one-sided 97.5 percent confidence level). Further, assume for illustrative purposes that the worst-case credit risk exposure at time t is equal to $[K \times s \times t^{1/2}]$, where K is a function of the desired confidence interval, s is the overnight volatility of the position's percentage change in price and t varies from 0 to T. Assume that the distribution of returns can be characterized by normal probability density function (pdf), with a zero mean.

Assume, for simplicity, that the standard deviation of the normal pdf comes from a stable stochastic process where the risk grows as a function of the square root of time. For illustrative purposes, we will also assume that the probability of default is uniformly distributed over the time period. If we integrate the worst-case function over the entire time period T and divide this result by the time period [T], then we can see that the cumulative average worst-case credit risk exposure is two-thirds of the worst-case credit risk exposure. In other words, ignoring present-value considerations, the energy trading firm needs only to perform the necessary integration to show that the cumulative average worst-case credit risk exposure is $2/3\ W_T$ (See Figure 2).This computation for time T can also be approached using an option-pricing framework.

**Figure 2 Credit exposure of an instrument expressed as credit exposure functions**




This add-on approach to estimate PFE measures has some limitations. For large or complex transactions, a multistep, simulation-based approach is more accurate and therefore should be used as a benchmark for several reasons. Energy price behavior is not well characterized by normal or lognormal distributions, thus the square-root-of-time rule does not apply.

Electricity or gas price spikes can dramatically alter the exposure to a counterparty in a very short time period. Accordingly, it is important that the measures of potential future exposure provide an indication of the possible extent of the damage coming from large market swings. A simulation framework can accommodate more realistic price processes with mean reversion and jumps. For example, in Figure 3, we can clearly observe the "jumps" in the price of the NYMEX natural gas contract for November 2004 delivery. Similar behavior is standard for spot electricity prices and has also been recently observed in other energy commodities such as crude oil, jet fuel and heating oil. The consequences for large users and distributors of those commodities that did not have the right hedg-

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ing programs will be felt in the coming months, forcing some of those firms into bankruptcy. On the week of Oct. 18, Star Gas Partners, one of the largest heating oil distributors in the US, announced that it may be forced into bankruptcy due to soaring heating oil prices and its inability to pass those price increases to their customers. Most airlines are suffering similar problems, and the conscious decision of many of those airlines not to hedge a substantial component of their jet fuel purchases has turned into a very costly gamble for an industry that was already in a delicate situation.

On the other hand, many energy contracts contain embedded price and volumetric options that could considerably amplify or reduce the potential exposure of a deal. Examples of those contracts are natural gas swing contracts and electricity full requirement contracts. Natural gas swing contracts allow users to swing up or down the amount of gas purchased at a fixed price for a predetermined number of times in a particular period. Full requirement contracts allow users to take as much power as needed at fixed prices.

Finally, in the simulation framework, we should also take into account netting, margining provisions, payment terms as well as management intervention levels. The simulation framework can also incorporate other components, such as market liquidity conditions and operations risks (outages, pipeline blowups, etc.).

Due to their complexity, PFE models should be thoroughly vetted before and after they are deployed for day-to-day use. Credit risk managers and analysts can provide valuable information regarding the quality of the output from the model and the source of discrepancies versus expectations. It is important to document the assumptions and steps in the calculations, as well as to undergo a robust backtesting analysis of the models on a regular basis. Internal and external auditors should confirm that the implementation and use of the PFE models is sound.

**Panel 1: Do derivatives contain embedded options to default?**

Credit risk managers know very well that when a firm is in a dramatic liquidity situation, one of its last resorts is to write options. A firm that is willing to sell options below market value is sending a clear warning signal that it may be facing financial difficulties. A similar situation occurs with other derivatives that do not contain embedded price optionality, such as swaps or forwards, although in these cases the option is reciprocal, as each of the counterparties can default on each other. Collateral can serve as a deterrent for counterparties to exercise their options to default by making the default option out of the money. If they default, they would lose their collateral. In the absence of collateral, the strike price of the option is zero. To the extent that derivative transactions have embedded default options, a counterparty credit charge should be applied to analyze the risk/return trade-off and capital reserves should be allocated to cover potential losses arising from those positions.

**Figure 3: NYMEX Natural Gas November 2004 Contract**


**2. Credit Loss Distributions**

The PFE is an important input for calculating potential losses, but in order to obtain an indication of expected losses, we need to include other variables. The probable loss on any transaction or portfolio of transactions depends on four variables:

✧ **Potential exposure:** amount exposed to credit risk;

✧ **Probability of Loss (PD):** probability of the counterparty defaulting;

✧ **Recovery rate(RR):** amount of the defaulted position that is likely to be recovered; and

✧ **Conditional Loss Given Default (LGD):** amount likely to be lost if the counterparty does indeed default.

The problem of measuring potential credit losses is complex due to the challenges associated with finding the best way of estimating each of these variables and determining an appropriate way of integrating them so that, given default, loss can be calculated.

Energy firms need to develop techniques to calculate the default rate path and the distribution around the default rate path, which is estimated by examining those distributions at specific points in the future. For example, as shown in Table 1 for senior

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unsecured debt, the default rate distribution at specific points over the life of a transaction can be modeled through analyses of Standard & Poor's or Moody's data concerning the default rates of publicly-rated institutions. Table 1 clearly shows a few examples of the widespread credit downgrades for electric utilities in the US since 2001, due to the Enron collapse and the meltdown of the largest wholesale power marketers.

**Table 1: Selected Moody's rating downgrades for US Electric Utilities**

| Company | Date | Rating |
|---|---|---|
| AMERCIAN ELECTRIC POWER CO. INC. | 10 FEB 2003 | Baa3 |
| | 11 DEC 2002 | Baa2 |
| AVISTA CORP. | 1 JUL 2003 | B2 |
| | 6 NOV 2002 | B1 |
| | 1 OCT 2002 | Ba1 |
| | 28 MAR 2002 | Baa2 |
| | 27 MAR 2001 | Baa1 |
| | 8 OCT 2001 | Ba1 |
| | 27 JUL 2000 | Baa2 |
| CALPINE CORP. | 20 OCT 2003 | Caa1 |
| | 2 APR 2002 | B1 |
| | 14 DEC 2001 | Ba1 |
| DUKE ENERGY CORP. | 17 JUN 2003 | Baa1 |
| | 23 DEC 2002 | A3 |
| | 16 JAN 2001 | Caa3 |
| | 5 JAN 2001 | Baa3 |
| | 6 JUL 2000 | A3 |
| PROGRESS ENERGY INC. | 7 FEB 2003 | Baa2 |
| | 24 APR 2002 | B2 |
| | 1 APR 2002 | Ba2 |
| | 9 MAY 2001 | Baa3 |
| TECO ENERGY INC. | 10 FEB 2004 | Ba2 |
| | 21 APR 2003 | Ba1 |
| | 24 SEP 2002 | Baa2 |
| | 27 MAR 2001 | A3 |
| TXU CORP. | 1 APR 2003 | Caa1 |
| | 21 FEB 2003 | B1 |
| | 13 DEC 2002 | Ba1 |
| | 3 SEP 2002 | Ba2 |

*Source: Moody's.*

Most institutions combine information gathered from agency data with their own proprietary default rate data (e.g., loan default data). They also analyze the credit spreads of securities – yields of specific securities over duration-equivalent, risk-free securities to generate a default rate distribution.

These estimates of future default rate distributions are typically calculated for each credit grade. For example, the distribution of future default rates can be characterized in terms of an expected default rate (e.g., 1 percent) and a worst-case default rate (e.g., 3 percent). The difference between the worst-case default rate and the expected default rate is often termed the "unexpected default rate" (i.e., 2 percent = 3 percent – 1 percent). Typically, the distribution is highly asymmetric. A worst-case default rate may be structured so that one can say there is a prespecified probability (e.g., 2.5 percent) of exceeding the worst-case default rate. The probability density function describes how the probability of default varies over time; clearly, the longer the maturity of the financial instrument, the greater the default rate.

The third factor needed to calculate counterparty credit loss is the recovery rate path. The distribution around the recovery rate path needs to be estimated at specific points in the future. Just like the other two variables, the recovery rate distribution can be used to determine an expected recovery rate or a worst-case recovery rate. For example, the recovery rate distributions may be modeled by means of Standard and Poor's or Moody's recovery rate data.

The estimates of future recovery rate distributions vary as a complex function of time. Recovery rate distributions do not typically follow a normal pdf (See Figure 4).

A simulation framework can integrate these three distributions – credit risk exposure, default and recovery data – in order to produce future credit loss distributions and associated expected credit loss metrics.

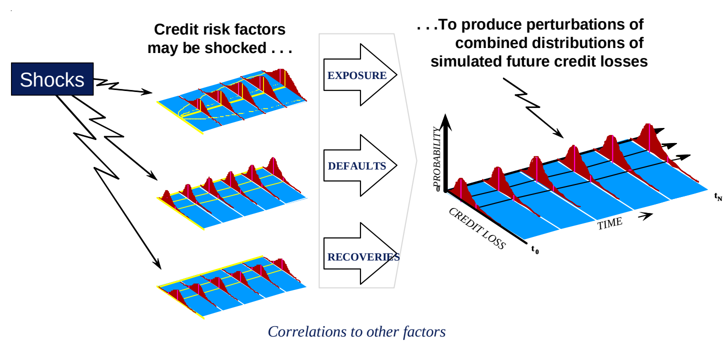
### 3. Charging traders for counterparty credit risk

Firms that do not have a credit risk capital charge system for traders (based on the unexpected potential loss for the firm in the event of default of counterparty, for example) are sending the wrong signals to risk-takers. Managements at those firms should not be surprised if they eventually find themselves taking considerable credit risk. Assume that a gas options trader has a large derivatives exposure with a small unrated firm. Assume further, that he wanted to offset that exposure, in the absence of a credit charge. The trader we find it easier to offset the original exposure with another counterparty of even more dubious credit standing rather than close the position.

Applying credit charges on a stand-alone basis can result in a significant adjustment to the value of the transaction for counterparties with significantly lower credit ratings than the firm conducting the valuation. There are several alternatives to adjust valuations in illiquid markets where credit is not explicitly priced. Risk managers should study the most appropriate way to adjust valuations in each market.

A "credit-related penalty" can be charged while the trade is "live" to account for the counterparty risk taken by the trader. That credit charge can be evaluated on a day-to-day or weekly

**Figure 4: Combining variables to produce credit loss distributions**




basis. Table 2 shows how to calculate credit penalties based on the current credit risk and the creditworthiness of the counterparty.

The credit penalty is calculated by multiplying the positive current exposure based on the current mark-to-market (MtM), less the value of the collateral posted by the annual credit

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spread adjusted for the horizon (e.g., in the case of a daily credit penalty for the basis swap, it would be calculated as the current exposure [$350,000] times the daily credit spread [1.50% x 1/365]). We can also appreciate the importance of collecting collateral on a continuous basis to avoid credit-related penalties. Observe that despite the fact the basis swap has a larger positive current MtM than the natural gas APO, the credit penalty of the basis swap is considerably lower due to the presence of collateral to offset potential credit losses and the lower credit spread associated with the counterparty due to their better internal rating.

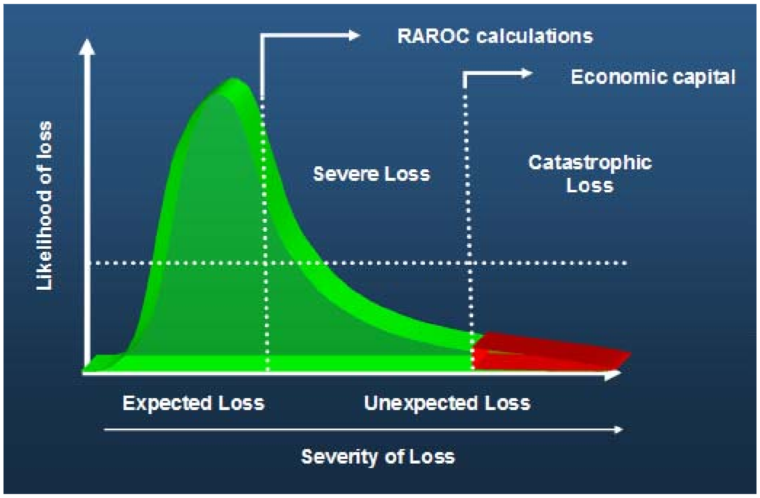
**Table 2: Example of Credit Risk Pricing into a transaction[2]:**

| | Current MtM | Current Exposure | Internal Rating | Annual Credit Spread | Daily Credit Penalty |
|---|---|---|---|---|---|
| **Natural Gas APO** | $875,000 | $650,000 | 7 | 275 bp | $48.97 |
| **Basis Swap** | $2,928,000 | $350,000 | 5 | 150 bp | $14.38 |

Risk charges for a new transaction can be measured on both a stand-alone and marginal contribution level. For example, if one transfers risk outside the firm, it can reduce both market and credit risk simultaneously. Traders need the appropriate information about the marginal contribution of a trade to both market and credit risk in order to measure the marginal effects. Sophisticated firms currently calculate the potential stand-alone and marginal credit exposure of every significant deal before giving the green light. In the pre-deal analysis, some firms also look for the best possible counterparty in terms of the diversified credit risk for the portfolio.

There is another application of credit spreads and default probabilities in determining ex-ante hedge effectiveness for accounting and economic purposes. In our previous article, we showed how marginal VaR at the counterparty level can provide an indication of the credit-related market risk. In a future piece, we will explore in more depth the impact of potential counterparty defaults and unstable correlations in setting up a hedge effectiveness program.

**Figure 5: Credit Loss Distribution, Expected and Unexpected Losses**




## 4. Capital at Risk

The credit value at risk (CVaR) of a credit portfolio is derived in a similar fashion as market VaR (MVaR). It is simply the distance from the mean of the percentile of the forward distribution, at the desired confidence level. Simplifying assumptions are typically made in order to estimate the portfolio's CVaR. The distribution of the rate of return of the portfolio of counterparties is typically assumed to be from a stable normal pdf.

Economic capital is the financial cushion that a firm uses to absorb unexpected losses, e.g., those related to credit events such as credit migration and/or default. Figure 5 illustrates how the capital charge related to credit risk can be derived:

In order to achieve a particular credit rating (e.g. AA), firms are expected to hold reserves against these unexpected losses at a given confidence level. The higher the credit rating desired, the lower the probability of incurring losses above the capital level over the period corresponding to the credit risk horizon.

Determining the economic capital allocated to each activity or business unit provides senior management with a mechanism to link risk and return, and therefore provide a risk/reward signal that can be used at different levels of the firm. An investment evaluation process based on economic capital considerations (where decisions are based on a risk-adjusted return basis, for example) encourages corporate managers to take risk into consideration explicitly at the time of allocating resources internally, and to make investment and divestment decisions.

Risk adjusted return on capital (RAROC) ratios relate the return on capital provided by a risk-taking business unit to the risk of the investment required to generate that return. RAROC enables management to answer such questions as: How can managers determine which businesses are the most efficient generators of revenue on a risk-adjusted basis? What type of returns should be expected given the risk assumed to generate them? We can produce ex-ante RAROC estimates to allocate capital once we have an estimate of both the expected returns (net of expenses and expected losses), as well as the capital required to sustain each activity. We can use the actual profits or losses achieved by each risk-taking unit to determine the ex-post risk-adjusted returns for performance measurement once the actual results are known.

## 4. Conclusion

Credit risk management has received a great deal of attention due to the dramatic failures of major energy-trading entities such as Enron, Mirant and NRG. Accordingly, energy and commodity firms have realized the vital importance of developing a strong credit culture throughout the organization, as well as having an independent and knowledgeable credit risk group. In this article, we have introduced credit risk in the context of a EWCRM program. A robust framework to measure and manage potential counterparty future exposures is a "must-have" capability due to the increased importance of counterparty risk.

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Finally, we have pointed out that economic capital and risk-adjusted return on capital (RAROC) analysis for counterparty risks is a critical part of a EWCRM framework. The increasing complexity and degree of interaction of the risks involved in running energy or commodity trading operation means that enterprise-wide risk education and awareness should be a critical item in the agenda of senior executives and directors of the boards in order to meet their fiduciary responsibilities.

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*The authors welcome your feedback and would like to thank Dr. Kevin Dowd and Chris Mammarelli from Black Swan Risk Advisors for helpful conversations and insights, and Moody's for providing the credit data shown in Table 1.*

**(Footnotes)**

**1** Current and potential credit exposure includes such items as energy delivered that has not yet been settled or any energy that must be delivered until the contractual obligation can be halted in the event of a default by the counterparty. These situations arise when the supply contracts do not contain immediate termination clauses that would allow for a quick interruption of supply in the event of a counterparty default.

**2** A natural gas average price option (APO) is an Asian-style option settled on the average of natural gas prices over a particular period of time. A locational basis swap is a swap in which payments are determined based on the basis between prices for the same commodity at two different locations.