CVA wrong-way risk: calibration using a quanto CDS basis

Tsz-Kin Chung and Jon Gregory discuss the calibration of a wrong-way risk (WWR) model using information from the quanto credit default swap market. Empirical evidence shows that implied foreign exchange jump sizes are significant for a wide range of corporates. For systemic counterparties, the credit valuation adjustment WWR add-on could be 40% higher than in the standard case, and choosing a proper jump-at-default WWR model is critical for capturing the impact

The wrong-way risk (WWR) modelling of credit valuation adjustments (CVAs) is known to be a challenging, if not intractable, problem. Aziz *et al* (2014) summarise the two main difficulties with modelling WWR as being (1) the lack of relevant historical data and (2) the potential misspecification of the dependency between credit spreads and exposures. In particular, it is not straightforward to link a binary default event to continuous risk factor movement and an exposure distribution. Traditional modelling approaches and the use of correlation are very prone to the misspecification problem due to the difficulty of estimating co-dependency parameters using relevant historical data. These correlation-based approaches also fail to address the specific WWR driven by causal linkages between exposure and counterparty default.

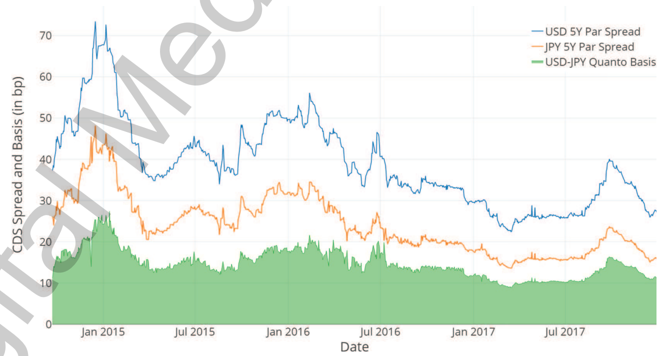
Against this background, recent studies have attempted to tackle the WWR problem from a different perspective: via an event risk modelling approach. Pykhtin & Sokol (2013) argue that WWR behaves differently for exposure to systemic important counterparties (Sics); they use a risk factor jump-at-default to capture the market impact of a Sic default on the economy. Turlakov (2013) discusses the challenges in correlation calibration for WWR and proposes a simple add-on approach to account for the increase in tail risk upon a counterparty default. Mercurio & Li (2015) introduce the jump-to-default (JtD) approach to CVA WWR modelling by using an additive risk factor jump or proportional jump at the time of default.[1]

In this article, we revisit WWR modelling by calibrating to information from the credit default swap (CDS) market. In particular, we study the market prices of a quanto CDS contract, which is designed to provide credit protection against the default of a reference entity and is denominated in a non-domestic currency (Brigo *et al* 2015). By analysing the contingent payout of a quanto CDS contract, we demonstrate how one can extract the market-implied information of the interaction between a foreign exchange jump risk and a credit default event. This important piece of market-implied information helps us to explain how WWR is being priced in the market, and it leads to an appropriate calibration of the WWR model for a forex-sensitive CVA portfolio.

The modelling of WWR will likely increase in importance for banks, especially since the proposals for a revised CVA capital charge have recommended an increased multiplier if a bank does not account for the dependence between exposure and counterparty credit quality in its CVA calculations.[2] Therefore, the modelling approaches proposed in this article not only let banks analyse the impact of CVA WWR in their portfolios but also help them to meet regulatory requirements on CVA capital calculation.

The rest of this article is structured as follows. The next section discusses a bivariate jump-diffusion model to explain the quanto basis. After that, we report our empirical analysis on calibrating the WWR model parameters to a quanto CDS basis under various assumptions. The difference between implied correlation and historical correlation regarding the forex risk factor and the credit spread is discussed. For illustration, we also compare the implied forex jump sizes from quanto CDS bases and over-the-counter forex options. We then provide numerical examples to illustrate the impact of CVA WWR using various modelling assumptions, calibration procedures and hypothetical portfolios.

1 Japanese sovereign quanto basis for the USD/JPY pair



A tale of two spreads

Figure 1 shows the Japanese sovereign CDS premium (five-year par spread), which represents the cost of buying credit protection against a Japanese sovereign default. The USD and JPY spreads correspond to the CDS contracts in which the currencies are denominated in USD and JPY, respectively. Note that these contracts should always trigger simultaneously, so the only major difference between them is the settlement currency in which the contingent default payment is made. There is a persistent basis between the two CDS spreads despite the fact that they reference the same entity. Indeed, the persistent quanto basis reflects a strong market-implied devaluation jump of JPY against USD upon a Japanese sovereign default, reflecting the fact that it is more expensive to buy protection in USD than in JPY. This shows the CDS market has been consistently pricing in WWR via a forex-credit interaction as a devaluation jump upon a credit default.

[1] *The JtD modelling approach has been widely used in financial engineering problems: see Chung & Kwok (2016) and the references therein.*
[2] *See www.bis.org/bcbs/publ/d424.htm.*

■ **Continuous time model.** The quanto basis can be explained through a bivariate jump-diffusion model. Under the domestic risk-neutral measure Q, we specify the dynamics of the forex risk factor $X_t = e^{x_t}$ and the correlated stochastic hazard rate $\lambda_t = e^{\phi(t)+z_t}$ as:

$$dx_t = (r - q - \tfrac{1}{2}\sigma^2 - \gamma\lambda_t)\,dt + \sigma\,dW_t^1 + \ln(1+\gamma)\,dI_t, \quad x_0 = \ln X_0$$

$$dz_t = -az_t\,dt + \eta\,dW_t^2, \quad z_0 = 0$$

where r and q are the domestic and foreign interest rates, respectively; σ is the forex rate volatility; a is the hazard rate mean reversion; η is the hazard rate volatility; and (W_t^1, W_t^2) are correlated standard Brownian motions with $\boldsymbol{E}^Q[dW_t^1\,dW_t^2] = \rho\,dt$. The forex jump is modelled by a time-inhomogeneous Poisson process I_t with intensity λ_t, and γ is the expected proportional jump size. The hazard rate follows a lognormal dynamics in which $\phi(t)$ is a deterministic function to fit the term structure of CDS spreads. For illustrative purposes, the model parameters are assumed to be constant.

To price the quanto contingent payout, we need a model that incorporates the link between a forex jump and credit name default. A simple tactic is to force the first jump of the Poisson process I_t to be at the default time τ (Mercurio & Li 2015). As a result, the forex risk factor can be expressed as:

$$X_t = X_t^{B}(1 + \gamma\mathbf{1}_{\{\tau\leqslant t\}})e^{-\int_0^{\min\{\tau,t\}}\lambda_s\gamma\,ds} \tag{1}$$

where:

$$X_t^{B} = X_0 e^{(r-q-\frac{1}{2}\sigma^2)t+\sigma\,dW_t^1}$$

is the baseline model without the jump feature.

Define:

$$S(t) = \boldsymbol{E}^Q[e^{-\int_0^t \lambda_s\,ds}] \quad\text{and}\quad S^*(t) = \boldsymbol{E}^{Q^*}[e^{-\int_0^t \lambda_s^*\,ds}]$$

to be survival probabilities under the domestic risk-neutral measure Q and foreign risk-neutral measure Q^*, which can be calibrated to the respective domestic and foreign CDS curves (Brigo *et al* 2015). It can be shown that hazard rates under Q^* and Q are related as (Chung & Kwok 2016):

$$\lambda_t^* = (1+\gamma)\lambda_t \exp\left(\int_0^t \rho\sigma\eta e^{-a(t-s)}\,ds\right) \tag{2}$$

Similar results have been obtained in Ehlers & Schonbucher (2006), El-Mohammadi (2009), Ng (2013) and Brigo *et al* (2015) under different setups. When the hazard rate follows lognormal dynamics, the survival probabilities $S(t)$ and $S^*(t)$ have to be calculated using numerical algorithm or closed-form approximations. For instance, efficient approximations on survival probability can be found in Li *et al* (2018) and the references therein.

From (2), it can be seen that the quanto basis can be calibrated by tuning the jump parameter γ and the correlation parameter ρ while holding the other parameters constant. In practice, it is more convenient to estimate these quanto parameters (γ, ρ) based on observed CDS spreads. Elizalde *et al* (2010) provide an easy-to-use approximation formula to link up primary and quanto CDS spreads based on a hedging argument. Applying this to the USD/JPY pair, the 'quanto basis ratio' is related to the model parameters as:

$$\frac{S_{\rm JPY}(T) - S_{\rm USD}(T)}{S_{\rm USD}(T)} \approx \gamma + \rho\sigma\eta A(T) \tag{3}$$

where $A(T)$ is the risky annuity for the USD-denominated contract with maturity T.

Empirical analysis

In this section, we apply the quanto rule-of-thumb formula in Elizalde *et al* (2010) to calibrate the quanto parameters (γ, ρ) against an observed quanto basis under various assumptions: (1) a JtD model, (2) a correlated hazard rate model and (3) a joint model with a JtD and a correlated hazard rate. The objective is to extend the analysis in Ehlers & Schonbucher (2006) and Brigo *et al* (2015) as well as examine which model assumption provides an efficient way of calibrating the quanto basis for a wide range of counterparties. We employ the IHS Markit CDS data set, which provides complete historical time series for more than 250 Japanese entity curves with tenor points ranging from 6 months to 30 years. The historical period is from September 22, 2014 to December 29, 2017.[3]

■ **JtD model and implied forex jump.** First, we pursue a pure JtD model with a deterministic hazard rate. We apply the quanto formula (3) and set $\eta = 0$. Hence, the implied forex jump size $\gamma^{\rm Imp}$ can be estimated as:

$$\gamma^{\rm Imp} = \frac{S_{\rm JPY}(T) - S_{\rm USD}(T)}{S_{\rm USD}(T)} \tag{4}$$

We take $T = 5$ and compute the implied forex jump for each observation based on (4). We report the historical mean as below.

In figure 2, we plot the historical mean-implied forex jump size for the top 30 counterparties in descending order. As can be noted immediately, Sics such as sovereign and large financial institutions top the list and their implied forex jump sizes are significantly negative (30–40%). This suggests the CDS market is pricing in significant forex WWR for these Sics. These are followed by large Japanese corporates, such as transportation (Central Japan Railway) and automobile makers (Toyota, Honda, Nissan), for which the implied forex jump sizes are sizeable around 10–20%. As we move down the spectrum, we see the implied forex jump size reduces gradually and stays around 10%. The empirical evidence shows the CDS market has been consistently pricing in the forex jump-at-default risk for a wide range of counterparties in Japan.

In figure 3, we report the average implied forex jump sizes by sector and rating. As expected, the implied forex jump size for government and financial institutions tops the ranking, followed by consumer services and consumer goods, which in Japan correspond to large corporates such as retail, transportation and automobiles. However, the categorisation of implied forex jump size against credit rating appears to be less conclusive. In general, we would expect the WWR impact to increase with growing credit quality, as shown previously by Winters (1999). One possible explanation is that the implied forex jump size is related primarily to systemic importance, which is determined by sector characteristics rather than credit rating. Hence, one might construct a proxy quanto basis curve based on the sector category, for it is less effective to proxy based on the rating category.

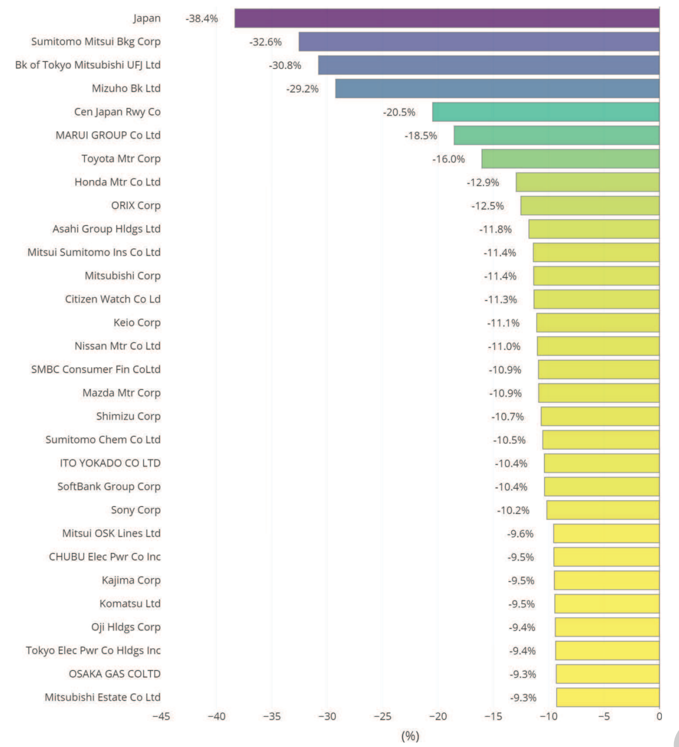
■ **Correlated hazard rate model and implied correlation.** Next, we turn off the jump feature and estimate a correlated stochastic hazard rate model. Applying the quanto formula (3) and setting $\gamma = 0$, the implied correlation $\rho^{\rm Imp}$ can be estimated as:

$$\rho^{\rm Imp} = \frac{1}{\sigma\eta A(T)}\frac{S_{\rm JPY}(T) - S_{\rm USD}(T)}{S_{\rm USD}(T)} \tag{5}$$

with $T = 5$. The volatility parameters (σ, η) are estimated based on the time series of daily log returns in the USD-denominated CDS par spread and the

[3] *More details can be found in the full paper, available at SSRN (https://ssrn.com/abstract=3188793).*

2 Implied forex jump size (γ^{Imp}) for selected Japanese names based on (4)



3 Implied forex jump size by (a) sector and (b) rating

The rating is based on the composite curve rating compiled by IHS Markit as of December 29, 2017

JPY/USD forex rate over the sample period. To keep the analysis simple, we want to use only observed CDS spreads (without hazard-rate bootstrapping), and hence the risky annuity is approximated using:

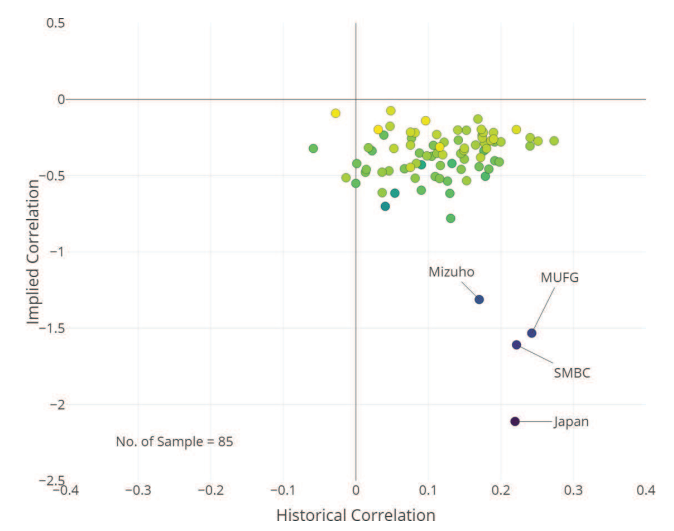
$$A(T) = \frac{1 - \mathrm{e}^{-(r+h)T}}{r+h}$$

by assuming a flat hazard rate $h = S_{\mathrm{USD}}(T)/(1-R)$ and a constant interest rate $r = 1\%$. We also compute the historical correlation ρ over the sample period for the purpose of comparison.

Figure 4 reports the scatter plot of the implied correlation (vertical axis) against the historical correlation (horizontal axis). There are several interesting conclusions: for most of the Japanese names, the historical forex credit correlations are positive, which contrasts with the negative correlations implied from the quanto basis. A positive correlation suggests the credit spread (probability of default) increases when the JPY is strong, hence reflecting right-way risk instead of WWR. This is perhaps not surprising because a strong JPY is detrimental to the profit of many large corporates in Japan, which are usually export oriented. This may be reflected in the time series dynamics of the credit spread and forex rate, leading to a positive correlation. However, such a positive historical correlation contradicts the market price of the quanto basis and leads to the mispricing of CVA WWR, which seems to be driven more by a causal linkage.

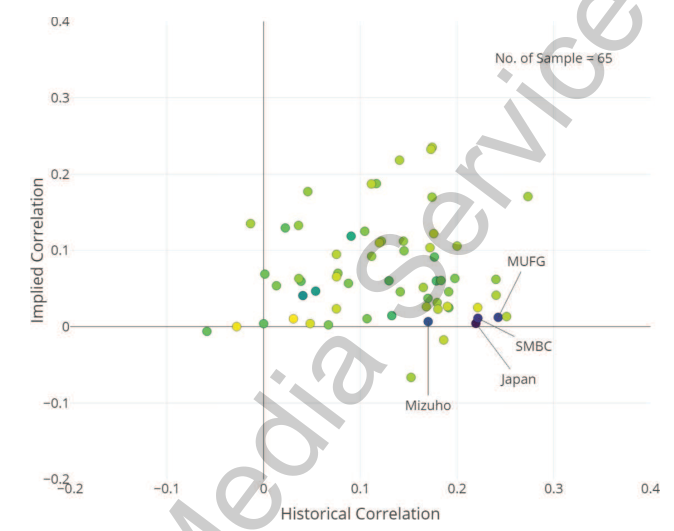
The implied correlations for some Sics (Japan sovereign and mega banks) are beyond the range of $(-1, 1)$, suggesting that even the correlation-based model cannot reproduce the market prices of the quanto basis spread. This is due to the fact that the denominator $\sigma\eta A(T)$ in (5) is constrained by the volatility parameters (σ, η) and maturity T. Such a model would also perform extremely badly from a hedging point of view, with large cross-gamma effects. A similar conclusion on Japanese corporate names has been made in Ehlers & Schonbucher (2006), although they did not apply systemic importance to it. In summary, the correlation-based approach to WWR modelling is misspecified, with both the size and direction of WWR being misrepresented. A proper forex WWR modelling framework should therefore include a JtD model at least as a complement to the traditional correlation-based approach.

4 Implied correlation (ρ^{Imp}) against historical correlation (ρ)



Implied correlation (ρ^{Imp}) is estimated based on (5) without the JtD effect. The marker intensity reflects the size of a five-year quanto basis

5 Implied correlation ($\rho^{\mathrm{Imp}}_{\mathrm{Adj}}$) against historical correlation (ρ)



Implied correlation ($\rho^{\mathrm{Imp}}_{\mathrm{Adj}}$) is estimated based on (6) after adjusting for the JtD effect. The marker intensity reflects the size of a five-year quanto basis

■ **Combining forex jump and correlated hazard rate.** The contradictory results between implied correlation and historical correlation may be explained by the joint modelling of the JtD effect and the correlated hazard rate. In practice, however, the calibration procedure becomes a bit tricky when decomposing the quanto effects of a JtD and a correlated hazard rate. Following Brigo *et al* (2015), the implied correlation after adjusting the JtD effect can be estimated by the difference between quanto spreads for two tenor points (T_1 and T_2) as:

$$\rho^{\mathrm{Imp}}_{\mathrm{Adj}} = \frac{1}{\sigma\eta(A(T_2) - A(T_1))} \times \left\{ \frac{S_{\mathrm{JPY}}(T_2) - S_{\mathrm{USD}}(T_2)}{S_{\mathrm{USD}}(T_2)} - \frac{S_{\mathrm{JPY}}(T_1) - S_{\mathrm{USD}}(T_1)}{S_{\mathrm{USD}}(T_1)} \right\} \tag{6}$$

when the jump size γ is constant. We apply (6) by using a one-year quanto basis ($T_1 = 1$) and a five-year quanto basis ($T_2 = 5$), with parameters (σ, η) estimated as aforementioned.

Figure 5 reports the implied-historical comparison after taking into account the JtD effect. As can be seen, most of the implied correlations become positive, although they are systematically smaller than the historical correlations. Moreover, we find the implied forex jump from a one-year quanto basis can explain more than 90% of a five-year quanto basis, suggesting the correlated hazard rate may only be explaining unimportant residuals. This is reflected by the implied correlations of Sics (Japan sovereign and mega banks) hovering around zero after they have been adjusted for the JtD effect. The joint modelling of the JtD and the correlated hazard rate might lead to over-fitting the observed quanto basis for these credit names.

In practice, the implementation of a joint model with the JtD and the correlated hazard rate for CVA pricing is not necessarily straightforward. A proper CVA-pricing model requires the joint modelling of a large number of risk factors in multiple asset classes as well as risk-neutral calibration against a wide range of financial instruments (Ng 2013). A parsimonious risk factor model is usually required for analytical tractability and efficient calibration. In view of this, the JtD setup seems to be a better candidate for pricing CVA WWR, since a single parameter γ is needed to parameterise the co-dependence between credit default and exposure (without adding an extra risk factor) as well as reproduce the market price of the quanto basis.

■ **Implying the jump size from forex options.** A number of studies have shown that deep out-of-the-money forex options contain useful information about the forex jump as anticipated by market participants, and the forex jump is closely linked to the possibility of a sovereign or systemic default in the economy (Hui & Chung 2012). Hence, the forex option-implied jump size can serve as a benchmark in calibrating the JtD model for Sics such as sovereign, global financial institutions and large corporates.

The analysis of this is reported in an extended version of the paper online.

Impact of CVA WWR

■ **WWR models.** In this section, we describe two approaches to CVA WWR calculation. We start with the standard CVA-pricing formula (Mercurio & Li 2015) with discretisation over the exposure grids $\{t_i;\, i = 0, 1, \dots, M\}$:

$$\mathrm{CVA} = N(0)(1-R)\sum_{i=0}^{M-1} \boldsymbol{E}^{Q}\left[\frac{V(X_{t_i}, t_i)^+}{N(t_i)} \mathbf{1}_{\{t_i < \tau \leqslant t_{i+1}\}}\right] \tag{7}$$

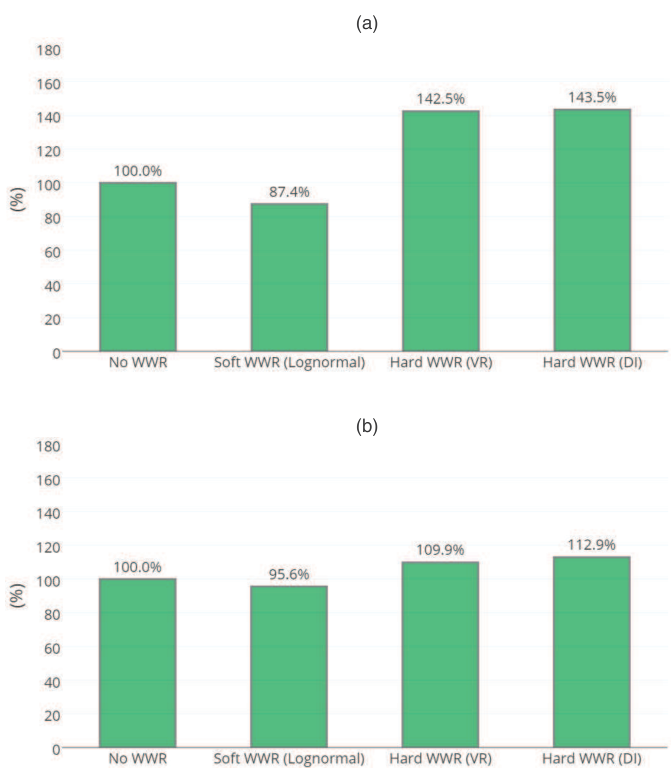
where X_{t_i} is the risk factor value at time t_i, $V(X_{t_i}, t_i)$ is the portfolio exposure at time t_i, $N(t)$ is the risk-free money market account and τ is the default time.

A standard approach is then to introduce a correlation between the risk factor and the hazard rate. By the law of iterated expectation, we can rewrite the CVA formula as:

$$\mathrm{CVA} = N(0)(1-R) \times \sum_{i=0}^{M-1} \boldsymbol{E}^{Q}\left[\frac{V(X_{t_i}, t_i)^+}{N(t_i)} (\mathrm{e}^{-\int_0^{t_i} \lambda_s \,\mathrm{d}s} - \mathrm{e}^{-\int_0^{t_{i+1}} \lambda_s \,\mathrm{d}s})\right] \tag{8}$$

in which the hazard rate λ_t is stochastic like those we assumed in previous sections. A common criticism of this modelling approach is the correlation

6 Impact of WWR (no collateral)



(a) Directional portfolio. (b) Non-directional portfolio. All numbers are normalised to the baseline CVA (no WWR). DI stands for the default indicator formula in (7) and VR is the variance reduction formula in (9)

7 Impact of WWR under collateralisation

(a) Directional portfolio. (b) Non-directional portfolio. The CVA numbers are normalised to the baseline CVA (no WWR) in figure 6. DI stands for the default indicator formula in (7) and VR is the variance reduction formula in (9)

between the hazard rate and the risk factor can only generate a weak dependency of default and exposure, and the resulting level of WWR is somewhat limited (see, for example, Aziz *et al* 2014).

The JtD CVA WWR approach has also been adopted recently by Pykhtin & Sokol (2013) and Mercurio & Li (2015). They assume a deterministic hazard rate $\lambda(t)$ and introduce a jump-at-default feature to the risk factor:

$$\mathrm{CVA} = N(0)(1-R)\sum_{i=0}^{M-1} \boldsymbol{E}^{Q}\biggl[\frac{V((1+\gamma)\mathrm{e}^{-\int_0^{t_i}\lambda(s)\gamma\,\mathrm{d}s}X_{t_i}^{\mathrm{B}}, t_i)^{+}}{N(t_i)}\biggr] \times (\mathrm{e}^{-\int_0^{t_i}\lambda(s)\,\mathrm{d}s} - \mathrm{e}^{-\int_0^{t_{i+1}}\lambda(s)\,\mathrm{d}s}) \qquad (9)$$

where we plug in the JtD risk factor in (1) for a deterministic hazard rate:

$$X_t = X_t^{\mathrm{B}}(1+\gamma\mathbf{1}_{\{\tau\leqslant t\}})\mathrm{e}^{-\int_0^{\min\{\tau,t\}}\lambda(s)\gamma\,\mathrm{d}s}$$

At the default time, the risk factor will jump proportionally by a fixed size of γ.

■ **Numerical examples.** In order to understand the impact of WWR modelling on CVA calculation, we investigate the following model setups:

- No WWR: a deterministic hazard rate model without JtD.
- Soft WWR: a correlated hazard rate model without JtD.
- Hard WWR: a JtD forex WWR model with a deterministic hazard rate.

We compute the portfolio CVA based on the variance reduction formula in (8) for the no-WWR and soft-WWR models, while (9) is used for the hard-WWR model. A brute-force simulation of the default indicator and CVA computation using the representation in (7) are also performed for verification. We use an implied forex jump size of 10% and calibrate the credit models to the average CDS spread for the Japanese financial names in our sample. A directional portfolio A (long USD) and a non-directional portfolio B consisting of forex forwards, cross-currency swaps and forex options for USD/JPY are used to illustrate the WWR impact.

■ **Non-collateralised portfolio.** Figure 6(a) shows the CVA with and without WWR, in which all CVA numbers are normalised to the no-WWR CVA baseline number. For the directional portfolio A, the impact of the risk factor jump of 10% is magnified and hard WWR increases the CVA by around 40%. The magnitude of the impact is similar to those reported in Mercurio & Li (2015) for a single trade currency swap. In contrast, the impact of soft WWR is only 13% by magnitude, with the reduction in CVA reflecting a form of right-way risk due to the mildly positive correlation estimated historically. To better understand the impact of the hard-WWR model, one can drill down to the conditional exposure paths as indicated by the term $V((1+\gamma)\mathrm{e}^{-\lambda\gamma t_i}X_{t_i}^{\mathrm{B}}, t_i)$ in (9). For the long USD portfolio A, the forex jump significantly increases the conditional exposure distribution and, hence, the expected exposure. The effect on the tail distribution characterises the event risk modelling feature of the JtD approach.

In the case of the non-directional portfolio B (part (b)), the impact of WWR is somewhat diluted. The soft- and hard-WWR models only introduce minor corrections of around 3% against the baseline CVA level. An investigation of the simulated mark-to-market paths reveals the forex jump extends the lower tail over a short time horizon, while the reverse effect is observed over a longer time horizon. Since CVA represents the expected loss due to counterparty default over the portfolio lifetime, the impact of a forex jump on the expected exposure profile across a time horizon can be somewhat neutralised. This shows CVA WWR can be highly portfolio dependent, and it is essential to accurately calculate the portfolio CVA in order to assess the level of WWR. Clearly, for a more balanced portfolio, the proposed Basel multiplier of 1.25 could be conservative due to the sophisticated dependence of CVAs on various pricing factors such as portfolio composition, the netting effect and collateral arrangement.

■ **Collateralised portfolio.** Next, we investigate the WWR impact on a collateralised portfolio. We consider a two-way credit support annex (CSA) agreement with thresholds H_B and H_C, and the collateral settlement is lagged. The collateralised exposure at time t is given by:

$$V^{\text{Coll}}(t) = V(t) - C(t)$$

where $C(t) = (V(t-\delta) - H_C)^+ - (-V(t-\delta) - H_B)^-$ represents the collateral balance after the last exchange. Obviously, the effectiveness of the collateral depends on how closely the lagged collateral tracks the portfolio value $V(t)$. For the hard-WWR model with JtD, the portfolio value $V(t)$ and the collateral value $C(t)$ could diverge, and the resulting gap risk might lead to a non-negligible collateralised CVA (Pykhtin & Sokol 2013).

For the collateralised CVA, we can extend the representation in (9) and run the Monte Carlo simulation twice: the first run computes the exposure conditional on the JtD and the second run computes the lagged collateral using the baseline model without a default jump. For example, in the case of zero thresholds, the collateralised exposure can be calculated as:

$$V^{\text{Coll}}(t) = V((1+\gamma)\mathrm{e}^{-\lambda\gamma t_i} X_B(t_i), t_i) - V(X_B(t_{i-1})\mathrm{e}^{-\lambda\gamma t_i}, t_{i-1})$$

For verification, we also perform a brute-force simulation of the default indicator and apply the representation in (7) to calculate the collateralised CVA.

We calculate the collateralised CVA for the non-directional portfolio B under a two-way CSA agreement with zero threshold and a minimum transfer amount, with a lag of three business days for the collateral settlement. (The precise modelling of the margin period of risk is beyond of scope of this paper and is left for future research.) The results are shown in figure 7. As expected, collateral is very effective in reducing the CVA for the baseline and soft-WWR models: the collateralised CVA is less than 10% of the non-collateralised CVA. However, collateral does not appear to be as useful to the hard-WWR model due to the presence of a gap risk upon the forex jump at the default time. The collateralised CVA remains significant and stands at around 50% of the non-collateralised CVA. This suggests one has to be careful when modelling gap risk of the possibility of a risk factor jump-at-default, as modelled by the hard-WWR model.

Conclusion

We have shown that implied WWR in Japanese forex markets is substantial, as illustrated by quanto CDS data. For systemic counterparties and a directional portfolio, the CVA WWR add-on could be 40% higher than the no-WWR baseline, and choosing a proper jump-at-default WWR model is critical for capturing the impact. In contrast, choosing a more traditional 'soft' WWR model with historical correlation fails to reflect the prices in the CDS market and could potentially lead to the mispricing of CVA WWR in terms of both direction and magnitude. With the active hedging of CVA becoming more common, and with future Fundamental Review of the Trading Book regulation requiring a WWR approach to be implemented, these are important conclusions. ■

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