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Banking Regulations on Credit Risk and Credit Value Adjustment

Exploring Counterparty Credit Risk in Interest Rate Swaps

Master's thesis in Finance and Investment
Supervisor: Florentina Paraschiv
May 2019

Master's thesis

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Preface

This thesis concludes our M.Sc. in Economics and Business Administration at the Norwegian University of Science and Technology (NTNU). It is a master thesis in the field of Finance and Investment. The work on this thesis has been very challenging, but it has also provided us with great insight into an elaborate and challenging subject that influences the banking sector.

We would like to thank our supervisor, Professor Florentina Paraschiv, at the Department of Economics for guidance and support throughout the semester. We would also like to thank an unnamed person in a Norwegian savings bank who provided us with their data and knowledge on the subject.

The authors take full responsibility for the content of this thesis.

Trondheim, May 23, 2019

Bjørnar B. Sæther   Stian Joachimsen

Abstract

In this thesis, we consider the credit value adjustment (CVA) calculations for interest rate swaps together with the changes made through Basel regulations from the Basel Committee on Banking Supervision (BCBS). We review the changes made from the first implementation of the 1988 Basel Accord until today as well as the changes in methods used for addressing credit risk and counterparty credit risk during this period. Our problem statement is:

How can banks manage counterparty credit risk under the Basel framework, and how could the CVA risk capital charge be calculated for a Norwegian savings bank with different counterparty risk levels and methods?

We compute the CVA for a portfolio of interest rate swaps with data provided from a Norwegian savings bank towards a Nordic counterparty with both an internal model method (IMM) and by using the simpler regulatory BA-CVA method from BCBS, before comparing the results. Our IMM is simulated by performing a Monte-Carlo simulation using the Hull-White framework, assuming that no wrong-way risk exists. We model several CVA risk capital charges for the IMM with different probabilities of default, both with real market data computed from credit default swap (CDS) spreads and fictive examples.

Our main findings indicate a lower CVA risk capital charge when computing with the IMM approach compared to the BA-CVA approach from BCBS. The results also show how the bank is exposed to their counterparty when changes happen in the counterparty CDS spreads. Should an unwanted situation happen to the counterparty, placing them under financial distress and resulting in higher CDS spreads, the savings bank will need to set aside more capital in order to meet the regulatory demands for counterparty credit risk exposures.

Sammendrag

I denne oppgaven ser vi på Credit Value Adjustment (CVA) beregninger for rentebytteavtaler sammen med endringene som er gjort gjennom Basel reguleringer fra Basel Committee on Banking Supervision (BCBS). Vi gjennomgår endringene fra den første Basel Akkorden i 1988 fram til i dag og ser på endringene i metodene som benyttes for å behandle kredittrisiko og motpartsrisiko under denne perioden. Vår problemstilling er:

Hvordan kan banker mitigere motpartsrisiko under Basel rammeverket, og hvordan kan CVA risikokapitalkravet beregnes for en norsk sparebank med forskjellige motpartsrisikonivåer og metoder?

Vi beregner CVA for en portefølje av rentebytteavtaler med data som er mottatt av en norsk sparebank mot en av deres nordiske motparter via både en intern modell metode (IMM) og ved å benytte den enklere regulatoriske BA-CVA metoden fra BCBS, før vi sammenligner resultatene. Vår IMM er simulert ved å benytte Monte-Carlo simuleringer og et Hull-White rammeverk, hvor vi antar ingen wrong-way risk eksisterer. Vi modellerer flere CVA risikokapitalkrav for IMM med forskjellige sannsynligheter for mislighold, både med ekte markedsdata beregnet fra kredittapsforsikringers (credit default swap) spread og med fiktive eksempler.

Hovedfunnene våre indikerer et lavere CVA risikokapitalkrav ved beregning med vår IMM sammenlignet med BA-CVA metoden fra BCBS. Resultatene viser også hvordan banken er utsatt til deres motpart når endringer skjer i motpartens CDS spread. Skulle en uønsket situasjon oppstå for motparten, som plasserer dem under en økonomisk krisesituasjon og resulterer i høyere CDS spreads, vil sparebanken måtte sette av mer kapital for å møte de regulatoriske kravene for motpartsrisiko eksponeringer.

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Abbreviations

BA-CVA – Basic Approach for CVA

BCBS – Basel Committee on Banking Supervision

BIS – Bank of International Settlements

CCP – Central Counterparty

CDS – Credit default swap

CEM – Current exposure method

CRM – Credit risk mitigation

CVA – Credit value adjustment

CCR – Counterparty credit risk

EAD – Exposure at default

EE – Expected exposure

FRA – Forward rate agreement

IMM – Internal model method

IRS – Interest rate swap

LGD – Loss given default

PD – Probability of default

SA-CCR – Standardized approach to counterparty credit risk

WWR – Wrong-way risk

1 Introduction

The Great Financial Crisis of 2007-2008 revealed a deficit in how banks measured and managed their risks compared to today, where risk management has been given much greater importance in financial institutions. As a result of the crisis some large institutions failed, such as Lehman Brothers, and several others had to be bailed out by national governments. A thought in the financial market was that if some financial institutions should fail, the national government would step in and rescue them from bankruptcy to reduce effects on the global economy, terming the phrase "too big to fail". When Lehman Brothers went bankrupt after the United States government decided not to step in and save them, the counterparty credit risk on all the derivatives Lehman Brother had sold were valued as much riskier than at conception. According to the Bank of International Settlements (BIS) the major part of losses that occurred during the credit crisis was not due to bankruptcies, but a result of the rising credit risk and devaluation of derivatives. As much as two thirds of the losses were because of the rising credit risk (BCBS, 2010). Because of this, the Basel accords were again revisited after the Basel II reform was published in 2004. Also, it resulted in the Basel III reform published in 2010, which they called "A global regulatory framework for more resilient banks and banking systems" (BCBS, 2010).

Our motivation for this thesis is to review the existing literature on credit risk and counterparty credit risk through the Basel reforms as well as publications by individuals with extensive knowledge on the subjects regarding credit risk modelling. The main result in our thesis is calculating what is called a Credit Value Adjustment (CVA) risk capital charge from interest rate swaps between a Norwegian savings bank and one of their Nordic counterparties, Nordea Bank ASA. To reach this CVA charge, we will detail the background and reasoning to why such a charge was implemented, before explaining the calculations and modelling which is required to achieve a result which is up to the standards of the Basel III regulations.

The rest of the thesis is structured as follows; in Chapter 2, we introduce financial markets and credit risk. In Chapter 3, we provide a theoretical background on rates and derivatives. In Chapter 4, we detail the CVA and methods for calculation. We then give a review of banking regulations in Chapter 5 before presenting our case study in Chapter 6 to demonstrate the methods previously explained. Finally, we add our concluding remarks in Chapter 7.

2 Financial Markets

In this chapter, we will give a brief introduction regarding the different aspects which financial institutions operate in and ways to reduce credit risk. Large parts of the theory for the subchapters are gathered from Hull (2018).

2.1 The Banking System

The word “bank” originates from the Italian word *banco*. The traditional role of the banks has been to take deposits and make loans, and the difference between interest charged on the loans is higher than the interest paid on deposits. This difference is needed to cover administrative costs and loan losses while providing a return on equity. Today most large banks engage in both commercial and investment banking. Commercial banking involves the deposit-taking and lending activities among other things, while investment banking is concerned with assisting companies in raising debt and equity, providing advice on mergers and acquisitions, major restructurings and other corporate finance decisions. Large banks are often involved in securities trading as well.

Hull (2018) describes that a banks operation gives rise to credit risk, market risk and operational risk. Credit risk is the risk that counterparties in loan transactions and derivatives transactions will default. Traditionally this has been the most significant risk facing a bank and usually is the type of risk where the most regulatory capital is required. Market risk is the risk relating to the possibility that instruments in the bank’s trading book will decline in value. Operational risk is the risk that losses are created because internal systems fail to work as they are supposed to or because of external events.

2.2 Markets

There are two types of markets for trading financial instruments, the *exchange-traded market* and the *over-the-counter* market (OTC market). The exchange-traded market consists of exchanges such as the New York Stock Exchange (NYSE) or Oslo Børs, which focus on the trading of stocks. Other entities such as the Chicago Board Options Exchange (CBOE) and CME Group (CME) are concerned with the trading of derivatives such as futures and options (Hull, 2018). The role of the exchanges is to define contracts so that the market participants can be sure that the trades they agree to will be honoured. Over-the-counter markets are an extensive network of traders who work for financial institutions, large corporations or fund managers. The OTC market is used for trading different products consisting of bonds, foreign currency and derivatives. Banks are active participants in the OTC market and often act as market makers for more commonly traded instruments. An advantage of the OTC market is that the terms of a contract are free to be negotiated by market participants in order to reach a mutually attractive deal. Trades in the OTC market are typically much larger than the trades executed in the exchange-traded market.

2.3 Credit Ratings

The Financial Times define the system of credit ratings as a method of measuring the creditworthiness of a debt issuer. These ratings are provided by the leading rating agencies of Moody's Investors Service, Standard & Poor's (S&P) and Fitch. A top rating by these agencies means there is almost no chance of the borrower failing to meet their contractual payments or full redemption of the amount. These companies rate companies with different scales, which is illustrated below in Figure 1, as shown in Afonso, Gomes and Rother (2006). A rating of AAA is the highest quality and termed investment grade, while a rating of BB+ and Ba1 from Moody's is termed as a speculative grade. Where the lower ratings indicate a higher chance for company defaults and a riskier investment.

Characterization of debt and issuer (source: Moody's)		Rating		
		S&P	Moody's	Fitch
Highest quality	Investment grade	AAA	Aaa	AAA
High quality		AA+	Aa1	AA+
		AA	Aa2	AA
		AA-	Aa3	AA-
Strong payment capacity		A+	A1	A+
		A	A2	A
		A-	A3	A-
Adequate payment capacity		BBB+	Baa1	BBB+
		BBB	Baa2	BBB
		BBB-	Baa3	BBB-
Likely to fulfil obligations, ongoing uncertainty	Speculative grade	BB+	Ba1	BB+
		BB	Ba2	BB
		BB-	Ba3	BB-
High credit risk		B+	B1	B+
		B	B2	B
		B-	B3	B-
Very high credit risk		CCC+	Caa1	CCC+
		CCC	Caa2	CCC
		CCC-	Caa3	CCC-
Near default with possibility of recovery		CC	Ca	CC
				C
Default		SD	C	DDD
		D		DD
				D

Figure 1. Characterization of debt and issuer (Afonso, Gomes and Rother, 2006).

2.4 Credit Risk and Counterparty Credit Risk

We will in this chapter give a brief explanation of the terms credit risk and counterparty credit risk (CCR). *Credit risk* is the possibility of a loss resulting from a borrower's failure to repay a loan or meet its contractual obligations. As stated in Zamore *et al.* (2018) There are three components for credit risk, which is default risk, spread risk and downgrade risk. Default risk is the risk that an issuer or counterparty will fail to fulfil the terms of a contractual obligation. Credit spread risk regards the loss or underperformance considering an increase in the credit spread. The credit spread is a sign of how financial markets will react to a deteriorating credit quality should there be any complications for the counterparty. Downgrade risk concerns decreasing credit ratings, an issuer faces downgrade risk if a credit rating agency lowers the credit rating compared to the previous rating that was given. These three risk components can, therefore, be related to each other.

While the term *counterparty credit risk* may sound very similar, being the risk arising from the possibility that one of the counterparties involved in a transaction may default on the amounts owed. One can see that it is directly related to the default risk of the specific counterparty and is something that must be considered before issuing bonds, stocks or making trades with said counterparty by taking precaution to ensure that credit risk is reduced or mitigated as best as possible.

While it is not possible to completely eliminate the possibility of a counterparty such as a bank failing, governments wish to make the probability of default as small as possible for any bank. By regulations, the thought is to create a stable economic environment where private individuals and businesses can trust the banking system. One of the major concerns of governments is what we call systematic risk, which concerns that if a large bank or financial institution should fail or default, other large banks or financial institutions will also fail resulting in a possible collapse of the financial system. If a financial institution gets into difficulties, the government will need to choose to save the institution to save the financial system or put the financial system at risk by letting the institution fail or default. As a result of the crisis, we now see a more significant use of credit risk mitigation techniques in order to reduce credit risk and counterparty credit risk, which will be detailed in the following chapter.

2.5 Credit Risk Mitigation Techniques

The banking sector and financial institutions use multiple different techniques in order to mitigate their exposure to credit risk called credit risk mitigation (CRM) techniques.

Exposures can be collateralized by first-priority claims, in part, or in whole by cash or other securities. Third parties can guarantee loan exposures, or banks can buy a credit derivative in order to offset different credit risks. Banks can also agree to net loans owed to them against deposits from the same counterparty. The Basel III framework (BIS, 2017) applies some general requirements for CRM techniques in paragraphs 117 to 124, which we will not go into detailing further. We will here give a brief overview of essential CRM techniques which are used by banks and financial institutions to reduce their exposures towards counterparties.

2.5.1 Margin

Margin is the collateral posted in OTC markets as well as exchange-traded markets. One can dilute this into two types of margin. *Variation margin* is the collateral posted that reflects the change in the value of a derivative portfolio and provides some protection against counterparty default. In order to allow for movements in the portfolio value during a period to default when no margin is being posted, some market participants require an *initial margin* in addition to variation margin. The initial margin can change as the portfolio and volatilities change and reflect the risk of a loss due to adverse market moves and costs of replacing the transactions. Most margins are posted in cash, but some agreements specify that securities can be posted instead.

2.5.2 Collateralized transactions

A collateralized transaction is a transaction where a bank has a credit exposure or a potential credit exposure. Where this exposure is hedged in whole, or in part, from collateral that is posted either by the counterparty or a third party on the counterparty's behalf. When banks take collateral, they can reduce their regulatory capital requirements through CRM techniques. When collateral is posted it is often referred to as margin (see above chapter).

2.5.3 ISDA Master Agreements and the Credit Support Annex

In what is called bilateral clearing, a pair of market participants enter into an agreement which describes how all of the future transactions between them will be cleared. This is usually done with an *ISDA master agreement*. ISDA stands for the International Swaps and Derivatives Association. An annex to the ISDA agreement is known as the *credit support annex* (CSA). The CSA describes collateral agreements between the counterparties. It describes how much (if any) collateral is to be posted by each side, what securities are acceptable, haircuts to securities etc. The primary purpose of the agreement is to define what happens when one of the parties' defaults, either on the agreements in the contract or by declaring bankruptcy.

2.5.4 Netting

Netting is a feature in the ISDA master agreements and between CCPs and their members. According to Hull (2018), netting states that all transactions between two parties are considered to be a single transaction when (a) collateral requirements are being calculated and (b) early terminations occur because of default. Netting reduces credit risk because the defaulting party cannot choose which transactions to default on.

A general example, according to Hull (2018) supposes that a financial institution has a portfolio of N derivatives outstanding with a counterparty. Without netting, the institution's exposure in the event of a default is:

$$\sum_{i=1}^{N} \max(V_i, 0) \tag{2.1}$$

Where V_i is the current value of the i'th derivative.

If we now view the same portfolio subjected to an ISDA master agreement with netting included its exposure in the event of a default is:

$$\max(\sum_{i=1}^{N} V_i, 0) \tag{2.2}$$

Showing that netting reduces credit risk because the defaulting party cannot choose which transaction to default on. Meaning it cannot choose to default on out-of-the-money transactions while keeping in-the-money transactions. If a counterparty defaults on one transaction covered by the ISDA master agreement, it must default on all transactions that the master agreement covers.

2.5.5 Clearing Houses and Central Counterparties

A clearing house stands in between two traders in a financial contract. The clearing house has several members, and trades by non-members have to be channelled through members for clearing. The members of the clearing house contribute to a guaranty fund that is managed by the clearing house. When a trade happens between two counterparties, Trader A sells the contract to the clearing house, and Trader B buys the contract from the clearing house. The advantage of this is that Trader A does not need to take in mind the creditworthiness of Trader B, and vice versa. Both traders only deal with the clearing house.

A trading house requires traders to provide cash or marketable securities as collateral when a trader has a potential future liability from a trade. Without posting a margin, the clearing house is taking the full risk if the market moves against the trader, and the trader does not fulfil his commitment. The clearing house aims to set margin requirements so that it is over 99% certainty that this will not happen. A central counterparty (CCP) plays a similar role to an exchange clearing house by standing in between two parties so that they do not have credit exposure to each other in a transaction. Like a clearing house, a CCP has members who contribute to a guaranty fund and provide margins. Regulations require standardized derivatives between financial institutions to be cleared through CCPs (Hull, 2018). A large CCP is SwapClear which is part of LCH Clearnet in London.

According to Hull (2018), it would be a disaster for the financial system if a major CCP such as LCH Clearnet's Swapclear or others were to fail. It is possible to design contracts between CCPs and members in a way that it is virtually impossible for CCPs to fail. This is detailed in his 2012 article (Hull, 2012) with a simple idea for a clause in the contract a CCP has with its members to make the members of the clearinghouse offset transactions of the defaulting member, where the other members pay the price of the defaulting member. For a more in depth review, we refer our readers to Hull (2012) on CCPs, their risks and how they can be reduced.

3 Theoretical Background

This chapter will provide an introduction and give information regarding the instruments which are used in our thesis. We will explain the terms of risk-free rates and detail the interest rate swap (IRS) and credit default swaps (CDS). A large part of the background is gathered from Hull (2018) and Gregory (2012). The mathematics behind the interest rate swap is gathered from Brigo and Mercurio (2006).

3.1 Risk-Free Rates and Discounting

In this chapter, we will elaborate on the term discount rate, which is used in our calculations when discounting the future cash flow for interest rate swap valuation. We describe the different types of rates, the risk-free rate, what market rate is most commonly used and the changes in market practice concerning the use of these rates. The risk-free rate is the rate of return on investment with zero risk over a period of time. Prior to the credit crisis in 2007, financial institutions used the London Interbank Offered Rate (LIBOR) and swap rates as their proxies for risk-free rates. After the crisis the institutions instead have begun using overnight indexed swap (OIS) rates as proxies for the risk-free rate.

3.1.1 Treasury Rates

Treasury rates might be natural to think of to be used as risk-free rates, as stated in (Hull, 2018). However, they are in practice regarded as artificially low. This is because the amount of capital a bank is required to hold to support an investment in T-bills and T-bonds are smaller than the capital required to support a similar investment in other low-risk-instruments.

3.1.2 LIBOR/Swap Rates

The use of LIBOR/swap rates instead of Treasury rates was because they are much closer to the implied risk-free rates. LIBOR rates are used as reference rates for hundreds of trillions of dollars in transactions around the world. It is compiled by asking 18 global banks to provide their quotes estimating the rate of interest to borrow funds from other banks. The highest and lowest four of the quotes are discarded, and the remaining quotes are averaged to determine the LIBOR fixing for the day (Hull, 2018). Now the LIBOR rates are determined to be less than ideal reference rates because the estimates are made by banks, and not from market transactions. For the Norwegian market, this is the Norwegian Interbank Offered Rate (NIBOR).

3.1.3 The OIS rate as the risk-free rate for discounting

Interest rate swaps, as used in our study, represent the biggest market share of interest rate derivatives. The valuation of IRS has long been considered as straight forward by practitioners. Researchers and market participants had all agreed for a standardized approach for valuing IRS. After the Great Financial Crisis of 2007-2009, the risk free rates for valuing interest rate derivatives has changed radically, according to Smith (2013).

Market rates, which used to be highly correlated before the crisis, were now incompatible with one another and included different liquidity and credit spreads. In other words, the previous rates included a credit risk component. Because of these changes, the old methods to value the interest rate derivatives became obsolete and less reliable (Mercurio, 2009). The significant shift in the valuation of interest rate derivatives was going from traditional LIBOR to overnight indexed swap (OIS) discounting, which happened after the great financial crisis. Hull (2018, pp. 191-192) describes an OIS as a swap where a fixed interest rate for a period is exchanged for the geometric average of overnight rates during the period. The relevant overnight rates are the rates in the government-organized interbank market where banks with excess reserves lend to banks that need to borrow to meet their reserve requirements. These reserve requirements are set by central banks that restrict commercial banks to keep a percentage of customer deposits as reserves which cannot be lent out. In the U.S. the OIS rate is known as the *fed funds rate* and is the weighted average of the overnight rates paid by borrowing banks to lending banks on that particular date. In other countries, we find similar overnight markets, such as the EONIA (Euro Over Night Index).

The spread between the LIBOR and OIS rates is an important measure of risk and liquidity. A higher spread is typically interpreted as an indication of a decreased willingness to lend by major banks. Hence, there are two reasons why OIS seems to be the correct risk-free rate. OIS is the rate with the least credit risk embedded, and it also represents the underlying rate for collateralised derivatives (Gregory, 2015).

The key point in swap valuation is all about discounting future cash flows. From Hull and White (2015), we can read that if we assume the OIS swap rates to be riskless, the riskless zero curve can be bootstrapped from OIS swap rates. If the zero curve is required for maturities longer than the maturity of the longest OIS swap, a natural approach is to assume that the spread between OIS swap rates and the LIBOR swap rates is the same for all maturities after the longest OIS maturity for which there is reliable data. Under OIS discounting, to determine the value of swaps which are based on LIBOR, it is necessary to determine the expected future LIBOR rate. This is the period between when the numeraire asset is a zero-coupon OIS bond maturing at time. These are the forward LIBOR rates. The impact of changing from LIBOR to OIS is small for short-dated instruments but becomes progressively larger as the lifespan of the instruments increases.

3.1.4 Stochastic Discount Factor

The time value of money needs to be considered by discounting cash flows. Meaning that having money today is better than having the same amount of money in the future. This is because investing the sum of money today will at least grow at the inflation rate. Brigo and Mercurio (2006) express the stochastic discount factor $D(t,T)$ between two time instants t and T as the amount at time t which is equivalent to one unit of currency payable at time T. This is given by:

$$D(t,T) = \frac{B(t)}{B(T)} = \exp\left(-\int_t^T r_s\, ds\right) \tag{3.1}$$

Where $B(t)$ is the value of the investment at time t. When dealing with interest rate products such as an IRS, the main variability that matters is the interest rates themselves. The investment $B(t)$ and discount factors $D(t,T)$ will need to be modelled through a stochastic process to find the evolution of r.

3.2 Introduction to Interest Rates Swaps and Derivatives

This chapter aims to present the reader to an interest rate swap (IRS), but before we can elaborate on the pricing and theory behind the IRS, we need to lay a foundation of how an IRS can be viewed as a combination of a zero-coupon bond and forward rate agreements. Further, we elaborate on the credit default swap and how the bootstrapping procedure is implemented to extract hazard rates needed for our case study.

3.2.1 Zero-Coupon Bonds

We first view the basic zero-coupon bond before expanding into forward rate agreements and interest rate swaps. We follow the definition and calculations from Brigo and Mercurio (2006, p. 4), which states that:

A T-maturity zero coupon bond (pure discount bond) is a contract that guarantees its holder the payment of one unit of currency at time T, with no intermediate payments. The contract value at time $t < T$ *is denoted by* $P(t, T)$. *Clearly* $P(T, T) = 1$ *for all T.*

Consider that we are at time t. A zero-coupon bond for the maturity T is then a contract that establishes the present value of one unit of currency to be paid at maturity T. We now have to take into account the relationship between the discount factor $D(t, T)$ as well as the zero-coupon bond price of $P(t, T)$. If rates r are deterministic, then D is deterministic as well and is $D(t, T) = P(t, T)$ for each pair of (t, T). But if the rates are stochastic, then $D(t, T)$ is a random quantity at time t which depends on the future evolution of rates r between time t and T. The zero-coupon bond price $P(t, T)$ which is the time t-value of a contract that pays at time T, has to be known at time t.

We further define the time to maturity $T - t$, as the amount of time in years from t to the maturity time $T > t$. For further elaboration on compounding and day-count conversions, we refer our readers to Brigo and Mercurio (2006).

3.2.2 Forward Rate Agreements

According to Brigo and Mercurio (2006), forward rates are characterized by three time instants. This is the time t at which the rate is considered, its expiry T and its maturity S, with $t \leq T \leq S$. Forward rates are interest rates which can be locked today for an investment at a future time. A forward rate can be defined through a prototypical forward rate agreement (FRA). An FRA can be viewed as a contract that also involves three time instants. These are the current time t, the expiry time $T > t$, and the maturity time $S > T$. The holder of the contract gets an interest-rate payment between times T and S. At the maturity, a fixed payment based on a fixed rate K is exchanged against a floating payment which is based on the spot rate $L(T, S)$ which resets in T with maturity S. This type of contract allows one party to lock in the interest rate between times T and S at a value of K, with the rates in the contract that are simply compounded.

At time S one receives $\tau(T, S)L(T, S)N$, where N is the contracts nominal value. The value of the contract in S is according to Brigo and Mercurio (2006, p. 11):

$$N\tau(T,S)(K - L(T,S)) \tag{3.2}$$

Where they assume that both rates have the same day-count convention. The expression above shows that if L is greater than K at time T, then the contract value is negative, should the value of L be lesser than K at time T the contract value is positive. Rewriting for the value of L from the simply-compounded spot interest rate $L(t,T)$ formula:

$$L(t,T) := \frac{1 - P(t,T)}{\tau(t,T)\,P(t,T)} \tag{3.3}$$

To get the formula:

$$N\left[\tau(T,S)K - \frac{1}{P(T,S)} + 1\right] \tag{3.4}$$

If we now consider the term $A = \frac{1}{P(T,S)}$ as an amount of currency held at maturity S, its value at time T is obtained by multiplying this amount A for the zero-coupon price $P(T,S)$:

$$P(T,S)A = P(T,S)\frac{1}{P(T,S)} = \tag{3.5}$$

Such that this term is the equivalent to holding one unit of currency at time T. One unit of currency at time T is then worth $P(t,T)$ units of currency at time t. Meaning that the amount $\frac{1}{P(T,S)}$ in S is equivalent to an amount of $P(t,T)$ at t.

If we now consider the other two terms in the contract value from Equation 3.2. The amount $B = \tau(T,S)K + 1$ at time point S is worth at time t:

$$P(t,S)B = P(t,S)\tau(T,S)K + P(t,S) \tag{3.6}$$

The total value of the contract at time t is then:

$$FRA(t,T,S,\tau(T,S),N,K = N[P(t,S)\tau(T,S)K - P(t,T) + P(t,S)] \tag{3.7}$$

Where there is just one value of K, which makes the contract fair at time t, meaning that the contract value is zero in t. This is obtained by equating to zero the FRA value. The resulting rate is what defines the simply-compounded forward rate. The simply-compounded forward interest rate is defined by Brigo and Mercurio (2006, p. 12) as follows:

The simply-compounded forward interest rate prevailing at time t for the expiry $T > t$ and maturity $S > T$ is denoted by $F(t;T,S)$ and is defined by:

$$F(t;T,S) := \frac{1}{\tau(T,S)}\left(\frac{P(t,T)}{P(t,S)} - 1\right) \tag{3.8}$$

It is the value of the fixed rate in a prototypical FRA with expiry T and maturity S that renders the FRA a fair contract at time t.

We can then rewrite the value of the FRA in terms of this simply-compounded rate as:

$$FRA(t,T,S,\tau(T,S),N,K) = NP(t,S)\tau(T,S)(K - F(t;T,S)) \tag{3.9}$$

To value an FRA, we only need to replace the interbank offered rate (LIBOR/NIBOR etc.) $L(T,S)$ in the payoff Equation 3.2, with the corresponding forward rate $F(t;T,S)$ and take the present value of the resulting quantity. We can then view the forward rate $F(t;T,S)$ as an estimate of the future spot rate $L(T,S)$ that is random at time t and based on the market conditions at time t.

3.2.3 Interest Rate Swaps

We now have the required background information needed to describe the interest rate swap. An IRS is a financial derivative where two parties agree to exchange future cash flows. The most basic form of an IRS is a plain-vanilla swap which is structured so that Counterparty A pays Counterparty B cash flows that equal a predetermined fixed interest rate on a principal, for a predetermined period of time. The fixed rate is most often exchanged for a floating interbank offered rate (LIBOR, NIBOR, etc.). In return, Counterparty A receives a floating interest rate on the same principal amount for the same period from Counterparty B, which could include a percentage add-on. This is shown by an example in Figure 2 below.

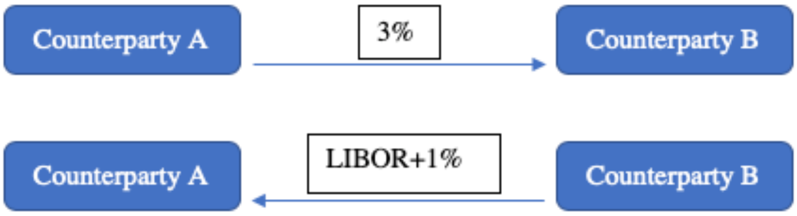

Figure 2. Example of a Plain Vanilla IRS

As stated in Hull (2018), the first swap contracts were set in the early 1980s, and since then, the market has seen a phenomenal growth. Swaps now have a position of central importance in the OTC derivatives market. Both interest rates in the swap are applied to the same notional principal, where the principle is "notional" because it is only used for determining the interest exchanges. The principal itself is not exchanged between the parties. As the contract matures through time, the discount factors and rates are subject to change so that the swap differs from its principal value. Here the swap will become an asset to one party and a liability for the other, subjected to how the interest rate changes.

Brigo and Mercurio (2006, p. 13) explains that if we discuss a prototypical Payer IRS, which exchanges payments between two differently indexed legs, starting from a future time instant, that at every instant T_i in a predetermined set of dates $T_{\alpha+1}, \dots, T_\beta$, the fixed leg pays out the amount:

$$N\tau_i K$$

Which corresponds to a fixed interest rate K, a nominal value N and a year fraction τ_i between T_{i-1} and T_i, and the floating leg pays the amount:

$$N\tau_i L(T_{i-1}, T_i)$$

That further corresponds to the interest rate $L(T_{i-1}, T_i)$ resetting at the previous instant T_{i-1} for the maturity given by the current payment instant T_i, with T_α as a given date. The floating-leg rate resets at dates $T_\alpha, T_{\alpha+1}, \dots, T_{\beta-1}$ and pays at dates $T_{\alpha+1}, \dots, T_\beta$. We set $\mathcal{T} \coloneqq \{T_\alpha, \dots, T_\beta\}$ and $\tau \coloneqq \{\tau_{\alpha+1}, \dots, \tau_\beta\}$.

In the real-world IRS market, the fixed leg usually has annual payments and the floating leg quarterly or semi-annual payments. We present a simplified version to ease the notation where the payments occur on the same dates and with the same year fractions. When the fixed leg is paid and floating leg is received, the IRS is termed as a Payer IRS, the other way around it is termed as a Receiver IRS.

The discounted payoff at a time $t < T_\alpha$ of a Payer IRS can be expressed as:

$$\sum_{i=\alpha+1}^{\beta} D(t,T_i)N\tau_i(L(T_{i-1},T_i) - K) \tag{3.10}$$

And the discounted payoff at a time $t < T_\alpha$ of a Receiver IRS can be expressed as:

$$\sum_{i=\alpha+1}^{\beta} D(t,T_i)N\tau_i(K - L(T_{i-1},T_i)) \tag{3.11}$$

If we view this latest contract as a portfolio of Forward Rate Agreements (FRAs) discussed in chapter 3.2.2, we can value each FRA, and add up the resulting values. We then obtain:

$$\begin{aligned} Receiver\ IRS\ (t,\mathcal{T},\tau,N,K) &= \sum_{i=\alpha+1}^{\beta} FRA(t,T_{i-1},T_i,\tau_i,N,K) \\ &= N\sum_{i=\alpha+1}^{\beta} \tau_i P(t,T_i)\big(K - F(t;T_{i-1},T_i)\big) \\ &= -NP(t,T_\alpha) + NP\big(t,T_\beta\big) + N\sum_{i=\alpha+1}^{\beta} \tau_i K P(t,T_i) \end{aligned} \tag{3.12}$$

We can then see the two legs of an IRS as two fundamental prototype contracts. Where the fixed leg can be seen as a coupon-bearing bond and the floating leg can be seen as a floating rate note. We can then view the IRS as a contract to exchange the coupon-bearing bond for the floating rate note, as stated in Brigo and Mercurio (2006). The authors (Brigo and Mercurio, 2006, p. 15) defines a typical coupon-bearing and a prototypical floating-rate note as follows:

A prototypical coupon-bearing bond is a contract that ensures the payment at future times $T_{\alpha+1}, \dots, T_\beta$ of the deterministic amounts of currency (cash flows) $c \coloneqq \{c_{\alpha+1}, \dots, c_\beta\}$. Typically, the cash flows are defined as $c_i = N\tau_i K$ for $i < \beta$ and $c_\beta = N\tau_\beta K + N$, where K is a fixed interest rate and N is bond nominal value. The last cash flow includes the reimbursement of the notional value of the bond.

If $K = 0$ the bond reduces to a zero-coupon bond with the maturity T_β and since each cash flow must be discounted back to current time t from payment times T, the current value of the bond is:

$$CB(t, \mathcal{T}, c) = \sum_{i=\alpha+1}^{\beta} c_i P(t, T_i) \tag{3.13}$$

The prototypical floating rate note is defined by Brigo and Mercurio (2006, p. 15) as follows:

A prototypical floating-rate note is a contract ensuring the payment at future times $T_{\alpha+1}, \dots, T_\beta$ of the LIBOR rates that reset at the previous instants $T_\alpha, \dots, T_{\beta-1}$. Moreover, the note pays a last cash flow consisting of the reimbursement of the notional value of the note at final time T_β.

To obtain the value of the note, we change the sign to the above value of the Receiver IRS with $K = 0$ (meaning no fixed leg), and add this to the present value $NP(t, T_\beta)$ of the cash flow N which is paid at time T_β we obtain:

$$-Receiver\ IRS\ (t, \mathcal{T}, \tau, N, 0) + NP(t, T_\beta) = NP(t, T_\alpha) \tag{3.14}$$

This means that a prototypical floating-rate note always is the equivalent to N units of its currency at the first reset date T_α. As such, if $t = T_\alpha$, the value equals N, such that the value of the floating-rate note at its first reset time is equal to its nominal value. This holds for $t = T_i$ aswell, for all $i = \alpha + 1, \dots, \beta - 1$, as the value of the note at all these instants are N. Furthermore, we need to define a forward swap rate so that the above IRS is fair at time t. To find this, we need to look for the specific rate K to value the above contract at zero. We follow the definition in Brigo and Mercurio (2006, p. 15):

The forward swap rate $S_{\alpha,\beta}(t)$ at time t for the sets of times $\mathcal{T}$ and year fractions τ is the rate in the fixed leg of the above IRS that makes the IRS a fair contract at the present time, i.e.m it is the fixed rate K for which $Receiver\ IRS\ (t, \mathcal{T}, \tau, N, K) = 0$. We easily obtain:

$$S_{\alpha,\beta}(t) = \frac{P(t,T_\alpha) - P(t,T_\beta)}{\sum_{i=\alpha+1}^{\beta} \tau_i P(t,T_i)} \tag{3.15}$$

If we then divide both the numerator and the denominator in the formula above by $P(t, T_\alpha)$ and notice the definition of F in terms of P's implies according to Brigo and Mercurio (2006, p. 16) that:

$$\frac{P(t,T_k)}{P(t,T_\alpha)} = \prod_{j=\alpha+1}^{k} \frac{P(t,T_j)}{P(t,T_{j-1})} = \prod_{j=\alpha+1}^{k} \frac{1}{1+\tau_j F_j(t)}, for\ all\ k > \alpha \tag{3.16}$$

Here the authors set $F_j(t) = F(t; T_{j-1}, T_j)$, and the formula for the forward swap rate can be written in terms of forward rates as:

$$S_{\alpha,\beta}(t) = \frac{1 - \prod_{j=\alpha+1}^{\beta} \frac{1}{1+\tau_j F_j(t)}}{\sum_{i=\alpha+1}^{\beta} \tau_i \prod_{j=\alpha+1}^{i} \frac{1}{1+\tau_j F_j(t)}} \tag{3.17}$$

3.2.4 Credit Default Swaps

A credit default swap (CDS) is a financial derivative which allows market participants to trade credit risks (Hull, 2018). This derivative product grew rapidly in use until 2007 and then declined. The simplest type of CDS is an instrument that provides an insurance against the default of a company or a bond, where the company/bond is known as the *reference entity,* and a default of the company is known as a *credit event*. The party which buys this insurance contract obtains the right to sell bonds issued by the reference entity for their face value when a credit event occurs, and the seller of the insurance is obligated to buy the bonds for the face value. The face value, or par value, of a bond is the principal amount the issuer will have to repay when it reaches maturity as long as it does not default. The buyer of a CDS contract must make periodic payments to the seller until the CDS contract expires or a credit event occurs, usually quarterly.

The total amount which is paid per year, as a percentage of the notional principle, to buy this protection, is known as the CDS spread. Several large banks are market makers which quote *bid* and *ask* prices. If the bid price is 250 basis points (bp), the market maker is willing to buy protection for 2.5% of the principle per year. If the asking price is 260bp, the market maker is willing to sell protection for 2.6% of the principle per year. If the notional principal is 100mill, the buyer will have to pay a yearly sum of:

$$0.025 * 100.000.000mill = 2.500.000mill$$

In case of a credit event, the seller is obliged to repurchase the bonds for the total face value minus the possible recovery rate (Lando, 2009). There are several advantages of using CDS contracts for default studies, according to Lando (2009). First of all, CDS trade in a variety of maturities, thus automatically providing a term structure for each underlying name. This as well as becoming more and more standardized and liquid. Meaning they do not require a benchmark bond for extracting credit spreads.

3.2.4.1 Credit spread calculation

A fair CDS spread is a spread that equals the expected discounted value of the premium leg and the expected discounted default leg at the date of the trade (O'Kane and Turnbull, 2003, Hull and White, 2000). Hence, to calculate the CDS spread (or price), we need to calculate the discounted values of the premium leg and the default leg. The pricing model presented here assumes that interest rates and default-time are independent (O'Kane, 2010). To do so we need to calculate the premium leg and the default leg. We know that the premium leg is the expected present value of all future payments. From Brigo, Morini and Pallavicini (2013) we can read that the default leg is the payment the seller of the CDS contract makes to the buyer in the case of a credit event. These two will be further explained in the following subchapters.

3.2.4.2 The Premium leg

We use the approach from O'Kane (2010) to model the CDS spread and start with the premium leg, which we described above. The present value is found by discounting all payments from today until the day a credit event occurs or to maturity of the CDS contract, whichever happens first. If the default occurs before the maturity date, T, then the protection buyer must pay a so-called accrued premium to the protection seller. O'Kane (2010) makes the assumption that the interest rates and the default time are independent. Further, he makes the simplification that the counterparty can only default in the middle of two payment dates. This is to simplify the calculation of the accrued premium. The present value of the premium leg can now be shown as:

$$PV_{PL}(T) = S_0(T) * DV_0(T) \tag{3.18}$$

Where:

- $S_0(T)$ is the CDS spread at time 0, for a contract with maturity T
- $DV_0(T)$ is the discounted values on payment days and the accrued premium between the last coupon payment and the time of default event

3.2.4.3 The Default Leg

The value of the default leg is the discounted value of the notional amount of the contract after the recovery. Because there is no knowledge of when the credit event may occur, we will have to find the following where we assume a notional of 1 (O'Kane (2010):

$$DL_{PV}(T) = E[e^{-\int_0^{\tau} r(s)ds} * (1 - R)1_{\tau \le T}] \tag{3.19}$$

Where:

- τ is the time for the credit event
- T is the maturity
- r is the risk-free rate
- R is the recovery rate
- $1_{\tau \le T}$ is the indicator function that equals 1 if $\tau \le t$ and 0 otherwise
- $DL_{PV}(T)$ is the present value of the default leg at $t = 0$

O'Kane (2010) further shows how we now can make the approximation of taking the sum over small timesteps instead of the integral over time. We then get the following expression:

$$DL_{PV} = (1 - R) * \sum_{n=1}^{T*M} e^{-\int_0^{t_n} r(s)ds} * [Def.prob(t_n) - Def.prob(t_{n-1})] \tag{3.20}$$

Where:

- M is the number of intervals each year
- $Defprob(t)$ is the default probability between time $t = 0$ and t, and we get the calculations for the default leg over small time steps

By using this equation, we now have an expression for the default leg. The only thing we need is the default probability as a function of time t for the reference entity. This will be elaborated on in chapter 3.3.3.

3.2.4.4 Modelling the CDS spread

The CDS spread is defined as the spread that equals the expected present value of the premium leg and the expected present value of the default leg at $t = 0$ (Gregory, 2012), O'Kane (2010) further proves that we find the CDS spread by equalling the two legs:

$$S_0(T) * DV_0(T) = (1 - R) * \sum_{n=1}^{T*M} e^{-\int_0^{t_n} r(s)ds} * [Def.prob(t_n) - Def.prob(t_{n-1})] \quad (3.21)$$

By solving for the CDS spread at $t = 0$ we get:

$$S_0(T) = \frac{(1 - R) * \sum_{n=1}^{T*M} e^{-\int_0^{t_n} r(s)ds} * [Def.prob(t_n) - Def.prob(t_{n-1})]}{DV_0(T)} \quad (3.22)$$

Equation 3.22 shows how at $t = 0$ the expected discounted premium leg and the expected discounted default leg equals out, and no payment is made between the parties. Instead, the spread determines how much a CDS buyer shall pay in coupon payments (O'Kane, 2010).

3.2.4.5 Bootstrapping the CDS Spreads

To calibrate the default intensities, we are using bootstrapping. Bootstrapping is an iterative process that starts with taking the shortest maturity contract to calculate the first survival probability, and so on (Cox, Ingersoll and Ross, 1985). We use a model where the default intensities $\lambda(t)$, also known as hazard rates, for the default time τ, is piecewise constant between quarterly timesteps, $\lambda_1, \lambda_2, \lambda_3 \cdots \lambda_{37}$, over a nine-year period. For this, we use the CDS spreads observed in the market, reportedly the *1 year, 3 year, 5 year, 7 year and a 10 year* CDS spread values following Castellacci (2008). Now we assume the hazard rate is piecewise constant between the quarterly time steps according to Equation 3.23:

$$\lambda(t) = \begin{cases} \lambda_1 \ \ if \ 0 \leq t \leq T_1 \\ \lambda_2 \ \ if \ T_1 \leq t \leq T_2 \\ \vdots \\ \vdots \\ \lambda_{37} \ \ if \ T_{36} \leq t \leq T_{37} \end{cases} \quad (3.23)$$

Given the different $\lambda(t)$ in Equation 3.23, we can now compare the model CDS spreads with the market CDS spreads for the different time periods. This by using Equation 3.22, where we use the default probability given in Equation 3.28 and Equation 3.29 in Chapter 3.3.3, where:

$$P[\tau > t] = \begin{cases} e^{(-\lambda_1 * \tau)} \ if\ 0 < \tau \le 1 \\ e^{(-\lambda_1 - \lambda_2 * (\tau - 1))} \ if\ 1 < \tau \le 2 \\ \vdots \\ \vdots \\ e^{(-\lambda_1 - \lambda_2 - \cdots - \lambda_{37} * (\tau - 36))} \ if\ 36 < \tau \le 37 \end{cases} \tag{3.24}$$

As we have mentioned before we want to find the piecewise constant hazard rate given the market spreads. In other words, we want to find the constant for each time step so that the model CDS spread equals the market CDS spread for each maturity, so that:

$$S_{market}(T) = S_{model}(T;\ \lambda_1,\ \lambda_2 \cdots,\ \lambda_{37}) \tag{3.25}$$

Where:

$$T \in [1,2,\ldots,37]$$

The procedure to find the hazard rates is, as we have already stated, referred to as bootstrapping and works in the following way:

1. Find $\lambda_{0,1}$ so that equation 3.25 holds, and $S_{market}(1) = S_{model}(1;\ \lambda_1)$
2. Given λ_1 from step one, find λ_2 so that equation 3.25 holds, so that $S_{market}(2) = S_{model}(2;\ \lambda_1, \lambda_2)$
3. Repeat for the rest

In each of the time steps, we must solve the one-dimensional, non-linear Equation 3.25, where both the market CDS spread for each time step is known and the model CDS spread is given by Equation 3.22.

The bootstrap methodology we now have presented will be the one we use in our case study to find the implied hazard rates and from those calculate the default probability.

3.3 Mathematical Definitions

This chapter aims to provide the reader with background regarding the main inputs required for calculating CVA, which will be further detailed in Chapter 6.

3.3.1 Exposure

The exposure of a contract is what an investor could lose in the event of a counterparty defaulting on their obligations or going bankrupt. The exposure depends on the instrument which is traded, where if the contract has a negative present value, it would be a liability to the investor. Should the contract, on the other hand, have a positive present value, it would be considered an asset to the investor to be received from the counterparty. Should the counterparty default on an asset, the value owed will not be received in full, and the exposure therefor equals its present value.

3.3.2 Loss Given Default

The loss given default (LGD) is the percentage of exposure the institution stands to lose if the borrower defaults (BIS, 2010). Theoretically, LGD can take any value between 0% and 100%. In other words, LGD equals one minus the recovery rate (R). In our thesis, we will apply a recovery rate of 40%, resulting in a LGD of 60%. This percentage originates from Altman and Kishore (1996, pp. 57-64) and is still widely used in both academia and as a market standard.

3.3.3 Probability of Default

We have already given an expression for the CDS spreads in Chapter 3.2.4. Now we are going to show how the actual default probabilities are determined. The default probability (PD) must be determined for the premium leg and, the survival probability need to be determined for the default leg. We will now specify what model we are going to use for this.

To model the PD of the counterparty we use an approach described both in Lando (2004) and (Brigo, Morini and Pallavicini, 2013) as intensity-based models which are used to calculate the continuous survival probability. Jarrow and Turnbull (1995) proposed that default occurs at a timepoint τ, with the probability of this happening defined as:

$$Pr[\tau < t + dt | \tau \geq t] = \lambda(t)dt \tag{3.26}$$

The PD in the time period $[t, t + dt]$, conditional there is no default in the previous period $[0, t]$, is given by the time dependent function $\lambda(t)dt$. $\lambda(t)$ is denoted as the hazard rate and is the default intensity as stated in Lando (2004), who further proves that the default time, τ, can be shown as:

$$\tau = \inf\left[t > 0: \int_0^t \tau(s)ds \geq E\right] \quad (3.27)$$

In words, this is the first time the integrated hazard rate reaches the level of the exponentially distributed random variable E. Lando (2004) further shows that the survival probability is:

$$\Pr(\tau > t) = e^{-\int_0^t \lambda(dt)}. \quad (3.28)$$

We can now easily make this an equation for the default probability:

$$\Pr(\tau \leq t) = 1 - e^{-\int_0^t \lambda(dt)}. \quad (3.29)$$

This model can be used both with the assumption of constant hazard rates and with the assumption of piecewise constant hazard rates. In our model, we are going to use a piecewise constant one, which allows the hazard rate to change for different maturities. The method relies on CDS quotes collected from the market, which is the recommended measure of default risk from the Basel III accord (BCBS, 2017).

3.3.4 Exposure at Default

The Exposure at Default (EAD) is along with LGD and PD used to calculate the capital requirement for credit risk for banks and financial institutions. EAD can be viewed as an estimation of how much a bank is exposed to a counterparty. The only viable methods for calculating EAD is now the standardized approach for counterparty credit risk, given in (BIS, 2014) or the use of internal model methods internally developed by banks. We will elaborate on the calculations further in Chapter 4.

3.4 Evolution of Credit Risk Theory and Credit Risk Models

In this chapter, we will introduce our readers to the evolution of credit risk modelling and theory, as this has had a significant impact on the procedures for measuring credit risk. Since the 1960s different concepts, models and theories surrounding credit risk have been developed. Some examples listed in Zamore *et al.* (2018) is bankruptcy prediction, distance-to-default, derivative pricing, default intensity, credit default swaps, contingent claims, counterparty risk and recovery rates. This chapter will provide insights into the evolution of credit risk modelling and some different risk instruments.

As stated in Zamore *et al.* (2018) the first modern quantitative model for credit risk was Altman's Z-score developed in 1968 (Altman, 1968), which is based on multivariate analysis of five accounting ratios. This Z-score was still being used by market players in 2012, even though it was 50 years old. The model faced criticism for being backwards looking considering accounting ratios come from historical information. This reason led to the evolution of new credit risk models such as the reduced form model and structural models. These structural models, which is based on the capital structure theory of Modigliani and Miller (1958), assume that default occurs when a firm's asset value is less than the debt value. This led to the works of Black and Scholes (1972, 1973) and Merton (1973, 1974). Black and Scholes (1973) used the options pricing model to price equity and debt, showing that debt value can be derived from call options. A problem with the Black-Scholes model is that the asset values of a firm cannot be directly observed (Zamore *et al.*, 2018). Merton (1974) continued the work of Black and Scholes by demonstrating that asset value could be calculated under some assumptions and then determine the PD. Merton called this the distance to default. Zamore *et al.* (2018) state that today, Merton's model is the most influential structural model in credit risk modelling.

Reduced-form models are able to determine PD without making assumptions on the source of the credit risk premium (Benzschawel, 2012) as stated in Zamore *et al.* (2018). These models are based on risk-neutral pricing theory, where a risky security's market value equals the present value of future cash flows discounted at the risk-free rate. Here the studies of Jarrow and Turnbull (1995) and Duffie and Singleton (1999) have been important for the risk-neutral pricing theory for credit risk modelling.

3.4.1 Credit Risk Evaluation Models

When reviewing credit risk modelling, Saunders and Cornett (2011) define two groupings of credit risk evaluation models, qualitative and quantitative. Qualitative factors focus on borrower characteristics, such as reputation, financial leverage, earnings volatility, collateral, and market factors such as business cycles, interest rates, etc. A judgment after reviewing these factors is made in order to grant or not grant credit to the borrower. Quantitative models attempt to obtain a credit score for the applicant used to determine the PD or to pool borrowers into segmented risk groups. When modelling credit risk by a quantitative measure, a problem of default risk occurs. Default risk is difficult to model because defaults rarely happen. To best produce a financial model, it must often include simulations, econometrics and optimization. Concerning the econometric techniques, these are statistical models where the PD is the dependent variable (Caouette, Altman, and Narayanan, 2008) as stated in Zamore *et al.* (2018). These models include linear probability, logit model, probit model, linear discriminant analysis and multiple regression (Altman and Saunders, 1997, Caouette, Altman and Nrayanan, 2008; Saunders and Cornett, 2011) as stated in Zamore *et al.* (2018). The Linear probability and logit models use historical data to compute the PD. The latter model uses logistical regression instead of linear and is together with the discriminant model the most dominating model used (Altman and Saunders, 1997).

In terms of structural and reduced-form models, which are the most popular models for quantitative credit risk, they can be seen as modern models trying to illustrate the default time (random time) and the recovery rates. Black and Scholes (1973) and Merton (1974) pioneered structural models and price firm-specific credit risks by focusing on the asset values of the firm. Here the default is modelled as an option, and researchers can price corporate liabilities by option pricing theory. Reduced form models developed by Jarrow and Turnbull (1995) and Duffie and Singleton (1999) focus on either default risk and downgrade risk, thus meaning the focus is shifted to external factors instead of the internal factors of asset values and capital structures. The reduced form models can then be classified into two groups, intensity based-models focusing on default time, and credit migration models focusing on changes in credit ratings (Bielecki and Rutkowski, 2004) as stated in Zamore *et al.* (2018).

3.4.2 The Factors Influencing Credit Risk

Three factors have an influence on credit risk, PD, LGD and EAD. The focus on recovery rate in credit risk models and its relation to the probability of default are limited (Caouette, Altman and Narayanan, 2008) as stated in Zamore *et al.* (2018). They can broadly be grouped into pricing models and credit portfolio value-at-risk (VaR) models. Pricing models were first developed by using the Merton approach and the assumption that PD and recovery rate depends on a firm's asset value, volatility and leverage. Recovery rate is thereby unrelated to PD. Even though the Merton approach has been popular, it has not shown to be practical due to the assumption of default time (at maturity of debt) and priority rules about multiple debs (Caouette, Altman and Narayanan, 2008) as stated in Zamore *et al.* (2018). Some examples of popular models in addition to Merton (1974) are those of Black and Cox (1976) and Vasicek (1984). Because of the low practicability of these models, new models overcame them by relaxing the assumption that default occurs at the maturity of the debt. In these new models, the default can occur at any time between the issue and the maturity of the debt. However, they still keep the assumption that default occurs when asset values reach a specified point (Zamore *et al.*, 2018). Newer articles are still using these models and the most prominent ones are Hull and White (1995) and Longstaff and Schwartz (1995). These models assess the recovery rate as a variable that is not dependent on asset values. Instead, it often sees it as a fixed ratio of debt value, and not dependent on PD. The complications with these models though are that the estimations for parameterization of asset values cannot be observed directly, and they do not incorporate rating changes in debt pricing (Zamore *et al.,* 2018).

To address these limitations, the reduced form models try to look outside the firm to determine PD. They state that an exogenic random variable determines PD, and the default occurs when there is a shift in the random variable. The default is then seen as an unpredictable Poisson event (Caouette, Altman and Narayanan, 2008) as stated in Zamore *et al.* (2018). Some examples of these models are the works of Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Lando (1998) and Duffie and Singleton (1999).

3.5 Wrong-Way Risk

Wrong-way risk (WWR) is according to Gregory (2012) the phrase generally used to indicate an unfavourable dependence between exposure and counterparty credit quality – i.e., the exposure is high when the counterparty is more likely to default and vice versa. The opposite, right-way risk, can also exist in cases where the dependence between exposure and credit quality is favourable. In the calculation of the CVA, it is usually assumed that the counterparty's probability of default is independent of the dealer's exposure to the counterparty.

WWR is often a natural and unavoidable consequence in financial markets and is further separated between general WWR and specific WWR. General WWR is when the counterparty's credit quality is correlated, for non-specific reasons, with macroeconomic factors that also affect the value of the underlying portfolio. An example may be the correlation of a particular type of counterparty to a particular type of interest rates or an index. Specific WWR is when the counterparty exposure is highly correlated with its default likelihood caused by idiosyncratic factors. This may arise through poorly structured transactions (e.g. an institution writing put options on its stock, a portfolio collateralized by own or related shares or bonds, or when there is a legal connection between the counterparty and the underlying issuer). A compelling case of idiosyncratic WWR arises when a bank hedges indirectly its bilateral CVA by buying credit default swap (CDS) protection on indices or other banks' CDS, which are highly correlated to their CDS (Saunders and Rosen, 2012).

For our calculations and simulations, we are going to use a portfolio of interest rate swaps. Although this is probably not the area with the most WWR, it is essential and highly relevant to consider a relationship between the interest rate and the counterparty PD. This relationship can be considered with both high and low interest rates. Where high rates might cause defaults, and low rates may be indicative of a recession where defaults are more likely.

The "alpha" multiplier in The Basel framework tries to adjust for WWR and is set equal to 1.4 or allows banks to use their internal models with a floor for an alpha of 1.2. According to Hull and White (2012), estimates of alpha reported by banks range from 1.07 to 1.10. As stated in Gregory (2012), Canabarro et al. (2003) reported only modest increases in the value of alpha when considering a market credit correlation as with WWR although this study was done with a large diversified portfolio. This will be further elaborated on in Chapter 5.

4 Credit Value Adjustment

We have now defined the components which will be used in the CVA calculations in the previous chapter. In this chapter, we provide the theoretical and practical information regarding the credit value adjustment (CVA) risk capital charge we calculate in our case study in Chapter 6. We present the different methods allowed for calculations as well as the formulas used. CVA in the Basel III frameworks is specified at a counterparty level, where CVA reflects the adjustment of default risk-free prices of derivatives. This was defined in the Basel II framework Annex 4 in BCBS (2005) should a counterparty potentially default. There is also CVA used for accounting which includes the effect of the bank's own default as well as constraints placed on calculations for accounting CVA, but this will not be discussed further as we focus on the regulatory CVA.

For some of the calculations, we refer our readers to the different BCBS documents specified in the text, as including all of the definitions and requirements specified would be excess for our thesis. CVA risk is defined by BCBS (2017, p. 109) as:

The risk of losses arising from changing CVA values in response to changes in counterparty credit spreads and market risk factors that drive prices of derivative transactions and securities financing transactions.

The CVA risk capital requirement is a calculation of a bank's CVA portfolio on a standalone basis which includes the bank's entire portfolio of derivatives transactions and must include risk reducing effects such as netting, collateral agreements and offsetting hedges. The capital requirement for CVA risk must be calculated by all the banks who are involved in derivatives transactions, except those transactions that are directly transacted with a qualified central counterparty. The BCBS approves two regulatory approaches for calculating CVA risk. The Standardized Approach (SA-CVA) with use of real market data, closely related to an Internal Model Method (IMM) approach requiring supervisory approval as well as the simpler Basic Approach (BA-CVA) which is presented in the following chapter. For banks with less engagement in derivative activities. If the aggregate notional amount of non-centrally cleared derivatives are less than or equal to 100 billion euro which is set as the materiality threshold, then any bank below this threshold can choose to use 100% of their counterparty credit risk (CCR) capital requirements as a proxy for their CVA capital.

4.1 BA-CVA

The basic approach (BA-CVA) comes in a *reduced* version for banks that do not actively hedge CVA risk, and a *full* version for banks that to actively hedge CVA risk by recognizing counterparty spread hedges. As the savings bank in our data set does not actively hedge CVA risk, we will not include a review of the full version but refer our readers to BCBS (2017, pp. 112-114) for further information regarding the full version.

The reduced version was designed to simplify the BA-CVA implementation for less sophisticated banks without hedging CVA. The reduced version ($K_{reduced}$) capital requirements for CVA risk are calculated as follows in BCBS (2017, pp. 110-112):

$$K_{reduced} = \sqrt{\left(p * \sum_c SCVA_c\right)^2 + (1 - p^2) * \sum_c SCVA_c^2} \tag{4.1}$$

Where:

- The summations are over all counterparties that are within the scope of the CVA risk charge.
- $SCVA_c$ is the CVA capital requirement that counterparty c would receive if considered on a stand-alone basis.
- $p = 50\%$. This is the supervisory correlation parameter. Its square $p^2 = 25\%$ represents the correlation between credit spreads of any two counterparties. p aims to recognize that the CVA risk which a bank is exposed to is less than the sum of the CVA risk for each counterparty. This given that the credit spreads of counterparties are not usually perfectly correlated.
- The first term under the root sign in the formula aggregates the systemic components of CVA risk. The second term aggregates the idiosyncratic components of CVA risk.

The stand-alone CVA capital for counterparty c is calculated as follows:

$$SCVA_c = \frac{1}{\alpha} * RW_c * \sum_{NS} M_{NS} * EAD_{NS} * DF_{NS} \tag{4.2}$$

Where:

- The summation is across all netting sets with the counterparty

- RW_c is the risk weight for counterparty c, which reflects the volatility of its credit spread. The risk weights are based on a combination of sector and credit quality of the counterparty. Credit quality is specified as investment grade (IG), high-yield (HY) or not rated (NR). If there exist no external ratings or the external ratings are not recognized within a jurisdiction, banks with supervisory approval can map an internal rating to an external rating and assign a risk weight corresponding to IG or HY; otherwise, the NR corresponding risk weight must be applied. These risk weights are specified in (BCBS, 2017, p. 112).
- M_{NS} is the effective maturity for the netting set NS. For banks with supervisory approval to use internal model methods (IMM), M_{NS} is calculated according to paragraphs 38 and 39 in Annex 4 of the Basel II framework (BCBS, 2005). For banks without supervisory approval to use IMM, M_{NS} must be calculated according to paragraphs 320 to 323 in Annex 4 in BCBS (2005), with an exception that the five-year cap in paragraph 320 is not applied. The formula for M_{NS} is shown below, where t is the time to the next cash flow and CF_t is the cash flow at time t.

$$M_{NS} = \frac{\sum_t t * CF_t}{\sum_t CF_t} \tag{4.3}$$

- EAD_{NS} is the exposure at default (EAD) of the netting set (NS), which is calculated in the same way which the bank calculates the minimum capital requirement for CCR detailed in Chapter 4.3.2.
- DF_{NS} is a supervisory discount factor.
  - This is set to 1 for banks using IMM when calculating EAD.
  - For banks not using IMM, it is $\frac{1-e^{-0.05*M_{NS}}}{0.05*M_{NS}}$. The supervisory discount factor is here averaged over time between today and the netting set's effective maturity date. The interest rate used for discounting is set to 5%, which explains the 0.05 in the formula above. The netting set effective maturity is defined as an average of actual trade maturities, which lacks discounting. The supervisory discount factor is added in order to compensate for this.
  - The product of EAD and effective maturity is a proxy for the area under the discounted expected exposure (EE) profile in the netting set. The IMM definition of effective maturity includes this discount factor, and DF is therefore set to 1 for IMM banks.

- $\alpha = 1.4$, and is used to convert effective expected positive exposure (EEPE) to EAD in both SA-CCR and IMM, which is the weighted average over time of effective expected exposure (EEE).

4.2 SA-CVA

Banks eligible to use the standardized approach for CVA (SA-CVA), which is more complex than the BA-CVA, must follow some important minimum criteria. The banks must be able to model the exposure, especially the credit spreads of less liquid counterparties and calculate the key risk measure and risk sensitivities of underlying market risk factors. The banks must also have a dedicated CVA desk for hedging activities. The SA-CVA must be calculated at a monthly frequency and reported to supervisors. Banks must also have the ability to produce SA-CVA calculations on demand if a supervisor should request it.

The regulatory CVA at a counterparty level must be calculated as the expectation of future losses (FL) resulting from the counterparty defaulting under the assumption that the bank itself has no risk of default (BCBS, 2017). These calculations must be based on inputs of the term structure of market-implied probabilities of default, market-consensus expected loss given default and simulated paths of discounted future exposure.

The term structure of the market-implied PD needs to be estimated from credit spreads that can be observed in the market. If the calculations are to be done towards counterparties which credit is not actively traded, the PD has to be estimated from proxy credit spreads for the counterparties. These proxies must estimate credit spreads from liquid peers with the help of an algorithm that discriminates on three variables: credit quality (rating), industry and region. A different proxy can be to map the illiquid counterparty to a single liquid reference name, for example mapping a municipality to its home country. This latest proxy must be justified to a supervisor. Should no credit spread of any counterparty peer be available, a bank can also use fundamental analysis of credit risk in order to proxy the spread, but should historical PDs be used the resulting spread must also relate to credit markets, and it cannot be solely based on historical PD.

When computing paths of discounted future exposures, they must be produced via the pricing of all derivative transactions with the counterparty on simulated paths for market risk factors. Discounting prices to today must be done using risk-free interest rates along the path (BCBS, 2017). An overview of risk-free rates is given in Chapter 3.1. All market risk factors must also be simulated as a stochastic process with an appropriate number of paths on a set of future time points to the maturity of the longest transaction. When determining the collateral that is available to the bank at a given exposure point in time, the model must assume that the counterparty will not post or return any collateral within a time period. The value which is assumed at this time period is known as the margin period of risk (MPoR). This MPoR cannot be less than a supervisory floor, which is set equal to 9 + N business days, where N is the re-margining period specified in the margin agreement. This means that should a margin agreement have daily or intra-daily exchanges of margin the minimum MPoR would be 9 + 1 equalling 10 business days.

When margining is included with counterparties this must be recognized as a risk mitigation and collateral management must be satisfied according to Annex 4, paragraph 51 (i)-(ii) in the Basel II framework of BCBS (2005). The bank must have documentation that is binding to all parties in the collateralized transaction, which is legally enforceable (BCBS, 2017). When simulating the exposure for margined counterparties, the simulation must also capture the effects of margining collateral along each exposure path, where all the relevant contractual features must be captured.

4.2.1 Calculation of the SA-CVA

The SA-CVA capital requirement is calculated as the sum of the capital requirements for delta and vega risks calculated for the entire CVA portfolio. When referring to delta risk, this measures the impact of a change in the price of the underlying asset. Vega risk measures the impact of a change in volatility. The capital requirements for the delta and vega risks are calculated as a simple sum of the delta and vega capital requirements calculated independently for six different risk types for delta, and five risk types for vega. Vega risk does not include counterparty credit spread risk. These risk types are:

1. Interest Rate (IR)
2. Foreign Exchange (FX)
3. Counterparty credit spreads
4. Reference credit spreads
5. Equity
6. Commodity

For a given risk type the sensitivity is calculated of the aggregate CVA, S_k^{CVA}, and the sensitivity of the market value of all hedging instruments in the CVA portfolio S_k^{Hdg}, to each risk factor k in the given risk type (BCBS, 2017). When calculating the sensitivities for vega risk, the volatility shift must be applied to both types of volatilities in exposure models, these are volatilities used for generating risk factor paths, and volatilities used for pricing. Continuing the calculation we need to obtain the weighted sensitivities WS_k^{CVA} and WS_k^{Hdg} for each risk factor k by multiplying the net sensitivities S_k^{CVA} and S_k^{Hdg} with the corresponding risk weight RW_k for the different risk weighs applicable to the different risk types. We will include the information for calculating with regard to interest rates but not for the other risk types. The formula follows from (BCBS, 2017, p. 199):

$$WS_k^{CVA} = RW_k * S_k^{CVA} \qquad , \qquad WS_k^{Hdg} = RW_k * S_k^{Hdg} \tag{4.4}$$

Where the net weighted sensitivity to the CVA portfolio S_k to risk factor k is obtained by:

$$WS_k = WS_k^{CVA} + WS_k^{Hdg} \tag{4.5}$$

The weighted sensitivities must then be aggregated into a capital charge K_b, within each bucket b for the different risk types given in section C.6 of BCBS (2017). The formula for K_b follows from BCBS (2017, p. 199):

$$K_b = \sqrt{\left[\sum_{k \in b} WS_k^2 + \sum_{k \in b} \sum_{l \in b; l \neq b} p_{kl} * WS_k * WS_l\right] + R * \sum_{k \in b} \left[\left(WS_k^{Hdg}\right)^2\right]} \tag{4.6}$$

Where p_{kl} is the correlation parameter applicable to the different risk types in Section C.6 in BCBS (2017) and R is the hedging disallowance parameter, set at 0.01 to prevent the possibility of perfect hedging of CVA risk. The bucket-level capital charges must then be aggregated within each risk type across the buckets, where the correlation parameter γ_{bc} which applies to the different risk types are specified in Section C.6 in (BCBS, 2017). The formula from (BCBS, 2017, p. 199) is then:

$$K = m_{cva} * \sqrt{\sum_b K_b^2 + \sum_b \sum_{c \neq b} \gamma_{bc} * K_b * K_c} \tag{4.7}$$

Where m_{cva} is a multiplier to compensate for a higher level of model risk in the calculation of CVA sensitivities. This multiplier has a default value of 1.25, but the value can be increased by the supervisory authority of the bank. This could be done, for example if the bank's exposure to a counterparty and the counterparties credit quality is not included in its CVA calculations.

For interest rates, the Basel III buckets, risk factors, sensitivities and correlations are set in Section C.6 (a) in (BCBS, 2017). The buckets for delta and vega risk are individual currencies, and the cross-bucket correlation γ_{bc} is set equal to 0.5 for all currency pairs. The Basel III framework states that domestic currencies will have delta risk factors which are absolute changes of the inflation rate and of the risk-free yields for the tenors of 1 year, 2 years, 5 years, 10 years and 30 years. Risk weights RW_k and correlations p_{kl} are given by Basel III (BCBS, 2017, p. 120) in Table 1 and Table 2 below:

Risk factor	1 year	2 years	5 years	10 years	30 years	Inflation
Risk weight	1.59%	1.33%	1.06%	1.06%	1.06%	1.59%

Table 1. Risk weights RW_k as set in BCBS (2017, p. 120)

	1 year	**2 years**	**5 years**	**10 years**	**30 years**	**Inflation**
1 year	100%	91%	72%	55%	31%	40%
2 years		100%	87%	72%	45%	40%
5 years			100%	91%	68%	40%
10 years				100%	83%	40%
30 years					100%	40%
Inflation						100%

Table 2. Correlations p_{kl} as set in BCBS (2017, p. 120)

For vega risk factors for interest rates, these are set as a simultaneous relative change of all volatilities for the inflation rate and a simultaneous relative change of all interest rate volatilities for a given currency. The sensitivity to the interest- or inflation rate volatilities is measured by shifting all interest- or inflation rate volatilities by 1% simultaneously in relativity to their current values and then dividing the resulting change in the aggregate CVA by 0.01 (BCBS, 2017). The risk weights for interest- and inflation rate volatilities are set to:

$$RW_k = RW_\sigma * \sqrt{6} \tag{4.8}$$

Where RW_σ is set to 55%. The correlations between interest- and inflation rate volatilities are set to $p_{kl} = 40\%$.

4.3 From CEM to SA-CCR

The SA-CCR replaced the Current Exposure Method (CEM) and the Standardized Method (SM) in 2014. Two approaches that were criticized for failing to treat margined and non-margined trades differently. Given the growing volume of trades being cleared and margined, the CEM and SM failed to recognize the risk-mitigation benefits according to (ISDA, 2019a). The widely used CEM was the simplest method and was valid for use until the end of 2016 (BCBS, 2014).

4.3.1 Current Exposure Method

The previous CEM approaches the calculation of exposure at default (EAD) by a replacement cost adjusted by a maturity-dependent add on times the notional (BCBS, 2005):

$$EAD = RC + Notional * Netting\ Factor * Addon \tag{4.9}$$

With the replacement cost (RC) containing the present value (V) and the volatility adjusted value of the collateral (C):

$$RC = \max(0, V - C) \tag{4.10}$$

The add on is given by (BCBS, 2005, p. 228) in Table 3 below.

	Interest Rates	FX and Gold	Equities	Precious metals except gold	Other commodities
One year or less	0.0%	1.0%	6.0%	7.0%	10.0%
Over one year to five years	0.5%	5.0%	8.0%	7.0%	12.0%
Over five years	1.5%	7.5%	10.0%	8.0%	15.0%

Table 3. Credit conversion factors used to calculate add-ons under the CEM (BCBS, 2005, p. 228).

Continuing, the netting factor for each netting set is:

$$Netting\ Factor = \frac{0.4 + 0.6 * \max\left(\sum_i PV_i, 0\right)}{\sum_i \max(PV_i, 0)} \tag{4.11}$$

For central counterparties, the static parameters are different and given by BCBS (2012):

$$Netting\ Factor = \frac{0.15 + 0.85 * \max\left(\sum_i PV_i, 0\right)}{\sum_i \max(PV_i, 0)} \tag{4.12}$$

And for simplicity by assuming constant credit spreads, meaning a constant PD and a constant recovery rate giving a constant LGD, the expected loss for CVA is:

$$Expected\ Losses = PD * LGD * (RC + Notional * Netting\ Factor * Add\ On) \tag{4.13}$$

This method for calculating EAD was valid until the end of 2016 and was then replaced by the new standardized approach for measuring counterparty credit risk exposures (SA-CCR) by BCBS in 2014, taken into action from January 2017 (BCBS, 2014).

4.3.2 SA-CCR

When measuring the exposures for derivatives via SA-CCR, the BSBC implemented a significant change in methodology to help include different treatment of margined and unmargined trades and other objectives. The goals are to incentivize banks to use margining to a greater extent. It also aimed to reduce national discretion, improve the risk sensitivity of the capital framework and reduce complexity for users. The CCR exposure under SA-CCR is the sum of the replacement cost (RC) of a position and its potential future exposure (PFE), multiplied by a regulatory multiplication factor (alpha), which is currently set at 1.4 and is set static to obtain a conservative buffer for model inaccuracies such as the implication of WWR. The formula follows from BCBS (2017, p. 47):

$$EAD = alpha * (RC + PFE) \tag{4.14}$$

The replacement cost (RC) is calculated according to paragraphs 130 to 145 of the counterparty risk standards (BCBS, 2014). The RC is shown in the following formula below, where V is the market value of the derivative, C is the value of the collateral, TH is the threshold amount stated in the collateral agreement, MTA is the minimum transfer amount, and NICA is the net independent collateral amount.

$$RC = \max(V - C; TH + MTA - NICA; 0) \tag{4.15}$$

Potential Future Exposure (PFE) is the amount for potential future exposure calculated according to paragraphs 146 to 187 of the counterparty credit risk standards (BCBS, 2014). Consisting of a multiplier times an add on.

$$PFE = multiplier * Add\ on \tag{4.16}$$

The multiplier in the PFE is defined in the following formula, where the floor is set at 5%. This component decreases as excess collateral increases, without reaching zero (floor).

$$Multiplier = min\left\{1; floor + (1 - floor) * exp\left[\frac{(V - C)}{2 * (1 - floor) * Add\ On}\right]\right\} \tag{4.17}$$

The add on consists of a supervisory factor (SF) shown in Table 4 from BCBS (2014), we have here chosen only to show the SF for the interest rate asset class, the table also shows the correlations and supervisory option volatility. The SF aims to convert the effective notional amount into Effective Expected Positive Exposure (EEPE) based on the measured volatility of the asset class. The effective notional is calculated in three maturity buckets which contribute amounts D_1, D_2 and D_3. The maturity buckets are shown in Table 5 below.

Asset Class	**Subclass**	**Supervisory Factor**	**Correlation**	**Supervisory Option Volatility**
Interest Rate		0.50%	N/A	50%

Table 4. Summary table of Supervisory Parameters

Time	**Maturity Buckets**
Less than one year	D_1
One year to five years	D_2
Over five years	D_3

Table 5. Maturity Buckets

The add on is:

$$Add\ on = SF * Effective\ Notional \tag{4.18}$$

Where the aggregation of the effective notional is calculated via the following formula:

$$Effective\ Notional = (D_1^2 + D_2^2 + D_3^2 + 1.4 * (D_1 * D_2 + D_2 * D_3) + 0.6 * D_1 * D_3)^{1/2} \tag{4.19}$$

Concerning netting sets, all the contributions within one netting set are aggregated within each maturity bucket through summation:

$$D_{1,2,3} = \sum_{Netting\ Set} \delta_i * d_i * MF_i \tag{4.20}$$

with trade-specific parameters:

$$MF_i = \left[\frac{\min(M; 1\ year)}{1\ year}\right]^{1/2} \tag{4.21}$$

Or:

$$MF_i = \frac{3}{2} * \left(\frac{MPOR}{1\ year}\right)^{1/2} \tag{4.22}$$

Where MF is the maturity factor (floored by 10 business days) and MPOR the margin period of risk if there is a margin agreement, if there does not exist a margin agreement Equation 4.21 is used. The parameter δ is the supervisory delta adjustment defined in Table 6 from BCBS (2014, p. 11). Where long in the primary risk factor means the market value of the instrument increases when the value of the risk factor increases. Short in the primary risk factor means the market value of the instrument decreases when the value of the primary risk factor increases.

$\boldsymbol{\delta}$	Long in the primary risk factor	Short in the primary risk factor
Instruments that are not options or CDO tranches	+1	-1

Table 6. Supervisory delta adjustments (BCBS, 2014, p. 11).

The factor d for interest rate and credit derivatives is then given by:

$$d = \frac{Notional\ [Local\ Currency] * [\exp(-0.05 * S) - \exp(-0.05 * E)]}{0.05} \quad (4.23)$$

Where S is the time interval of the starting date of the contract, and E is the time interval until the end of the contract.

In our case study in Chapter 6 we use the SA-CCR to calculate the CVA risk capital charge with the BA-CVA approach to compare with the IMM detailed in the following chapter.

4.4 Internal Model Method

In this chapter, we introduce the method used by larger banks and financial institutions to manage and measure CCR exposures and computing the resulting CVA charge, the IMM. This is also the model we do our best to construct in the case study of our thesis. By using this method, banks have to construct an analytical engine which is up to regulatory standards as the IMM is subject to prior supervisory approval. In order to qualify for an IMM for measuring counterparty credit exposures, the model must estimate the potential future distribution for changes in the market value of all transactions, including those in a netting set (BCBS, 2018). We will further discuss the components for an IMM, the Monte Carlo simulation process and the CVA calculations under IMM.

Regarding CCR, the BCBS noted that the IMM-CCR is more risk-sensitive than standardized approaches as it allows the banks to take the specific composition of their exposures and relevant risk factors, volatilities and correlations into account, as well as supplementing this by the back-testing requirement set by the BCBS. But the BCBS also found inconsistency in studies performed where there was considerable variability in the outcome of the CCR models. Because of these inconsistencies the BCBS choose to keep the Internal Model Method for CCR but implement a floor based on a percentage of the applicable standardized approach, which for derivative exposures is the SA-CCR. As we elaborate on the implementation and features of the IMM large parts of the following chapters are gathered from Zhuang (2017)

4.4.1 Constructing an Internal Model Method

Internal model methods encourage the bank to build consistent pricing and analytical environments in order to estimate exposures of portfolios with accuracy. According to

Zhuang (2017), motivation for implementing an IMM is that it can result in significant capital savings once the implementation is approved by regulators. To quantify the CCR using the IMM approach, a bank needs to build a CCR management infrastructure, which is a centralized analytical engine to provide an on-demand calculation of credit exposures at counterparty levels. This engine has to support netting and margining agreements to estimate the distribution of potential replacement costs, or exposure to price movements in OTC derivative trading.

A main component to the analytical engine is the Monte Carlo simulation process, which simulates behaviours of market risk factors related to the trades made at future time points based on their assumed evolution dynamics, covariance structures and volatilities estimated from historical time series (Zhuang, 2017). Financial institutions likely have portfolios of multiple transactions to different counterparties, the exposures of the bank to each counterparty is the sum of the replacement costs of all the position it has towards that counterparty. One can then compute the potential credit risk exposure to the counterparty over the longest life of the transactions in the portfolio using a Monte Carlo simulation. Every transaction in the portfolio is revalued using simulation paths at discrete intervals, where the mark-to-market values of the then simulated portfolio scenarios at future time points can be obtained. Afterwards, the distributions of simulated mark-to-market prices are calculated at specified confidence levels. Based on these distributions, the regulatory required expected positive exposure (EPE), potential future exposure (PFE) or other elements for quantifying counterparty exposures can be computed.

To elaborate on the implementations of the IMM some assumptions must be mentioned. According to Zhuang (2017), the evolution dynamics of market factors are assumed to follow lognormal distributions. This is an industry standard that is supported by academic research and empirical evidence, and is thus commonly used by financial practitioners. However, different dynamics are also used to simulate market factor evaluations, where financial institutions are free to choose simulation dynamics if they can prove to regulators that the models are robust and stable when analysing sensitivities, stress testing and back testing. Another assumption is that the portfolio remains constant within the simulation process. This means that no transactions happen for the entire life of the portfolio during the simulation, and the simulation will need to be run frequently, usually every day, in order to update the market factors and portfolio structures. The Monte Carlo simulation also uses covariance structures and volatilities, which are calibrated to historical profit and loss movements, remaining constant during the simulation period, which implicates a simplification of market reality.

4.4.2 Framework of the Monte Carlo Simulation

A Monte Carlo Simulation framework emulates the historical price movements and the behaviour of underlying market factors relevant to the portfolio during future dates. Some examples for common market factors required for OTC derivatives are interest rates, credit spreads, foreign exchange rates and others. Assuming that x_i represents a market factor, and assume that x_i is lognormal distributed, then we can simulate the market factor, according to Zhuang (2017, p. 61) with the dynamic of:

$$\frac{dx_i}{x_i} = \mu_i dt + \sigma_i dW_i(t) \tag{4.24}$$

With the property that:

$$dW_i(t) * dW_j(t) = \rho_{ij} dt \tag{4.25}$$

Where the drift μ_i, volatility σ_i, and correlations ρ_{ij}, are assumed to be constant, and the volatilities and correlations parameters should periodically be updated from historical data.

For every simulation date, all trades in the portfolio is priced using the pricing libraries from the front offices, which are rigorously validated and already approved by regulators. According to Zhuang (2017), it was difficult to apply these pricing libraries in the past to estimate counterparty credit exposure because of the intensity and complexity of the computations. The rare events of defaults and credit rating changes have small probabilities, and without a significant number of simulation paths, these rare events are hard to capture. Each trade in the portfolio must be evaluated at future time points for thousands of simulated future scenarios. This is easier today with an increase in computing power and integration processes.

The future exposures to a counterparty can be visualized through exposure profiles which are obtained by calculations of the statistics of the exposure distributions on each simulation date. The expected positive exposure profile (EPE) is obtained by computing the expectation of exposure on each simulation date. The potential future expose is obtained by computing a high-level, 97.7% or 99%, percentile of exposure on each simulation date.

The scenario generation, pricing and framework can be visualized in Figure 3 below, as illustrated by Zhuang (2017, p. 62).

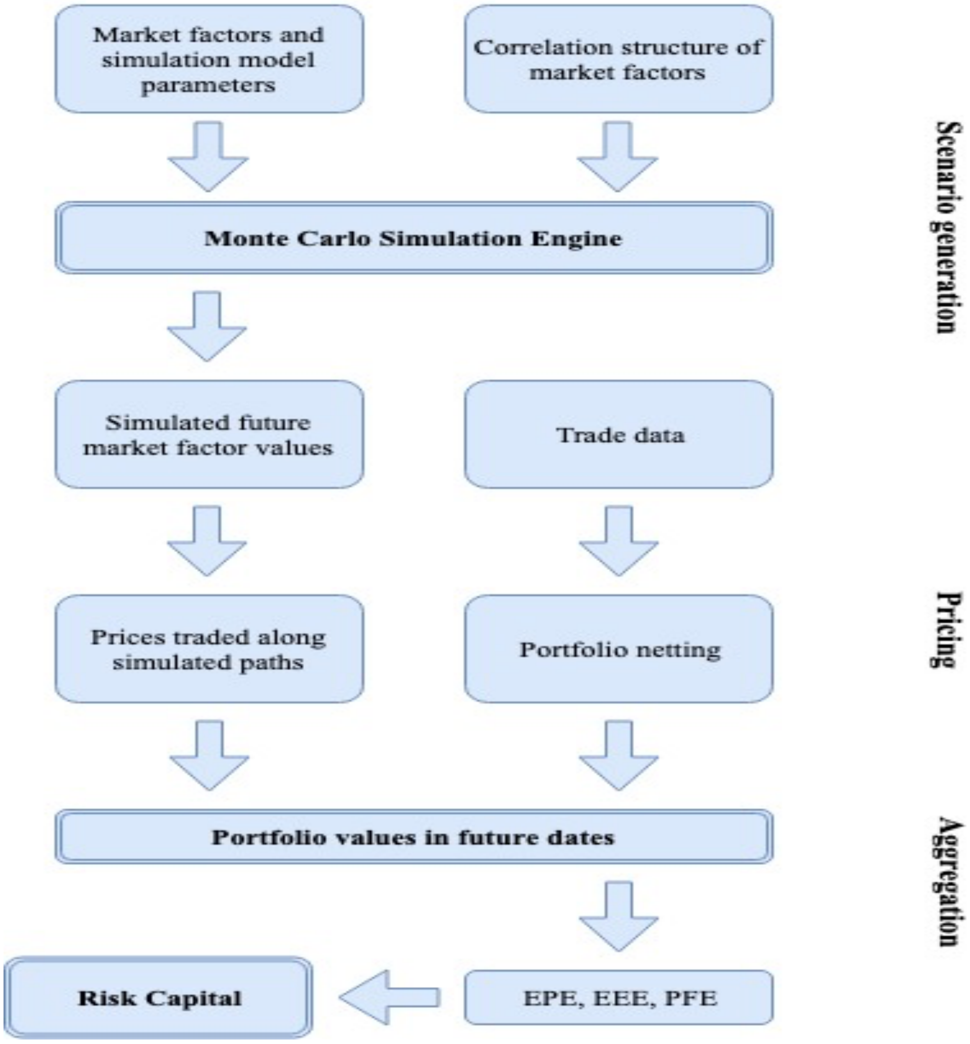

Figure 3. Three components in counterparty risk management framework Zhuang (2017, p. 62).

We will now describe the implementation process for these three components.

Consider P as the portfolio of trades against a counterparty and assume that P consists of N related trades. These trades are noted $A_1, A_2, \dots, A_N$. Margining is not taken into consideration for simplicity. Valuation of the instruments in the portfolio on a discrete set of future simulation dates is based on simulated market factors at these future time points. t_o is the valuation date (current date) and $t_1, t_2, \dots, t_n$ is the set of future dates where the market risk factors are simulated, and t_n is the longest maturity of the trades. To specify, M_j is the time period (in units of years) between valuation day and maturity of trade A_j for $j = 1, 2, \ldots, N$. M is defined as the longest time period as:

$$M = max\{M_j : j = 1,2, \ldots, N\} \qquad (4.26)$$

We can determine the number of steps required for the simulation process if the simulation is carried out on a set of equal length time grids by letting l be the length of time of the unit time interval of the simulation and denoting the required number of time steps for the simulation process by n by the following formula:

$$n = \left\lceil \frac{M}{l} + 1 \right\rceil \qquad (4.27)$$

The length of the time step has to be constant during the simulation process and the use of granular time steps at the beginning of the simulation indicates confidence in the simulated mark-to-market values. All market factors that are relevant to the trades in P must be simulated together. The exposure of P against the counterparty at a confidence level α is the maximum set of values $\{P(t_k): k = 0,1,2, \ldots, n\}$, where $P(t_k)$ is the α-th percentile of the set of portfolio values under the simulated market factor values at a specific future time point t_k.

If we assume that the number of simulations is S, and let m be used to index the simulated scenarios: $m = 1,2, \ldots, S$, we can calculate the potential market value of each transaction at each future date of simulated paths. We let $A_j^m(t_k)$ be the potential market value of trade A_j at time t_k under the m-th scenario. Further, we let $P^{(m)}(t_k)$ be the current exposure of the portfolio at time t_k under the m-th scenario and then have:

$$P^{(m)}(t_k) = \sum_{j=1}^{N} A_j^{\sim(m)}(t_k) \qquad (4.28)$$

Where $A_j^{\sim(m)}\ (t_k)$ is defined as:

$$A_j^{\sim(m)}(t_k) = \begin{cases} A_j^{(m)}(t_k), \text{if nettable} \\ \left[A_j^{(m)}(t_k)\right]^+, \text{otherwise.} \end{cases} \tag{4.29}$$

We define $[x]^+ = \max\{0, x\}$ and describe the basic simulation algorithm in six steps as described in Zhuang (2017, pp. 64-65):

1. Compute the portfolio value at time t_0. This value should match the market price of the portfolio and checked by tolerance tests.
2. Set $m = 1$
3. Call market factors simulation process to generate values of relevant market factors over the time interval $[t_0, t_1]$
4. Compute the value of the portfolio at time t_1
5. Repeat step 3 to step 4 for time steps $t_1, t_2, \dots, t_n$ in order to compute $P^{(1)}(t_2), P^{(1)}(t_3), \dots, P^{(1)}(t_n)$
6. Set $m = m + 1$. Repeat the scenario simulation process steps 2 to step 5 S times to obtain:

$$\left\{\left[P^{(m)}(t_0)\right]^+\right\}_{m=1}^{S}, \left\{\left[P^{(m)}(t_1)\right]^+\right\}_{m=1}^{S}, \left\{\left[P^{(m)}(t_2)\right]^+\right\}_{m=1}^{S}, \left\{\left[P^{(m)}(t_n)\right]^+\right\}_{m=1}^{S}$$

The α-th percentile of the above sequences are denoted by $PFE_\alpha(t_k), k = 0, 1, 2, \dots, n$, and form the portfolios PSE profile with the α confidence interval. Peak PFE at α confidence level, denoted by PFE_α is given by Zhuang (2017, p. 64) in the following formula:

$$PFE_\alpha = \max\{PFE_\alpha(t_k) : k = 0,1,2, \dots, n\} \tag{4.30}$$

We can also compute the expected positive exposure (EPE), that is defined as the maximum of expected positive exposure at each of the time steps $t_0, t_1, t_2, \dots, t_n$. At time step t_1 we compute:

$$EPE(t_k) = \frac{1}{S} \sum_{S}^{m=1} \left[P^{(m)}(t_k)\right]^+ \tag{4.31}$$

And the EPE profile consists of all $EPE(t_k)$ for $k = 0,1, \dots, n$. The peak EPE of P is the maximum of the sequence $\{EPE(t_k)\}_{k=0}^{n}$.

For calculating the effective expected positive exposure (EEPE) an accurate calculation of expected exposure (EE) and EPE must be computed with the same sophistication of models as the PFE. Expected exposure at time t, is denoted by EE_t, and is the average positive exposure at t. Meaning $EE_t = EPE(t)$. The effective expected exposure noted effective EE is recursively computed as:

$$\text{effective } EE_t = \max\{\text{effective } EE_{t_{k-1}}, EE_{t_k}\} \qquad (4.32)$$

Where the effective EPE is defined as the average effective EE during the first year of future exposure. Should all contracts in the netted portfolio mature within under a year, then the effective EE is defined as the average of effective EE until all contracts in the portfolio mature. Further on the effective EPE is computed as a weighted average of effective EE in the formula below:

$$\text{effective } EPE = \sum_{min\{1y, maturity\}}^{k=1} \text{effective} EE_{t_k} * \Delta_k \qquad (4.33)$$

Where $\Delta_k = t_k - t_{k-1}$. However, note that the Δ_k weights allow a case when future exposure is calculated at dates which are not equally spaced over time.

With all these computed quantities, the exposure value can be calculated as the product of α and effective EPE:

$$Exposure\ value = \alpha * \text{effective } EPE \qquad (4.34)$$

Where the alpha parameter was explained in Chapter 3.5.

4.4.3 CVA Under the IMM

The CVA formula for banks with IMM approval for CCR is shown in (BCBS, 2010, p. 31) and is the formula we applied for our CVA calculations in the following case study. The CVA capital charge calculation must be based on the following formula for the CVA of each counterparty:

$$CVA = (LGD_{MKT}) * \sum_{i=1}^{T} Max\left(0; exp\left(-\frac{s_{i-1} * t_{i-1}}{LGD_{MKT}}\right) - exp\left(-\frac{s_i * t_i}{LGD_{MKT}}\right)\right) * \left(\frac{EE_{i-1} * D_{i-1} + EE_i * D_i}{2}\right) \qquad (4.35)$$

Where:

- t_i is the time of the i-th revaluation time bucket, starting from $t_0 = 0$
- t_T is the longest contractual maturity across the netting sets with the counterparty
- s_i is the credit spread of the counterparty at tenor t_i
- LGD_{MKT} is the loss given default of the counterparty based on the spread of a market instrument of the counterparty or appropriate proxy
- The first factor within the sum represents an approximation of the market implied marginal PD occurring between times t_{i-1} and t_i.
- EE_i is the expected exposure to the counterparty at revaluation time t_i
- D_i is the default risk-free discount factor at time t_i, where $D_0 = 1$

As stated earlier, the IMM needs prior regulatory approval for financial institutions to be allowed to use IMM for counterparty credit risk management. The most important qualifications in obtaining approval are the ability to demonstrate the concepts and soundness of the modelling framework, the calculations accuracy, as well as the stability and the robustness of the model performance. The measuring of counterparty credit risk exposures has proven to be a complex topic and many of the tools used for managing CCR exposures such as collateral, margining and central clearing all have an impact on the modelling aspects.

5 Banking Regulations

5.1 Introduction

This chapter will provide background information for the case study in our thesis by reviewing banking regulations. The chapter is structured from articles surrounding credit risk and counterparty credit risk after the implementation of the Basel Accords. We will focus on the Basel I, II and III accords and give an implication of the changes regarding counterparty credit risk during the period. The goal of the BCBS is to enhance financial stability worldwide and is the global standard setter for prudential regulation of banks. It provides a forum for cooperation on banking supervisory matters, and its mandate is to strengthen the regulation, supervision and practices of banks (BCBS, 2019). The Bank for International Settlements (BIS) publications from BCBS regarding the Basel accords will provide technical and theoretical literature on regulations. Regarding the changes to measure counterparty credit risk exposures from the CEM to the SA-CCR introduced in Chapter 4.3, we also address some criticism regarding implementation the SA-CCR.

In 1988, an agreement known as the Basel Accord set the start for international standards for banking regulations. Since 1988, these regulations have been an evolutionary process, where new regulations replace, modify or complement older ones. The later 1998 Basel Accord is now known as Basel I, and Basel II was a significant overhaul regarding regulations that were implemented by many banks in the world around the year of 2007 (Hull, 2018). Basel III was first published in 2010 and later finalized in December of 2017.

When starting to review the topics concerning credit risk and counterparty credit risk, we quickly found ourselves with an overwhelming number of articles containing ideas, innovations, models and studies on the subjects. The topics have been more greatly studied during the last 10 years, seeing a spike in the amounts of publications occurring after the Great Financial Crisis. A search on web of science with the most relevant fields of study showed 9570 records on the topic *credit risk* and 347 records on the topic *counterparty credit risk*.

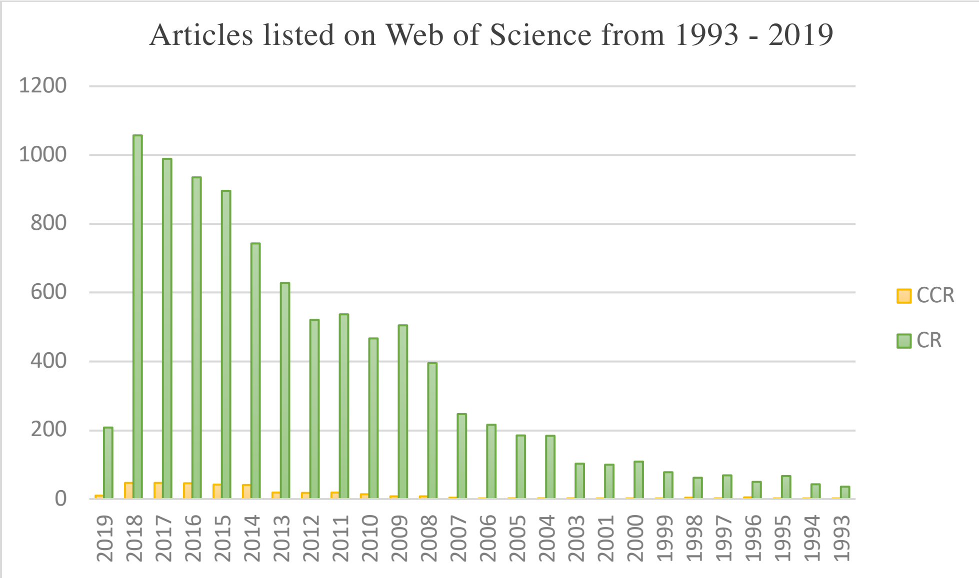

Figure 4. Articles listed on Web of Science from 1993-2019 (Web of Science, 2019).

As illustrated in Figure 4 above, we can see an increase in published documents from 2004 and until 2018, with a large jump from 2007 to 2008 as a result of studying the events of the Great Financial Crisis and its implications for global financial markets.

5.2 The Evolution of Basel and other Banking Reforms

This chapter will provide an overview of the evolution of the reforms implemented by the BCBS during the years before and following the Great Financial Crisis. We also discuss the reasoning to why regulatory changes were required. Further detailing the importance and reasoning for why studying credit risk and counterparty credit risk became a larger topic for banks and financial institutions. We will address some criticism towards Basel II as the cause for the crisis and give thoughts on why we think this criticism was unjust.

5.2.1 The 1988 BIS Accord – Basel I

The 1988 BIS Accord was the first attempt to create risk-based standards for capital adequacy on an international level. The accord did face criticism for being too simple but was still signed by all 12 members of the Basel Committee and considered a significant achievement. The Accord paved the way for large increases in the resource's banks devoted to measure, understand and manage risks. The BCBS here set out the minimum capital requirements for financial institutions, requiring institutions to maintain a minimum of 8% of capital based on a percentage of their risk-weighted assets.

A key innovation from the 1988 Accord was the Cooke ratio. Which, according to Hull (2018) considered credit risk exposures that are both on-balance-sheet and off-balance-sheet. It is based on the banks' total risk-weighted assets, which is a measure of the banks' total credit exposure. If we consider an example of an interest rate swap from Hull (2018, pp. 350-353) the credit equivalent amount was calculated as:

$$\max(V, 0) + aL$$

Where:

- V is the current value of the derivative to the bank
- a is an add-on factor
- L is the principal amount.

The first term, $\max(V, 0)$, is the current exposure. Should the counterparty default today and the current value be positive, then the contract is an asset to the bank, and the bank is liable to lose the current value. On the other side, if the counterparty defaults today and the current value is negative, then the contract is an asset to the counterparty and there will be neither a gain nor a loss to the bank. Therefore, the bank's exposure is $\max(V, 0)$. The last term, the add-on amount, is an allowance for the possibility that the exposure could increase in the future.

This credit equivalent amount was later also known as the current exposure method (CEM) which is discussed in Chapter 4.3 and was still used until the implementation of the new standardized approach for measuring counterparty credit risk exposures (SA-CCR) in 2014.

5.2.2 Basel II

Basel II was initially published in June 2004 (BCBS, 2004) in order to create an international banking regulation standard to apply control over how much capital banks need to set aside in order to protect against financial and operational risks. It was the second of the BCBS recommendations, and unlike the first Basel I accord, where the focus was on credit risk, the reform tried to take the awareness of risk to a higher level. Basel II integrates Basel I capital standards with national regulations, setting a minimum of capital requirements for financial institutions, to assure that banks keep adequate capital for the different risks they expose themselves to, both from lending and investment activities.

Basel II was based on three Pillars. The first Pillar (Pillar 1) specifies the maintenance and calculations of minimum regulatory capital requirements for credit risk in the banking book that reflects the credit risk of counterparties. The requirement remained the same as the 1996 amendment to the 1988 Accord, stating that banks should hold a total capital equal to 8% of its risk-weighted assets. The second Pillar (Pillar 2) is concerned with a supervisory review process, where supervisors are needed in order to ensure that banks have a process in place to maintain the minimum required capital levels. The supervisory role also requires an encouragement to banks to develop and use better risk management techniques and to evaluate and further strengthen these techniques (Hull, 2018). The third Pillar (Pillar 3) aims to develop a set of disclosure requirements to allow market participants to view the capital situation of a bank or financial institution. This gives shareholders and potential shareholders additional information about the risk management decisions the institution takes and how they allocate their capital.

While the Basel II standard covered the risk of a counterparty default, it did not address the credit valuation adjustment (CVA) risk, and as Cannata and Quagliariello (2009) states, several economists, policy-makers and market operators blamed the Basel II framework for the Great Financial Crisis. We will list some of the main problems concerning Basel II, which made it a target for these accusations, listed by Cannata and Quagliariello (2009).

The average level of capital required for banks to set aside was meant to be too low, and thus resulting in the collapse of several banks. Furthermore, the capital accord, which interacts with fair-value accounting, was said to cause remarkable losses in portfolios due to the problem of assets being mark-to-market valued. This results in balance-sheet losses affecting capital rations, making balance-sheets more exposed to asset-fluctuations, and making banks raise new capital or reduce lending. The Basel II framework also delegated credit risk to non-banking institutions such as rating agencies, which are subject to a conflict of interest when issuing ratings on risky products sold by financial institutions. There was also an assumption that the banks' internal models for measuring their risk exposures was superior to other methods but could result in banks assessing their risk exposures lower than they should be.

However, was Basel II a reason for the crisis? One of the good things about the Basel II accord was the wish to update the previously mentioned Basel I framework by focusing not only on credit risk, but also include the measures of the creditworthiness of a counterparty (CCR) and strengthening risk management systems. Another issue why Basel II may have been an innocent target for the accusations was the fact that the actual implementation of the framework was postponed to 2010 in the United States, which was the centre of the crisis. In Europe, most banks were allowed to push the implementation to 2008 (Cannata and Quagliariello, 2009). So, this means that most banks were actually still operating under the Basel I framework when the crisis started. It is also worth mentioning that many banks may have already reviewed their credit standards and risk management procedures to make it easier to implement Basel II, which could result in them misjudging their exposures.

5.2.3 Basel III

Basel III is an internationally agreed set of measures developed by the BCBS in response to the financial crisis of 2007-2009. The new measures are aimed at strengthening the regulation, supervision and risk management of banks. The two main objectives are to strengthen global capital and liquidity regulations to promote a more resilient banking sector, as well as improving the banking sectors ability to absorb financial and economic shocks. The first Basel III proposals were published in December 2009, and after comments from banks, a quantitative impact study (QIS) as well as several international summits, the final version was published in December 2010, and revised in June 2011 (BCBS, 2010). The finalization of the Basel III post-crisis regulatory reforms was published in December 2017 (BCBS, 2017) and included the implementation of the SA-CCR from BCBS (2014). It also included a revised CVA framework which is to be implemented by January 2022.

The initial phase of the Basel III reforms introduced a capital charge for potential mark-to-market losses as a result of deterioration in the creditworthiness of a counterparty in a derivative instrument transaction. This risk is known as CVA risk, which was a significant source of losses for banks during the Great Financial Crisis and was higher than losses from defaults in some instances (BCBS, 2017). A bank calculates CVA for each of its derivative counterparties. This quantity is the expected loss because of the possibility of default by the counterparty. The CVA calculation can change because the risk factors underlying the value of the derivatives with the counterparty changes, or the credit spreads that can be applied to the counterparty's borrowing changes. The BCBS agreed to revise the framework in order to enhance its risk sensitivity, strengthen its robustness and improve its consistency. The Basel III framework consists of six parts to the regulations. The six parts are:

1. Capital Definition and Requirements
2. Capital Conservation Buffer
3. Countercyclical Buffer

4. Leverage Ratio
5. Liquidity Risk
6. Counterparty Credit Risk

In our thesis, we will only focus on the CCR part and we refer our readers to BCBS (2017) for information about the first five parts. The former CVA framework did not cover an exposure component of CVA, which is an important driver of CVA risk. It is directly related to the price of the transaction, but as the prices are sensitive to variability in market risk factors, so the CVA also depends on those factors. In order to strengthen the robustness of CVA, the revised Basel III framework (BCBS, 2017) now consists of a Standardized Approach (SA-CVA), and a Basic Approach (BA-CVA). To improve accuracy, the standardized and basic approaches have been designed to be consistent with the approaches used in the revised market risk framework. Here the standardized CVA approach is based on fair value sensitivities to market risk factors and the basic approach is benchmarked to the standardized approach.

Some felt the Basel III reform was too complicated while others argued that the efforts of the BCBS were not enough. However, as Stefan Ingves, the Governor of Sverige's Riksbank and Chairman of the BCBS states in Ingves (2012), there is no easy way to reach a global consensus on these technical matters. In his view, the Basel III reforms and fundamentally enhances national and global financial stability.

5.2.4 Basel III in the EU - CRD IV and CRR

The Capital Requirements Directive (CRD) IV is intended to implement the Basel III agreement in the European Union (EU). The directive includes requirements for the quality and quantity of capital, a new basis for liquidity and leverage requirements, new rules for counterparty risk and new macroprudential standards including a countercyclical capital buffer as well as capital buffers for systemically important institutions (Bank of England, 2019). The EU text was first formally published in June 2013 (European Union, 2013b) and the legislation was applicable from 1 January 2014, and full implementation should happen at latest by 1 January 2019 (Regjeringen, 2019). CRD IV is made up of the CRD 2013/36/EU (European Union, 2013b) and the Capital Requirements Regulation (CRR) 575/2013 (European Union, 2013a). CRD IV also applied changes to rules on corporate governance and introduced standardised EU regulatory reporting.

The status for implementation of CRD IV and CRR into the European Economic Area (EEA) agreement is under consideration (Regjeringen, 2019). By incorporating CRD IV into the EEA-agreement all of the conditions of the directive as well as CRR would be implemented in Norway, but the Norwegian Government states that the contents of the directive are already in place according to Norwegian law, with only small changes needed to be made for the incorporation. Since Norwegian corporations are already regulated according to the demands for CRD IV/CRR, the EEA-agreement will not have any negative economic or administrative consequences for Norwegian corporations. It will rather make sure that the corporations get the same rights in the EEA-market as companies based in the European Union.

5.2.5 MiFID II and MiFIR

A new directive and regulation to regulate the market for financial instruments were implemented in the EU in January 2018 called Markets in Financial Instruments Directive (MiFID) II, directive 2014/65/EU and MiFIR, regulation No. 600/2014 (Finanstilsynet, 2018). The directive makes changes in the current regulations linked to permissions, business practice and the organization of financial corporations. The MiFIR regulations expanded on the reporting demands both pre- and post-trade for stocks to also include other types of financial instruments. A demand to trade derivatives on organized marketplaces was also put into action. As these do not directly refer to counterparty credit risk they will not be discussed further. However, we included them to show that new regulations are quickly being implemented into the financial industry.

5.3 Critique regarding the regulations and future developments

We will in this chapter, provide the reader with thoughts and critiques regarding the implementation of the Basel Regulations, especially the change from CEM to SA-CCR. We gathered letters and reviewed studies from users of these practices to illustrate possible flaws with the SA-CCR. To specify which parties are issuing concerns, we divide the chapters further to the remarks from the organizations and institutions in order to make it easier for our readers to differentiate between them.

5.3.1 Response Letter from ISDA

On the 18th of March 2019, the International Swaps and Derivatives Association (ISDA) posted a response letter together with the American Bankers Association (ABA), the Bank Policy Institute (BPI), and the Futures Industry Association (FIA), we will note these as the

“Associations”. The letter was posted to the Board of Governors of the Federal Reserve System (FRB), the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC), hereby noted as the “Agencies”. The letter (ISDA, 2019b) states that the development of SA-CCR will have multiple implications for the U.S capital framework by replacing the CEM in the calculation of counterparty credit risk and credit value adjustments.

The Associations support the move from CEM to a more risk-based measure and believe that an appropriately revised version of the SA-CCR would be a major improvement over the current framework. There are also negative impacts of the change to be considered. The Associations see elements of the proposed rulemaking to have a significant negative impact on liquidity in the derivatives market and hindering of the development of capital markets, particularly the potential implication costs for commercial end-users, who benefit using derivatives for hedging purposes. Stating that this could weaken the users’ balance sheet and reduce their attractiveness from an investment perspective.

In order to support their comments on the proposed changes, The Associations conducted an in-depth Quantitative Impact Study (QIS) to demonstrate the impact. This study was started in early 2017 (ISDA, 2019a) and conducted with input from nine financial institutions which account for 96% of the total derivatives notional outstanding at the top 25 bank holding companies. In their QIS results, they show that exposure at default would remain flat, whereas CCR default standardized risk-weighted assets, would increase by 30% in comparison to CEM (ISDA, 2019a, p. 70). The impact is much greater at the derivatives business level, and the data from the QIS demonstrates the need for changes to ensure that SA-CCR more accurately reflects the risk in the derivatives market.

The Associations response to the Agencies is to strongly urge them to consider and act upon the feedback to avoid unintended consequences and still achieve regulatory objectives. Specifically to reconsider the supervisory factors for commodity and equity classes set by the BCBS (2014), to provide a more risk-sensitive treatment of initial margin for calculating RWA, and to reconsider the application and calibration of the alpha factor. This in order to avoid disproportionate impacts on the cost of doing business resulting from reduced hedging, allowing for netting of all transactions covered by a qualifying master netting agreement, and to ensure that SA-CCR does not negatively impact client clearing. We refer our readers to the letter (ISDA, 2019a) for a detailed description of the proposed changes as well as the results of the QIS using the BCBS own hypothetical portfolios.

The QIS shows that the conservative calibration and lack of risk sensitivity in SA-CCR could lead to a surge in exposures and capital requirements during a time when the BCBS has been directed not to further introduce significant increases to capital requirements. Further impacting derivatives end users including corporates, sovereigns and pension funds (ISDA, 2019b). The briefing paper (ISDA, 2019a) also addresses that the alpha factor of 1.4 set for IMM in 2005 was calibrated using studies dating back to 2003 and does not reflect the current market environment, specifically regarding larger portfolio diversification effects and wider clearing and margining practices. ISDA analysis suggests that the alpha value should fall to 1.01 if recalibrated accurately.

Seeing that the SA-CCR was finalized in 2014 (BCBS, 2014), and should already be implemented by now, substantial technical changes to the framework may not be practicable. However, applying a 40% increase to all exposures, when SA-CCR already is conservatively designed and calibrated, could have a negative impact on the availability and costs of hedges to the end users. ISDA (2019a) states that removing alpha from the SA-CCR calculations could better align actual exposures and capital requirements while still obtaining the risk-sensitive methodology and recognition of margin.

5.3.2 Moody's Analytics Risk Perspectives

Moody's Analytics Risk Perspectives, a magazine delivering insights to risk practitioners in global financial markets, published an article written by Séror (2016) in November 2016 on the Basel III SA-CCR adaption and implementation status. The writer asked some of their banking clients on feedback regarding the implementation of SA-CCR. The major challenge that banks faced was the granularity requirements for computation data in SA-CCR in comparison to CEM, as well as the banks approach to collateralization which now is more driven by the margin reform changes and central clearing.

5.3.3 The FIA, IFF and GFMA

The FIA is a leading global trade organization for futures, options and centrally cleared derivatives. The Institute of International Finance (IFF) is a global association of the financial industry supporting the industry in risk management and development of industry practices.

The GFMA addresses the increasingly important global regulatory agenda and brings together three of the world's leading financial trade organizations.

In September 2018 FSB (2018) published a comment to on the consultative report of the Derivatives Assessment Team (DAT) on "incentives to centrally clear OTC derivatives". Their comment states that the post-crisis reforms have been successful in achieving their goals, but the G20 reforms have significantly constrained client clearing capacity. They wish that the SA-CCR should be modified to recalibrate what they state is an excessively conservative alpha multiplier and correlation assumptions, as well as try to recognize the effect if initial margins more meaningfully. They state that they support the adaptation of SA-CCR as a replacement for CEM as the CEM overstates derivative exposures due to the conservative assumptions in the methodology regarding netting and lack of differentiation between margined and unmargined trades. However, as SA-CCR should better reflect the underlying risk of cleared derivatives, they see flaws in the BCBS formulation of SA-CCR which prevent it from accurately measuring the derivative exposures and incentivizing the use of clearing.

The FIA, IFF and GFMA proposed six solutions to the problems above. They wish to allow for an offset of initial margin, as client initial margin, reduces the bank's exposure should a client default. The SA-CCR fails to recognize the exposure-reducing effect of initial margin which results in an overstatement of exposure and in turn, disincentivizes client clearing. Further on they want the BCBS to reconsider the exponential formula and 5% floor that the SA-CCR uses to calculate the benefits of collateral, that understates the risk reducing benefits of initial margin. They also state that the 1.4 alpha multiplier is based on outdated data which does not reflect the current market practices in regard to portfolio diversification, clearing and margining. This leads to inflated exposure values and disincentivizes the use of clearing and the FIA, IFF and GFMA suggest to either reduce or remove this alpha factor. Further on they wish that the SA-CCR should be amended to allow for greater diversification benefits when calculation the potential future exposures, as well as review the SA-CCR methodology regarding netting sets and associated collateral processes to more accurately reflect the exposures associated with cleared portfolios.

The document also states that the FIA conducted a member study in 2016 detailed in Appendix B of (FSB, 2018), showing that the introduction of SA-CCR without incorporating an offset for client initial margins would increase clearing members total leverage exposure compared with an option to offset this exposure. The member study also showed that compared to the existing CEM without offsetting, the SA-CCR would increase clearing members leverage exposure to clients using derivatives to hedge their economic risks. Further, the study proposes that should SA-CCR be implemented as it is set out in the final standard, it would make it more difficult for clearing members to offer clearing services to clients. For further information regarding the study, we refer our readers to Appendix B in (FSB, 2018).

5.3.4 ISDA and AFME

ISDA and the Association for Financial Markets in Europe (AFME) also published a position paper in March of 2017 regarding the standardized approach for CCR (AFME, 2017). Here the position paper also reports that a key concern in the industry is that the SA-CCR will result in a significant increase in exposures and capital requirements, which in return will constrain the ability for banks to support their users demand for derivative products at an acceptable cost. They state that this is supported by the ISDA SA-CCR QIS previously mentioned in Chapter 5.3.1 showing that the SA-CCR EAD for netting set 5 (all interest rates), the SA-CCR EAD was 23% higher than IMM EAD and twice the previous CEM EAD (AFME, 2017, p. 6). The position paper also states that the conservatively calibrated alpha multiplier, which was set in 2003 to 1.4 no longer reflects the current market and regulatory environment. Further on they also address the limited recognition of the effects of initial margin for reducing exposures and the SA-CCRs lack to reflect diversification benefits across hedging sets within an asset class. They state that this is overly conservative and risk sensitive and compared to internal model methods severely overstates exposure at defaults.

5.3.5 European Banking Authority

The European Banking Authority (EBA) posted a response to the European Commission's CFA on standardized approach for CCR in November 2016 (EBA, 2016) assessing the impact of the SA-CCR as a result from the Basel III monitoring exercise from 2016. The EBA also refers to the ISDA and AFME regarding the industry feedback on lowering the alpha factor and the insufficient potential future exposure reduction from initial margin.

5.4 Remarks

After the Great Financial Crisis, weaknesses in risk management practices associated with derivatives were revealed, and where CVA risk was a significant source of unexpected losses for banks. This led the BCBS to include a significant strengthening of its framework for counterparty credit risk (CCR) in its Basel III response to the crisis (BCBS, 2018). CCR is a complex risk to assess because it is a hybrid between credit and market risk, such that it depends both on changes in the creditworthiness of the counterparty as well as movements in underlying market risk factors. The risk-based capital charges for CCR in Basel III covers the risk of counterparty default and a credit valuation adjustment. The risk of counterparty default was covered in Basel I and Basel II, but the Basel III reforms introduced a new capital charge for the risk of loss by deterioration in the creditworthiness of the counterparty. This mark-to-market loss is known as CVA risk, and it captures the changes in counterparty credit spreads and other market risk factors.

After an in-depth review of the articles and publications regarding regulations on credit risk and counterparty credit risk under the Basel standards, we find that there could be some pitfalls to the new regulatory introductions. As stated earlier, The FIA, IFF and GFMA share the view of ISDA concerning the SA-CCR problems regarding the removal or reduction of the alpha parameter of 1.4 in the Basel III standards for counterparty credit risk. Which can constrain the banks' ability to supply derivative products towards end users. Although the change from CEM to SA-CCR has been mostly seen as a better approach, it is not perfect.

Otherwise, the regulatory changes to Basel III from Basel II have mostly been positively received regarding the development of a more sound and resilient banking system. Even if Basel II received criticism and accusations to be the culprit of the crisis, we found that it should not have been a target for these accusations since the actual implementation of the framework did not happen before the crisis started in the US. We find it interesting to see how banks will continue to adapt to regulations and if regulators will address the key issues illustrated by the responding parties above.

6 Case Study and Results

In this chapter, we present the data and the portfolio that is used in our case study and review the results after computing a CVA risk capital charge for two interest rate swaps netted against each other between our savings bank and their counterparty. For our calculations, we simulate an IMM-CVA as well as calculating the simpler BA-CVA. This is done to compare the different results and see if the implementation of an IMM could be preferable for the Norwegian savings bank in our study. All results are given in the currency NOK.

The IMM-CVA charge is a result of Monte Carlo simulations done in MATLAB. The MATLAB codes are included in Appendix A. We input the data given below and run 1000 simulations to obtain the most likely outfall and accurate result of the CVA charge. Our focus is on the default intensities and how they are assumed to be piecewise constant over different timesteps. The main goal is to see the differences in the unilateral CVA as we are going to vary the default intensities in our simulations. By doing this, we will get the results showing how much risk capital the Norwegian savings bank will have to set aside because of the possibility of their counterparty defaulting. In our simulations, we assume that the savings bank is free of default risk.

6.1 Portfolio

For calculating CVA, we received a real portfolio of interest rate swaps from a Norwegian savings bank. This portfolio consists of 43 interest rate swaps against five different counterparties where the swaps are netted against each other with each counterparty (payer against receiver). These swaps are not centrally cleared. As we have not seen the ISDA master agreements, we will not be adding collateral in our simulations, even though we know that they are margined. For simplistic reasons, we will only be using two of these IRS towards the counterparty. We use these two IRS to add netting to the simulations, as one of the swaps is a receiver swap and the other a payer swap. To make the result as realistic as possible, we use real CDS market data for the counterparty with different time periods to calculate the default intensities, as well as fictive data for research purposes. The following Table 7 details the IRS parameters used in our simulations of the CVA under IMM and BA-CVA.

Parameter	Receiver	Payer
Time=0	15.03.2019	15.03.2019
Maturity	15.06.2025	15.06.2025
Reference Floating Rate	3-month NIBOR	3-month NIBOR
Principal Amount	100MNOK	48MNOK
Latest Floating Rate	1,37%	1,37%
Add-on Floating Rate	0,67%	0%
Fixed Rate	2,20%	2,09%
Cash Flow Frequency	Yearly	Yearly
Number of Simulations	1000	1000

Table 7. IRS Parameters used in our simulations

The alpha (α) is set to the standard value of 1.4 as referenced in Chapter 3.5. We would also like to note that in our simulation approach will consider the PD to be independent of the exposure and because of this, we disregard any WWR as discussed in Chapter 3.5. Hence, the regulatory capital we end up with might be a lesser amount than what a full regulatory simulation would achieve. The risk factors on IRS are the interest rates themselves, and we will follow the actual market where the floating rate on the swaps in our portfolio is referenced to the 3-month NIBOR. The calculation is somewhat complex and consists of several steps summarized below.

1. Interest rate simulation based on historical market data.
2. Swap prices are computed for every future scenario at certain time points.
3. Portfolio exposure is computed for the MtM values.
4. The portfolio exposure is then discounted.
5. Probability of default is calculated based on CDS data and fictive data.
6. Putting the different results together, we achieve the CVA risk capital charge.

6.2 Discount Curve

To discount the cash flows from the swaps and adequately value the swaps, a discount curve is necessary. The initial discount curve is simply made by a linear interpolation of the risk-free interest rates of different maturities. These initial rates were gathered from Thomson Reuters Eikon and consists of the NIBOR 3m, and the NIBOR 6m, as well as the swap derived zero curve for the other maturities. All rates state back to Mars 15th, 2019. Note that as discussed in chapter 3.1, the preferred rate for discounting are OIS-rates. However, as there does not exist a traded OIS-market in Norway, we will be using traded rates in our thesis.

Because of this, the discount curve is not actually risk-free as discussed in chapter 3.1. A result of this will be a slight error due to "double counting" parts of the CVA values computed under IMM. This is not a big issue for our thesis, although for a financial institution, it should be considered. The discount rates used in the simulations are shown in Table 8 below, resulting in the yield curve illustrated in Figure 5.

Maturity (months)	Rate
3	1,37%
6	1,46%
12	1,81%
60	1,90%
84	1,98%
120	2,09%

Table 8. Discount Rates

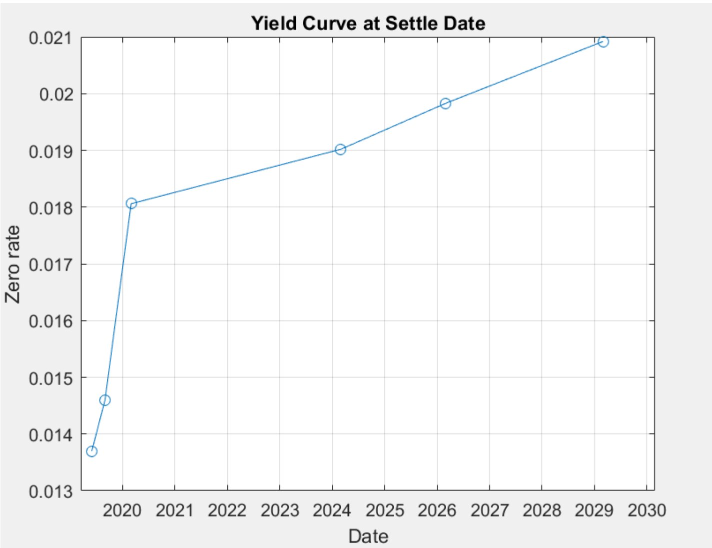

Figure 5. Initial Yield Curve at Settlement Date.

6.3 Interest Rate Simulations

The interest rate simulations are based on the three-month NIBOR, and the six-month NIBOR, as well as the swap derived zero curve of the NIBOR. These datasets are gathered from Thomson Reuters Eikon so that a Monte Carlo simulation may be executed. As the underlying variable affecting the market value of the interest rate swaps is the 3m NIBOR interest rate, we need to choose a framework to model such a variable. As the short rate is typically instantaneous and continuously compounded, it approximates the behaviour of the interest rate. If we also assume that short rates are normally distributed it leads us to Gaussian short-rate models. The assumption of normal distribution allows for analytical pricing formulas for the short–rate (Brigo, Morini and Pallavicini, 2013).

The simulations are performed using the Hull-White One-Factor model following Mathworks (2019). This is one of the most popular interest rate evolution models and was first described in 1990. A general definition of a single factor model, according to Brigo, Morini and Pallavicini (2013) is:

$$dr(t) = [\theta(t) - \alpha(t)r(t)]dt + \sigma dW(t), \tag{6.1}$$

Where:

- dr is the change in interest rate because of an infinitesimal increment of the time dt
- $\alpha(t)$ is the mean reversion rate
- σ is the volatility of the rate
- dW is a Weiner process
- $\theta(t)$ is the drift function

and the drift function is defined as:

$$\theta(t) = F_t(0,t) + aF(0,t) + \frac{\sigma^2}{2a}(1 - e^{-2at}) \tag{6.2}$$

Where:

- $F(0,t)$ is the instantaneous forward rate at time t
- $F_t(0,t)$ is a partial derivative of F with respect to time

The most important advantage of the Hull-White model is that it can be fitted exactly to the initial term structure of the interest rates. The chosen interest rate model should model the interest rates realistic enough, with a good trade-off between the rates and computational tractability. We are keeping both α and σ constant to reduce complexity. If they were kept varying, it would not have yielded a much better fit according to Brigo, Morini and Pallavicini (2013).

Returning to the interest rate simulation, the two constants α and σ are supposed to be gathered from Swaption rates, but due to time limitations, this will not be done in our thesis. Instead, we are using the two parameters as they are already exemplified in Mathworks (2019) as $\alpha = 0.2$ and $\sigma = 0.015$.

Equation 6.1 is used to simulate the short rates. The entire interest rate curve is then further expanded from the short rate by using Equation 6.3, which is a built in MATLAB function.

$$R(t,T) = -\frac{1}{(T-t)} lnA(t,T) + \frac{1}{(T-t)} B(t,T)r(t) \qquad (6.3)$$

Where:

$$lnA(t,T) = ln\frac{P(0,T)}{P(0,T)} + B(t,T)F(0,t) - \frac{1}{4\alpha^3}\sigma^2(e^{-\alpha T} - e^{-\alpha t})^2(e^{2\alpha t} - 1) \qquad (6.4)$$

And:

$$B(t,T) = \frac{1 - e^{-\alpha(T-t)}}{\alpha} \qquad (6.5)$$

Where:

- $R(t,T)$ is the zero rate at time t for a period of $T-t$
- $P(t,T)$ is the price of a zero - coupon bond at time t that pays one dollar at time T

The MATLAB functions implementing Equation 6.3 are used in this thesis without any further explanations, as we consider it to be outside the narrow scope of this thesis. After interpolating the risk-free rate between all future times, a discount surface is obtained for all future time steps with different tenors. In Figure 6 below, we see the yield curve evolution obtained in one of our interest rate simulations. Note that in the following figures the notation Jan19 to Jan25 means from January 2019 to January 2025.

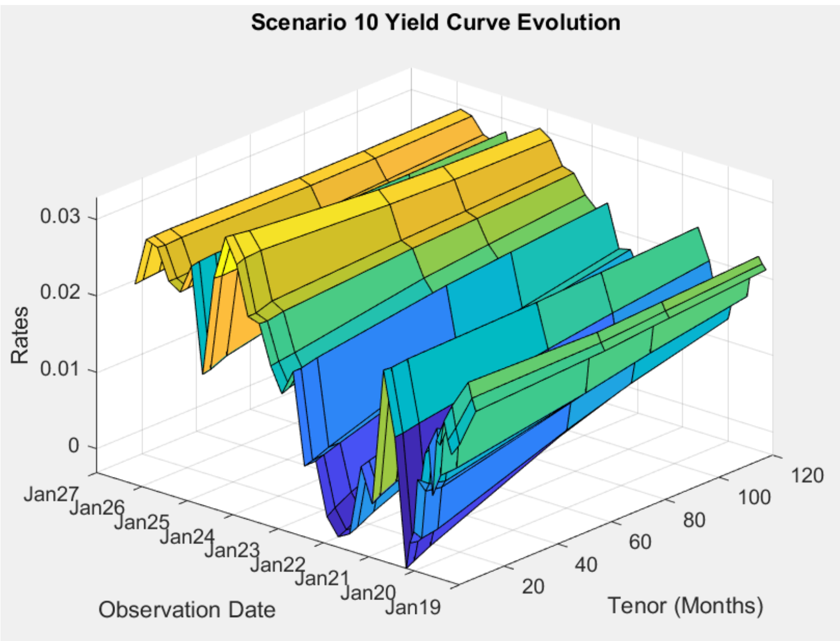

Figure 6. Yield Curve Evolution for one Scenario

6.4 Valuing the Interest Rate Swap

As we already mentioned in Chapter 3.2.3, we value the receiver swap with Equation 3.11 and the payer swap with Equation 3.10. For each of the 1000 scenarios in the Monte Carlo simulation, the swaps are priced at each future time point. At this point, an approximation is performed in MATLAB. This function calculates the MtM price on our two swaps at each time step. Because the swaps are priced on dates not necessarily the same as the cash flow dates, the swaps' current floating rate will not be specified in the zero curve at that date. To accurately price the two swaps, we need the floating rate from the previous cash flow date. This is the point when the swaps floating leg was determined for the current period. We estimate these latest floating rates by interpolating between the interest rate curves we got in each interest rate path. The latest floating rate we use is simply the interpolated one-year rate at the previous coupon date, interpolated between the rate curves we simulated. Figure 7 below shows the MtM price evolution of a portfolio consisting of one receiver IRS (blue line) and one payer IRS (orange line).

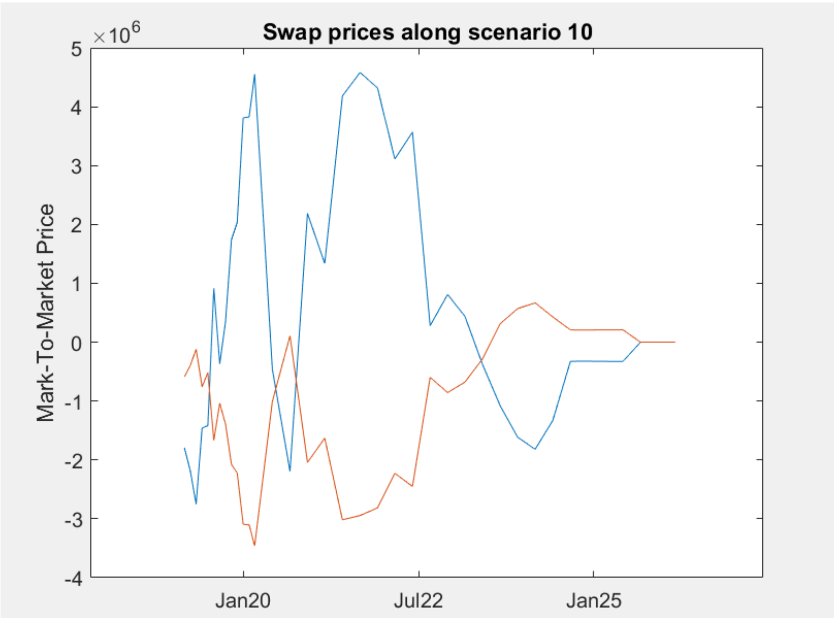

Figure 7. Swap prices along one scenario

As expected, we see that the MtM swap prices move in opposite directions for the receiver and payer swap in Figure 7 above. The difference in the range of movement can be explained by the different principal amounts for the two swaps, as shown in Table 7.

6.5 Calculating the Expected Exposure

We have already described the formulas for calculating EE for the IRS contracts in Chapter 4.4.2. It might require a large number of simulations to calculate, depending on the number of contracts one holds. This is done in three steps by generating scenarios. We generate future market scenarios by simulation, using evolution models on the risk factors at selective discrete points in time. As we mentioned in Chapter 6.3, we are here using the Hull-White one-factor model on the interest rate, which is the market risk factor.

We assume that there is no collateral posted. Hence the exposure is solely given by the positive value of the portfolio, and zero in the case of negative value. In MATLAB, we simulated the EE for 1000 different scenarios shown in Figure 8, containing all the positive exposure values which are already imposed by the model.

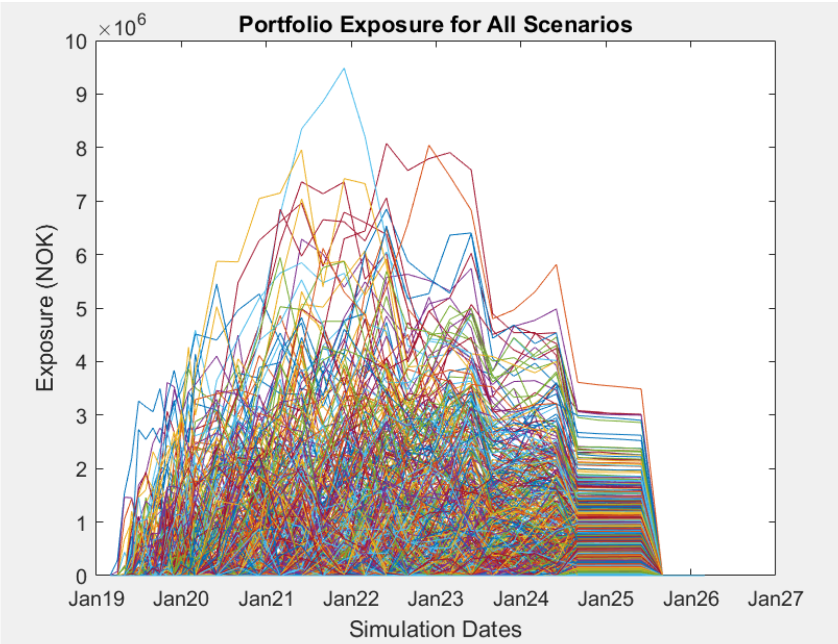

Figure 8. Portfolio Exposure for All Scenarios

We further show the different portfolio exposure profiles in Figure 9. If we then discount the EE with the zero rate curve, we find the discounted exposure for the portfolio illustrated in Figure 10 below.

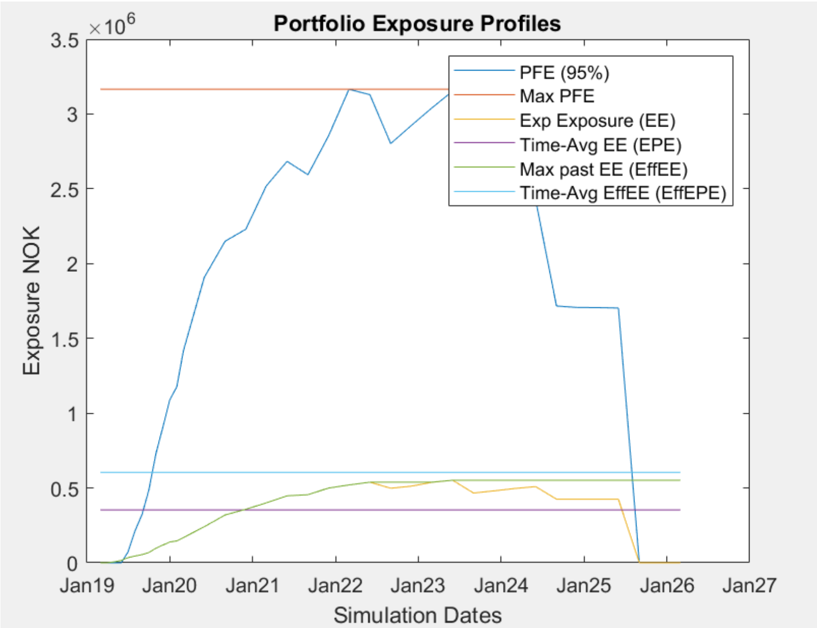

Figure 9. Portfolio Exposure Profiles

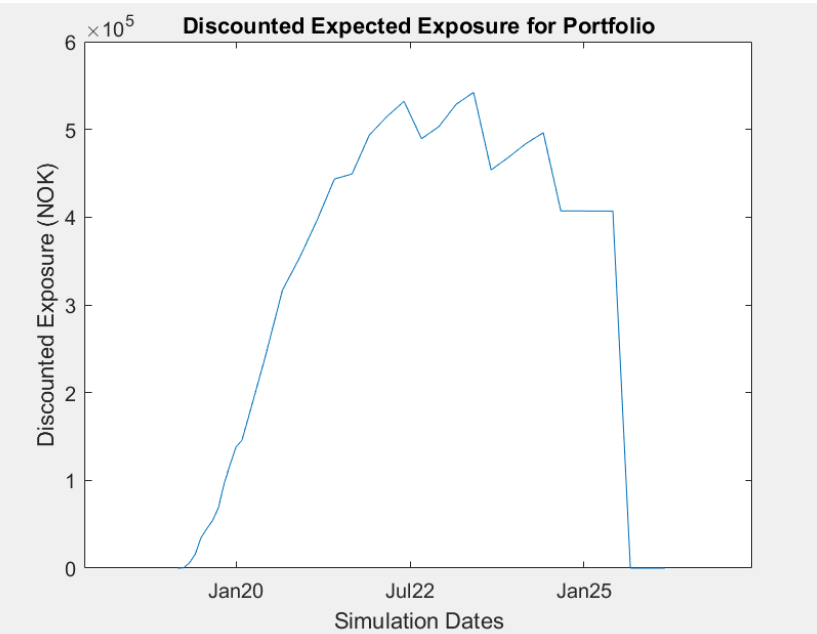

Figure 10. Discounted Expected Exposure for Portfolio

As seen in Figure 10. above the discounted EE for our portfolio starts at zero when the contract is first initiated and rises to about 500.000NOK before again dropping to zero when reaching maturity.

6.6 Credit Default Swaps and Default Intensities

We have extracted CDS data from Thomson Reuters Eikon on 29 April 2019 towards the counterparty which is used in our simulation process. After collecting the data, we computed the continuous survival probabilities for each time step using Equation 3.28 before we bootstrapped the CDS spreads as detailed in Chapter 3.2.4.5 to extract the hazard rates.

Following we present Figure 11 showing the historical evolution of the CDS spreads for the different maturities of 1, 3, 5, 7 and 10 years

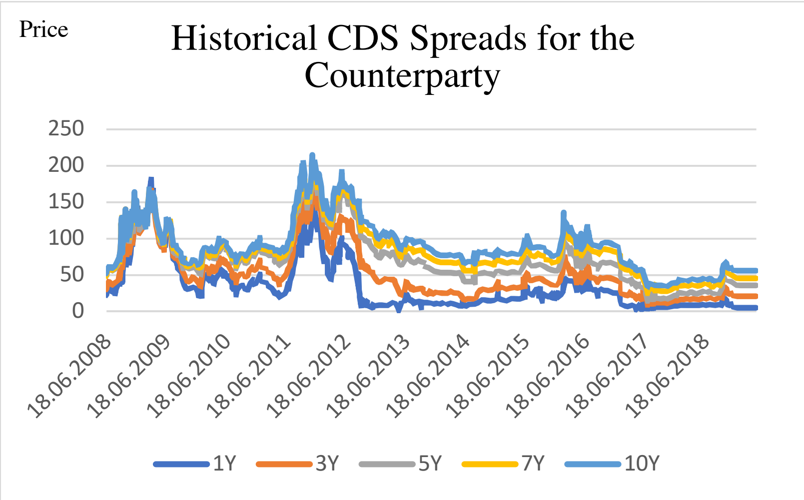

Figure 11. Historical CDS spreads for the counterparty

For our low risk scenario, we use market data from 01. August 2018 and data from the 25. November 2011 is used for our medium risk scenario. These dates were times of either very low or very high risk. For research purposes, we will also add three fictive spread scenarios to produce extreme CVA values. In the first example, we will increase medium risk the values even higher. For the second scenario, we will keep the values constant for the entire period. In the third scenario, we will apply drastic changes to the CDS spread over the ten-year period, meaning the spread increases more than it usually does between two maturities. The data inputs are illustrated in Table 9 below.

Maturity	**1 Year**	**3 Year**	**5 Year**	**7 Year**	**10 Year**
Low risk	12,84	18,70	22,23	31,07	37,56
Medium risk	145,81	179,81	200,37	207,80	214,44
High risk	220	250	290	320	350
Constant spread	200	200	200	200	200
Drastic change	10	60	180	380	500

Table 9. CDS Spread Data Inputs

To calculate the PD for the different scenarios using Equation 3.24, combined with the explained bootstrapping procedure for hazard rates detailed in Chapter 3.2.4.5, we achieve through simulations the following PD curves illustrated in Figure 12 below.

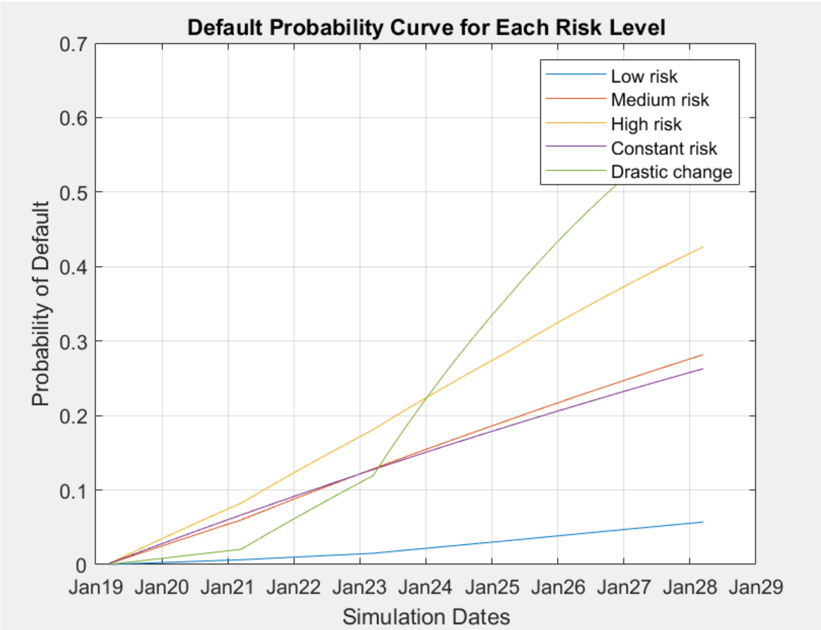

Figure 12. Default Probability Curves for Each Risk Level

As we expected, the different risk levels yielded default probabilities following their CDS spread and the difference between their spreads, where higher CDS spreads result in higher default probabilities. The default probabilities are all seen rising in time, which is a result of the future being unpredictable and a difficulty to perceive future outcomes.

6.7 IMM-CVA Results

We will now show and elaborate on the results of our case study. We use the following formula, as we explained in Chapter 4.4.3. Where the LGD is set at 60% as detailed in Chapter 3.3.2.

$$CVA = (LGD_{MKT}) * \sum_{i=1}^{T} Max\left(0; exp\left(-\frac{s_{i-1} * t_{i-1}}{LGD_{MKT}}\right) - exp\left(-\frac{s_i * t_i}{LGD_{MKT}}\right)\right) * \left(\frac{EE_{i-1} * D_{i-1} + EE_i * D_i}{2}\right) \quad (4.35)$$

After providing the necessary inputs and extracting the required simulations, we arrive at the IMM-CVA risk capital charge for each risk level illustrated in Figure 13 below.

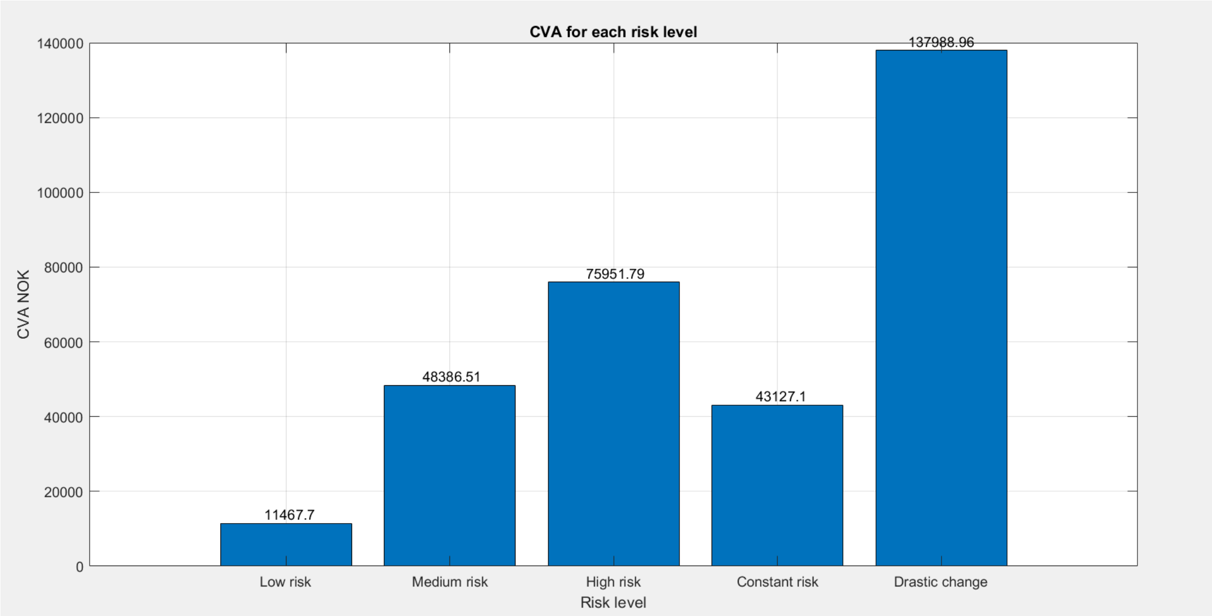

Figure 13. IMM-CVA for each risk level

6.8 BA-CVA Results and comparison with IMM-CVA

To illustrate the difference CVA risk capital charges between the of the BA-CVA method with SA-CCR, and the IMM we have made the calculations according to the BCBS documents as well and expect these to give a higher capital charge. Formulas and abbreviations are given in chapter 4.1. We quickly recall the formulas needed for our calculations below before showing our inputs. RW_c are given by the Basel documents as previously stated and is 5%. The alpha multiplier is set at 1.4. The main difference between the BA-CVA and the IMM is that one does not use counterparty CDS spreads for estimating PD, but the risk weights given in the BCBS documents and calculate EAD and PFE. The results of our calculations are as follows:

$$\mathrm{SCVA_c} = \frac{1}{alpha} * RW_c * \sum_{NS} M_{NS} * EAD_{NS} * DF_{NS}$$

$$DF_{NS} = \frac{1 - \mathrm{e}^{-0.05*M_{NS}}}{0.05 * M_{NS}}$$

$$M_{NS} = \frac{\sum_t t * CF_t}{\sum_t CF_t}$$

$$Addon^{IR} = Supervisory\ Factor * Effective\ Notional$$

$$Addon^{IR} = 0.5\% * 401\ 106\ 705 = \mathbf{2\ 005\ 533}\ \boldsymbol{NOK}$$

$$multiplier = min\left[1; floor + (1 - floor) * exp\left(\frac{V - C}{2 * (1 - floor) * Addon^{aggregate}}\right)\right]$$

$$multiplier = \min(1; 0.56848786) = \mathbf{0.56848786}$$

$$PFE = multiplier * addon$$

$$PFE = 0.56848786 * 2\,005\,533 = \mathbf{1\,140\,121\,NOK}$$

$$EAD = \alpha * (RC + PFE)$$

$$EAD = 1.4 * (0 + 1\,140\,121) = \mathbf{1\,596\,170\,NOK}$$

We now have all the necessary input to calculate the stand alone CVA towards the counterparty. This is the same as the risk charge $K_{reduced}$ because we calculate only towards one counterparty.

$$\text{SCVA}_c = \frac{1}{alpha} * RW_c * \sum_{NS} M_{NS} * EAD_{NS} * DF_{NS} = \mathbf{55\,604\,NOK}$$

	IMM LOW RISK	**IMM** MEDIUM RISK	**IMM** HIGH RISK	**IMM** CONSTANT RISK	**IMM** DRASTIC CHANGE	**BA-CVA**
CVA	11 468	48 386	75 952	43 127	137 989	55 604

Table 10. CVA risk capital charge comparison. All numbers in NOK

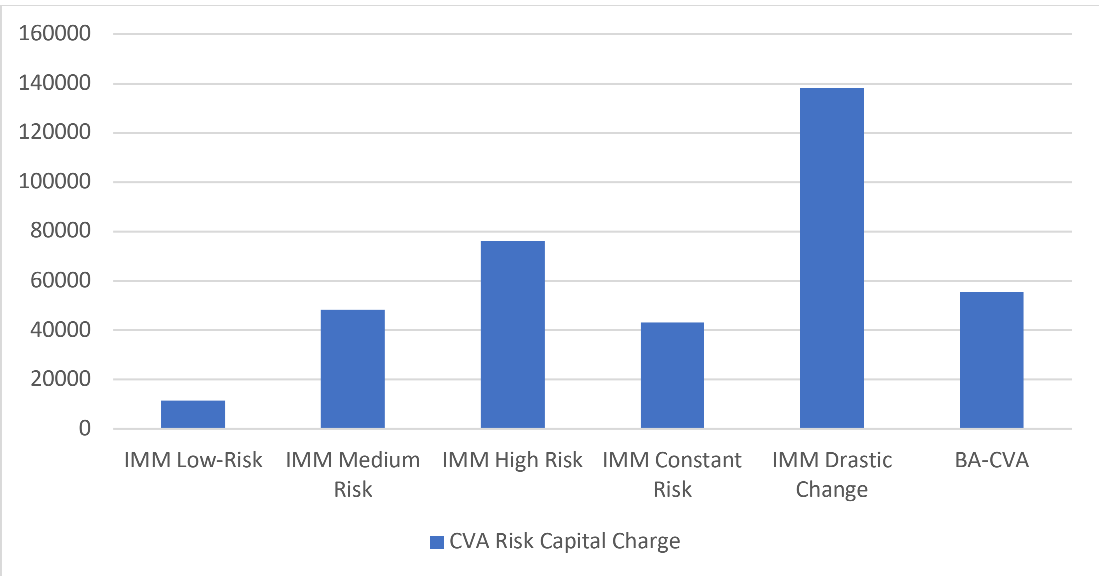

Figure 14. CVA risk capital charge comparison. Numbers in NOK

As we see in Table 10 and Figure 14 the IMM generates a lower CVA capital charge for the low risk period, then the BA-CVA as the latter method uses the BCBS formula inputs for SA-CCR and the stand-alone CVA instead of the more detailed IMM. This could be expected, according to Zhuang (2017) and discussed in Chapter 4.4.1. There are no simulations run for future interest rate paths and default probabilities. All calculations are done using previously mentioned BCBS methods for pricing and discounting and results in a BA-CVA charge of NOK 55.604 NOK.

Compared to the IMM-CVA, where the IMM Medium Risk scenario based on CDS spreads from the time period with the highest stress during the last 10 years, the BA-CVA results in a higher CVA risk capital charge. This implies that even during the period of highest risk of counterparty default, the BA-CVA charge with SA-CCR requires the bank to put aside more capital today than it would should the counterparty now exist in a stressed situation. The question then becomes if it would be reasonable for the savings bank to invest in an IMM in order to reduce the CVA charge.

7 Concluding Remarks

As detailed in our thesis, we find that CVA is an adjustment to the fair price of the derivative instrument in order to account for CCR. The CVA can then be viewed as the price of CCR. In Basel III, the purpose of the CVA risk capital charge is to capitalise the risk of CVA changes in the future. Under the Basel II framework banks were required to hold capital against variability in market values of derivatives but not hold capital against changes in CVA.

The main contribution of our thesis is a critical review of banking regulations regarding CCR and the development of said regulations following the Great Financial Crisis. We also calculate the CVA charge for a Norwegian savings bank by two different methods to compare the impact on the capital charge using different approaches. This is something we have not seen done towards Norwegian banks in existing literature and could be of interest to the savings bank. Based on own management views, the bank can determine to use the BA-CVA approach, or if an IMM for measuring CCR exposures should be implemented.

The different methods for computation cover a broad spectrum of complicated methodologies concerning modelling aspects of credit risk. We detail the more simplistic BA-CVA method in comparison to what can be a complex internal model method. We have shown some examples of why the SA-CCR still faces problems for implementation in financial institutions, but it is still regarded as a better option than the previous CEM.

Our results indicate a lower CVA risk capital charge when computing it with the IMM approach compared to the BA-CVA approach from BCBS. The results also show how the bank is exposed to their counterparty when changes happen in the counterparty CDS spreads. Should an unwanted situation happen to the counterparty, putting them under financial distress and resulting in higher CDS spreads, the savings bank will need to set aside more capital in order to meet the regulating demands for counterparty credit risk exposures.

A question regarding the advantages and disadvantages of implementing an IMM is worth mentioning. We find that CVA provides valuable insights into the understanding of counterparty credit risks. As shown, the Norwegian savings bank we used in our case study could reduce their CVA risk capital charge if an IMM is implemented compared to the BA-CVA approach. It is difficult to conclude whether the IMM will always result in a lower charge seeing as we only applied the CVA for a set of netted interest rate swaps and not on other types of derivatives. However, for smaller institutions with small portfolios not containing advanced derivative contracts, the BA-CVA might be more cost effective considering the costs of implementing and maintaining the IMM in order to sustain supervisory approval.

Some limitations to our thesis must be mentioned. If we had gained access to the ISDA master agreements with the supporting credit support annex, we would like to include margining, and collateralized transactions as the use of margining is now a much more common industry practice than before and during the Great Financial Crisis. Further, we would like to run simulations on the full portfolio of interest rate swaps that we received from the savings bank, as well as other derivatives. There are also the implications of wrong-way risk which has received more attention after the crisis, this was excluded for simplicity, although it would be interesting to study further and include in the calculations of the CVA. We also assume that only one of the parties in the swap agreement can default, which might not be considered plausible. But considering that the defaulting party cannot correctly price its own derivatives portfolio right before the default happens, this is not a significant problem.

We still feel that we present a much-needed overview of the process for implementing new regulations and computing CVA risk capital charges according to BCBS standards for banks without large derivative portfolios. Further, we hope to see banks and financial institutions continue to work together with the BCBS to build a more resilient and sustainable financial system to reduce the chances of a possible future financial crisis.

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9 Appendix A – MATLAB codes

```
% Read swaps from spreadsheet
swapFile = 'data/IRS_Nordea.xlsx';
cdsFile = 'data/CDS_Nordea.xlsx';

swaps = readtable(swapFile);
swaps.LegType = [swaps.LegType ~swaps.LegType];
swaps.LegRate = [swaps.LegRateReceiving swaps.LegRatePaying];
swaps.LegReset = ones(size(swaps,1),1);
swaps.Maturity = datenum(swaps.Maturity);

numSwaps = size(swaps,1);

% Create RateSpec from the Interest-Rate Curve

Settle = datenum('1-March-2019');

Tenor = [3 6 12 5*12 7*12 10*12]';
ZeroRates = [0.0137 0.0146 0.01806 0.01902 0.01983 0.02092]';

ZeroDates = datemnth(Settle,Tenor);
Compounding = 4;
Basis = 0;
RateSpec = intenvset('StartDates', Settle,'EndDates', ZeroDates, 'Rates',
ZeroRates,'Compounding',Compounding,'Basis',Basis);

% Monte carlo

N = 1000;
simulationDates = datemnth(Settle,0:12);
simulationDates = [simulationDates datemnth(simulationDates(end),3:3:74)]';
numDates = numel(simulationDates);

% Compute Floating Reset Dates

floatDates = cfdates(Settle-360, swaps.Maturity, swaps.Period);
swaps.FloatingResetDates = zeros(numSwaps,numDates);
for i = numDates:-1:1
   thisDate = simulationDates(i);
   floatDates(floatDates > thisDate) = 0;
   swaps.FloatingResetDates(:,i) = max(floatDates,[],2);
end

% Setup Hull-White Single Factor Model

Alpha = 0.2;
Sigma = 0.015;

hw1 = HullWhite1F(RateSpec, Alpha, Sigma);
```

```
% Simulate scenarios

% Use reproducible random number generator (vary the seed to produce different random
scenarios).
prevRNG = rng(0, 'twister');

dt = diff(yearfrac(Settle,simulationDates,1));
nPeriods = numel(dt);
scenarios = hw1.simTermStructs(nPeriods, 'nTrials', N, 'deltaTime', dt);

% Restore random number generator state
rng(prevRNG);

% Compute the discount factors through each realized interest rate scenario.
dfactors = ones(numDates, N);
for i = 2:numDates
   tenorDates = datemnth(simulationDates(i-1),Tenor);
   rateAtNextSimDate = interp1(tenorDates,squeeze(scenarios(i-1,:,:)),
simulationDates(i),'linear','extrap');
   % Compute D(t1,t2)
   dfactors(i,:) = zero2disc(rateAtNextSimDate, repmat(simulationDates(i), 1,
N),simulationDates(i-1), -1,3);
end
dfactors = cumprod(dfactors,1);

% Compute all mark-to-market values for this scenario
values = hcomputeMTMValues(swaps, simulationDates, scenarios,Tenor);

[exposures, expcpty] = creditexposures(values, swaps.CounterpartyID,
'NettingID',swaps.NettingID);

% Compute entire portfolio exposure
portExposures = sum(exposures, 2);

% Compute exposure profiles for entire portfolio
cpProfiles = exposureprofiles(simulationDates,exposures);
portProfiles = exposureprofiles(simulationDates,portExposures);

% Get discounted exposures for counterparty, for each scenario
discExp = zeros(size(exposures));
for i = 1:N
   discExp(:,:,i) = bsxfun(@times,dfactors(:,i),exposures(:,:,i));
end

% Discounted expected exposure
discProfiles = exposureprofiles(simulationDates, discExp, 'ProfileSpec','EE');
discEE = [discProfiles.EE];

CDS = readtable(cdsFile);
CDSDates = datenum(CDS.Date);
MarketDates = [datemnth(CDSDates(1),0:3:108)]';
```

```
CDSSpreads = table2array(CDS(:,2:end));

ZeroData = [RateSpec.EndDates RateSpec.Rates];

% Calibrate default probabilities for each risk level
DefProb = zeros(length(MarketDates), 5);
for i = 1:size(DefProb,2)
    probData = cdsbootstrap(ZeroData, [CDSDates CDSSpreads(:,i)], Settle, 'probDates',
MarketDates);
    DefProb(:,i) = probData(:,2);
end


Recovery = 0.4;
CVA = (1-Recovery) * sum(discEE(2:end,:) .* diff(DefProb));
CVA = round(CVA, 2);
% PLOT GRAPHS

% Yield curve at settle date
% subplot(4,4,1);
figure;
plot(ZeroDates, ZeroRates, 'o-');
xlabel('Date');
datetick('keeplimits');
ylabel('Zero rate');
grid on;
title('Yield Curve at Settle Date');

% Yield curve evolution for specific scenario
scenario = 10;

% subplot(4,4,2);
figure;
surf(Tenor, simulationDates, scenarios(:,:,scenario))
axis tight
datetick('y','mmmyy');
xlabel('Tenor (Months)');
ylabel('Observation Date');
zlabel('Rates');
ax = gca;
ax.View = [-49 32];
title(sprintf('Scenario %d Yield Curve Evolution\n',scenario));


% Rate Simulation for specific rate
% subplot(4,4,2);
figure;
plot(simulationDates, squeeze(scenarios(:,1,:)), '-');
xlabel('Observation Date');
datetick('keeplimits');
ylabel('Rate');
```

```
grid on;
title('Hull-White Short Rate Simulation');

% Swap prices along specific scenario
% subplot(4,4,3);
figure;
plot(simulationDates, values(:,:,scenario));
datetick('x','mmmyy','keeplimits')
ylabel('Mark-To-Market Price');
title(sprintf('Swap prices along scenario %d', scenario));

% View portfolio value over time
% subplot(4,4,4);
figure;
totalPortValues = squeeze(sum(values, 2));
plot(simulationDates, totalPortValues);
title('Total MTM Portfolio Value for All Scenarios');
datetick('x','mmmyy','keeplimits')
ylabel('Portfolio Value (NOK)')
xlabel('Simulation Dates')

% Portfolio exposure for all scenarios
% subplot(4,4,5);
figure;
totalPortExposure = squeeze(sum(exposures, 2));
plot(simulationDates, totalPortExposure);
title('Portfolio Exposure for All Scenarios');
datetick('x','mmmyy')
ylabel('Exposure (NOK)')
xlabel('Simulation Dates')

% Portfolio discounted EE
% subplot(4,4,6);
figure;
plot(simulationDates,sum(discEE,2))
datetick('x','mmmyy','keeplimits')
title('Discounted Expected Exposure for Portfolio');
ylabel('Discounted Exposure (NOK)')
xlabel('Simulation Dates')

% Plot of the cumulative probability of default for each risk level.
% subplot(4,4,8);
figure;
plot(MarketDates,DefProb)
legend('Low risk', 'Medium risk', 'High risk', 'Constant risk', 'Drastic change')
title('Default Probability Curve for Each Risk Level');
xlabel('Date');
grid on;
ylabel('Cumulative Probability')
datetick('x','mmmyy')
ylabel('Probability of Default')
xlabel('Simulation Dates')
```

```matlab
% CVA for each risk level
% subplot(4,4,9);
figure;
bar(CVA);
ax=gca;
ax.YTickLabel=cellstr(num2str(ax.YTick'));
labels = {'Low risk', 'Medium risk', 'High risk', 'Constant risk', 'Drastic change'};
set(gca,'xticklabel',labels)
text(1:length(CVA),CVA,num2str(CVA'),'vert','bottom','horiz','center');
title('CVA for each risk level');
xlabel('Risk level');
ylabel('CVA NOK');
grid on;

% Portfolio Exposure Profiles

figure;
plot(simulationDates,portProfiles.PFE, ...
   simulationDates,portProfiles.MPFE * ones(numDates,1), ...
   simulationDates,portProfiles.EE, ...
   simulationDates,portProfiles.EPE * ones(numDates,1), ...
   simulationDates,portProfiles.EffEE, ...
   simulationDates,(portProfiles.EffEPE * 1.4) * ones(numDates,1));
legend({'PFE (95%)','Max PFE','Exp Exposure (EE)','Time-Avg EE (EPE)', ...
   'Max past EE (EffEE)','Time-Avg EffEE (EffEPE)'})

datetick('x','mmmyy')
title('Portfolio Exposure Profiles');
ylabel('Exposure NOK')
xlabel('Simulation Dates')
```

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