Best market practice for calculation and reporting of wrong-way risk

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Introduction

The global financial crisis has illustrated the importance of the correct quantification of counterparty risk that arises from bilateral over-the-counter (OTC) derivative contracts. A significant amount of effort in quantifying counterparty risk by means of credit value adjustment (CVA) and debt value adjustment (DVA) has been the consequence. Regulatory capital requirements under Basel III and accounting standards such as IFRS 13 contain significant provisions for CVA capitalization and reporting. In line with these changes, most banks with material OTC derivative portfolios have some sort of "CVA desk" with the responsibility of pricing and managing CVA.

Wrong-way risk (WWR) is a natural feature that is added to the already complex framework for CVA quantification. WWR is a well-known relationship where the exposure to a counterparty is adversely related to that counterparty's default probability. In the global financial crisis, the potential dangers of WWR were illustrated, for example, when banks lost billions of dollars because of largely uncollateralized trades with monoline insurance companies.[1] WWR is also seen by CVA desks in hedging where comovements between credit spreads and other market variables can lead to losses caused by cross-gamma.

Regulators have identified general WWRs, which are driven by macroeconomic relationships, and specific WWRs, which are driven by causal links between the exposure and default of the counterparty, as critical to measure and control. Not surprisingly, Basel III has made strong recommendations over quantifying and managing WWR. Additional requirements aim in part to capitalize WWR, such as the use of stressed market data for calibration and a more conservative "alpha factor" definition.[2] In addition, qualitative and operational requirements regarding the identification and control of general and specific WWR have been identified.

Clearly, WWR must be addressed for correctly pricing trades, more accurately managing CVA and meeting regulatory requirements. However, WWR is very difficult to identify and to model because of the often subtle macroeconomic and structural effects that cause it. This report summarizes the causes and empirical evidence for WWR and detail the different modeling approaches and regulatory reporting with reference to best market practice.

Empirical evidence and examples

Empirical evidence and examples of WWR span various asset classes.

Interest rate products

Most banks have a CVA that is predominantly defined by interest rate products. The identification of WWR through the relationship between interest rates and credit spreads is therefore important. A clustering of corporate defaults in the US during periods of falling interest rates is most obviously interpreted as a recession, which leads to both low interest rates because of central bank intervention and a high default rate environment.[3] This has also been experienced in the last few years by banks on uncollateralized receiver interest swap positions that have moved in-the-money together with a potential decline in the financial health of the counterparty (for example, a sovereign or corporate). This effect can been seen as WWR that creates a cross-gamma effect by means of the strong linkage of credit spreads and interest rates, even in the absence of actual defaults.

The empirical evidence could be explained by a negative correlation between interest rates and credit spreads. However, such an approach might not be appropriate because it implies that a high interest rate environment leads to a low default rate environment that is caused by falling credit spreads. Misspecification can be a major issue in WWR modeling. An alternative and better specification might be to correlate the volatility of interest rates with credit spreads, which could lead to an approach whereby both significantly low and high interest rates regimes can be coupled with higher default rates.[4] This approach would be much harder to implement from a modeling point of view because of the prerequisite for some stochastic volatility interest rate model. As a result, basic CVA models might not be complex enough to properly incorporate WWR.

FX products

A currency contract must be considered in terms of a possible link between the relevant FX rate and the default probability of the counterparty. In particular, a potential weakening of the currency received by the counterparty vis-à-vis the paid currency should be a WWR concern. An obvious case would be in trading with a sovereign and paying their local currency. Another way to look at a cross-currency swap is that it represents a loan that is collateralized by the opposite currency in the swap. If this currency weakens dramatically, the value of the “collateral” is strongly diminished. A weakening of the currency could indicate a slow economy and therefore a less profitable time for the counterparty. Or, the default of a sovereign or large corporate counterparty could itself precipitate a currency weakening.

Introducing a correlation between the credit spread of the counterparty and the FX rate in question could generate a relationship that should be considered as general WWR. However, the WWR can also be specific because of a very clear link between the default of the counterparty and weakening of a currency. This effect has been well understood since the Asian crisis, whereby some dealers suffered heavy losses on cross-currency trades that involved Asian currencies and counterparties that were Asian banks. The implication is that, more extreme than a correlation, a jump occurs in the relevant FX rate at the counterparty default time. An examination of residual currency values upon default of the sovereign found average values that range from 17 percent (triple-A) to 62 percent (triple-C), which indicate the market implied jump of the FX rate involved at the default time of the counterparty.[5] A consideration of the impact of a default on FX rates illustrates that a pure correlation approach between the exchange rate and the hazard rate is not able to explain empirical data.[6]

This FX jump is also very clearly seen in quanto Credit Default Swaps (CDS) quotes on, for example, European sovereigns for Italian CDS (Table 1). The cheaper quotes in Euros versus US dollars are clear indications in risk-neutral probabilities of a devaluation of the Euro were Italy to default. Implied "devaluations" for the Euro of 91 percent for Greek default, 83 percent for Italian default and 80 percent for Spanish default have been reported.[7] The CDS market therefore enables a WWR effect in currencies to be observed and potentially also hedged against; this is probably the only time that WWR can be observed by using market prices.

Maturity	USD	EUR
1Y	50	35
2Y	73	57
3Y	96	63
4Y	118	78
5Y	131	91
7Y	137	97
10Y	146	103

Table 1: CDS quotes (midmarket) on Italy in both US dollars and Euros from April 2011.

Credit derivative products

In CDS contracts, a very clear WWR effect exists because the exposure is driven by the credit spread of the reference entity while the default probability depends on the counterparty credit spread. In the case of a strong relationship between the credit quality of the reference entity and the counterparty, such as buying single-name protection on a bank from another bank, the specific WWR is extreme. Credit derivatives are typically not easy to fit into a WWR framework with other asset classes because of the specific relationship between the default times of the reference entity and counterparty.

The bankruptcy of Lehman Brothers, a significant dealer and reference entity in the CDS market, illustrates how important WWR in credit derivative contracts can be. The failure of the risk transfer by banks to monoline insurers on structured credit products illustrated that specific WWR can essentially wipe out the perceived economic value of a transaction. Because the CDS market is heavily collateralized, an assessment of the benefit of collateral is critical to the WWR evaluation.

Commodity products

Commodity products are often argued to have right-way risk because of the hedging practices of the counterparties concerned. For example, an oil company that is hedging its exposure to low oil prices with an oil swap will create right-way risk for a bank. From the bank's perspective, exposure on the contract will happen when oil prices are high, which is when the oil company is unlikely to be in financial distress.[8] Another important concept arises in certain situations, however.

Consider a bank that is entering into an oil receiver swap with an airline. Such a contract enables the airline to hedge their exposure to rising oil prices, which is important because aviation fuel is a significant cost for the airline industry. From the bank's point of view, such a swap has exposure when the price of oil is low, but at this point, the credit quality of the airline should be sound because of their reduced fuel costs. The result could be right-way risk, but a potentially different linkage can be created instead. A low price of oil might be created by a severe recession, in which case the airline might also be expected to be in financial distress. This opposite effect, which was caused by low passenger numbers, was seen in the recent credit crisis. What might be perceived as a general right-way risk situation might also have specific WWR in relation to a strong price move caused by a systemic factor.

Regulatory requirements

The new Basel III regulation increases the focus on identifying and dealing with WWR. Guidance and implementation of a Pillar 1 capital charge for WWR currently remain unaddressed, but a greater burden has been placed on the following activities in terms of identification and management with respect to general WWR:

- Identification of exposures that give rise to a greater degree of general WWR
- The design of stress tests and scenario analysis that specifically include WWR factor evolution, such as credit spreads strongly correlated with interest rates or FX moves, to identify risk factors that are positively correlated with counterparty credit worthiness and to address the possibility of severe shocks occurring when relationships between risk factors have changed
- Continuous monitoring of WWR by region, industry and other relevant categories
- Generation of reports for appropriate senior management and board members explaining WWR and the mitigating action being taken

A bank is exposed to "specific WWR" if future exposure to a specific counterparty is highly correlated with the counterparty's probability of default. A bank must have procedures to identify, monitor and control cases of specific WWR that begin at inception and continue throughout the life of the trade. Specific WWR is clearly viewed as often being caused by badly designed trades that potentially should not even exist. The requirements are:

- Each separate legal entity to which the bank is exposed must be separately rated, and the bank must have policies for the treatment of a connected group of entities for the identification of specific WWR.
- Transactions with counterparties where specific WWR has been identified should be treated differently when the Exposure at Default (EAD) for such exposures is being calculated.
- Instruments with a legal connection between the counterparty and the underlying issuer, and for which specific WWR has been identified, are not considered to be in the same netting set as other transactions with the counterparty.
- For single-name credit default swaps where a legal connection exists between the counterparty and the underlying issuer and where specific WWR has been identified, the EAD must be based on the assumption that the counterparty is in default.

In addition to these qualitative factors, banks with IMM (internal model method) approval have additional quantitative burdens designed to capture WWR. Such burdens include the use of stressed historical data and an implicit charge by means of the so-called alpha factor.

The alpha factor

Banks with IMM approval can use the loan equivalent approach based on expected positive exposure (EPE) to define capital requirements. However, two adjustments must be made to correct for imperfections in such an approach. The most important of these is the alpha factor, which adjusts for the concentration caused by the finite number of counterparties and the correlation between exposures and without which the EPE would be the true loan equivalent measure. The alpha factor is typically prescribed as 1.4 but can be lowered subject to a floor of 1.2 if a bank has approval to calculate the alpha factor in appropriate internal models.[9]

Another role of the alpha factor is to adjust for general WWR in the portfolio, which has been viewed by regulators as an increasingly important role since the global financial crisis. As a result, an alpha of 1.4 is no longer seen as obviously conservative. Indeed, banks that seek IMM approval must usually include some modeling of the general WWR. Here, a balance is necessary between a conservative modeling of portfolio counterparty risk that leads to a relatively high calculated alpha factor and a less conservative approach that might lead to the local regulator's imposing a conservative alpha directly.

Stressed market data

One of the significant changes to regulatory capital rules in response to the global financial crisis is to use a period of stressed data for calibrating risk models. This is the case for market risk Value at Risk (VaR) in what has been generally known as "Basel 2.5" and is also the case for calculating IMM exposures, by means of the effective expected positive exposure (EEPE), for counterparty risk purposes.

The danger in calibrating risk models with historical data is that benign and quiet periods tend to precede major crises. As a result, risk measures are particularly low at the worst possible time. Indeed, the higher leverage levels that such low-risk measures support might then increase the likelihood and severity of any crisis, a problem typically known as procyclicality. To correct for procyclicality, under Basel III, one must use stressed inputs when computing EEPE. Examples include volatility and correlation. These stressed inputs must use three years of historical data that include a one-year period of stress, which is typically defined as increasing CDS spreads. This stressed period must be used in addition to the "normal" period of at least three years of historical data, which itself should cover a full range of economic conditions. The exposure at default must be calculated on the set of parameters that result in the highest EEPE at the portfolio and not by counterparty level, that is, the maximum of the normal and stressed exposure calculations.

The use of the stressed period should resolve the procyclicality problem by ensuring that EEPE does not become artificially low during quiet periods in financial markets. In addition, the use of stressed EEPE should improve the coverage of general WWR because the dependencies that contribute to this are likely to be more apparent in stressed periods. The choice of the period of stress is subjective: some banks have made the assumption that the last three years of data in the current period is already stressed.

Modeling WWR

A number of different modeling approaches can be used for computation of WWR.

Impact of WWR on unilateral CVA

Clearly WWR will increase the unilateral CVA, but the nature and magnitude of this increase is very hard to define without detailed modeling. The unilateral CVA can be written as:

$$CVA = LGD_C.E[I(0 < \tau_C < T)D(\tau_C)V^+(\tau_C)]$$

Where:

- LGD_C is the counterparty loss given default
- τ_C is the counterparty default time
- $I()$ is the indicator function
- T is the time horizon
- $D(\tau_C)$ is the discount factor at default
- $V(t)$ is the value of the counterparty portfolio at time t, and $x^+ = max(0, x)$

The latter formula demonstrates that, to incorporate WWR, the counterparty exposure $V^+(\tau_C)$ and the counterparty credit events must be simulated jointly.

Obviously, calculating the conditional exposure is not at all easy because it depends on the counterparty's future behavior. Two equivalent portfolios of trades with different counterparties might have the same unconditional exposure but different conditional exposures.

Another problem that is apparent when WWR is thought of in terms of the conditional exposure is in relation to the credit quality of the counterparty. The smaller the counterparty default probability, the higher the conditional exposure. This condition is generally seen in modeling frameworks because the more unexpected the default, the higher the conditional exposure; it requires accurate computation of the long tails of the loss distribution.

WWR and bilateral CVA

The unilateral approach to CVA neglects the effect of the possibility that the institution defaults before the counterparty defaults. If the default of the institution is taken into account, then the pricing formula for CVA should be modified as follows:

$$\begin{aligned} BCVA = \quad & LGD_C . E[I(0 < \tau_C < T)D(\tau_C)V^+(\tau_C)] \quad \}\ \text{CVA} \\ & + LGD_I . E[I(0 < \tau_I < T)D(\tau_I)V^-(\tau_I)] \quad \}\ \text{DVA} \end{aligned}$$

Where:

- the terms are as defined in the previous equation
- the institution itself represented by $\boldsymbol{I}$ and
- $V^-(\tau_I)$ is the negative exposure of the institution
- The conditioning on the CVA and DVA terms is different since the exposure and negative exposure are related to counterparty and institution own default respectively[10]

Two likely situations can arise for computing BCVA:

- The counterparty and institution default are linked to the exposure in similar ways, for example, a bank buying CDS protection from another bank that is perhaps in the same region. In such a case, it seems likely that the CVA and DVA terms would be calculated with reference to the same simulations.
- The counterparty and institution are related to the exposure in different ways, for example, a bank trading a commodity swap with an oil producer. In such a case, the CVA and DVA should reference two different sets of simulations. In this example, the CVA would be computed with some WWR assumptions, whereas the DVA would most likely be quantified under normal independence assumptions unless the bank's own credit quality was considered significantly related to commodity markets.

All these issues can be addressed in the Algorithmics® Mark-to-Future® framework. In cases where DVA is seen as a component of funding value adjustment (FVA), WWR modeling is not relevant because this term is not related to default.

Challenges with modeling wrong-way risk

Quantitative analysis of WWR involves modeling the relationship between credit spreads and exposure. At a high level, three potential pitfalls are:

- *Lack (or irrelevance) of historical data.* Unfortunately, WWR can be subtle and not revealed by any historical data analysis. Indeed, many of the events of the global financial crisis, especially those that involved large dependencies, were not in any way borne out by historical data prior to the crisis, analysis based solely on correlation measures or both.
- *Misspecification of relationship.* How the dependency between credit spreads, or default probability, and exposure are specified might be inappropriate. For example, rather than being the result of a correlation, such a dependency might be a result of a causality or some systemic factor. Although independence between two random variables does imply zero correlation, the reverse is not true. Therefore, a credit spread that shows zero historical correlation with another market variable does not prove that no WWR exists.
- *Difficultly in representing dependency involving default events.* Modeling dependency involving (binary) default events and more continuous exposure distributions is difficult and often intractable as (for example) has been seen with the pricing of portfolio credit derivative structures.

Hazard rate approaches

An obvious modeling technique for WWR is to introduce some process for the hazard rate and correlate this with the other underlying processes required for modeling exposure. This introduction can be done relatively tractably. Hazard rate paths can be generated first, and exposure paths need only be simulated in cases where some default is observed, or, alternatively, importance sampling can be used to ensure default and correct for the change of probability measure. In addition, such an approach is relatively easy to calibrate. The correlation parameters can be observed directly by means of historical time series of credit spreads and other relevant market variables.

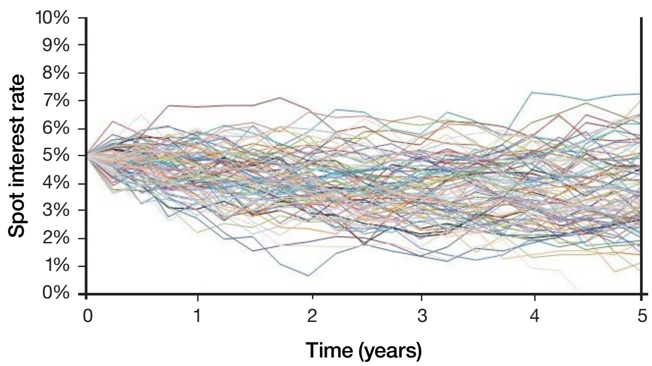

Figure 1: Interest rate simulations that are conditional on counterparty default for a correlated interest rate and hazard rate (credit spread) approach. A correlation of -90 percent is used.

Simple correlated hazard rate approaches generate only very weak dependency between exposure and default, however. Figure 1 shows conditional-upon-default interest rate paths from a Gaussian interest rate model correlated to a lognormal hazard rate process.[11] Although, as expected, the conditional interest rate paths show a downward trend, the effect is clearly not particularly strong even though the correlation is close to the maximum negative value.

A more direct hazard rate approach has been proposed by linking the conditional default probability parametrically to the exposure. One functional form proposed is to define the hazard rate that is driving default as $h(t)=ln[1+exp(a+bV(t))]$, where $V(t)$ is the future value of the portfolio and a and b are parameters.[12] Similar approaches have been described previously for the pricing of credit risky convertible bonds.[13] The function $a(t)$ can be calibrated can be calibrated to the credit spread curve of the counterparty and therefore there is just one parameter, b, that controls the dependency. Positive values of b correspond to WWR.

Regarding calibration, an intuitive calibration based on a what-if scenario is possible.[14] Alternatively, the parametric relationship can be calibrated directly to historical data. This calibration involves calculating the portfolio value for dates in the past and looking at the relationship between the value and the counterparty's CDS spread (hazard rate). If the portfolio has historically shown high values together with larger than average counterparty CDS spreads, WWR is indicated. Obviously, the current portfolio of trades with the counterparty must be similar in nature to that used in the historical calibration and the historical data must show a meaningful relationship.

Copula approaches

The simplest and most tractable approach to modeling general WWR is to specify a dependency directly between the counterparty default time and exposure distribution (Figure 2). To specify the dependency, one maps the exposure distribution at each point in time onto a univariate distribution. The exposures are sorted in descending order, although other more complex approaches can be used, and then mapped by a quantile-mapping procedure.[15] Positive dependency leads to an early default time being combined with a higher exposure as is the case with WWR; negative dependency leads to an early default time being combined with low exposure, as is the case with right-way risk. Note that recalculating the exposures is not necessary because the original unconditional values are sampled directly. The conditional exposures and corresponding CVA are then calculated easily with Monte Carlo simulation. The advantage of this method is that precomputed exposures are used directly, and WWR is essentially added to the existing CVA calculation methodology.

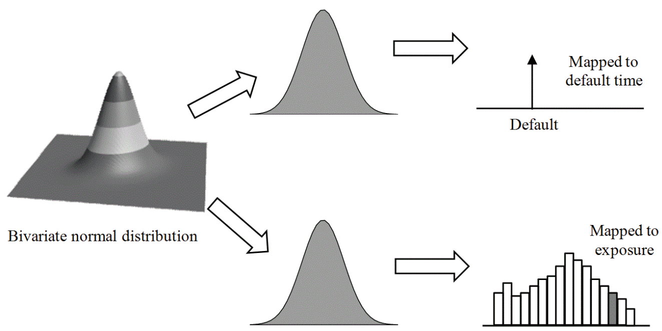

Figure 2: Illustration of the copula approach to modeling general WWR, assuming a Gaussian copula

The simplest choice of copula in this approach is Gaussian. Regarding calibration of the resulting correlation structure, using multifactor models and a principal component approach to calibrate based on historical data has been suggested and estimates have been given in several publications.[16] Clearly other choices of copulas can result in different behavior, but the existence of sufficient data for calibration of more advanced approaches is not clear.

Structural approaches

The advantage of the direct copula approach is that it can be implemented on top of any existing exposure simulation. However, the obvious difficulty is the calibration of the correlation term structure given the opaque specification of dependency. Several structural models have been suggested to resolve this difficulty whereby the default process and market risk factors that define portfolio exposure profiles are correlated.[17]

Namely, the default event of a counterparty is represented as the first hitting time of the counterparty creditworthiness index to a deterministic boundary (Figure 3). This idea represents significant development of the Merton model that was designed for pricing credit risky bonds.

The exposure process is defined by the market risk factors. The market factors are correlated to the creditworthiness index with the underlying correlation estimated from historical data with equity often used as a proxy for the firm value. The most challenging problem in the structural approach is the calibration of the default boundary, a deterministic curve that defines the unconditional default time distribution as a distribution of the first hitting time of the firm value process.

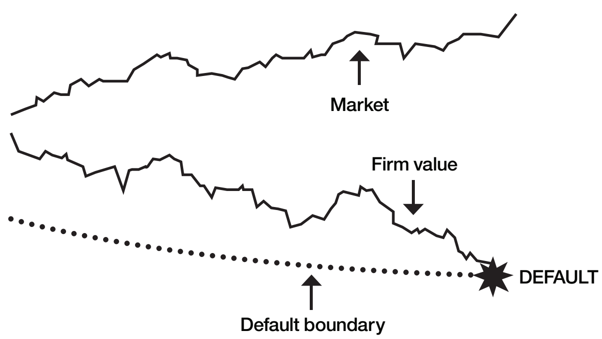

Figure 3: Structural approach to credit risk modelling.

In the structural approach, the default boundary can be calibrated numerically to the counterparty default probability.[18] Several techniques have been proposed to solve this numerical problem.[19] The most efficient numerical solution is based on the Fast Fourier Transform.[20] The Fast Fourier Transform approach appears to be even more efficient than the "static copula" approach that was developed for pricing credit derivatives.[21]

The structural approach enables one to develop a consistent framework both for pricing and risk management applications. One particular framework is based on a very elegant idea of conditional independence of the credit processes: conditional on the values of the macro-economic risk factors, credit migration events are conditionally independent.[22] The conditional independence property brings analytical tractability in the computation of conditional probabilities of the credit events and allows for an efficient computation of the risk measures of the credit risky portfolios. From an implementation point of view, the aggregation of the conditional results can be done analytically, without additional Monte Carlo sampling.

The conditional independence property is also very useful in pricing credit derivatives and analysis of CVA and DVA, and a methodology suitable for pricing complex credit has been presented.[23] The default boundary techniques can be adjusted to incorporate credit migration effects.

Specific WWR approaches

For cases where a specific WWR is clear, alternative and asset class specific approaches should be used. An obvious example of clear specific WWR is the FX example, which can be implemented by a simple jump of the FX rate at the counterparty default time.[24] In the likely absence of any quanto CDS quotes, such a parameter would typically be estimated heuristically.

Credit derivatives clearly also contain significant specific WWR.[25] With respect to credit derivatives in particular, the impact of collateral on WWR is important. In such a case, the speed of the counterparty default is important. And, when a large systemic counterparty defaults, the WWR impact is likely to be significant (even with a collateral agreement in place) because conditional exposure is higher for higher credit quality counterparties.[26] Nevertheless, specific WWR is often not considered in collateralized CDS positions unless a very strong effect exists. A long protection CDS with a very clear and strong dependence between reference entity and counterparty and an index CDS, where the counterparty is a component of the index, are two examples.

Except for the Quanto CDS shown in Table 1, one important point about specific WWR is that data for calibration of models and hedging is very limited. As such, it is reasonable to expect that simple pragmatic models and overhedging can be used.[27]

Emerging market practices

WWR practices are evolving quickly in response to recent experiences (for example, the European sovereign debt crisis) and the regulatory guidelines of Basel III. The following observations are from the 2013 Deloitte/Solum CVA Survey:

- Many banks still do not have advanced WWR models in place and rely on qualitative rules for pricing WWR into trades.
- The concept of some "alpha factor" that defines the total general WWR for the entire portfolio is often used and precomputed at periodic intervals.
- Some banks use predefined general WWR scenarios that are updated periodically and have automatic triggers in place.
- Stress testing is often used to identify general WWR by jointly simulating extreme credit spreads and risk factor scenarios.
- Specific WWR trades are recorded at origination with direct assessment of the counterparty, trade type (and collateral).
- Identification of specific WWR is often required prior to trade approval.[28]

A common way to represent general WWR is to apply a gross-up factor to the exposure. Such a factor, a component of the regulatory alpha factor, can be represented at the portfolio level as:

$$WWR = \frac{EC_{WWR}}{EC_{Ind}}$$

Where:

- EC_{WWR} is the economic capital calculated taking into account correlations between the market risk factors and credit drivers and
- EC_{Ind} is the economic capital calculated under the assumption that market risk factors and credit drivers are independent.

The EC is usually defined as a high quantile of the loss distribution. The factor defined in the equation should be computed periodically with an economic capital model that includes market-credit dependency. The result provides a crude adjustment by which exposures and CVAs could be scaled up because of the presence of general WWR.

Accounting CVA and CVA pricing calculations generally ignore WWR, which is added only in specific cases. Such cases include long-dated cross currency swaps, credit derivatives, repos with a legal connection between the counterparty and collateral. A misalignment of CVA approaches is commonly seen between front-office, regulatory and accounting functions. Most often, certain types of specific WWR are quantified in front-office pricing and regulatory approaches but ignored in accounting.

CVA sensitivities are often mainly based on a "bump and run" approach. With the assumption of no WWR, credit sensitivities are trivial to calculate. As a result, WWR is not commonly incorporated into the calculation of CVA Greeks although the cross-gamma effect that arises from market-credit codependencies is well-known and sometimes hedged. Methods such as adjoint differentiation are becoming increasingly common, which will allow in the future for more advanced sensitivity calculations, including WWR.

WWR and CVA risk measures

Counterparty credit risk (CCR) can be measured with historical scenarios and risk-neutral scenarios. If being estimated with respect to historical measure for the purpose of allocating EC, CCR is characterized by several measures of risk that include expected counterparty portfolio losses, quantiles of the portfolio loss distribution and their sensitivities. New risk measures, however, can specifically capture the WWR of the counterparty.[29] These risk measures can be computed in the Algorithmics Mark-to-Future framework. The idea of the framework is to accumulate prices of the counterparty portfolio under each scenario at every time step in the Mark-to-Future tables.

The exposure profile of the counterparty portfolio then becomes scenario-dependent and correlated to the structural variables determining the credit events.

Computing counterparty WWR (historical measure)

The steps for computing counterparty WWR based on historical measures are:

1. Access the Mark-to-Future table for the counterparty of interest and use zero correlations between market risk factors and credit indexes to compute distribution of the portfolio losses. This distribution is computed over all scenarios and all time steps. **This computation takes into account correlation between the counterparty and the underlier or underliers**.
2. Find quantile of the counterparty loss distribution, $Q_1(p)$. The value of the parameter p is usually $p=0.999$ (99.9%); the number of MC scenarios, N, for valuation of the loss distribution depends on the parameter, p: $N=N(p)$.
3. Compute counterparty loss distribution while taking into account correlation of the exposure and default probabilities. In this case, the conditional default probabilities, which are used to find the counterparty loss distribution, are computed with correlations between market risk factors and credit drivers.
4. Find the quantile of the latter distribution, $Q_2(p)$. The latter risk measure gives estimation of the EC for counterparty losses.
5. Find the difference $WWR(p) = Q_2(p) - Q_1(p)$.
   Notice that the quantile computation and the computation of the loss distributions are done as a post-processing of the simulation results: resimulation of the CP exposure is not required.
6. Compute alpha-risk measure: $\alpha(p) = Q_2(p) / Q_1(p)$.

Measure: CVA amount (counterparty)

The steps for the CVA amount (counterparty) measure are:

1. Access the exposure results for the counterparty of interest (through time and scenario). Ensure that these exposures are discounted.
2. Access the default times for the counterparty under each path. For those paths with non-zero default times, index the default time to the proper time slot.
3. Calculate the loss under that path as Exposure*(1-recovery) where recovery is the recovery mean specified at the counterparty level.
4. If you are calculating counterparty level results and not position or netting node, adjust the loss under that path with Counterparty Default Adjustment (CDAdjustment). In some cases, the CDAdjustment will produce a gain. If the total gain from CDAdjustment exceeds the total loss at the counterparty level, replace the net loss with zero at the counterparty level.[30]
5. Average the losses for all paths. Return the result.

Calculating the CDAdjustment

To calculate the CDAdjustment,[31] the conceptual representation of the credit derivatives by Mark-to-Future is used in the Portfolio Credit Risk Engine (PCRE). Each counterparty default is described by a 2xM table, where M is the number of credit states that span market scenarios and time. These tables must be discounted to today with the Future Value Factor attribute. Because the interest rates and FX factors are known in the market scenarios, discounting of the Mark-to-Future tables does not represent any technical problem.

For each counterparty default:

1. Access the results for both the counterparty and the underlying name.
2. Use the default times of each to calculate gains or losses on the instrument with the current PCRE logic. Allocate to either the counterparty or underlying consistent with the current PCRE logic.
3. A few additional rules need to be added to the current PCRE logic to address CVA:
    - Gains on counterparty default are not allowed. However, the underlying name can recognize both gains and losses as adjustments.
    - Migration gains or losses will not be recognized; only default losses are taken into account. The potential underlying name migration will only serve to determine the appropriate default loss for the counterparty.
4. Store the adjustments for the counterparty and underlying under each path.
5. Repeat steps 1-4 for the next counterparty default that is storing cumulative adjustments for the counterparty or underlying.

Because all the counterparty defaults in the book are processed, a single adjustment figure is obtained for each name, whether the name is a counterparty or underlying in your counterparty defaults, and each path. Call these figures the CDAdjustment.

CVA amount (RiskTaker)

Consistent with the current CVA algorithm, the appropriate RiskTaker exposures are derived by multiplying the positions by “-1” and re-applying netting and collateral (and properly adjusting the CSA details) to represent how the counterparty views the bank’s exposures. These exposures are run through the same algorithm as in the counterparty case, but in this case they are indexed to the default times of the RiskTaker. The CDAdjustment must be calculated by multiplying the counterparty default tables by “-1” and cycling through the loss-related. After the loss under every path is calculated, average the losses for all paths and return the result.

Measure: CVA amount (Bilateral)

By this point, a loss figure has been calculated under every path for every counterparty, including CDAdjustments where required. In addition, a loss figure for the RiskTaker against all counterparties, including CDAdjustments where required, has been calculated. To calculate the bilateral case, the default times for the counterparty and RiskTaker are examined under every path. The loss of whichever one (counterparty or RiskTaker) defaults first is used. The RiskTaker loss is treated as a negative number. If they both default on the same time step for a given path, calculate the net loss as: Counterparty Loss—RiskTaker Loss. Average the bilateral losses for all paths and return the result.

Measure: CVA rate (Counterparty)

The CVA rate is the rate that would have to be charged on the exposures in order to get back the CVA amount. The rate is calculated as:

$$CVA_{R,CP} = \frac{CVA_{A,CP}}{\sum_{j=1}^{k} \mathrm{E}\{\hat{E}(t_j) \cdot d(0,t_j)\} \cdot (1-\hat{r}) \cdot \Delta(t_{j-1},t_j)}$$

Where:

- $CVA_{A,CP}$ represents the CVA Amount (Counterparty) calculated above,
- $\mathrm{E}\{\hat{E}(t_j) \cdot d(0,t_j)\}$ represents the expected discounted exposures of the CP,
- $\hat{r}$ represents the recovery rate (or minimum recovery rate) of the CP,
- $\Delta(t_{j-1},t_j)$ represents the time factor between time steps,
- k represents the number of time steps.

Measure: CVA rate (RiskTaker)

The rate is calculated as:

$$CVA_{R,RT} = \frac{CVA_{A,RT}}{\sum_{j=1}^{k} \mathrm{E}\{\hat{E}(t_j) \cdot d(0,t_j)\} \cdot (1-\hat{r}) \cdot \Delta(t_{j-1},t_j)}$$

Where:

- $CVA_{A,RT}$ represents the CVA of the Risk Taker.

(We use here notation from the previous sections)

Measure: WWR adjustment (CP) and WWR adjustment (RT)

The WWR adjustments are computed as a difference between the CVA under the assumption that credit spreads and exposures are uncorrelated and the CVA already computed. The CVA measure can be either bilateral or unilateral.

Recommendations

Of the various approaches to quantifying WWR, which is best market practice?

Hazard rate approaches for WWR are generally inappropriate because of the only fairly weak dependence introduced. Although more extreme representations such as including jumps or parametric forms might produce more reasonable behavior, these approaches are difficult to calibrate.[32]

For estimation of the alpha factor linked to IMM approval, a copula method is reasonable and has been adopted by a number of banks with IMM approval.[33] Such an approach is very tractable and can be implemented easily on top of an existing exposure simulation by using the precomputed exposure directly. Although the estimation of the correlation parameters is not easy, it is less relevant because the purpose will be presumably to estimate a relatively conservative alpha factor by consideration of a reasonable range of correlations.

For more advanced modeling of general WWR, the structural approach is more appropriate despite the greater complexity in building such a framework.[34] The required correlation between the default process and the market factors that are driving the exposure can be estimated, for example, with the relevant historical time series. Such an approach requires an extension of the correlation model between the exposure risk factors to include the counterparty default process. The model is then generic and potentially captures codependencies for any asset class and risk factor. After it is implemented, the approach need not be significantly slower than a traditional CVA implementation because of the efficient way that market factors can be simulated conditional upon counterparty default events.

Finally, for specific WWR, it is important to combine asset class specific models with hedging analysis and collateral modeling. Qualitative considerations are just as important as quantitative ones because specific WWR trades are often best avoided completely. Although market practice is evolving to model general WWR for the entire portfolio, specific WWR is still seen as being difficult to model. Banks typically use a combination of qualitative rules, stress tests and scenario analysis together with some asset class specific modeling.

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