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THESIS SYNOPSIS

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Pricing counterparty credit risk - An analysis of the Credit Valuation Adjustment

Ph.D. Dissertation

Supervisor:
Péter Medvegyev CSc
Professor

Budapest, 2019

Department of Finance

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Contents

1 Research and topic selection background

The dissertation focuses on counterparty credit risk management and the Credit Valuation Adjustment (CVA).

Counterparty credit risk refers to the risk of losses due to the default of a counterparty in an OTC derivative contract.[1] This type of financial risk belongs to the family of credit risk, and mainly the 2008 crisis has drew attention to its relevance. The pricing of counterparty credit risk refers to a way of measuring this risk and the price itself is called the credit valuation adjustment. CVA is an adjustment to the value of a risk free contract so that the new price reflects the possible losses due to the default of the parties. The adjusted price is called risky price.

The history of counterparty credit risk dates back to the beginning of the OTC markets, but until the 2008 crisis it was considered to be insignificant. Market practices before the crisis treated counterparty credit risk as negligible (Pykhtin and Rosen, 2010), or its pricing was the privilege of large dealers when they entered into a transaction with smaller counterparties (Skoglund et al., 2013). As Cesari et al. (2009) point out, the crisis revealed that it is of utmost importance that all parties engaging in derivatives transactions measure, hedge and capitalize counterparty credit risk. Thus the models of counterparty risk management started to develop. In general, these models are described by Bielecki and Rutkowski (2013) as follows: the objectives of the quantitative models of credit risk are to price and hedge such contracts that are exposed to credit risk.

After the crisis the topic received a huge amount of attention that was the result of multiple factors. The crisis removed the "too big to fail" perception from the market and the default risk of all institutions became a real problem. This coupled with huge losses realized due to actual default events and more importantly due to the movement of the CVA. Regulators started to address the problems and put focus on the CVA with the increased capital requirements. All of the above happened in the middle of a boom in the OTC market, which inflated the value of the counterparty credit risk outstanding on the market. Besides the practical applications, the theoretical aspect of the topic was also engaging for researchers due to the inherent complexities of the field. Therefore the relevance of the CVA was unquestionable. In the last couple of years, the significance of the CVA decreased primarily due to market reforms like the clearing requirements of the standardized OTC derivatives or the mandatory bilateral margining of non-cleared derivatives and also due to decreased activity in the OTC markets. At the same time new adjustments, collectively referred as XVAs emerged that inherited several properties from the CVA. Nevertheless the topic is still critically important and it carries a large number of questions to be answered.

The field of credit valuation adjustment can be split into multiple subcategories. First

[1] Counterparty credit risk can be defined more broadly as it arises from securities financing transactions as well. I restrict the definition used here to OTC derivatives, because those represent the main focus area of the dissertation.

one can differentiate between accounting and regulatory CVA. The accounting CVA is the price adjustment factor that I described above. The regulatory CVA is the by-product of the accounting CVA, which refers to the specific capital requirements due to the movement of credit valuation adjustment.

The complexity of the credit valuation adjustment is arising from its components. Due to the pricing nature of the problem, one needs to compress multiple factors like default times, actual obligation size or the loss given default to a single number. The topic of credit valuation adjustment can be further split into subcategories based on the individual components. Therefore one can distinguish between default time and exposure models when modeling CVA. As a result, the calculation of the credit valuation adjustment is a complex and computationally intensive task even for a vanilla product.

The primary purpose of the dissertation is to give a comprehensive view about the credit valuation adjustment that is supplemented by other goals: Besides performing a comprehensive review of CVA, I would like to highlight and introduce some specific area of the topic in more details. In addition, I would like to develop and extend the available toolkit by building new methods and improving existing ones. Also, I want to highlight and assess gaps related to the CVA calculation, and if possible resolve them. Due to space limits I will not be able to cover all aspects of the topic, but in order to stick to the comprehensive view, each chapter can be assigned to one of the subcategories described above. Chapters 2 and 3 are meant to cover different aspects of the (accounting) credit valuation adjustment and the regulatory CVA is analyzed in chapter 4. Chapter 1 is a general introduction that reviews the literature of the field and Chapter 5 concludes the dissertation. This framework allows me to achieve my goals in a structured manner. Also I can highlight the alternative dimensions of the topic, because among others I explain the theorethical challenges, investigate the technical challenges of numerical methods used for the calculation, challenge the group of risk factors relevant for CVA and present the topic from the regulators' point of view. Also, this framework creates a bottom-up structure by building up the CVA starting from its components.

2 Methods used in the dissertation

The credit valuation adjustment is the solution of a complex numerical problem that relies on quantitative methods. Therefore in the dissertation I deal with quantitative models that are of significant relevance with respect to both theoretical and practical aspects. Within the field of economics the models belong to the area of mathematical finance.

In chapter 1 of the dissertation I introduce the basics of credit valuation adjustment. I define the most important measures of counterparty risk like exposure amounts and default probabilities. The CVA is equal to the expected loss due to the default of the counterparties in the derivative contract. Formalizing this definition and solving the semi-analytic formulas rely on the main results of quantitative finance.

As the credit valuation adjustment relies on exposure and default time models I perform a detailed analysis of these models. The credit exposure models use derivative pricing methodologies and statistical aggregation methods to determine future exposure amounts. The main output of these models is the future exposure distribution or a certain statistical measure of that. Therefore these models rely primarily on stochastic and statistical analysis. Besides the analytical solutions due to the varying complexity of the applications, one often needs to use numerical techniques to determine the exposure distributions.

The most often used approaches rely on some form of Monte Carlo simulations. Exposure profiles that are one of the main inputs of the CVA can be calculated as follows: First, future values of underlying factors are simulated on a discrete time grid up to the maturity of the derivatives contract. Next, the derivative instrument is priced at all time steps on all simulated paths. From the prices the exposure amounts are determined. Finally for each time step on the grid, the exposure amounts are averaged across paths to determine the expected exposure amount.

This approach requires a large number of simulated paths that makes it computationally intensive. In fact, the second step requires analytical derivative pricing that is not always possible so alternative approaches are used as well. In the dissertation, I use Multi Level Monte Carlo and Least Squares Monte Carlo approaches for resolving some of these limitations. In both cases, I describe a step-by-step algorithm to define new methodologies.

In chapter 3, I deal with the default probability aspect of the credit valuation adjustment. Over the dissertation, I use reduced form default modeling that is extended in section 3 with the effect of rating migrations. I start with the Markov-process based approach of Lando (1998), but my model exhibits the looping default problem in a Non-Markovian set-up. The looping default problem arises from one of the first applications of the default contagion models by Jarrow and Yu (2001). In these models the default intensity process of a company depends on the default event of its peers. At the same time the peers' default intensities depend on the company's default event as well. This creates a recursive problem that is called the looping default. In this set up one is not able to simulate the intensity processes of the companies independently. Since the work of Jarrow and Yu (2001) multiple solutions of the looping default problem have been proposed. Yu (2007) introduced the total hazard construction algorithm. Leung and Kwok (2005) relied on the survival probability measure to overcome the difficulties of the simulation. In some cases the Markov chain based solution by Walker (2006) and Leung and Kwok (2009) can also be used. I will extend the total hazard construction approach and give a detailed numerical algorithm that allows the application of the rating contagion model.

In section 4, I use analytical techniques to formalize the Expected Shortfall measure of a portfolio that contains CVAs and their hedges. This sensitivity based approach allows me to derive the regulatory capital formula. With the step by step derivation one can see the main assumptions behind the regulatory model and perform a comparison of the analytical model and the actual portfolio behavior to the regulatory formula that drives the CVA capital requirements.

In all sections numerical examples are used to illustrate the approach. This way I can assess the proposed approach from a practical point of view. The outputs of the numerical examples are presented in figures or tables.

3 Main results

3.1 Introducing Multi Level Monte Carlo to exposure profile calculation

There are two main differences between lending risk and counterparty credit risk. Over the life of a standard loan, partners can clearly be categorized as lender or borrower and the amount owned by the borrower is well known for both parties. These two conditions are not true for an OTC derivative contract. The contract's value depends on the actual underlying market factors, therefore its value changes constantly. Even the sign of the value can change day-by-day that would swap the role of the lender and borrower. This is the main reason why determining the credit exposure amount is a complex, computationally intensive problem.

The experience of the 2008 crisis and the regulatory pressure forced the risk management departments of banks to go through a significant development. The measurement and pricing of counterparty credit risk have became more complex than ever. Today, banks' counterparty risk management processes use a huge amount of computational resources. A particularly computational intensive task is the calculation of the expected exposure profile that is one of the main inputs of the credit valuation adjustment.

In the first part of chapter 2 I propose an alternative method for calculating the expected exposure profile. The standard way to determine the expected exposure profile relies on Monte Carlo simulation. As a first step multiple thousands of paths of the underlying market variables are simulated on a discrete time grid until the maturity of the contract. Next, the derivative instrument is priced at all time steps on all simulated paths and the exposure amounts are determined. Finally for every time step on the grid, the exposure amounts are averaged across paths to determine the expected exposure amount.

As this approach requires a large number of simulated paths, the computational requirements can grow significantly. For a bank with thousands of counterparties and potentially millions of contracts the computational time is critical. I propose the Multi Level Monte Carlo (MLMC) approach to reduce the running time.

The Multi Level Monte Carlo method was originally developed for numerical integration problems by Heinrich (2001). The first financial application can be linked to Giles (2008). Since then it has became an important tool of financial mathematics, but the first application in counterparty risk management was performed by Hofer and Karlsson (2017). They estimate the CVA with different external parameters using the Multi Level Monte Carlo method.

In contrast to previous studies that used a model parameter to distinguish between different levels of the MLMC, I use the time dimension to separate the calculation layers. My method is applicable to derivative contracts that depend on underlying dynamics with the exact simulation schemes. This limits the scope of my results, but it still covers a wide range of models.

The main idea behind the model can be formalized as follows. The expected exposure at t is defined as:

$$EE(t) = \mathbb{E}[E(t)], \tag{1}$$

where $E(t)$ is the exposure at t. For a derivative contract with $T < \infty$ maturity, we start on the $[a, b]$ interval, where $[a, b] \subset [0, T]$. We would like to estimate the profile on this interval. Let $k = 0, 1, ..., L$ denote the level of the MLMC and we use the grid set-up proposed by Heinrich (2001). The profile is estimated with the following points:

$$\left\{ EE(t_j) | t_j = a + \frac{j(b-a)}{2^L}, j = 0, 1, ..., 2^L \right\} \tag{2}$$

This means that at every step we estimate the middle point between the already estimated points on the previous level. This allows us to utilize that around the quantity to be estimated we already know some values of the profile. Based on Hofer and Karlsson (2017), if there is a high correlation among these, then we can use an estimation methodology similar to the control variates technique.

Let t_{j+} and t_{j-} denote the succeeding and preceding time points of t_j. If we assume that $\widehat{EE}(t_{j+})$ and $\widehat{EE}(t_{j-})$ are known, then for the interim point we can apply the following estimator:

$$\widehat{EE}(t_j, t_{j-}, t_{j+}) = \frac{1}{N_{\text{MLMC}}} \sum_{n=1}^{N_{\text{MLMC}}} \left(E^{(n)}(t_j) - \frac{E^{(n)}(t_{j-}) + E^{(n)}(t_{j+})}{2} \right) + \frac{\widehat{EE}(t_{j-}) + \widehat{EE}(t_{j+})}{2}, \tag{3}$$

that is for the estimation at t_j we use the previous level's estimated values for the neighboring time points as control variates. Equation 1 confirms the applicability of this approach:

$$EE(t_j) = \mathbb{E}\left[\widehat{EE}(t_j, t_{j-}, t_{j+}) \right]. \tag{4}$$

Hofer and Karlsson (2017) and Giles (2008) simulated the full paths of all underlying factors on each level and reached high correlation by re-using the paths. In my case, at every time step I need the underlying factors from the same time point, therefore I can avoid simulating the whole path of the factors. The high correlation is achieved by using the same random sample multiple times.

The power of the approach comes from using different number of simulated paths (N_{MLMC}) on each level. The previously estimated profile points improve the estimator, therefore the number of paths can be reduced as we move between levels. This relaxes the computational efforts and improves the computational time. In the dissertation I propose an algorithm that details the implementation of the approach.

In spite of the relation to the control variates technique, I point out that the error of the previous estimators are carried over to the next level. This reduces the efficiency of the approach. Still numerical results suggest that the mean squared error of the estimated profiles quickly drops below the standard Monte Carlo estimator's MSE. As the MLMC

Figure 1: Mean Squared Error compared to the theoretical value

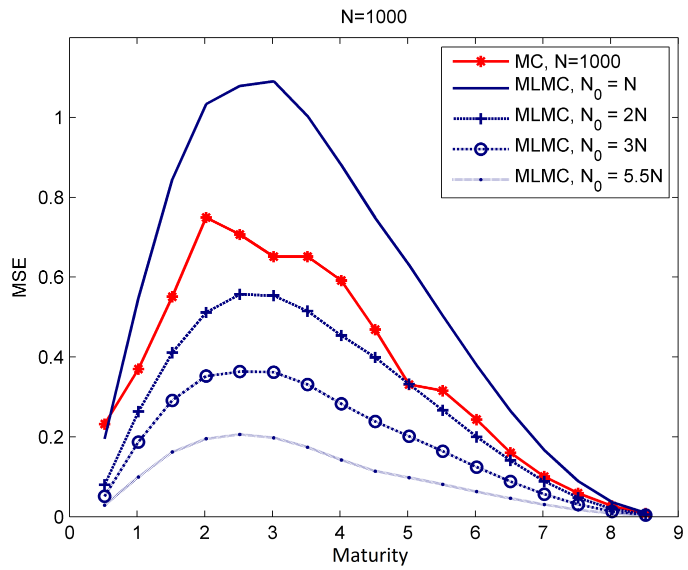
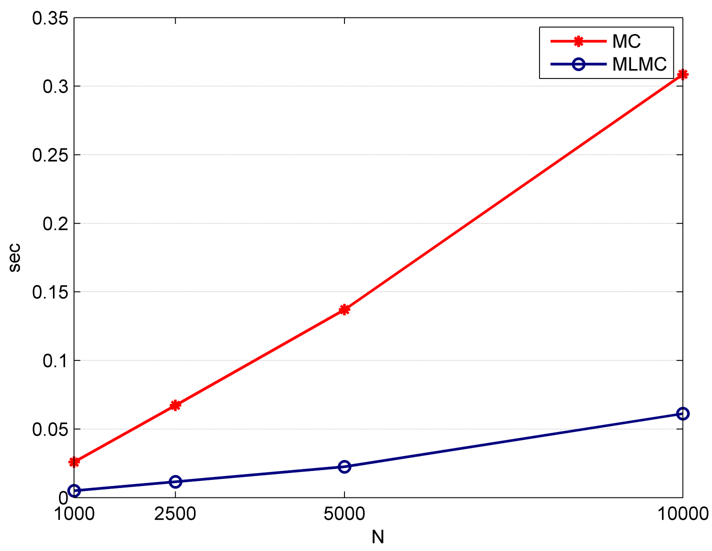


Figure 2: Average Running Time



uses fewer simulation points due to the reduction in path numbers between levels, we can increase the initial number of paths to multiples of the original level to use the same amount of simulations like the standard Monte Carlo method produces. The MSE with different number of initial paths is illustrated in figure 1. At the same time, I compared the running time of the two approaches. The results in figure 2 show that the new approach reduces the computational time significantly.

Summary

In the dissertation, I propose a new technique to simulate expected exposure profiles. My method relies on the Multi Level Monte Carlo approach and is applicable to models where an exact simulation scheme exists for the underlying stochastic factors. I review some of the previous applications of the Multi Level Monte Carlo method and place the approach among those. I develop an algorithm for the implementation of the method and test it by using a numerical example. In contrast to previous studies that used a model parameter to differentiate the levels of the MLMC, I use the time dimension. The new method improves the computational requirements and as such it reduces the computational time significantly.

3.2 Extending the Least Square Monte Carlo method with collateral delay and more efficient memory consumption

As I described earlier, the second step in the exposure profile calculation includes the analytical pricing of the derivative contract. Without analytical formula the pricing should be performed with other techniques. In case of complex derivatives, often Monte Carlo simulations are used for pricing. If we want to calculate the expected exposure for such products, we would hit the computational limits early, as we would perform an embedded Monte Carlo simulation at all points of another Monte Carlo simulation. We need an alternative approach to the embedded simulation.

In practice, the so called American Monte Carlo (AMC) approach is a common alternative. There are multiple versions of the AMC method, but these all date back to the Longstaff-Schwartz approach originally developed for pricing American options. Besides using it for the pricing of products with early exercise feature, the approach developed by Longstaff and Schwartz (2001) and other AMC methods made their way to the field of counterparty credit risk as well.

Cesari et al. (2009) used them for expected exposure calculation, while Brigo and Pallavicini (2007) referred to a process relying on an AMC method to determine the credit valuation adjustment. The AMC method most similar to the original approach by Longstaff and Schwartz (2001) is called Least Square Monte Carlo (LSMC) ((Kan et al., 2010), (Karlsson et al., 2016), (Joshi and Kwon, 2016)).

One often neglected aspect of the LSMC method was highlighted by Joshi and Kwon

(2016). They pointed out that the regression equation was used only for the early exercise decision and not for approximating the price. They incorporated this observation to the CVA calculation and added minimal transfer amount and collateral thresholds to the model. One important feature, the delay of the margin was nevertheless not incorporated by them.

In the dissertation, first I incorporate the margin period of risk into the LSMC approach proposed by Joshi and Kwon (2016). The main equation developed by Joshi and Kwon (2016) approximate CVA in the following form:

$$CVA \approx LGD \sum_{i=1}^{m} \mathbb{Q}(t_{i-1} < \tau \leq t_i) \mathbb{E}\big[D(0, t_i)\Pi(t_i, T) 1_{(f_i > 0)}\big]. \tag{5}$$

where f_i is the estimation of the so called continuation value based the regression. The main result of Joshi and Kwon (2016) is that they use the regression for estimating only the exercise decision. For estimating the actual price, they use the sum of the discounted cash-flows ($\Pi(t_i, T)$) on each path.

To account for the margin period of risk, I modify the equation 5 as follows:

$$CVA \approx LGD \sum_{i=1}^{m} \mathbb{Q}(t_{i-1} < \tau \leq t_i) \mathbb{E}\Big[D(0, t_i)(\Pi(t_i, T) - K_i) 1_{(f_i - K_i > 0)}\Big], \tag{6}$$

where the available collateral is equal to the collateral set by the CSA delayed by a certain ζ time, i.e. $K_i = C_{i-\delta}$ and $t_{j+\delta} - t_j = \zeta$.

As a next step I point out that one of the disadvantages of the approach is the significant memory consumption. The LSMC approach first calculates the value of the underlying factors proceeding forward on the time grid. Then it moves backward and estimates the early exercise decisions. As it is clear from equation 6, one cannot estimate the exposure contribution to the CVA at time t_i, because the collateral amount is not available at this time point. Therefore it is suggested that the second step goes back to t_0 without estimating collateral and as a new third step the algorithm starts moving forward in time again to estimate the exposure values and calculate CVA. During these multiple rounds of iteration, the algorithm keeps the values of the underlying factors, exposure paths and collateral values in the memory, which is a limited resource. To reach accurate results, one needs to increase the number of simulation paths to high levels. The more path is used, the larger the memory consumption of the approach is. So the memory requirements of the LSMC can easily exceed the available resources.

Therefore I introduce a method to reduce the memory consumption of the LSMC that relies on the approach developed by Chan et al. (2006) and Hu and Zhou (2017). The main idea is to save only the seed of the random number generator at every time step, when we simulate the paths of the underlying factors forward in time instead of their actual values. This will allow me to re-simulate the values whenever those are needed and not to overload the memory of the system. In the dissertation I develop an algorithm to describe the advanced LSMC approach with memory consumption reduction. The algorithm can be divided into two main steps: estimation and evaluation. In the estimation step the coefficients of the regression are estimated, while in the evaluation step the terms of the equation 6 are calculated.

I test the algorithms on products with and without early exercise option. I show that our approach generates accurate results with around 30% memory reduction. Nevertheless, due to the re-simulation of the underlying factors, the running time increases. This increase is not too significant, especially when the number of simulation paths is high. The main results for a cancellable swap are presented in figures 3 and 4.

Figure 3: Memory consumption with different number of underlying paths for a cancellable swap

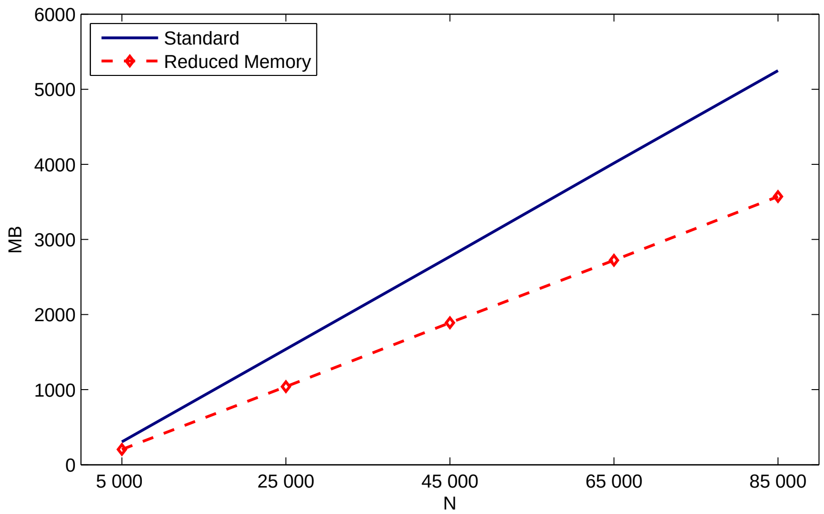
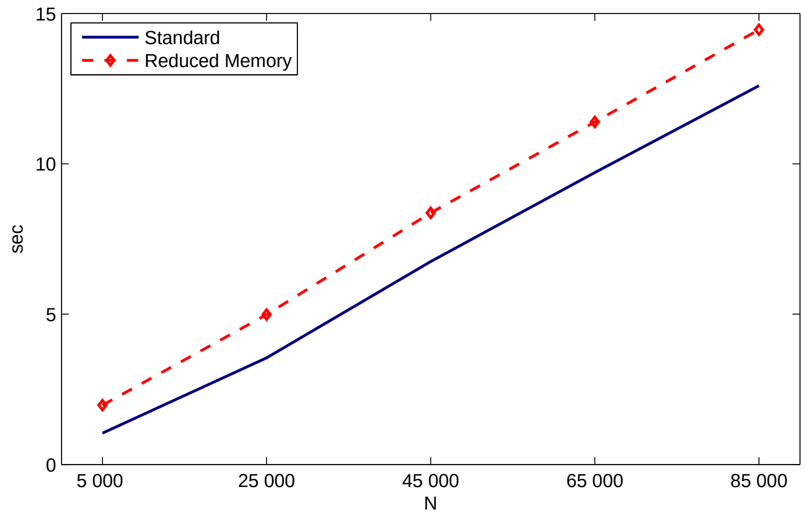


Figure 4: Running time with different number of underlying paths for a cancellable swap



Summary

American Monte Carlo methods are often used for the credit valuation adjustment calculation of complex derivative products. The applicability of the approach can be easily extended if we incorporate the cash-flow effects of customized collateral agreements.

I propose an AMC based approach for the calculation of the CVA that incorporates the delay of the margin. One of the main disadvantage of the extended LSMC technique is the increased memory consumption. Increased memory requirement could result in the reduction of accuracy if the user does not have sufficient memory capacity. Therefore the other purpose of the section is to relax this limitation. I introduced a technique from the American option pricing to the field of risk management, that resulted in lower memory requirements without increasing the running time significantly.

After introducing the margin period of risk to the collateral modeling, I formalized CVA calculation algorithms for products with and without early exercise feature. Then I tested the approach on two numerical examples. The results suggest that the approach results in 30% memory reduction.

3.3 Incorporating contagious effects of rating announcements into CVA calculation

Rating agencies act as major institutions of the financial markets. On the one hand they are responsible for providing ratings on market participants to reduce the informational asymmetry encompassing investors. From this point of view, a rating announcement should convey new information that is expected to impact the market factors and participants. On the other hand rating agencies try to limit the number of their actions to reduce rating volatility. To achieve that, after an event impacting the credit quality of a company, they often wait before an announcement to confirm its permanence. This suggests that a rating announcement is often based on stale data and questions its relevancy.

The significance of default contagion in the Credit Valuation Adjustment (CVA) modeling has been pointed out in many papers. Jorion and Zhang (2009) show that the increase in the spread of peers around and even days after default event are statistically significant. Recent empirical research suggests that not only defaults, but rating change announcements by large rating agencies are also contagious. Norden and Weber (2004) find that Moody's and S&P downgrades cause significant spread movement before and also on the announcement date. Micu et al. (2004) conclude that all types of rating events (actual rating change, review for rating change or outlook change) significantly impact CDS spreads on the announcement day and thus convey relevant information to the market participants. In fact these studies only deal with the direct impact on the company that was rated (event firms) and not on its peers (non-event firms).

Wengner et al. (2015) are the first who investigate the spillover effects of rating announcement. They find that CDS spreads change significantly around upgrades and downgrades for both event and non-event firms. They observe that a downgrade of a company in an industry decreases the CDS spread of its peers suggesting that a downgrade benefits the non-event firms. On the contrary, in case of upgrades the spread of the non-event firms increases. For event firms they conclude that spreads change significantly across all companies, but the size of the change is different among industries.

The impact of these migrations is usually not captured in the Credit Valuation Adjustment calculation, while credit spreads contribute significantly to its value. I propose an extended framework that incorporates the empirical observations. In the dissertation, I investigate the effects of the contagion caused by rating migration on CVA by extending the default contagion framework. For this purpose I use a scaling of the intensity process that can be formalized as follows.

Let's assume N companies and K possible rating categories. The initial ratings of the companies are collected in $S_0 = \left[\eta_1^0, \eta_2^0, ..., \eta_N^0\right]$ where $\eta_i^0 \in \{1, 2, ..., K\}$ for $i = 1, ..., N$. I will refer to the initial rating of company i. as an element of the S_0 vector, i.e. $S_0[i] = \eta_i^0$ where $i = 1, ..., N$

Let $\lambda_j^i(t)$ denote the intensity process at t of company i transitioning to state j conditional on the previous rating migrations:

$$\lambda_j^i(t) = \lambda_j^i(t|T_n, S_n, G_n^i, R_n^i), \tag{7}$$

where $T_n = \{t_1, t_2, t_3, ..., t_n\}$ is the set of all previous rating change times, i.e. $t_n < t$. $\mathcal{S}_n = \{S_0, S_1, ..., S_n\}$ is the set of rating history of each company, where $S_k = \left[\eta_1^k, \eta_2^k, ..., \eta_N^k\right]$ are the ratings after the k. transition. Finally $G_n^i = \{g_1^i, g_2^i, ..., g_{\hat{n}}^i\} \subseteq T_n$ contains all the time points when i migrated and $r_u^i \in R_n^i$ are the rating classes to where i moved at g_u^i.

In the model the conditional intensity process $(\lambda_j^i(t|T_n, S_n, G_n^i, R_n^i))$ can be formalized as:

$$\begin{aligned}
\lambda_j^i(t|T_n, \mathcal{S}_n, G_n^i, R_n^i) = \\
a_j^i(t) \Bigg(1 + \sum_{h=1}^{n} \Big(& d_1^{\text{le}}\big(1_{(S_h > S_{h-1})}\mathbf{1}\big) + d_1^{\text{fel}}\big(1_{(S_h < S_{h-1})}\mathbf{1}\big) \\
& + d_2^{\text{le}}\big(1_{(S_h > S_{h-1})}[i]\big) + d_2^{\text{fel}}\big(1_{(S_h < S_{h-1})}[i]\big) \\
& + d_3 \sum_{v=1}^{N} 1_{((S_h[v]=K)\cap(S_{h-1}[v]\neq K))}\Big) e^{-p(t-t_h)} \Bigg),
\end{aligned} \tag{8}$$

where $a_j^i(t)$ is the unconditional intensity process, $\mathbf{1} = [1, 1, ..., 1] \in \mathbb{R}^{N\times 1}$, and $1_{(.)}$ refers to the indicator process, that is interpreted on the elements of the vectors.

The comparison $(S_h > S_{h-1})$ and $(S_h < S_{h-1})$ are done on the elements of the vectors too. Rating transitions are split to downgrades $(1_{(S_h > S_{h-1})})$ and upgrades $(1_{(S_h < S_{h-1})})$. The $\mathbf{1}$ multiplier is used to aggregate the elements of the vector across companies, alternatively we refer to the element i of the vector by using the notation $[i]$.

The conditional intensity process is the result of the multiplication of the unconditional intensity process and a scaling factor. The scaling factor depends on the history of the rating changes and the $\{d_1^{\text{le}}, d_1^{\text{fel}}, d_2^{\text{le}}, d_2^{\text{fel}}, d_3, p\}$ model parameters. d_1^{le} and d_1^{fel} denote the sensitivities to the rating changes of any company, while d_2^{le} and d_2^{fel} refer to the sensitivity to the own rating change. d_3 is the value of the multiplier after a default event. Finally p is responsible for the speed of the decay of impacts.

The above framework allows me to incorporate the observations of Micu et al. (2004), Finnerty et al. (2013), Wengner et al. (2015) and Jorion and Zhang (2009) to the model. With suitable parameter setting, the factor in equation 8 decreases the intensity process of companies $i' \neq i$ after the downgrade of i, while increases it for i. A default event increases the intensity process of all companies. Recent event receives larger weight due to the exponential decay.

The scaling of the intensity process based on observed rating migrations and defaults inherits the looping default problem. The difficulty arises from the fact that when simulating the intensity process to determine the timing of the subsequent rating movement of a given company, one needs to consider all rating movements of other companies, which in fact also depend on the rating path of the first company. In this general framework described above there is no analytical solution of default times available, therefore we need to find an alternative approach to utilize our model for pricing counterparty credit risk. In the dissertation, besides formulating a framework that incorporates the empirical observations, I propose an algorithm that allows the application of our model. This algorithm is an extension of the total hazard construction originally proposed by Yu (2007). The main contribution of this algorithm is that it resolves the looping default problem, so one can analyze the impact of the contagious rating migrations.

The results of some numerical examples suggest that the impact of the contagious effect of the rating migrations on the credit valuation adjustment can be significant. The impact depends on the initial rating of the company analyzed and the composition of the industry. Table 1. shows that unilateral CVA changes significantly if the industry's rating composition is concentrated and the decay parameter takes a low value. In a more heterogeneous industry the impact of rating contagion is small.

The results suggest that the bilateral credit valuation adjustment can magnify the impact of rating migration contagion. This is due to the nature of the bilateral CVA that incorporates the default probabilities of both parties. As a result it accumulates the impact of the contagious effects. Table 2. shows that the bilateral CVA on derivative contracts between parties from different industry groups can change significantly even when the speed of the exponential decay is high. This observation holds for deals with or without collateralization. Nevertheless, I cannot claim that the impact of the rating migration contagion is always significant as the change in bilateral CVA on transactions between counterparties from more heterogeneous groups is minor.

Table 1: Unilateral Credit Valuation Adjustment with different underlying assumptions

$p = 0.4$				
	Aa	Baa	B	Ca&C
No contagion	0,311	0,386	0,610	1,088
Contagion - Group 1	0,299	0,371	0,585	1,068
Contagion - Group 2	0,317	0,390	0,609	1,089
Contagion - Group 3	0,335	0,410	0,631	1,106

$p = 0.7$				
	Aa	Baa	B	Ca&C
No contagion	0,311	0,386	0,610	1,088
Contagion - Group 1	0,303	0,376	0,595	1,077
Contagion - Group 2	0,313	0,390	0,610	1,088
Contagion - Group 3	0,324	0,401	0,625	1,099

$p = 1$				
	Aa	Baa	B	Ca&C
No contagion	0,311	0,386	0,610	1,088
Contagion - Group 1	0,306	0,380	0,600	1,080
Contagion - Group 2	0,313	0,388	0,611	1,088
Contagion - Group 3	0,322	0,396	0,622	1,096

The industry composition is captured by the different groups. Group 1: Aa; Aa; A; Baa, Group 2: Aa; Baa; B; Ca&C, Group 3: Ca&C; Caa; Caa; B. Under different scenarios the counterparty is assumed to start with ratings Aa, Baa, B, Ca&C.

Table 2: Bilateral Credit Valuation Adjustment - Group 1 vs Group 3

	No Contagion	Contagion					
		$p = 0.4$	$p = 0.7$	$p = 1$	$p = 0.4(\%)$	$p = 0.7(\%)$	$p = 1(\%)$
Without Collateralization							
Group 1 - Aa vs Group 3 - Baa	**-0,048**	-0,084	-0,073	-0,063	177,1%	152,2%	133,0%
Group 1 - B vs Group 3 - Baa	**0,337**	0,287	0,304	0,314	85,2%	90,3%	93,3%
Group 1 - Ca&C vs Group 3 - Baa	**0,897**	0,861	0,873	0,881	96,0%	97,3%	98,2%
With Collateralization							
Group 1 - Aa vs Group 3 - Baa	**-0,010**	-0,014	-0,013	-0,011	144,5%	126,7%	113,7%
Group 1 - B vs Group 3 - Baa	**0,044**	0,038	0,040	0,042	86,4%	90,6%	94,6%
Group 1 - Ca&C vs Group 3 - Baa	**0,142**	0,136	0,138	0,140	95,9%	97,1%	98,4%

Summary

In chapter 3, I focus on the impact of credit rating announcements on the credit valuation adjustment. I review the empirical results of the literature and illustrate why the contagious effects of rating migrations should be incorporated into the credit valuation adjustment calculation.

Then I propose a model framework that reflects the impact of the up- and downgrades on both event and non-event firms. This model can be considered as an extension of the infectious defaults model. Since the model inherits the looping default problem, I had to develop a general algorithm to simulate default times. To resolve this difficulty, I propose an extended version of the total hazard construction method developed by Yu (2007). Finally I analyze a numerical example to estimate the impact of rating migrations in the model.

The results suggest that the impact of contagious effect of the rating migrations on the credit valuation adjustment can be significant. In industry groups where the initial credit ratings are concentrated, the default probabilities can change significantly. This affects the value of unilateral credit valuation adjustment that can move to either direction. When I decrease the persistence of the contagious effects then the changes observed in the unilateral CVA disappear. The bilateral credit valuation adjustment reacts somewhat differently as it aggregates the changes in the default probabilities across counterparties. Therefore I see significant deviations even with lower persistence of the contagion. In other cases when I analyzed more heterogeneous industry groups the changes in the CVA are less significant.

3.4 Formalizing the model background and assessing the impact of the new CVA capital requirements

Perhaps the most often cited sentence in the literature of the credit valuation adjustment was published by the Basel Committee on Banking Supervision: "During the global financial crisis, however, roughly two-thirds of losses attributed to counterparty credit risk were due to CVA losses and only about one-third were due to actual defaults."[2]

This sentence was disclosed when the Committee introduced the Basel III capital requirements. Since then CVA capital reserves have become standard practice. Nevertheless, regulatory CVA is being reformed.

Basel Committee on Banking Supervision issued a proposal on the framework of the new CVA capital requirement in July of 2015. This document had been followed by an industry wide quantitative impact study and multiple further guidance from the Committee until the new framework was finalized in December of 2017.

Based on the new rules, there are two approaches available for banks to determine the CVA capital requirements: Standard and Basic approaches. In chapter 4, we analyze the

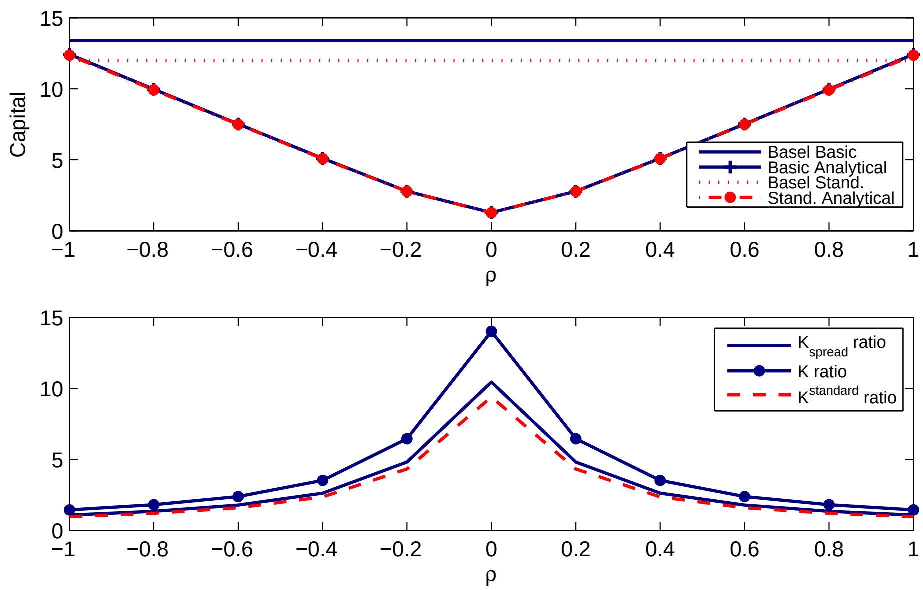
[2] http://www.bis.org/press/p110601.htm

Basic CVA approach.

The Basic CVA relies on the standardized method of the Basel III regulation. In the first half of the chapter, I introduce the basic building blocks of the Basic CVA approach and show how the combination of those forms the regulatory formula. Particularly, I review the capital charge for the spread and the exposure components and I propose a model framework that allows the quantification of these. Next I set up a portfolio of CVAs, as derivatives and their hedges. The new BCBS formula estimates the capital charge as the Expected Shortfall measure of this portfolio with 97.5% confidence level. Finally, I show what kind of simplifications are implemented by the regulators to transform the ES formula to the regulatory formula.

After deriving the regulatory formula, I start analyzing it. During the numerical examples I compare the regulatory formula, with the actual ES measure. First I investigate the role of the correlation in the capital requirements. This is particularly important as the level of correlation is fixed in the BCBS formula, therefore it could result in underestimated capital requirements. I test the impact of the original proposal and the QIS options for various portfolios. For the original proposal I find that the CVA capital levels are much higher than under the Basel III regime, and the actual capital requirement remains always below the level prescribed by the regulators. The QIS and the final risk weights decrease the capital requirement levels, but still overestimate the actual needs. The level of the overestimation is the highest for well diversified portfolios, where the correlation is zero. The approach is illustrated for an average portfolio in figure 5.

Figure 5: The impact of correlation for an average portfolio



As a next step I analyze the role of the hedging. It is well known, that the regulatory CVA is not aligned with the accounting CVA. This mismatch can actually cause real P&L impact, as it happened with Deutsche Bank when they lost 94 million euro due to hedging according to their capital requirements (Carver, 2013). One of the requirement of the new approach is to better align the regulatory and the accounting CVA, therefore I test if the hedging alignment is part of the rule. I show that there is further room to improve on this. On the one hand, I illustrate that even under the new rules a perfectly hedged portfolio has a positive capital requirement. On the other hand, an imperfect hedge can result in lower capital requirement than the actual need. This is shown in figures 6 and 7.

Figure 6: IG Portfolio

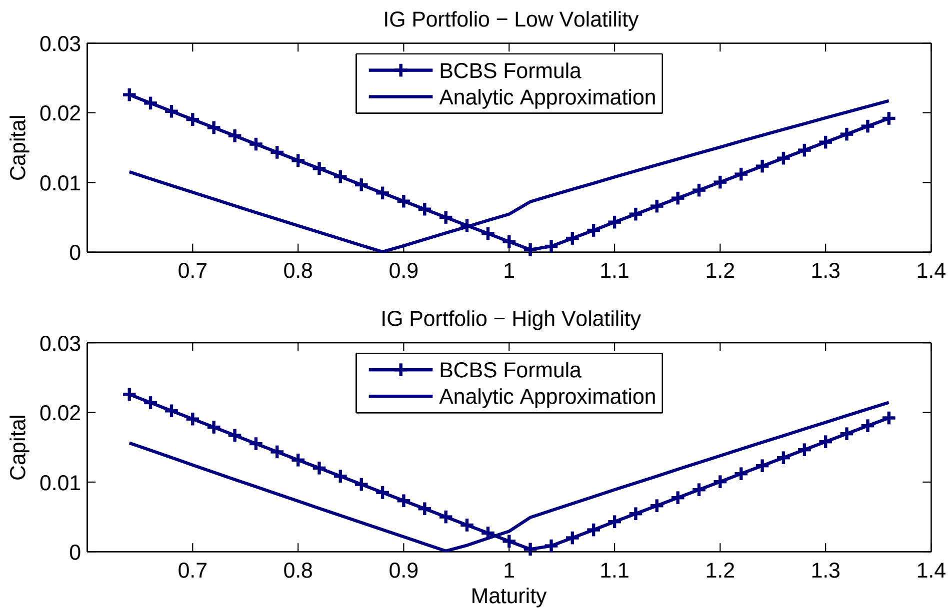
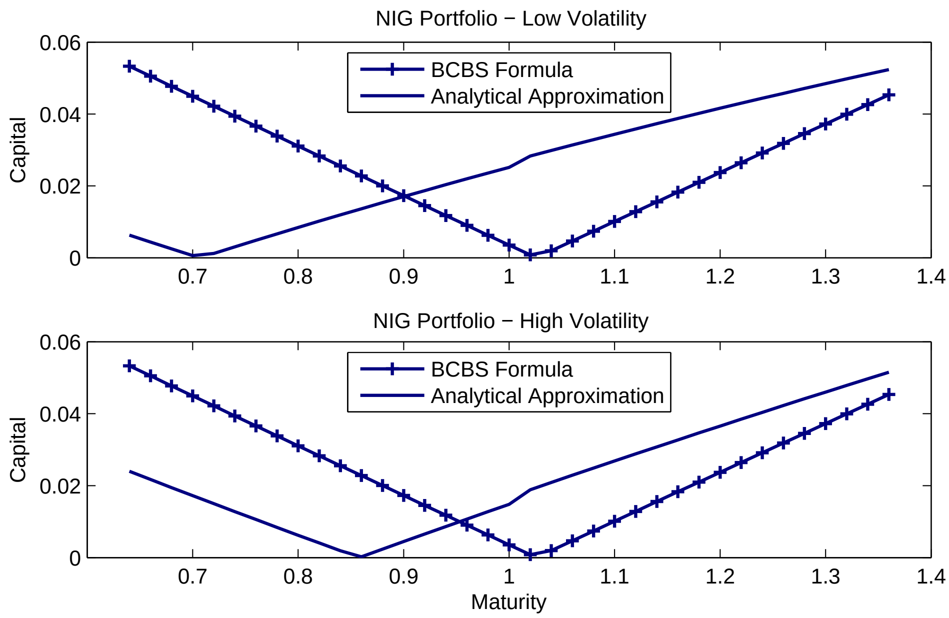


Figure 7: NIG Portfolio



Summary

In chapter 4 of the dissertation, I focus on the regulatory CVA and its reforms that are being finalized. There are two main results of this chapter. First I derive the analytical background of the regulatory formula. This allows us to understand the formula better, and challenge the assumptions used when deriving it. The second result focuses on the impact assessment of the new regulatory CVA framework. Actual impact assessment can be completed by the industry wide quantitative impact studies, but it is important to put more focus on certain aspects of the framework. Therefore I test the impact of the correlation and hedging in the new rule. On the one hand, I conclude that the insensitivity of the formula to the correlation results in significant overestimation of the capital. On the other hand, I show that the mismatch between P&L and capital hedging still persists and can have a significant impact.

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