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# Double Impact on CVA for CDS: Wrong-Way Risk with Stochastic Recovery

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## Abstract

Current CVA modeling framework has ignored the impact of stochastic recovery rate. Due to the possible negative correlation between default and recovery rate, stochastic recovery rate could have a doubling effect on wrong-way risk. In the case of a payer CDS, when counterparty defaults, the CDS value could be higher due to default contagion while the recovery rate may also be lower if the economy is in a downturn. Using our recently proposed model of correlated stochastic recovery in the default time Gaussian copula framework, we demonstrate this double impact on wrong-way risk in the CVA calculation for a payer CDS. We also present a new form of Gaussian copula that correlates both default time and recovery rate.

## 1. Introduction

Counterparty credit risk has been a hot topic. In the recent document of Basel Committee's reform proposal [3], counterparty credit risk is identified as a key area where capital requirement needs to be strengthened. How to value counterparty credit risk in the form of credit valuation adjustment (CVA) is an active research field as of late, see for example [2, 5, 6, 7, 8, 14]. All these papers have tried to capture the wrong-way risk that counterparty defaults when the market value of a credit default swap (CDS) contract is high, through assumptions of correlation or contagion between defaults. However, one aspect that is missing is that recovery rate is usually not deterministic, but instead is stochastic and could be negatively correlated with default rate, see Altman [1] and references therein. In an economic downturn, default rates are higher than usual and recovery rates are also lower at the same time. This could lead to a doubling effect on CVA in case of wrong-way risk, where counterparty credit quality is negatively correlated with total exposure to the same counterparty. A CVA calculation without the consideration of stochastic recovery could easily underestimate the counterparty credit risk. An obvious example would be the default of Lehman Brothers in the credit crisis. The recovery rate after the Lehman CDS auction was set at 8.625 cents on the dollar for senior unsecured debt. The recovery rate on OTC contracts might be different due to netting and collateral posting, and also depending on the bankruptcy workout process. It is the purpose of this paper to start quantifying this double impact of wrong-way risk.

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One reason that recovery effect was not seriously considered in the previous work is because a consistent stochastic recovery modeling framework was lacking until the recent work of Bennani-Maetz [4] and Li [13]. Although their work has been focused on modeling of CDO senior tranche risk, there is no reason why the framework cannot be used in other credit areas to capture the recovery risk. In this paper, we will focus on how stochastic recovery deepens the wrong-way risk on a payer CDS contract. The other area that the recovery modeling might help is downturn LGD in the Basel capital calculation, which will be discussed in a separate paper.

In a previous paper, we discussed a simple way to calculate CVA for CDS on super senior ABS CDO [11]. It turns out that the method was too simplistic in that it totally ignored wrong-way risk and stochastic recovery effect. Armed with our stochastic recovery model, it seems to be the right time to revisit it. We will illustrate the wrong-way risk and recovery effect through an example of a payer CDS deeply-in-the-money with a stressed counterparty.

The paper is organized as follows. In section 2, we will detail our model [13] of stochastic recovery in a default time copula framework and derive the copula function correlating both default time and recovery in the Gaussian case. In section 3, we will setup our model for the bilateral CVA calculation on an OTC payer CDS contract. In section 4, we first give a numeric example of a break-even CDS. Then we compare the new method with the simple method discussed in our previous paper [11] to show the double impact from wrong-way risk and stochastic recovery in the case of a deeply-in-the-money CDS with a stressed counterparty. Section 5 concludes the paper.

## 2. Stochastic Recovery in the Default Time Copula Framework

In the default time copula framework of D. Li [10], the joint distribution of default times is determined by the marginal default time distributions (given by default probability curve) and the default time copula. In the following, we will build a correlated stochastic recovery model in a one factor Gaussian copula setup, following our recent work [13]. It is straight forward to extend the model to multi-factor or non-Gaussian copula cases.

In the Gaussian copula setup, a latent variable  $V_i = \sqrt{\rho_i}Z + \sqrt{1-\rho_i}\varepsilon_i$  drives the default of obligor  $i$  of a credit portfolio, where  $Z$  and  $\varepsilon_i$  are independent normal random variables  $\sim N(0,1)$  and  $Z$  is the systematic factor. The default event  $1_{\tau_i \leq t}$  can be characterized by  $V_i \leq v_i = \Phi^{-1}(p_i(t))$ , where  $\tau_i$  is the default time random variable,  $p_i(t)$  is the cumulative default probability of the obligor  $i$  and  $\Phi(x)$  is the standard cumulative normal distribution function. In other words, we can define the default time random variable as

$$\tau_i = p_i^{-1}(\Phi(V_i)) \quad (1)$$

We can assume that stochastic recovery is driven by another latent variable  $W_i = \sqrt{\beta_i}Z + \sqrt{1 - \beta_i}\xi_i$  through a time-independent cumulative distribution function  $F_R(r)$ , where  $\xi_i$  is another independent normal random variable. In a previous paper [12], we specify that stochastic recovery is defined by  $R_i = F_R^{-1}(\Phi(W_i))$  conditional on  $\tau_i \leq t$  or  $V_i \leq \Phi^{-1}(p_i(t))$ . The recovery defined this way is not the spot recovery at default and may lead to inconsistency. To build a consistent stochastic recovery model, we have to start with the spot recovery (or recovery upon default) at an arbitrary time  $t$ .

We have

$$\tau_i = t \quad \leftrightarrow \quad V_i = \Phi^{-1}(p_i(t)) \quad (2)$$

Conditional on default at time  $t$  or  $V_i = \Phi^{-1}(p_i(t))$ ,  $W_i$  follows a normal distribution with mean  $\sqrt{\rho_i\beta_i}\Phi^{-1}(p_i(t))$  and standard deviation  $\sqrt{1 - \rho_i\beta_i}$ . To ensure that  $F_R(r)$  is indeed the marginal cumulative distribution for the spot recovery at time  $t$ , we define

$$R_i = F_R^{-1}\left(\Phi\left(\frac{W_i - \sqrt{\rho_i\beta_i}\Phi^{-1}(p_i(t))}{\sqrt{1 - \rho_i\beta_i}}\right)\right) \quad (3)$$

Thus

$$P(R_i \leq r \mid \tau_i = t) = P\left(F_R^{-1}\left(\Phi\left(\frac{W_i - \sqrt{\rho_i\beta_i}\Phi^{-1}(p_i(t))}{\sqrt{1 - \rho_i\beta_i}}\right)\right) \leq r \mid \tau_i = t\right) = F_R(r) \quad (4)$$

Conditional on  $\tau_i = t$  or  $V_i = \Phi^{-1}(p_i(t))$ ,  $Z$  follows a normal distribution with mean  $\sqrt{\rho_i}\Phi^{-1}(p_i(t))$  and standard deviation  $\sqrt{1 - \rho_i}$ , while  $\xi_i$  still follows the standard normal distribution. If we fix  $Z = z$ , then the conditional spot recovery distribution will be

$$\begin{aligned} &P(R_i \leq r \mid \tau_i = t, Z = z) \\ &= \Phi\left(\frac{-\sqrt{\beta_i}z + \sqrt{1 - \rho_i\beta_i}\Phi^{-1}(F_R(r)) + \sqrt{\rho_i\beta_i}\Phi^{-1}(p_i(t))}{\sqrt{1 - \beta_i}}\right) \end{aligned} \quad (5)$$

Conditional on the systematic factor  $Z$ , obligor defaults are independent and the conditional default probability for obligor  $i$  is given by

$$p_i(t, z) = p(\tau_i \leq t \mid Z = z) = \Phi\left(\frac{\Phi^{-1}(p_i(t)) - \sqrt{\rho_i}z}{\sqrt{1 - \rho_i}}\right) \quad (6)$$

Now we can derive the distribution for conditional period recovery rate defined as

$$\begin{aligned}
& P(R_i \leq r \mid \tau_i \leq t, Z = z) \\
&= \frac{1}{p_i(t, z)} \cdot \int_0^t \Phi \left( \frac{-\sqrt{\beta_i} z + \sqrt{1 - \rho_i \beta_i} \Phi^{-1}(F_R(r)) + \sqrt{\rho_i \beta_i} \Phi^{-1}(p_i(s))}{\sqrt{1 - \beta_i}} \right) \cdot dp_i(s, z) \quad (7) \\
&= \frac{1}{p_i(t, z)} \cdot \Phi_2 \left( \frac{-(1 - \rho_i) \sqrt{\beta_i} z + \sqrt{1 - \rho_i \beta_i} \Phi^{-1}(F_R(r))}{\sqrt{1 - \beta_i + \rho_i \beta_i - \rho_i^2 \beta_i}}, c_i(t, z); -\tilde{\rho}_i \right)
\end{aligned}$$

where

$$c_i(t, z) = \frac{\Phi^{-1}(p_i(t)) - \sqrt{\rho_i} z}{\sqrt{1 - \rho_i}} \quad \text{and} \quad \tilde{\rho}_i = \frac{\sqrt{\rho_i \beta_i (1 - \rho_i)}}{\sqrt{1 - \beta_i + \rho_i \beta_i - \rho_i^2 \beta_i}}$$

We also have

$$\begin{aligned}
& P(1_{\{\tau_i \leq t\}} \cdot 1_{\{R_i \leq r\}} \mid Z = z) = P(R_i \leq r \mid \tau_i \leq t, Z = z) \cdot P(\tau_i \leq t \mid Z = z) \\
&= E \left[ 1_{\{\varepsilon_i \leq \frac{\Phi^{-1}(p_i(t)) - \sqrt{\rho_i} z}{\sqrt{1 - \rho_i}}\}} \cdot \Phi \left( \frac{-\sqrt{\beta_i} z + \sqrt{1 - \rho_i \beta_i} \Phi^{-1}(F_R(r)) + \sqrt{\rho_i \beta_i} \Phi^{-1}(p_i(\tau_i))}{\sqrt{1 - \beta_i}} \right) \mid Z = z \right] \\
&= E \left[ 1_{\{\varepsilon_i \leq \frac{\Phi^{-1}(p_i(t)) - \sqrt{\rho_i} z}{\sqrt{1 - \rho_i}}\}} \cdot \Phi \left( \frac{-\sqrt{\beta_i} z + \sqrt{1 - \rho_i \beta_i} \Phi^{-1}(F_R(r)) + \sqrt{\rho_i \beta_i} (\sqrt{\rho_i} z + \sqrt{1 - \rho_i} \varepsilon_i)}{\sqrt{1 - \beta_i}} \right) \mid Z = z \right] \\
&= \Phi_2 \left( \frac{-(1 - \rho_i) \sqrt{\beta_i} z + \sqrt{1 - \rho_i \beta_i} \Phi^{-1}(F_R(r))}{\sqrt{1 - \beta_i + \rho_i \beta_i - \rho_i^2 \beta_i}}, c_i(t, z); -\tilde{\rho}_i \right) \quad (8)
\end{aligned}$$

The unconditional period recovery distribution can be calculated as follows

$$P(R_i \leq r \mid \tau_i \leq t) = \frac{1}{p_i(t)} \int_{-\infty}^{\infty} P(1_{\{\tau_i \leq t\}} \cdot 1_{\{R_i \leq r\}} \mid Z = z) \cdot \phi(z) dz = F_R(r) \quad (9)$$

where  $\phi(x)$  is the normal distribution function. So the marginal distribution of period recovery rate is the same as the marginal distribution of spot recovery rate and is time-independent. If  $F_R(r)$  has the same expected recovery of  $R^{MKT}$  as that assumed by the single name CDS market, then the model is automatically consistent with the single name CDS market. Note that, in a dynamic model, the spot recovery distribution  $F_R(r)$  could be time dependent, then the integration in equation (7) would be more complicated.

Consider two obligors with correlated default and recovery rate, here we derive the copula of default time and recovery rate. Conditional on  $Z$ , the default and recovery processes are independent for the two obligors, and we have

$$\begin{aligned}
& P(1_{\{\tau_1 \leq t_1\}} \cdot 1_{\{R_1 \leq r_1\}} \cdot 1_{\{\tau_2 \leq t_2\}} \cdot 1_{\{R_2 \leq r_2\}} \mid Z = z) \\
&= \Phi_2 \left( \frac{-(1-\rho_1)\sqrt{\beta_1}z + \sqrt{1-\rho_1\beta_1}\Phi^{-1}(F_{R_1}(r_1))}{\sqrt{1-\beta_1 + \rho_1\beta_1 - \rho_1^2\beta_1}}, c_1(t_1, z); -\tilde{\rho}_1 \right) \\
&\quad \cdot \Phi_2 \left( \frac{-(1-\rho_2)\sqrt{\beta_2}z + \sqrt{1-\rho_2\beta_2}\Phi^{-1}(F_{R_2}(r_2))}{\sqrt{1-\beta_2 + \rho_2\beta_2 - \rho_2^2\beta_2}}, c_2(t_2, z); -\tilde{\rho}_2 \right)
\end{aligned} \tag{10}$$

Integrating over  $z$ , we will have the copula as

$$\begin{aligned}
C(p_1(t_1), F_{R_1}(r_1); p_2(t_2), F_{R_2}(r_2)) &= P(\tau_1 \leq t_1, R_1 \leq r_1; \tau_2 \leq t_2, R_2 \leq r_2) \\
&= \int_{-\infty}^{+\infty} P(1_{\{\tau_1 \leq t_1\}} \cdot 1_{\{R_1 \leq r_1\}} \cdot 1_{\{\tau_2 \leq t_2\}} \cdot 1_{\{R_2 \leq r_2\}} \mid Z = z) \cdot \phi(z) dz \\
&= \Phi_4(\Phi^{-1}(p_1(t_1)), \Phi^{-1}(F_{R_1}(r_1)), \Phi^{-1}(p_2(t_2)), \Phi^{-1}(F_{R_2}(r_2)); \Sigma_\rho)
\end{aligned} \tag{11}$$

where  $\Phi_4$  is the 4-variable cumulative normal distribution and the correlation matrix is defined as

$$\Sigma_\rho = \begin{pmatrix} 1 & 0 & \sqrt{\rho_1\rho_2} & \frac{(1-\rho_2)\sqrt{\rho_1\beta_2}}{\sqrt{1-\rho_2\beta_2}} \\ 0 & 1 & \frac{(1-\rho_1)\sqrt{\beta_1\rho_2}}{\sqrt{1-\rho_1\beta_1}} & \frac{(1-\rho_1)(1-\rho_2)\sqrt{\beta_1\beta_2}}{\sqrt{(1-\rho_1\beta_1)(1-\rho_2\beta_2)}} \\ \sqrt{\rho_1\rho_2} & \frac{(1-\rho_1)\sqrt{\beta_1\rho_2}}{\sqrt{1-\rho_1\beta_1}} & 1 & 0 \\ \frac{(1-\rho_2)\sqrt{\rho_1\beta_2}}{\sqrt{1-\rho_2\beta_2}} & \frac{(1-\rho_1)(1-\rho_2)\sqrt{\beta_1\beta_2}}{\sqrt{(1-\rho_1\beta_1)(1-\rho_2\beta_2)}} & 0 & 1 \end{pmatrix}$$

This can be proven through the following result

$$\begin{aligned}
& \int_{-\infty}^{+\infty} \Phi_2(a_1 z + b_1, c_1 z + d_1; \rho_1) \cdot \Phi_2(a_2 z + b_2, c_2 z + d_2; \rho_2) \cdot \phi(z) dz \\
&= \Phi_4 \left( \frac{b_1}{\sqrt{1+a_1^2}}, \frac{d_1}{\sqrt{1+c_1^2}}, \frac{b_2}{\sqrt{1+a_2^2}}, \frac{d_2}{\sqrt{1+c_2^2}}; \Sigma \right)
\end{aligned} \tag{12}$$

where

$$\Sigma = \begin{pmatrix} 1 & \frac{\rho_1 + a_1 c_1}{\sqrt{(1+a_1^2)(1+c_1^2)}} & \frac{a_1 a_2}{\sqrt{(1+a_1^2)(1+a_2^2)}} & \frac{a_1 c_2}{\sqrt{(1+a_1^2)(1+c_2^2)}} \\ \frac{\rho_1 + a_1 c_1}{\sqrt{(1+a_1^2)(1+c_1^2)}} & 1 & \frac{c_1 a_2}{\sqrt{(1+c_1^2)(1+a_2^2)}} & \frac{c_1 c_2}{\sqrt{(1+c_1^2)(1+c_2^2)}} \\ \frac{a_1 a_2}{\sqrt{(1+a_1^2)(1+a_2^2)}} & \frac{c_1 a_2}{\sqrt{(1+c_1^2)(1+a_2^2)}} & 1 & \frac{\rho_2 + a_2 c_2}{\sqrt{(1+a_2^2)(1+c_2^2)}} \\ \frac{a_1 c_2}{\sqrt{(1+a_1^2)(1+c_2^2)}} & \frac{c_1 c_2}{\sqrt{(1+c_1^2)(1+c_2^2)}} & \frac{\rho_2 + a_2 c_2}{\sqrt{(1+a_2^2)(1+c_2^2)}} & 1 \end{pmatrix}$$

If we define

$$\begin{cases} X_1 = \sqrt{\rho_1} \varepsilon + \sqrt{1-\rho_1} \varepsilon_1 - a_1 Z \\ Y_1 = \sqrt{\rho_1} \varepsilon + \sqrt{1-\rho_1} \varepsilon_2 - c_1 Z \\ X_2 = \sqrt{\rho_2} \xi + \sqrt{1-\rho_2} \xi_1 - a_2 Z \\ Y_2 = \sqrt{\rho_2} \xi + \sqrt{1-\rho_2} \xi_2 - c_2 Z \end{cases}$$

where  $\varepsilon, \varepsilon_1, \varepsilon_2, \xi, \xi_1, \xi_2, Z$  are independent standard normal random variables, then

$$\begin{aligned}
& \int_{-\infty}^{+\infty} \Phi_2(a_1 z + b_1, c_1 z + d_1; \rho_1) \cdot \Phi_2(a_2 z + b_2, c_2 z + d_2; \rho_2) \cdot \phi(z) dz \\
&= E(X_1 \leq b_1, Y_1 \leq d_1, X_2 \leq b_2, Y_2 \leq d_2)
\end{aligned}$$

which leads to the equation (12).

Equation (11) can be compared with the standard Gaussian copula of default times with fixed recovery

$$C(p_1(t_1), p_2(t_2)) = P(\tau_1 \leq t_1, \tau_2 \leq t_2) = \Phi_2(\Phi^{-1}(p_1(t_1)), \Phi^{-1}(p_2(t_2)); \sqrt{\rho_1 \rho_2}) \tag{13}$$

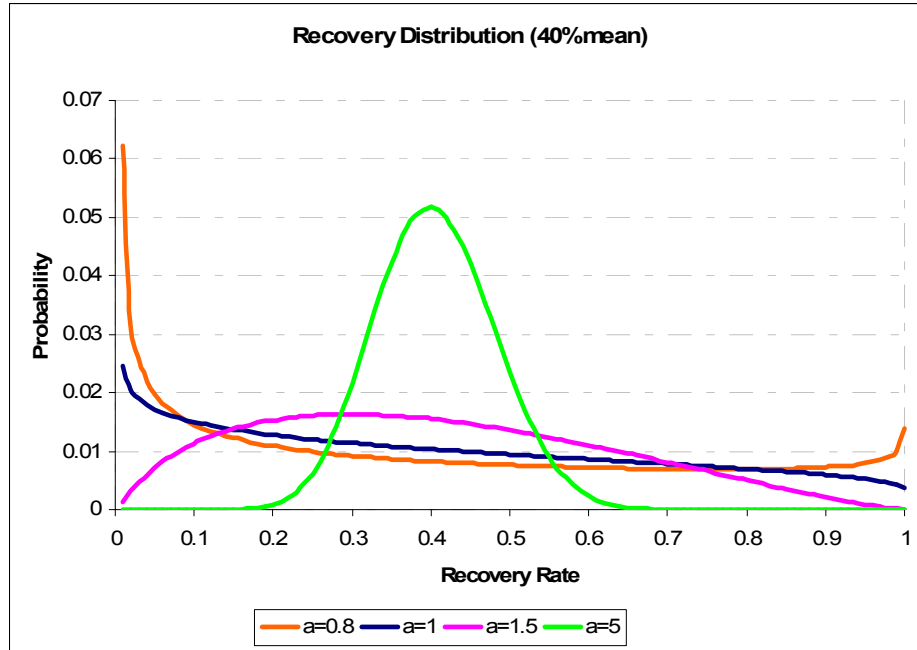
Note that, in equation (11), default time and recovery of the same obligor are not correlated, this is because recovery is always conditional on default. The correlation

between default times is the same as the standard Gaussian copula. The cross correlation between default time and recovery of different obligors will be smaller than the correlation between the respective Gaussian drivers. Finally, the correlation between recoveries of different obligors is also smaller than the correlation between the recovery Gaussian drivers. The copula for default time and recovery is still Gaussian. However, the correlation matrix cannot be generated by a simple one-factor model. Equation (11) can be easily extended to more than two obligors, multi-factors and other types of copulas.

For CVA calculation, we need the conditional expected loss for obligor  $i$  before time  $t$

$$L_t^i(z) = \int_0^1 (1-r) \cdot d_r P(1_{\{\tau_i \leq t\}} \cdot 1_{\{R_i \leq r\}} | Z = z) = \int_0^1 P(1_{\{\tau_i \leq t\}} \cdot 1_{\{R_i \leq r\}} | Z = z) \cdot dr \quad (14)$$

For numeric purpose, we consider the recovery distribution discussed in [13], which is similar to the beta distribution as shown in the Figure below.



It has the following form

$$F_R(r) = P(R \leq r) = \Phi(a \cdot \Phi^{-1}(r) - \sqrt{1+a^2} \Phi^{-1}(r_0)) \quad (15)$$

or, for the density function,



$$f_R(r) = a \cdot \frac{\phi(a \cdot \Phi^{-1}(r) - \sqrt{1+a^2} \Phi^{-1}(r_0))}{\phi(\Phi^{-1}(r))} \quad (16)$$

where  $a \geq 0$  and  $0 \leq r_0 \leq 1$ . This distribution will simplify calculation for Gaussian copula model. The expected recovery rate is  $r_0$  and the variance of recovery rate is

$$V(R) = \Phi_2\left(\Phi^{-1}(r_0), \Phi^{-1}(r_0); \frac{1}{1+a^2}\right) - r_0^2 \quad (17)$$

Assume  $r_0 = R^{MKT}$ . When  $a$  goes to zero, the variance goes to the maximum value  $R^{MKT}(1 - R^{MKT})$ , which corresponds to the case where  $R$  takes the extreme value of 0 or 1. When  $a$  goes to infinity, the variance goes to zero and the distribution reduces to a constant recovery  $R^{MKT}$ .

The original spot recovery equation (3) can be written as

$$R = \Phi\left(\frac{\sqrt{\beta_i} Z + \sqrt{1-\beta_i} \xi_i - \sqrt{\rho_i \beta_i} \Phi^{-1}(p_i(t))}{a \sqrt{1-\rho_i \beta_i}} + \sqrt{1 + \frac{1}{a^2}} \Phi^{-1}(R^{MKT})\right) \quad (18)$$

Then we have

$$\begin{aligned} & P(R_i \leq r \mid \tau_i = t, Z = z) \\ &= \Phi\left(\frac{-\sqrt{\beta_i} z + \sqrt{1-\rho_i \beta_i} \cdot (a \Phi^{-1}(r) - \sqrt{1+a^2} \Phi^{-1}(R^{MKT})) + \sqrt{\rho_i \beta_i} \Phi^{-1}(p_i(t))}{\sqrt{1-\beta_i}}\right) \end{aligned} \quad (19)$$

The expected conditional spot recovery is

$$\begin{aligned} r_i(t, z) &= \int_0^1 r \cdot d_r P(R_i \leq r \mid \tau_i = t, Z = z) \\ &= \Phi\left(\frac{\sqrt{\beta_i} z + \sqrt{1-\rho_i \beta_i} \cdot \sqrt{1+a^2} \Phi^{-1}(R^{MKT}) - \sqrt{\rho_i \beta_i} \Phi^{-1}(p_i(t))}{\sqrt{1-\beta_i + a^2(1-\rho_i \beta_i)}}\right) \end{aligned} \quad (20)$$

The expected conditional loss up to time  $t$  is

$$L_i^t(z) = \int_0^t (1 - r_i(s, z)) \cdot dp_i(s, z) = \Phi_2(c_i(t, z), b_i(z); -\hat{\rho}_i) \quad (21)$$

where  $c_i(t, z)$  is defined in equation (7) and

$$b_i(z) = -\frac{(1-\rho_i)\sqrt{\beta_i}z + \sqrt{1-\rho_i\beta_i}\sqrt{1+a^2}\Phi^{-1}(R^{MKT})}{\sqrt{1-\beta_i+a^2(1-\rho_i\beta_i)+\rho_i\beta_i-\rho_i^2\beta_i}}$$

$$\hat{\rho}_i = \frac{\sqrt{\rho_i\beta_i(1-\rho_i)}}{\sqrt{1-\beta_i+a^2(1-\rho_i\beta_i)+\rho_i\beta_i-\rho_i^2\beta_i}}$$

Conditional on  $Z$ , the expected recovery rate will be time-dependent through  $p_i(t)$ .

### 3. Bilateral Counterparty Risk with Stochastic Recovery

The general bilateral counterparty risk pricing formula without netting or collateralization has been derived in Brigo and Capponi [7] (see equations (2.6) and (2.7) in their paper). We write down the formula for the bilateral CVA for the investor at valuation time  $t$ ,

$$BR - CVA(t, T, LGD_{0,1,2}) = E_t \left\{ LGD_2 \cdot 1_{\tau_2 \leq \tau_0 \wedge T} \cdot D(t, \tau_2) \cdot [NPV(\tau_2)]^+ \right\} - E_t \left\{ LGD_0 \cdot 1_{\tau_0 \leq \tau_2 \wedge T} \cdot D(t, \tau_0) \cdot [-NPV(\tau_0)]^+ \right\} \quad (22)$$

where the subscripts 0, 1, 2 are for investor, reference credit (in the case of a CDS contract) and counterparty,  $\tau$  is the default time variable,  $D(t, \tau)$  is the deterministic discount factor,  $NPV(\tau)$  is the net present value of future (after  $\tau$ ) cashflows of the OTC contract valued at  $\tau$  not subjected to counterparty risk, the loss given default  $LGD$  is one minus the recovery upon default,  $T$  is the maturity of the OTC contract. The contract value with counterparty risk will be the contract value without counterparty risk minus  $BR - CVA$ .

Brigo and Capponi [7] combine Gaussian copula of default times with a stochastic intensity model to study the impact of default correlation and credit spread volatility on the bilateral CVA of a CDS. They assume constant LGDs, thus ignore the double impact from negatively correlated recovery rates. The present paper will use a simple model to demonstrate the double impact from recovery. We will use the one-factor Gaussian copula model with stochastic recovery described in the previous section where the uncertainty in the systematic factor contains all the randomness in the default probability curve and defaults are independent conditional on the systematic factor. The problem with this model as a dynamic model has been discussed in the literature, see for example the recent paper of Hitier and Huber [9]. In this simple model, we will be able to demonstrate the double impact from correlated defaults and recovery rates. However, we will not be able to study the impact of credit spread volatility, since this is not a true dynamic model. We notice that it is possible to apply our Gaussian copula model of default time and recovery to the Brigo-Capponi framework to add stochastic recovery effect in addition to default correlation and spread volatility.

We assume, conditional on the systematic factor  $Z$ , the default probability curve is deterministic and takes the form in equation (6). The bilateral CVA can be written as

$$BR - CVA(t, T, LGD_{0,1,2}) = E_t \left\{ E \left[ LGD_2 \cdot 1_{\tau_2 \leq \tau_0 \wedge T} \cdot D(t, \tau_2) \cdot [NPV(\tau_2)]^+ | Z \right] \right\} \\ - E_t \left\{ E \left[ LGD_0 \cdot 1_{\tau_0 \leq \tau_2 \wedge T} \cdot D(t, \tau_0) \cdot [-NPV(\tau_0)]^+ | Z \right] \right\} \quad (23)$$

Let  $t = 0$  and assume the premium cashflows and payments of default losses all happen on discrete time steps  $T_0 = t, T_1, \dots, T_N = T$ . We also assume that, if counterparty and the reference credit default in the same time period, CVA loss will be  $LGD_2 \cdot LGD_1$ . This is an estimate which is somewhat justified by the fact that there is lag between reference name default, CDS auction and loss payment from counterparty. We arrive at the following approximation

$$BR - CVA(t, T, LGD_{0,1,2}) \\ = E_t \left\{ E \left[ \sum_{i=1}^N LGD_2 \cdot 1_{T_{i-1} < \tau_2 \leq T_i} 1_{\tau_0 > T_i} \cdot D(T_0, T_i) \cdot [NPV(T_i)]^+ | Z \right] \right\} \\ + E_t \left\{ E \left[ \sum_{i=1}^N LGD_2 \cdot 1_{T_{i-1} < \tau_2 \leq T_i} 1_{\tau_0 > T_i} \cdot D(T_0, T_i) \cdot LGD_1 \cdot 1_{T_{i-1} < \tau_1 \leq T_i} | Z \right] \right\} \\ - E_t \left\{ E \left[ \sum_{i=1}^N LGD_0 \cdot 1_{T_{i-1} < \tau_0 \leq T_i} 1_{\tau_2 > T_i} \cdot D(T_0, T_i) \cdot [-NPV(T_i)]^+ | Z \right] \right\} \quad (24) \\ = E \left[ \sum_{i=1}^N (L_{T_i}^2(Z) - L_{T_{i-1}}^2(Z)) \cdot P(\tau_0 > T_i | Z) \cdot D(T_0, T_i) \cdot [NPV(T_i)]^+ | Z \right] \\ + E \left[ \sum_{i=1}^N (L_{T_i}^2(Z) - L_{T_{i-1}}^2(Z)) \cdot P(\tau_0 > T_i | Z) \cdot D(T_0, T_i) \cdot (L_{T_i}^1(Z) - L_{T_{i-1}}^1(Z)) \right] \\ - E \left[ \sum_{i=1}^N (L_{T_i}^0(Z) - L_{T_{i-1}}^0(Z)) \cdot P(\tau_2 > T_i | Z) \cdot D(T_0, T_i) \cdot [-NPV(T_i)]^+ | Z \right]$$

where, in the last equation, for a payer CDS contract,

$$NPV(T_i) | Z = \left\{ P(\tau_1 > T_i) \cdot E_{T_i} \left[ -S_1 \cdot \sum_{j=i+1}^N \alpha_j \cdot D(T_i, T_j) \cdot P(\tau_1 > T_j | T_i) \right. \right. \\ \left. \left. + \sum_{j=i+1}^N LGD_1 \cdot D(T_i, T_j) \cdot P(T_{j-1} < \tau_1 \leq T_j | T_i) \right] | Z \right\} \quad (25) \\ = -S_1 \cdot \sum_{j=i+1}^N \alpha_j \cdot D(T_i, T_j) \cdot P(\tau_1 > T_j | Z) + \sum_{j=i+1}^N D(T_i, T_j) \cdot (L_{T_j}^1(Z) - L_{T_{j-1}}^1(Z))$$

where  $S_1$  is the fixed premium rate of the CDS contract and  $\alpha_j$  is day count fraction. For simplicity, we have ignored the accrued premium. We also ignore the situation that investor and counterparty default in the same period. Greater accuracy can be achieved through Monte Carlo simulation instead of bucketing time into payment periods.

In the numeric calculation, all we need are the conditional survival probability  $1 - p(T_i, z)$  and conditional expected loss  $L_{T_i}(z)$  up to each time point  $T_i$  conditional on  $Z = z$ , which have explicit formula in section 2, see equations (6) and (21). The final BR-CVA will be calculated as integration over the Gaussian variable  $Z$ .

## 4. Numerical Results

We consider a five-year payer CDS on a reference name. Since we are more interested in wrong-way risk with stochastic recovery effect, we will assume the protection buyer is almost default-free. Interest rate is assumed to be constant at 4%. We experiment with two spread levels 120 bps and 250 bps applied to either counterparty or reference name. The effects of correlation between defaults and recovery rates and the volatility of recovery rates are considered. We expect recovery correlation to closely follow default correlation and assume they are equal in the numerical calculation. The results are presented in Table 1 and Table 2.

In general, when default correlation increases, CVA also increases. Adding correlated stochastic recovery, CVA will increase with the volatility of recovery rate. But the stochastic recovery effect is not as strong as default correlation for wrong-way risk. Keep in mind that volatility of recovery is capped at 49% if mean of recovery is fixed at 40%. We notice that the same phenomenon appears here as first discussed in Brigo and Chourdakis [6]. In table 1, when the default correlation is extremely high, CVA drops significantly. This is because reference name almost always default before the counterparty so that the counterparty risk is much smaller.

Next we consider a 5 year CDS contract that is deeply-in-the-money with a stressed counterparty. The deal premium is 5 bps while the current market spread is either 15% or 25% for the reference name or the counterparty. The results are presented in Table 3 and Table 4. Note that CVA is a loss for investor, but is a gain for counterparty.

In a previous paper [11], we discussed two simple methods to calculate CVA for a deeply-in-the-money CDS contract on a super senior ABS CDO tranche with a distressed counterparty. The first method is to add the counterparty CDS spread to Libor curve to discount the cashflows, which is only valid when spread is small and was used by the monoclones to calculate their CVA. The second method uses an approximation to adjust the discount curve by default probability and recovery when the exposure is almost always positive and there is no correlation between counterparty and the underlying credit. We compare the results from these two methods (called method 1 and method 2) with the new method discussed in this paper. The first method always gives a higher

CVA than the second method, while the second method matches closely with the new method when there is no correlation. However, with correlation and recovery volatility getting higher, CVA based on the new method could be much higher than both method 1 and method 2. This reflects how wrong-way risk and stochastic recovery affects CVA value. However, when correlation is extremely high and the reference name has worse credit quality than that of counterparty, CVA would drop much lower since default time of the reference name is usually earlier than that of counterparty.

To complete the discussion, we also consider the risk of investor default in this stressed situation. We assume investor 5 year CDS spread to be 500 bps. The results are listed in table 5 and table 6. The total CVA is less due to bilateral effect, but it could still be at elevated level in case of higher default correlation and higher volatilities for correlated recovery rates.

## 5. Conclusion

In this paper, we apply our model of stochastic recovery in a default time Gaussian copula framework to quantify the wrong-way risk due to negatively correlated default and recovery rate in bilateral CVA calculation, using payer CDS as an example. We follow the general framework for calculating bilateral CVA discussed in Brigo and Capponi [7], but use our one-factor default time Gaussian copula model with stochastic recovery to describe the future uncertainty in default probabilities and recovery rates. We find that, for a payer CDS contract, CVA normally increases in magnitude with default correlation and volatility of correlated recovery rates. However, in the special case when the reference name has worse credit quality than the counterparty and default correlation is extremely high at the same time, CVA could be much smaller even with high recovery volatility, which confirms the results discussed in Brigo and Chourdakis [6]. The effect of the negative correlation between default and recovery rate does increase the CVA noticeably but is not as strong as the default correlation between counterparty and the reference name. We also revisit a simple method for CVA calculation on a deeply-in-the-money CDS with a stressed counterparty proposed in a previous paper [11]. We find that the simple method does not capture the wrong-way risk due to correlated defaults and lower recovery rates in economic downturn.

Further research is needed to build a true dynamic model with stochastic recovery to quantify and hedge counterparty credit risk.

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## Tables

Default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>20%</b>	23.17	23.19	34.42	39.75
<b>60%</b>	68.88	69.06	99.32	113.31
<b>90%</b>	92.27	92.34	108.13	111.45
<b>99%</b>	28.23	28.24	28.38	27.31

**Table 1.** The counterparty CVA in basis points for the case when counterparty break-even 5 year CDS spread is 120 bps and reference name break-even 5 year CDS spread is 250 bps, which is also the contract spread. Both have the same recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. Compare with the base case CVA = 3 bps where there is no default correlation.

default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>20%</b>	26.13	26.12	38.35	44.21
<b>60%</b>	88.93	89.18	130.69	152.23
<b>90%</b>	200.27	200.55	251.43	280.41
<b>99%</b>	296.33	296.47	316.03	324.68

**Table 2.** The counterparty CVA in basis points for the case when counterparty break-even 5 year CDS spread is 250 bps and reference name break-even 5 year CDS spread is 120 bps, which is also the contract spread. Both have the same recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. Compare with the base case CVA = 3 bps where there is no default correlation.

default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>0%</b>	925.36			
<b>20%</b>	936.32	936.70	1015.12	1062.69
<b>60%</b>	933.60	934.27	1050.34	1109.64
<b>90%</b>	755.35	755.80	796.70	793.59
<b>99%</b>	346.88	347.01	353.09	348.90

**Table 3.** The counterparty CVA in basis points for the case when counterparty break-even 5 year CDS spread is 1500 bps, reference name break-even 5 year CDS spread is 2500 bps but contract spread is set at 5 bps. Both have the same recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. The contract value without counterparty default risk is 4800.89 bps for the investor. CVA from method 1 is 1060.69 bps, while CVA from method 2 is 925.12 bps.

default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>0%</b>	1146.86			
<b>20%</b>	1226.23	1226.74	1336.07	1403.53
<b>60%</b>	1468.02	1468.98	1675.22	1807.90
<b>90%</b>	1940.89	1941.62	2107.35	2220.89
<b>99%</b>	2320.54	2320.82	2364.15	2384.13

**Table 4.** The counterparty CVA in basis points for the case when counterparty break-even 5 year CDS spread is 2500 bps, reference name break-even 5 year CDS spread is 1500 bps but contract spread is set at 5 bps. Both have the same recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. The contract value without counterparty default risk is 3863.56 bps for the investor. CVA from method 1 is 1421.91 bps, while CVA from method 2 is 1146.45 bps.

default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>0%</b>	802.03			
<b>20%</b>	802.29	802.49	850.11	882.66
<b>60%</b>	798.23	798.53	856.88	890.13
<b>90%</b>	666.11	666.33	674.23	657.33
<b>99%</b>	274.09	274.14	268.81	259.72

**Table 5.** The counterparty bilateral CVA in basis points for the case when investor break-even 5 year CDS spread is 500 bps, counterparty break-even 5 year CDS spread is 1500 bps, reference name break-even 5 year CDS spread is 2500 bps but contract spread is set at 5 bps. All three have the same correlation and recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. The contract value without counterparty default risk is 4800.89 bps for the investor.

default correlation $\rho_d$	no correlation with recovery $\rho_r = 0$	same correlation for recovery $\rho_r = \rho_d$ with <b>a=200</b> or <b>vol=0.07%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=1</b> or <b>vol=28.13%</b>	same correlation for recovery $\rho_r = \rho_d$ with <b>a=0.01</b> or <b>vol=48.77%</b>
<b>0%</b>	1020.65			
<b>20%</b>	1084.00	1084.29	1156.99	1206.63
<b>60%</b>	1318.31	1318.79	1447.14	1542.88
<b>90%</b>	1850.07	1850.51	1971.70	2065.54
<b>99%</b>	2247.75	2247.95	2279.86	2294.94

**Table 6.** The counterparty bilateral CVA in basis points for the case when investor break-even 5 year CDS spread is 500 bps, counterparty break-even 5 year CDS spread is 2500 bps, reference name break-even 5 year CDS spread is 1500 bps but contract spread is set at 5 bps. All three have the same correlation and recovery distribution with mean at 40%. The parameter **a** determines the volatility of the recovery distribution. The contract value without counterparty default risk is 3863.56 bps for the investor.



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