

Technical Note: On Wrong Way Risk

Ignacio Ruiz*

February 2012

Version 1.0.2

Forthcoming publication in the Journal of Financial Transformation

Abstract

Wrong Way Risk can be of crucial importance when computing counterparty risk measurements like EPE or PFE profiles. It appears when the default probability a given counterparty is not independent of its portfolio value. There are a number of approaches in the literature but, to the author's knowledge, they all fail to provide either a computationally efficient approach or an intuitive methodology, or both. This technical note tackles this problem and describes an intuitive and fairly easy method to account for Wrong Way Risk with minimal added computational effort.

1 Why a Wrong Way Risk Model is Needed

When computing and pricing counterparty risk, the existence of wrong way risk (WWR) should substantially affect our risk measurements.

WWR appears when there is a dependency between the portfolio value and the default probability of the counterparty linked to that portfolio. For example, say our portfolio is one single equity put option which we have bought from Morgan Stanley, with Bank of America being the option's underlying. In counterparty risk, the potential exposure must be measured subject to *default of the counterparty*. The question we have to tackle then is how much could that option be worth in the future in the event of Morgan Stanley defaulting. Morgan Stanley and Bank of America are both SIFIs¹ in the US,

*Founding Director, iRuiz Consulting Ltd, London. Ignacio is a contractor and independent consultant in quantitative risk analytics and CVA. Prior to this, he was the head quant for Counterparty Risk, exposure measurement, at Credit Suisse, and Head of Market and Counterparty Risk Methodology for equity at BNP Paribas. Contact: ignacio@iruizconsulting.com

¹Systemically Important Financial Institutions

and so we can reasonably assume that Bank of America stock prices will be highly affected by the event of Morgan Stanley defaulting. So, our exposure to this put option can be much higher than that given by a model which does not take this dependency into account.

The opposite effect (i.e., when the exposure is likely to decrease in the event of counterparty default) also exists, and it is typically called Right Way Risk (RWR). From a risk management and CVA pricing standpoint, both effects are important as, should models not capture this dependency, counterparty risk measurements will over- (RWR) or underestimate (WWR) risk. From a regulatory point of view, WWR is more important, as regulators allow capital models to be conservative but never aggressive.

2 Existing Modeling Approaches

There are a number of models in the literature that tackle this topic [1, 3, 4]. They can be broadly split in two families: models with a joint probability distribution function driving exposure values and defaults [1, 4], typically using a Gaussian copula with a correlation ρ , and those that model the dependency between portfolio exposure and counterparty default events using an analytical approach linking portfolio value with default intensity [3]. All of these models use a change of measure. Some[1] implement that change of measure in the evolution of the risk factors, while others[3, 4] implement it in the calculation of risk measurements (e.g., EPE² or PFE³). In the latter case, each scenario i and time point j in a typical Monte Carlo simulation has a weight $w_{i,j}$ assigned to it when calculating risk measurements.

On the one hand, copula-driven models tend to be computationally intensive, as they require the simulation of random paths from joint distributions. On the other hand, analytical models are faster to compute, but they require an analytical expression linking the value of the portfolio of trades with the default probability of the corresponding counterparty.

To the author's knowledge, the attempts so far to make that link have used methodologies which are subjective to the portfolio manager's views and/or not possible to corroborate with actual data.

This technical note offers a methodology to overcome these issues and provides a framework of driving WWR models using market data. The proposed method requires minimal additional computational effort.

²Expected Positive Exposure

³Potential Future Exposure

3 Leveraging from Market Information

The setup is the following: we typically have a Monte Carlo engine for Counterparty Risk that produces scenarios in a number of future time points. After netting is applied [1, 2], we obtain a grid of portfolio valuations from which EPE, PFE, and other risk measurements can be calculated. We want to assign a weight to each of those scenarios. Those weights will contain the required information about the counterparty default probability in each scenario and time step. If there is no WWR, then each weight can be equal to one.

We can attempt to put a weight to each scenario based on the value of the *portfolio*, as done in a number of public methodologies [3, 4], but portfolio compositions change over time, so any past analysis is difficult, and extrapolation to the future can also be an issue.

3.1 Linking Exposures to Default Probabilities

Most existing counterparty risk setups include an equity model. Also, we know that, loosely speaking, there is an inverse relationship between equity prices and CDS spread levels for a given company; that is, the lower the equity value of a company, the higher the default probability and, hence, the higher the credit spread.

Default events are rare, so back-testing can be difficult if not impossible. However, we are not interested in that default back-test information right now. What we want is to find a weight $w_{i,j}$ for each scenario and time point, so that the calculation of risk measures like EPE or PFE can be done with this information so that each weight should represent the counterparty default probability in that scenario and time step. Assuming that, at each point in time, the CDS market data accounts for the link between the default probabilities and equity prices, then we can use that data to get a handle on the latter link. Provided that our existing Monte Carlo engine for Counterparty Risk contains a model for equities (this can be easily typically incorporated if it does not exist), and that each simulated scenario will contain a realization of the equity price of the portfolio counterparty, then we can assign a default probability to each scenario. It should be noted that this can be done even when the portfolio does not contain any trade with the counterparty's equity as an underlying: all we have to do is model the underlying's equity price with the appropriate dependency structure of the risk factors driving the portfolio valuation.

In order to assess this method, the author studied the history of the company Ford, Ford was picked because it has recently been close to default and yet didn't do so, hence it offers a good example with a wide range of credit spread values and equity prices. Figure 1 shows the Ford equity price versus its one year CDS spread⁴.

⁴The CDS spread tenor was chosen to be one year because it represents a good measure of the probability of imminent default. Shorter tenors might not be liquid enough, hence data quality could be

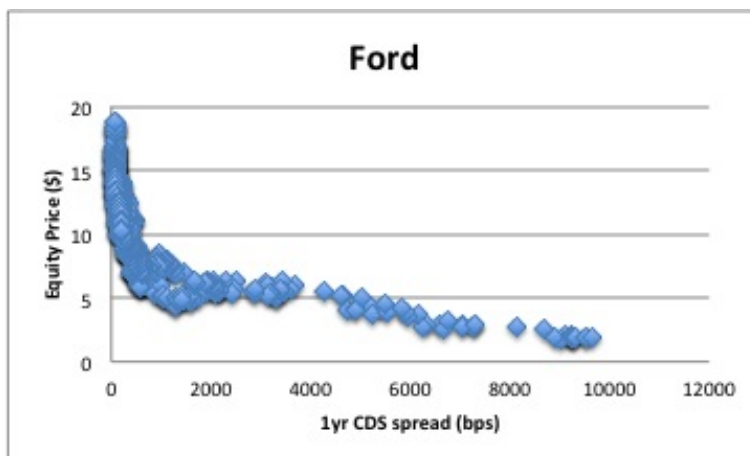


Figure 1: 1 year spread vs. equity price for Ford Co, from Aug 2007 to Dec 2011. Source: Bloomberg.

Assuming that the default intensity (λ) (i.e., the hazard rate) is a good representation of the default probability, and that the proxy $s = \lambda(1 - R)$ is good, where s represents the credit spread and R the recovery rate, we can obtain a series of data points linking default intensity and equity prices. This is shown in Figure 2.

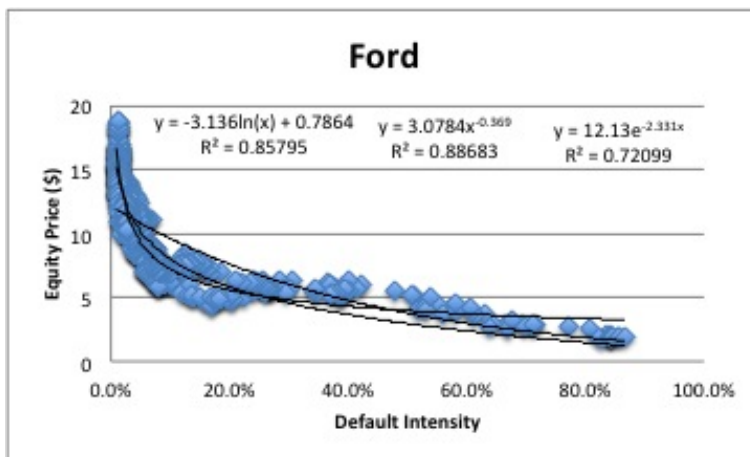


Figure 2: Default intensity vs. equity price for Ford Co, from Aug 2007 to Dec 2011.

Once we have these plots showing the inverse default probability vs equity price, we can try to fit a number of analytical expressions to it. The author tried several fits using a least squared regression technique; three of them are shown in Figure 2. The one that seemed to deliver the best results was $Eq = 3.0784/\lambda^{0.369}$, where Eq represents the equity price.

an issue.

Figure 2 displays an example of the strong dependency between equity prices and default intensity that we were looking for. We can now easily attach a weight $w_{i,j}$ to each scenario and time step in the valuation grid of a portfolio of trades with Ford Co. as the counterparty. This way, we can easily and efficiently account for Wrong Way Risk.

Finally, it must be noted that if we already have a credit and default model in the Monte Carlo engine used for counterparty risk, and if that model accounts for dependency to other asset classes, then the default intensity simulated by that credit model can be used directly instead of having to go through equity price simulations.

4 Conclusions

This technical note sketches a simple way to account for Wrong Way Risk in counterparty risk calculations. All that is needed is an equity model with the appropriate dependency structure with the risk factors driving the portfolio value, and a calibration of the default intensity to equity prices via the CDS market data. The risk measurement calculations like EPE or PFE can then get computed using a weighting per scenario and time step.

For illustration purposes, we have in this note used a simple least square regression technique for the calibration of the default intensity to Ford Co equity price. More sophisticated approaches can be used; for example, an inflation adjustment of equity prices could be appropriate.

Acknowledgements

The author would like to thank Professor John Hull for the interesting conversations they have had on this topic which, to a high extent, provoked this investigation.

References

- [1] G. CESARI, J. AQUILINA, N. CHARPILLON, Z. FILIPOVIC, G. LEE, AND I. MANDA, *Modelling, Pricing, and Hedging Counterparty Credit Exposure: A Technical Guide*, Springer Finance, first ed., 2010.
- [2] J. GREGORY, *Counterparty Credit Risk: The New Challenge for Global Financial Markets*, Wiley, first ed., 2009.
- [3] J. HULL, *Cva and wrong way risk*, Risk Minds Conference, Geneva, 2011.
- [4] D. ROSEN, *Cva, wrong-way risk and basel iii*, Risk Minds Conference, Geneva, 2011.