

A comparison of the Basel III capital requirement models for financial institutions

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Abstract

The purpose of this report is to implement and compare the two Basel III standard methods on how to calculate the capital requirement for financial institutions, related to counterparty credit risk. The models being the Standardized Approach for Counterparty Credit Risk (SA-CCR) and the Internal Model Method (IMM). The SA-CCR model is a simpler and more standardized model with prescribed methods while the IMM model is a more flexible model optimized to the specific portfolio. Because of this, the IMM model requires more work to implement. The comparison of these two models is done by looking at a small number of transactions from the Bank's trading book and computing the Exposure At Default (EAD) that these would give. Both models are used to compute this, and these results are compared. To obtain EAD the transactions need to be priced and their Net Present Value (NPV) needs to be calculated. One need simulated interest rates to do so, which is done using Monte Carlo simulations. For this, a Hull-White process is used to simulate the interest rates and the parameters of this process is calibrated using market data.

Out of the two models, the IMM model is the more complex one. It requires both normal and stressed data as input parameters and it also needs to be validated. The validation of the model is done by doing something called "backtesting" on it, which investigates if the model created does give the expected results. Backtesting is performed by taking the interest rate for one day and then creating a confidence interval using this date, predicting where the rate will be 10 days into the future. This confidence interval is then compared with the true value 10 days into the future to see if the prediction does in fact cover the actual value. If so, the prediction does give us a credible result, so this is a way of checking how good the model is.

The result was that the usage of the IMM model, instead of the SA-CCR, would lead to the institute being required to hold 11 % less capital. However, this result is based on only one type of instrument and tested for only a fraction of the institute's total trading book, so it would require some testing on a bigger scale to really ensure this result. Another thing that could improve this work is if a different simulation process, other than Hull-White, would be used. Some alternative methods that could potentially give a better result and other future improvements are discussed.

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1 Glossary

D: Day

W: Week

M: Month

Y: Year

Portfolio: A collection of trades.

Tenor: The time remaining of a transaction or financial instrument. When we talk about tenor on loans, and therefor Interest Rate Swaps, the tenor represents the time left for the next payment on the loan.

Maturity: The date where the life of a transaction or financial instrument ends.

Basis point (bp): $1 \text{ bp} = 0.01\%$

Monte Carlo simulation with mean reversion: Monte Carlo simulation is a method to estimate expected value for some known distribution by random sampling N paths from that distribution. The method is then based on that the average of the paths will converge to the actual expectation when N is large. When we use mean reversion, we do not draw random samples. Instead, a term is added that draws the samples towards a chosen mean reversion.

Q-measure: Also known as risk neutral measure. It is a measure where the value of a financial asset is the sum of future pay-off discounted with the risk-free rate.

P-measure: Also known as the real-world measure. It is a measure where the value of a financial asset is the sum of future pay-off discounted with their own rates that reflects the risk of the asset. Instead of the assumption of risk-free rate a probability based on historical data is used.

Hedge: A hedge is an investment made with the purpose of reducing the current risk held. A common method is obtaining assets with similar security but with opposite position.

Haircut: It is defined as the difference in percentage between an assets market value and its amount that could be used as collateral in for example a loan [8].

2 Introduction

Since the financial crisis 2008 many more regulations and requirements are imposed on financial institutes, trying to prevent such a crisis from occurring again. Two of the main regulators for this are the European Union (EU) and the Basel Committee on Banking Supervision (BCBS). Members of BCBS are all the countries in G20 along with Sweden and some more. The BCBS has created a framework for financial institutions to be more financially secure and sustainable, a framework that the EU has taken a lot of inspiration from. Rising from this was different methods on how to model the capital requirement a financial institution must hold when trading derivatives. The capital requirements are based on the risk of the counterparties traded with. Since the financial crisis 2008, financial institutes are required by the EU regulations to calculate this risk, and the Capital Requirements Directive IV implementing the Basel III standards has presented a few different methods that can be used for this. The two methods currently in use are the Standardized Approach for Counterparty Credit Risk (SA-CCR) and the Internal Model Method (IMM), and these are the ones that will be considered and investigated further in this report.

We will come back to defining what counterparty credit risk is more in depth later in the report, but just to understand the context, it is the risk that the counterparty of a trade would default before the last settlement of the transaction is made [12].

The SA-CCR method was introduced by BCBS 2017 to replace the older methods SM and CEM, with the aim to be more risk-sensitive while still being quite simple, compared to the two preceding ones. This approach is easier to implement since it is computed using prescribed formulas, while the other method, the IMM method, is more tailored to that specific portfolio since it is computed using a range of complex, sophisticated modelling assumptions of all the underlying risk factors. This model is quite advanced, and it is therefore very costly to implement, and maintain, so generally it is only the largest banks globally who have gained approval and uses this approach today.

2.1 Background

These models are in place to determine the required capital the financial institute must hold. Capital requirements are standardized regulations that determines how much liquid capital the bank must hold, based on their overall holdings. Liquid capital considers securities or assets that easily could be sold. The capital requirement is expressed as a ratio determined by the weighted risk of the bank's portfolio. This is determined by regulatory agencies. It is normally affected and altered as a consequence of pressure from the public or if there is an uncertain investment climate. The financial crisis of 2008 is such an example that lead to a lot of regulatory interventions [8]. The capital requirements are therefore in place to secure that the impact a possible defaulting counterparty may have to the financial institute, and everyone affected by it, are not devastating.

2.1.1 The need of modelling the risk

After the financial crisis in 2008 the absence of an awareness of the counterparty risk was emphasised. Counterparty risk is the risk that the counterparty may not be able to fulfil their part of the contract before or at the time of maturity. Counterparty risk in derivatives can be seen as a combination of the market risk of the underlying asset and the risk of the counterparty defaulting.

When counterparty risk is not fully considered in over the counter (OTC) derivatives markets it can lead to substantial losses. Before the crisis 2008 some larger financial institutions in USA such as the Lehman Brothers were assumed to have no counterparty risk so the risk that they would not be able to fulfil their end of a contract was not considered. This had large effects on the financial market later when they filed for bankruptcy. The crisis led institutions such as the European Union to enforce new regulations regarding OTC derivatives, central counterparties and trade repositories [8], [4].

In 2012 EU, with assistance of the BCBS, presented new regulations on how banks and financial institutions manage counterparty risk. In 2014 the BCBS on Banking Supervision published a revised paper on standardised approach of measuring counterparty credit risk (SA-CCR). SA-CCR is the updated model that is in use today. Beside SA-CCR financial institutions can apply to use an Internal Model Method (IMM) instead. To be allowed the use of an IMM model, financial institutions in Sweden must get approval for their model from Finansinspektionen (FI) [10].

IMM is generally more expensive and require more work for the financial institution to create and maintain. The reason to change and use IMM is that it can lower the financial institution's capital requirement because the institution can more accurately represent the exposure for their specific trade book in the model. When calculating the capital requirement, the financial institutions need to use either SA-CCR or IMM to calculate the Exposure At Default (EAD) for each counterparty. That is then multiplied with the specific risk factors for that counterparty [5].

2.2 Project description and aim

In this project we will implement and compare the two Basel III standard methods on how to calculate the capital requirement based on counterparty credit risk. To do this, we start by doing a literature study of counterparty credit risk and present relevant concepts related to this and explain why it is an important factor for a bank to take into consideration when trading. To be more resilient towards any unforeseen risks or volatility in the market financial institutions are required to hold some liquid capital stated by the EU commission. As mentioned above, credit institutes today have two model options on how to calculate how much of their total trading book they must hold as a liquid buffer, the SA-CCR model or the IMM model. Each of the two models will be discussed more in depth in section 3, and then be compared to each other.

The aim of the project is to study the Bank's trading book, and more specifically

interest rate swaps, investigate and analyze the difference in the Bank's capital requirements using the internal model method (IMM) over the standardized approach for measuring counterparty credit risk (SA-CCR) prescribed by BCBS. To do the analysis and identify potential differences, calculations on the capital requirements are made, using both methods, and some simulations of possible market movements.

As it is now, the Bank analyzed does not have an IMM-model so one of the aims in this project is to look into the requirements put up by Finansinspektionen [6] and the EU commission of such a model to better know what this would mean for the Bank, if they were to develop and implement one in the future.

The data from the Bank's trading book are classified so the data used in the results will be anonymous and altered for this reason. The calculations of capital requirements are based on two factors. One factor is the Bank's valuation of counterparty risk factor that is classified information and will not be taken into consideration in this report. The risk factor is equal in both models, it only depends on the counterparty traded with, so we do not need it to compare the two models. Instead, we only look at the second factor Exposure At Default (EAD) for both models.

2.3 Structure of the report

After this short introduction and description of the project, the following chapter, chapter 3, will present all relevant theory needed to implement these models. The implementation of the models is described in chapter 4. Thereafter the results found are presented in chapter 5, followed by a discussion and further analysis of the results in chapter 6. Finishing up, the conclusions are found in chapter 7 and then in chapter 8 and 9 the references and appendices are presented.

3 Theory

In this chapter we will present the theory that we found interesting and relevant to know to understand the research topic better. On top of this we have also had several meetings throughout the project with people at the Bank who have knowledge in relevant fields, especially when it comes to how to implement this theory on the portfolio of the Bank.

3.1 Derivatives

A derivative is a financial contract between two or more parties that derive its value from an underlying asset or a group of assets. The price of the derivative depends on the fluctuations of the underlying asset. These contracts can be traded on an exchange or over the counter. Exchange-traded derivatives are heavily regulated and more standardized. OTC derivatives are traded between two private parties and are unregulated. Because of this OTC derivatives are viewed to carry larger risk.

Derivatives are commonly used to access certain markets and hedge positions. For example hedge against risk by complimenting the portfolio with trades with the opposite risk [8]. Because the value of a derivative is derived through the changes in the underlying asset the price is exposed to similar market risk factors. Underlying risk factors affect the market risk which means that it affects the counterparty risk for a derivative since this is market risk driven. The market risk is the risk that the underlying risk factors changes in a way that decreases the value of the derivative. If the risk factors changes so the value of the derivative instead increase, the risk of the counterparty not being able to fulfil their part increase as well [10].

Another useful term to be acquainted with is what a clearing house is and its function. It works as an intermediary between the two parties selling and buying financial instruments and takes the opposite position of each side of the trade. This is a way of avoiding counterparty credit risk for the institute and instead let a middle party take the risk. The clearing house also improves the efficiency of the markets and adds stability to the financial system. To trade using clearing houses one has to be a member of that house, and the members pay fees which works as a buffer to pay back the losses for the transactions lost if one of the members were to default. In return the clearing house help the members trade with each other, trades that normally would not have been possible to do, or very complicated to initiate [11].

3.2 Interest rate swap

A forward contract where a stream of future interest payments is exchanged for another based on a predetermined amount is called an interest rate swap (IRS). It is usually an exchange between a fixed interest rate and a floating rate. The purpose of the exchange is to decrease or increase exposure to changes in interest rates or to obtain lower interest rate. This is a tool for companies to manage the risk that accompanies having floating rate. There exist three different variants of interest rate swaps, fixed-to-floating, floating-to-fixed and float-to-float [2].

Fixed-to-floating

An example of fixed-to-floating consider a company which can issue a bond at a good fixed interest rate to their investors. To achieve this, they therefore enter a swap with a counterparty where the company is paid a fixed rate and pay the counterparty a floating rate. The swap is designed to follow the maturity and cash flow of the fixed-rate bond the company issued and is netted with the fixed-rate payment to the counterparty. Let the chosen floating rate be the preferred floating-rate index, that usually is equal the regions IBOR-rate one-, three- or six-month tenor. The company will then receive the chosen IBOR-rate either added or subtracted with a spread that represent the conditions in the market for both interest rate and its credit rating [2].

Floating-to-fixed

A common case of floating-to-fixed interest rate swap is when companies instead of getting a fixed-rate loan take a loan with floating rate and enters a swap to achieve a fixed rate. The counterparty take on the risk that follows having floating rate and make all payments based on the floating rate. The fixed-rate part of the swap is the borrowing rate for the company [2].

Float-to-Float

Companies usually enter a float-to-float swap if they want to change the type or tenor of their current floating rate. For example, they can swap from a three-month to six-month tenor to either get a more attractive rate or a better matched payment flow. It can also be used to change the index of the floating rate [2].

3.2.1 Zero coupon rate

The simplest interest rate derivatives are zero coupon bonds. A zero coupon bond is a bond that pays full face value at time of maturity T . The price of the bond is defined as following if we have continuous compounding:

$$p(t, T) = e^{-R(t, T)(T-t)} \quad (1)$$

where t is the current time, T is the maturity and $R(t, T)$ is the yield to maturity. The price at maturity is assumed to be $p(T, T) = 1$. The yield to maturity is given by

$$R(t, T) = -\frac{\ln p(t, T)}{T-t}. \quad (2)$$

The yield is different for each maturity T [16].

3.2.2 Term Structure

Term structure is the relationship between the rate and different maturities. Using the calculations above we can see the term structure as the collection of yields, $R(t, T)$ introduced in equation 2, for different maturities T where $T = t, \dots, \infty$. This collection is used to predict future trajectories of the rate. These future expected changes in interest rate are used to predict future rate. The current long-term rates are used to predict short rates. The term structure is created using either long-term zero rates, forward rates or discount factor. Given a term structure the zero rates, forward rates as well as discount factors can be found for different tenors and a zero-rate-curve, forward-curve and discount curve can be created [2].

The term structure can be created with different tenors, denoted τ . When creating a swap, a tenor for the forward-curve and discounting-curve is assigned. The forward-curve is used for estimation of the forward rate. The discounting-curve is used for discounting the cashflows to get the present value [2].

3.2.3 Valuating an interest rate swap

An interest rate swap has two legs. The first leg represents the original future interest payments, and the second leg is the exchanged future interest rate payments. The present value of the interest rate is the sum of future interest payments, also called cashflows, for both legs. Calculating future cashflows for fixed rates is simple because the future rate is known and constant. When calculating future cashflows based on floating rate is more complicated. To be able to evaluate the future cashflows the floating rate needs to be estimated. A common method is to estimate the short rate, $r(t)$, through Monte Carlo simulations based on Hull-White dynamics presented below.

$$dr(t) = (\theta(t) - ar(t))dt + \sigma dW(t), \quad (3)$$

where $\theta(t)$ is the time varying mean reversion, a control how fast the simulation converges to the mean reversion and σ is the standard deviation. The strength of the Hull-White models is its simplicity while still being able to fit the interest rate term structure without introducing arbitrage. By keeping the parameter a and σ constant we keep the model and calibration simpler [2].

3.2.4 Netting

Most financial institutions, such as the Bank, have many different trades with various counterparties which is referred to as the Bank's portfolio or trading book. When evaluating the exposure towards one counterparty it is usually the netted value of the portfolio of trades towards the counterparty that is evaluated.

Netting is a collection of trades that are grouped into a netting set and evaluated as the combined values of each trade within the netting set. In case of default the value that will be owed is the net value of all trades with the counterparty. The total exposure will be reduced because the positive and negative values within the set will offset each other. Netting sets are based on legal agreements between the parties involved and usually follow the recommendations from the

International Swaps and Derivation Association. It is not uncommon that there exist multiple netting sets between counterparties [8].

3.3 Measuring Risk

3.3.1 Risk

Market risk represents the effect changes in market price has on a portfolio. Market prices fluctuation will affect the value of the portfolio. Depending on how the market prices change the portfolio has positive or negative changes, such as an increase or decrease in value. Market risk represent the result with negative changes.

Credit risk is the default risk for cash products such as mortgages or loans. These risks are usually known in advance and therefore simple to calculate. Counterparty credit risk (CCR) or counterparty risk represents the default risk that follows trading of derivatives. The future value of derivatives is unknown and therefore we can only calculate an estimation of the value. Counterparty credit risk is usually viewed as a combination of market- and credit risk.

Exposure is defined as the value that the party would lose in case of a default. The risk of default can be influenced by market risk. Another feature of counterparty risk is the asymmetry of potential losses that is not a part of market risks. This depends on the net value of the outstanding transactions after reviewing netting and collateral agreements. The resulting net value can be positive or negative. A positive net value means that the defaulted counterparty will not be able to fulfill their part of the contract. The surviving party will have a claim on that value from the time of default and can expect to get a fraction of the claim. The resulting value the surviving party gets is unknown and usually not included in the calculations of exposure. If the net value is negative the surviving party is forced to pay the counterparty the owed amount.

3.3.2 Exposure At Default

The exposure at default (EAD) is a key component when calculating the required capital a bank must hold in relation to counterparty risk. It can be seen as the notional of a bond or a loan, or the size of the position concerned. EAD is calculated on the netted portfolio.

The calculation of EAD differs depending on if the transaction considered has a rather fixed exposure, such as loans, or a more uncertain underlying exposure, such as transactions in derivative portfolios. If the underlying exposure is more towards the uncertain kind, which makes the calculation more challenging compared to if the exposure would be fixed, then it is quite trivial to calculate. The reason that EAD calculations for derivative portfolios are more complicated is because the credit exposure is mainly driven by changes in risk factors. Risk factors being interest rates and FX rates, for example. And the correlation and rules regarding netting and collateral make the calculation more complex and difficult to present in one simple regulatory formula.

3.3.3 Effective Expected Positive Exposure

The definition of Expected Positive Exposure (EPE) is the average exposure over all time horizons. It can also be viewed as the weighted average of the Expected Exposure (EE), where the expected exposure is the estimated exposure. Because EPE is an average it will not be able to effectively capture large exposures over small time periods. Usually, EPE gives an underestimation of the exposure on short dated transactions and does not properly capture the "rollover risk". To avoid these problems another metric was introduced, Effective Expected Positive Exposure (EEPE) for regulatory capital calculations. EEPE is the average of the effective PE, which is a non-decreasing representation of EPE as shown in figure 1. Broadly speaking EEPE operate under the assumption that a decreasing EPE is the result of a maturing transaction that will be replaced [8].

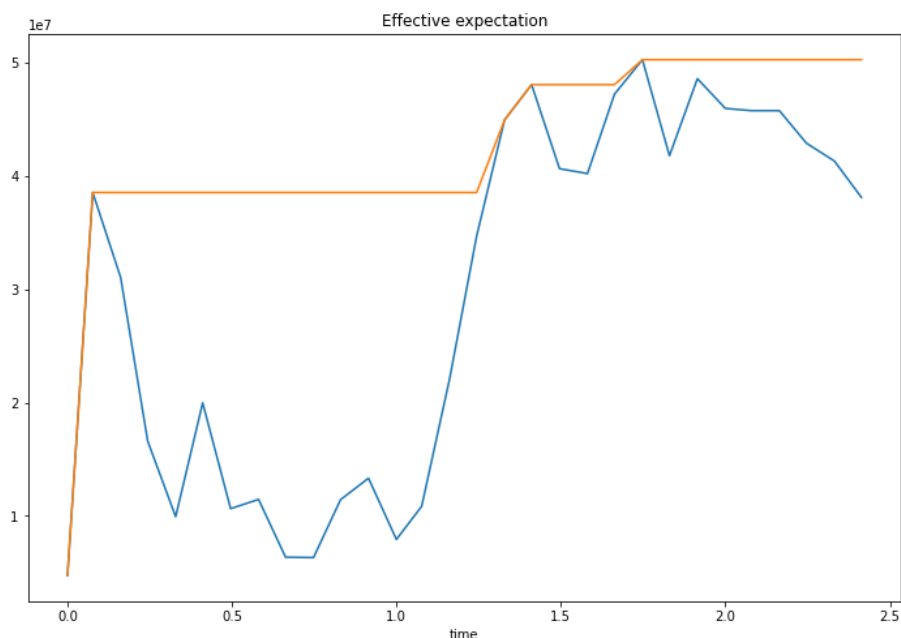


Figure 1: The figure shows the effective expectation as the orange line calculated on the EPE, presented as the blue line. As we can see in the figure the effective expectation is a non-decreasing representation of EPE.

3.3.4 Wrong-way risk

Wrong-way risk (WWR) is a term that describes the positive co-dependency between the considered counterparty's exposure and credit quality. This means that an increase of the probability of default of the counterparty would give an increase of the exposure as a result, for example. This term is usually divided into two sub-groups, called General WWR and Specific WWR. General WWR concerns risks that are driven by macroeconomic behaviours, and specific WWR is more related to the structure of specific trades or counterparty exposures. An example of specific WWR can be a company who is writing put options on its

own stock. BCBS describes specific WWR as normally being caused by badly designed transactions and that they should not have been made in the first place. This type of risk requires that there are procedures for identifying, monitoring and controlling transactions where specific WWR could appear.

WWR is very important for banks using the IMM approach to consider. For them, general WWR is partly represented through the stressed EPE calculation, but they may have to model the general WWR with macroeconomic factors being the primary risk drivers as well. But it could be included in the estimated α -parameter used when calculating EAD too, where α is determined by the choice of capital requirement method.

However, WWR is important to consider for banks who do not use the IMM approach also. These banks do not have to model WWR, but they instead need to put more effort into identification and management related to general WWR [8].

3.3.5 Replacement Cost

The value of the Replacement cost (RC) is dependent on whether the transaction is margined or not, but generally it is introduced to capture the loss occurring if a counterparty were to default and all the transactions with it ceased immediately [15]. A transaction is considered margined if the transaction requires the parties to make regulatory deposits in collateral to reduce the exposure of the transaction. In most cases cash is the collateral used for this [9]. An unmargined transaction, on the other hand, does not have a margin based on the present value of the transaction regularly exchanged between the counterparties. Collateral may however exist in the transaction, but it will not be considered to be a margined transaction if the collateral is not a regular asset and exchanged between the counterparties. When two parties enter a contract the terms of the margin agreement are determined and often a clearing house is used for holding the collateral during the term of the contract.

Variational margin is controlled by a clearing house where the members make variable margin payments that is based on the price movement of the transactions. The payment works as collateral to decrease the exposure the transaction holds. If the counterparty would default the buyer is only exposed to the change in value since the last collateral payment made, and not the entire value of the transaction. For example, consider company A entering a contract with company B with an initial value of 1000 SEK. Company B would then pay company A 1000 SEK as collateral. If the value then increase to 1200 SEK to the next payment date company B needs to pay company A the difference in value between the last evaluation date and the current one. This results in company B paying company A $1200 - 1000 = 200$ SEK. If the value instead would decrease company A will pay back company B the collateral difference. This evaluation continues to be made at pre-determined dates until the contract has reached its maturity [8].

If the transaction is unmargined, the RC would be the loss in place if a counterparty were to default and all transactions be stopped completely. The value

would therefore be defined as the greater of either the current market value of the derivative contracts subtracted by the net haircut collateral held by the bank or zero. In other words, this means that RC is a measure of the bank's current exposure, so if the bank owes a counterparty money there is no exposure towards them as long as the bank can replace all trades and sell all collateral at current market prices instantly. Mathematically this is expressed as:

$$RC_{unmargined} = \max(V - C, 0) \quad (4)$$

where V is the value of derivative transactions in the netting set and C being the haircut value of net collateral held. These are calculated using the NICA methodology. NICA stands for Net Independent Collateral Amount and considers the amount of collateral that the bank can use to compensate its exposure if the counterparty of the contract were to default.

If the transactions instead are margined, the RC is the loss occurring if a counterparty defaults at a present or future time, under the assumption that the closeout and replacement of transactions are made instantaneously. But in this case, there may also be the margin period of risk, which would be the period from that the last change of collateral is made before default until the replacement of the trades in the market have been made. So in this case, RC is defined as the highest exposure allowed without triggering a need for the variation margin. Mathematically this is expressed as:

$$RC_{margined} = \max(V - C, TH + MTA - NICA, 0) \quad (5)$$

with V and C being the same as in the unmargined case. TH being the positive threshold that determine whether the counterparty need to give the bank collateral or not. MTA being the least amount applicable for the counterparty to transfer.

What separates the two calculations of RC from each other in the unmargined case compared to the margined case is the $TH + MTA - NICA$ term. That expression represents the highest exposure allowed before triggering a call for the variation margin, and it depends on the value of collateral that must be maintained. When subtracting NICA from $TH + MTA$ it makes the calculation more accurate and reflects the real level of exposure that do not trigger a margin call as well as the effect of the collateral involved [13].

3.3.6 Potential Future Exposure

The other parameter needed to calculate the EAD for the SA-CCR model, other than RC, is the Potential Future Exposure (PFE). This add-on represents the potential change of a trades value during a certain period in time. How to calculate the PFE also varies depending on if the transactions are margined or unmargined.

For the unmargined case, the PFE represents a conservative potential increase in exposure over a one-year time period seeing from the present date. For the margined case the PFE is put together by an aggregated add-on component consisting of add-ons calculated for each asset class and a multiplier taking excess

collateral or negative mark-to-market values for the transactions into account. The function of the multiplier is to allow for partial recognition of excess collateral and therefore scales down the aggregated add-on when excess collateral is present [13]. Mathematically this is expressed as:

$$PFE = multiplier \cdot AddOn^{aggregate} \quad (6)$$

where $AddOn^{aggregate}$ is the aggregate add-on component and multiplier is defined as a function of the three inputs: V , C and $AddOn^{aggregate}$ which can be seen below in more detail.

The PFE also shows the risk-reducing property of excess collateral. The BCBS added the multiplier component as a safety measure to the PFE which decreases as the excess collateral increases but without ever reaching zero since the multiplier is floored at five percent of the PFE add-on. How the collateral held affects the replacement cost depends on whether the collateral is less or greater than the net market value of the derivative contracts. If the collateral held is lower, the current replacement cost will be positive, and the multiplier will equal one. That means that the PFE in this case equals the full value of the aggregate add-on. If the collateral held instead is greater, the current replacement cost will be zero and the multiplier be less than one. That means that the PFE in this case is less than the full value of the aggregate add-on. If the current value of the derivative transaction is negative that will also trigger the multiplier to be activated [8]. Mathematically this is shown as:

$$multiplier = \min(1; Floor + (1 - Floor) \cdot \exp(\frac{V - C}{2 \cdot (1 - Floor) \cdot AddOn^{aggregate}})) \quad (7)$$

where $Floor$ is the floor of the PFE add-on set to be 5 %, V is the value of the derivative transactions in the netting set, and C is the haircut value of net collateral held.

When calculating the add-ons there are no consideration taken however the diversification of different asset classes may be beneficial but one simply aggregates the respective add-ons for each asset class. Mathematically this is expressed as:

$$AddOn^{aggregate} = \sum_a AddOn^{(a)} \quad (8)$$

where a represents a specific asset class. A derivative transaction is grouped into the asset class based on its primary risk driver [13].

3.4 Internal Model Method

Under Basel II 2004 the Internal Model Method (IMM) was developed to allow banks and financial institutions to improve their measures of capital requirements for a variety of counterparty credit risk scenarios. At this time the alternative would be to use the standardized method (SM) that was highly criticized because of its reliance on external rating-based information. Many larger

institutions would rather use scenarios and information tailored to the firm. Therefore, the IMM was introduced as an alternative approach that is more risk-sensitive and better aligned with the firm’s internal risk management.

To be allowed to use the IMM approach the bank needs to gain regulatory approval of their model. The model needs to fulfil several requirements due to its complexity compared to the standardized model. One of the most important parts of the requirements is to be able to recognize, measure, control and validate the counterparty credit risk one year into the future. This is referred to as Potential Future Exposure (PFE) by BCBS and differs from the potential future exposure presented in section 3.3.6 that is used in the standardized approach that only considers credit risk for current default value.

The most common method used to calculate expected exposure is Monte Carlo simulation and diverse stress tests. Stress tests are different scenarios based on the trading book such as market swings or varying interest rates. The regulatory agency FI has its own stress scenarios that the derived model will be regularly subjected to. If the Bank’s IMM does not pass the agencies test the Bank loses its approval of using its IMM model until the model is re-calibrated and meet the required standards.

The IMM requires advanced modelling of all underlying risk factors that needs to be resilient to extreme market scenarios. Such a model is expensive for banks to both create and maintain. However, an IMM model allows the bank to more accurately model all underlying risk factors and the future exposure of transactions. It also allows full netting among asset classes, given that legal and operational requirements are met, and collateral benefits, such as threshold and initial margin, and modelling of future collateral. Once this is obtained, the exposure at default can be calculated, and this is done by using the following formula,

$$\text{EAD} = \alpha \cdot \text{EEPE} \tag{9}$$

where EEPE is the Effective Expected Positive Exposure and α is normally set to be 1.4, a value determined by the BCBS [8]. However, when it comes to the IMM model the institute can apply to FI and obtain permission to use another value of the α parameter. In some cases, FI could also require an institute to use a higher α as well. This is usually enforced when FI determine that the WWR is poorly validated. If an institution wants to use its own estimation of α it should ”equal the ratio of internal capital from a full simulation of CCR exposure across counterparties and internal capital based on EPE”. When estimated like this, α can never be lower than 1.2 [18].

The α factor is there to account for deviations that might occur in the calculated situations and ”corrects for the finite size and concentration of the portfolio in question”. However, it is rather uncommon that institutions use any other value than what is predetermined. Aspects that could lower the α value used is if the institute holds a very large portfolio, if the average default probabilities are larger, if the correlations are larger or if the confidence levels are higher [8].

According to BCBS the IMM model has some minimum requirements that needs to be fulfilled. The regulations we will focus on in this report are stressed EPE and Backtesting.

3.4.1 Stressed Expected positive exposure

EPE needs to be calculated using parameters derived based upon stressed data. This is to prevent procyclicality which is a problem that can occur when using recent historical data where there exists a tendency of quiet periods being followed by major crisis. Because of this the risk measures are exceptionally low at the worst times. The low-risk measures can lead to higher leverage levels that in turn can increase the likelihood and amplitude of a crisis.

To prevent procyclicality it is necessary for the bank to evaluate the EPE with stressed inputs. If the model is calibrated on historical data that dataset must include three years of historical data where one-year period is taken from a stressed period. These datasets should cover more economic conditions. The exposure at default needs to be calculated with the set of parameters that gives the highest EPE at the portfolio level. The use of stressed data should reduce the likelihood of artificially low EPE during quiet periods and therefore reduce the appearance of procyclicality problems [8].

3.4.2 Backtesting

Backtesting is used to evaluate how well a model perform on historical data. It allows the trader to analyze potential risk and to see profitability that the strategy or model may have. According to BCBS the EPE must be backtested which comes with several considerations to cope with realistically. This is usually done by backtesting the underlying risk factors. In addition, the model needs to run for a year and be regulatory evaluated of its accuracy on modelling underlying risk factors before it can be used [1].

To simplify the large OTC derivative books that large financial institutions may have it is possible to use something called "representative portfolios". It is important that these portfolios are chosen so that they reflect the important risk factors and correlations the bank may be exposed to [8].

3.5 Standardized Approach for Counterparty Credit Risk

The SA-CCR model was developed by the BCBS with the purpose to replace the two previous models in use, the Current Exposure Method (CEM) and the Standardized Method (SM) and to address some deficiencies that the previous methods had. The Standardized Approach for Counterparty Credit Risk (SA-CCR) has been effective since 1 of January 2017. The main metric that SA-CCR wishes to measure is the Exposure At Default (EAD) for the counterparty credit risk. This approach was developed to be suitable for most types of derivatives, to be easy to implement and to improve the risk sensitivity of the capital framework [13]. As can be read in [8], SA-CCR was developed to be "A new, more risk-sensitive approach that aims to balance simplicity and risk sensitivity". In order to give a fair result the SA-CCR method has been calibrated

using benchmark results obtained with the IMM method from various banks [8].

The EAD is calculated by adding the two components Replacement Cost (RC) and Potential Future Exposure (PFE) together and multiplying this by a factor called α . For this model α equals 1.4 based on the α -parameter set by the BCBS normally used in the IMM model [13]. The PFE used in the calculation is, just like for the CEM method, closely linked to AddOn factors, but it is also sensitive to the maturity in the contract [8]. Below we present the formula for calculating the EAD using the SA-CCR model.

$$EAD = \alpha \cdot (RC + PFE) \quad (10)$$

When calculating PFE for the SA-CCR model there are four important dates to consider, i being the considered instrument.

- The maturity date, M_i , being the date when the contract may still be active at latest. This appears in calculations in the maturity factor which scales down adjusted notional for all asset classes when considering unmarginated trades.
- The start date, S_i , being the first date of the time period specified by an interest rate or credit contract.
- The end date, E_i , being the last date of the time period specified by an interest rate or credit contract. The start and end date are used in the definition of supervisory duration, and the end date also specifies which maturity category a certain interest rate contract would fall into.
- The latest contractual exercise date, T_i , which is used for determining the delta of the option.

If the derivative considered are referencing another underlying interest rate or credit instrument the time period will always be the one determined by the underlying instrument.

To calculate the trade-level adjusted notional amounts for interest rates and credit derivatives one would multiply the trade notional amount, converted to the domestic currency, and the supervisory duration SD_i . The SD_i is given by the following formula:

$$SD_i = \frac{e^{-0.05 \cdot S_i} - e^{-0.05 \cdot E_i}}{0.05} \quad (11)$$

This formula is floored by ten business days and if the instrument considered are already ongoing, the start date is set to zero. The parameters used in this formula are defined at the trade level and considers both the size of the position and its maturity dependency, if there is one.

When calculating PFE using the SA-CCR model there is also the minimum time risk horizons to consider. This includes the lesser of either one year or the remaining maturity for unmarginated transactions, also floored at ten business

days. So, for these transactions the adjusted notional at the trade level must be multiplied by:

$$MF_i^{(unmargined)} = \sqrt{\frac{\min(M_i; 1 \text{ year})}{1 \text{ year}}} \quad (12)$$

where M_i is the remaining maturity of transaction i floored by 10 business days.

If the transaction instead is margined, one must consider the type of derivative to determine the minimum margin period of risk. If the transaction is a non-centrally cleared derivative affected by daily margin agreements the Margin Period Of Risk (MPOR) is at least ten business days. When considering a centrally cleared derivative affected by daily margin agreements between clearing members and their clients, the MPOR is five business days. This means that for a margined transaction the adjusted notional at the trade level should be multiplied by:

$$MF_i^{(margined)} = \frac{3}{2} \sqrt{\frac{\text{MPOR}_i}{1 \text{ year}}} \quad (13)$$

with MPOR_i being the margin period of risk for the margin agreement containing transaction i .

When it comes to add-ons for interest rate derivatives, they are in place to capture the risk of maturities being imperfectly correlated between different derivatives. To cope with this, the interest rate derivatives are divided into different maturity categories, also called buckets, based on the end dates of the transactions. Normally the ones considered would be transactions less than one year, transactions between one and five years and transactions over five years. Within the same category the SA-CCR model fully recognizes offsetting positions and across categories it partly recognizes offset. Summing the add-ons for each hedging set together of interest rates derivatives transacted with a counterparty in a netting set gives us the add-on for interest rate derivatives. A hedging set in this context is a set where all the transactions in it would have similar risk sensitivities [8]. Then the add-on for a hedging set of interest rate derivatives needs to be calculated in two steps. First, the effective notional $D_{jk}^{(IR)}$ is calculated for time bucket k of hedging set j according to:

$$D_{jk}^{(IR)} = \sum_{i \in (Ccy_j, MB_k)} \delta_i \cdot d_i^{(IR)} \cdot MF_i^{(type)} \quad (14)$$

where the notation $i \in (Ccy_j, MB_k)$ refers to trades of currency j that belong to maturity bucket k . δ_i denotes the supervisory delta adjustments and $d_i^{(IR)}$ represents the trade-level adjusted notional for trade i of the asset class IR . This means that the effective notional for each time bucket and currency is the sum of the trade-level adjusted notional amounts multiplied by the supervisory delta adjustments and the maturity factor.

Secondly, the aggregation across maturity buckets for each hedging set is calcu-

lated using the following formula:

$$\begin{aligned} \text{EffectiveNotional}_j^{(IR)} = & [(D_{j1}^{(IR)})^2 + (D_{j2}^{(IR)})^2 + (D_{j3}^{(IR)})^2 + \\ & 1.4 * D_{j1}^{(IR)} * D_{j2}^{(IR)} + 1.4 * D_{j2}^{(IR)} * D_{j3}^{(IR)} + \\ & 0.6 * D_{j1}^{(IR)} * D_{j3}^{(IR)}]^{1/2} \end{aligned} \quad (15)$$

However, banks can choose to not recognize offset between different maturity buckets, and if so, the following formula should be used instead.

$$\text{EffectiveNotional}_j^{(IR)} = |D_{j1}^{(IR)}| + |D_{j2}^{(IR)}| + |D_{j3}^{(IR)}| \quad (16)$$

Then the add-on on the hedging set level is calculated by multiplying the effective notional and the interest rate supervisory factor together.

A supervisory factor is a predetermined factor based on what asset class the transaction being made belongs to and reflects the volatility of the asset class. The factor converts the effective notional amount into Effective EPE, EEPE, based on how volatile the asset class is [13]. The table showing all supervisory factors for the different asset classes is presented in appendix 9.1 below.

$$\text{AddOn}_j^{(IR)} = SF_j^{(IR)} \cdot \text{EffectiveNotional}_j^{(IR)} \quad (17)$$

And aggregation across hedging sets is calculated by simply summing them together:

$$\text{AddOn}^{(IR)} = \sum_j \text{AddOn}_j^{(IR)} \quad (18)$$

What can be worth noting here is that RC is calculated at the netting set level, whereas PFE is calculated for each asset class within a given netting set and then aggregated [13].

4 Methodology

The implementation of the two models has been made in python, using mainly the package QuantLib which is an open-source package developed for financial purposes. For the SA-CCR model we also found a package online called sa-ccr which we could use to implement a lot of functions from [3].

In order to calculate the required capital the Bank must hold, stated by regulations, one must consider the Bank's exposure and how risky the counterparty of the trade is. The formula for doing so is:

$$\text{Capital} = \text{EAD} \cdot \text{risk factor} \quad (19)$$

where the risk factor represents counterparty credit and market risk of the portfolio and EAD is the exposure at default. EAD refers to the exposure the Bank may have if the given counterparty would default for that specific trade. How to calculate it varies depending on if you are using SA-CCR or IMM. The risk factor is equal for both models. So, since the risk factors are equal for both models and classified information we will not present them in this report, and we will therefore move forward with analyzing and comparing the EAD for each model. The portfolio and calculation of the net present value (NPV) is the same for both methods.

4.1 Portfolio

The portfolio that will be evaluated in this report is Swedish IRS where both legs have corresponding payment schedule. This means that all future cashflows for both legs are made on the same dates. In addition we will only look at currently active IRS. Further, we will not consider any other type of trades in our calculations.

We need to begin with creating the portfolio we want to evaluate. This will be done by creating swap objects for each trade and putting them in a list that will be our portfolio. For each trade we need to define the schedule for both the floating and fixed leg that tells us which dates the cashflows will be calculated and then paid. To accurately valuing the swap, we need to know the swap's day counter. Then we need to assign a term structure for the forward rate, the Ibor-index and latest fixing rate that will be used when evaluating the future floating rate. The term structure is created using zero rate market data that is interpolated using linear interpolation. In addition to this information, we need the notional value and fixed rate.

We decided to use QuantLibs VanillaSwap objects to represent our swap object in the code. The term structure, Ibor index and schedule is created with QuantLib methods as well.

When calculating the interest rate of a derivative the choice of accrual method in the contract is important to take into consideration. Mainly, there are three different methods:

- 30/360, saying that there are 30 days each month and 360 days in a year.

- Actual/365, where the interest rate is divided by 365 days in a year, and then multiplied by the actual number of days in a month to get the monthly accrual rate.
- Actual/360, calculated similarly to the Actual/365 method, but using 360 days for a year and multiplying it by the actual amount of days in a given month.

Using the 30/360 method results in a daily accrual amount slightly higher than the Actual/365 method since the interest rate is divided by 360 days and not by 365 days, which more resembles the actual number of days in a year. However, the total amount of interest is lower using 30/360 since it only accrues for 30 days, even in months where there are 31 days, compared to Actual/365 which is slightly higher since the interest is accrued over more days. Then comparing these two with the Actual/360 one can see that the Actual/360 is the method resulting in the highest amount of interest paid since it has the highest daily accrual rate being divided by a lower number of days per year, and the highest monthly accrual amount since it is accrued over the actual number of days in a month [7].

4.2 Net Present Value of Swaps

When we calculated the present value of the trade today, we need to address a swap-pricing-engine for each swap that is based on the chosen discounting term structure. The term structure is created using market data that is interpolated in the same manner as the term structure used when we create the swap objects. However, the term structure is usually based on market data with different tenors for the forward rate and discount factor. This discounting term structure is used to find the present value of the future cashflows.

When finding the NPV for an interest rate swap we sum all discounted cashflows for both legs. For a floating leg we use the floating rate that is fixed before every payment date. This fixed floating rate is used for the calculation of the cashflow. Consider a Interest Rate Swap with on fixed leg and one floating leg that begins at timepoint $s = 6M$ and mature at time $T = 51M$ if today is $t = 0$. A cashflow scheme is presented in the figure below where we have payments every 3M.

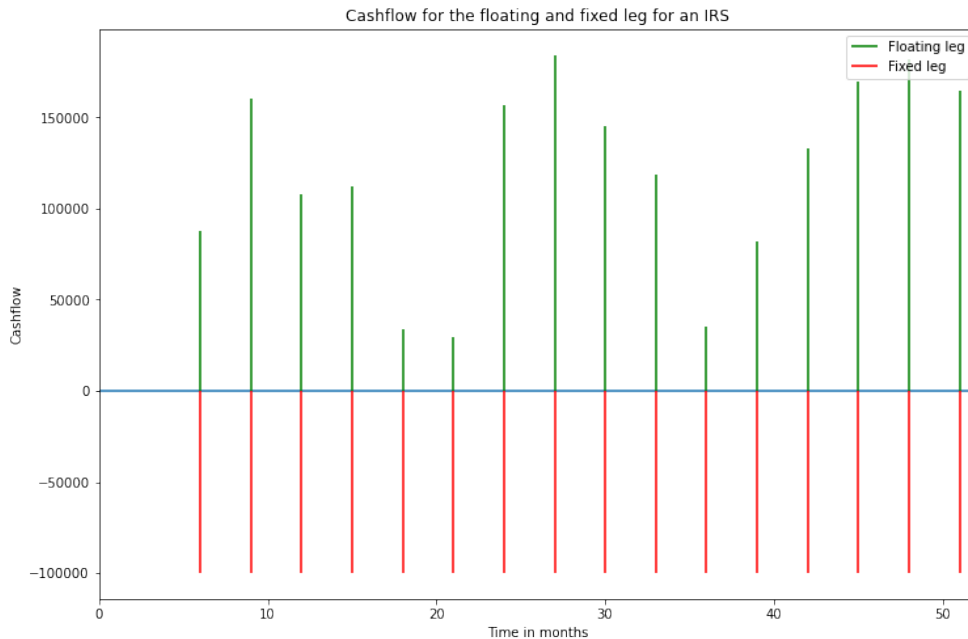


Figure 2: The figure represents the cashflow for the fixed respective floating leg for an Interest Rate Swap (IRS). The begin looking at time $t = 0$ where the IRS begin at time $s = 6M$ and end at $T = 51M$.

The PV, or NPV, is obtained by looking at the difference between the sum of every floating cashflow, green line, respective fixed cashflow, red line. Worth noting, in this report we only evaluate active IRS which means that $t \in [s, T]$.

4.3 Method for IMM

For IMM we want to find the exposure at default (EAD) that is calculated by equation 9. As mentioned before the α factor is set to 1.4 and EEPE is calculated by simulating future market scenarios and calculating an effective expectation of the positive net present value of all scenarios. We do this process for both market data and stressed data where the process with the highest EAD is the process we are required to use.

To validate our method, we will use backtesting. According to European Central Bank the best way to evaluate our model is to look at our underlying riskfactors. Because we evaluate a portfolio of IRS our underlying risk factor is interest rate [1].

4.3.1 Simulating interest rate

The one factor Hull-White method, presented in section 3.2.3, under risk neutral measure has the following dynamics

$$dr_t = (\theta(t) - ar(t))dt + \sigma dW^Q(t), \quad (20)$$

where $\theta(t)$ is the mean reversion over time, a is the mean reversion speed, and σ , the historical volatility. The $\theta(t)$ parameter is time dependent and is based on the forward rate term structure. The term structure is created using zero rates with linear interpolation.

The mean reversion speed, a , and historical volatility, σ , is calibrated using ATM swaption data. We use the tenor, maturity and implicit volatility from the ATM swaption to create swaption helper objects. These swaption helpers are assigned a Jashmidean discount pricing engine and is then used in QuantLib's Levenberg Marquardt optimization method to calibrate the parameters a and σ .

Levenberg Marquardt optimization method, also known as damped least squares method, is commonly used to solve least square curve fitting problems. It is an iterative procedure where we give a function $f(x_i, \beta)$ replace the parameter vector β with a new parameter vector $\beta + \delta$. This function is then approximated as

$$f(x_i, \beta + \delta) \approx f(x_i, \beta) + \mathbf{J}_i \delta \quad (21)$$

where $\mathbf{J}_i = \frac{\partial f(x_i, \beta)}{\partial \beta}$ is the gradient. The expression for the sum of all square errors is presented below, where \mathbf{y} is the real value.

$$S(\beta + \delta) \approx \sum_{i=1}^m [y_i - f(x_i, \beta) - \mathbf{J}_i \delta]^2 \approx \|\mathbf{y} - f(\mathbf{x}, \beta) - \mathbf{J} \delta\|^2, \quad (22)$$

It has its solution in the zero gradient with respect to the parameter vector β . If we differentiate $S(\beta + \delta)$ with respect to β and put it equal to zero we get the following equation.

$$(\mathbf{J}^T \mathbf{J}) \delta = \mathbf{J}^T [\mathbf{y} - f(\mathbf{x}, \beta)] \quad (23)$$

Levenberg's contribution to this equation is adding a non-zero dampening term, λ which yields the following expression

$$(\mathbf{J}^T \mathbf{J} - \lambda \mathbf{I}) \delta = \mathbf{J}^T [\mathbf{y} - f(\mathbf{x}, \beta)], \quad (24)$$

where \mathbf{I} is the identity matrix. The λ parameter is updated at each iteration. Because we solve this problem by finding the minima it is important to have good initial guesses for the parameters so we find the global minima and not the local minima [17].

Using this method, we derive our parameters that are used to create our one-factor Hull-White process which the simulated paths are drawn from using a Gaussian random sequence generator. All the mentioned methods are implemented using the QuantLib library.

4.3.2 Pricing for all scenarios

Further, we want to calculate the net present values for each path by calculating the discounted cashflow at each payment date for every floating leg in the portfolio. The cashflow is dependent, as can be seen in figure 2, on the floating

rate. Since the floating rate is not known we want to estimate the forward rate. The forward rate is found through the respective curve. With the estimated forward rate we can calculate the cashflow. The cashflow needs to be discounted back to the present value. Discounting factors for each future payment date is found through the discount curve. Both curves are derived from the respective term structures which are created by calculating Hull-White zero bond price, $P(t, T)$, based on the simulated short rate. The forward- and discount curve used to price an IRS are specified in the contract for a trade. We calculate the Hull-White zero bond price that we then scale to correspond with the chosen tenor, τ , on the term structure. The Hull-White zero bond prices $P(t, T)$ are given by the following equation:

$$P(t, T) = e^{A(t, T) - B(t, T)r_t}, \quad (25)$$

where $A(t, T)$ solve

$$A_t(t, T) = \theta(t)B(t, T) - \frac{1}{2}\sigma^2 B^2(t, T) \quad (26)$$

$$A(T, T) = 0, \quad (27)$$

and $B(t, T)$ solve

$$B_t(t, T) = \frac{1}{a}\{1 - e^{-a(T-t)}\} \quad (28)$$

$$B(T, T) = 0. \quad (29)$$

The solutions of $A(t, T)$ and $B(t, T)$ therefore look as follows

$$A(t, T) = \int_t^T \left\{ \frac{1}{2}\sigma^2 B^2(s, T) - \theta(s)B(s, T) \right\} ds \quad (30)$$

$$B(t, T) = \frac{1}{a}\{1 - e^{-a(T-t)}\}. \quad (31)$$

The observed forward rate curve is given by $f^*(t, T) = -\frac{\partial \log(P^*(t, T))}{\partial T}$ where $P^*(t, T)$ is the observed bond price. Since both $A(t, T)$ and $B(t, T)$ are deterministic functions our model have an affine term structure. It follows that the forward rates are given by

$$f(0, T) = B_T(0, T)r_0 - A_T(0, T) \quad (32)$$

$$= e^{-aT}r_0 + \int_0^T e^{-a(T-s)}\theta(s)ds - \frac{\sigma^2}{2a^2}(1 - e^{-aT})^2. \quad (33)$$

Given a $\theta(t)$ that solves equation 33, we calculate the theoretical bond price for a Hull-White model under martingale measure according to the equation below.

$$P(t, T) = \frac{P^*(0, T)}{P^*(0, t)} \exp \left\{ B(t, T)f^*(0, t) - \frac{\sigma^2}{4a}B^2(t, T)(1 - e^{-2at}) - B(t, T)r_t \right\}, \quad (34)$$

where $B(t, T)$ is given by equation 31 [2]. Further, we want to find the zero bond price for tenor τ , which is given by scaling the zero bond price as follows.

$$P_\tau(t, T) = P(t, T) \frac{P_\tau^*(t, T)}{P^*(t, T)}, \quad (35)$$

where P^* and P_τ^* are the observed bond prices. With the estimated bond prices we create both the forward- and discount curve.

Doing this for all simulations, for all evaluated time points, will result in two matrices, one with the discounting term structure and one with the forward term structure. Each row will represent one simulated path and each column a time point, as demonstrated in figure 3 below.

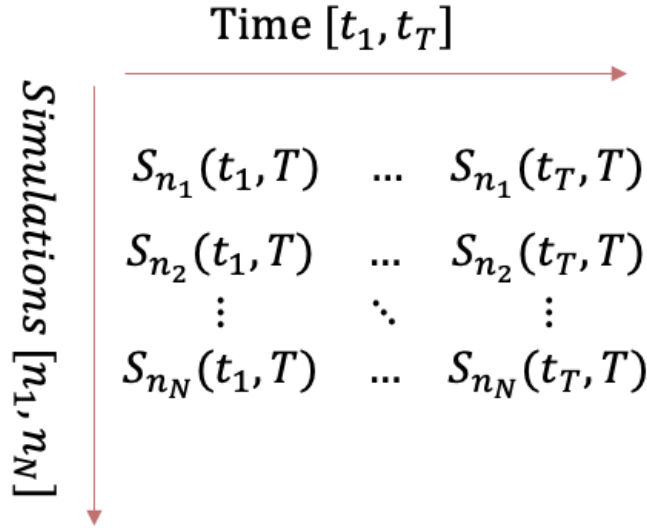


Figure 3: The resulting matrix of term structure curves for every simulation at every time point. Each node $S_{n_k}(t_i, T)$ represent a term structure curve based on the discount factors calculated for path n_k at time point t_i . The matrix has the shape $N \times T$ where N is the number of simulated paths and T the size of the time grid.

At every node in this matrix we have a term structure curve, either a forward- or a discount curve. We create a new exposure matrix with the same dimensions where every node represent the exposure for that path, at that time point. For every node in the exposure matrix we calculate the present value by calculating the future discounted cashflow using the forward- and discount curve for the respective node. The present value calculated on date t_i to maturity T is calculated with the following formula:

$$PV = \sum_{t=t_i}^T \frac{f_t}{M} N d_t \quad (36)$$

where $\frac{f_t}{M}$ is the forward rate for that period and d_t the discount factor for each payment date t .

In the code we use the swap object's own NPV method. We find the forward curve and discount curve and link them to the swap object. The swap object will then use these curves and the previously assigned pricing engine to find all future cashflows and discount them back to the present value. The pricing engine used is a discounting pricing engine.

4.3.3 Stress calibration

Stress tests are an important tool to understand the bank's weaknesses and it means that we want to analyze the NPV under certain stressed market scenarios. In this report we used stressed input data that we obtained by shifting the current zero rates a fixed number of basis points. The shifted input data represents a current market scenario that is less optimal than what the actual market today looks like. In this report we chose to shift the input data so it reflects the market scenario taken from our simulated rate one year ahead at quantile 80%. An 80% quantile should capture a market scenario that is considered being worse than today, but at the same time being realistic. This will affect the mean reversion of our simulation of the future rate. According to BCBS we need to use the input data, real or stressed, that results in the highest EAD [18].

4.3.4 Calculating EAD

EAD is given by equation 9

$$EAD = \alpha \cdot EEPE.$$

From the methods presented above we get the net present value of each trade. The exposure is equal to the net present value in this case. However, we want to find the netted exposure for the entire portfolio. The methods for the IMM mentioned above is done per trade and the resulting exposure is then netted. The netting is done by taking the sum over all simulated exposures for every trade. Because we are only interested in the positive exposures of the portfolio, we floor to zero the exposure after netting, so all negative exposures are put to zero.

To derive the EAD we need to calculate the EEPE for the first year of future exposure. If the derivative matures in less than a year, we look at the average for the remaining time of the contract. EEPE is calculated as a weighted average of effective EPE as:

$$EEPE = \sum_{k=1}^{\min(1\text{Year}, T)} EEPE_{t_k} \cdot \Delta t_k \quad (37)$$

where Δt_k is the time step. We use a constant time step which makes the weights constant $\frac{1}{N}$, where N is the number of time steps. With these changes the above equation becomes equal to a standard average over the number of time steps taken during a year or for the remaining time of the contract.

4.3.5 Backtesting

The risk factor present in our model is the simulated rate and therefore the factor we want to backtest. We use historical zero rate data and will compare this to the simulated zero rate. Given a time point t as evaluation date we recalibrate our model using the market data at time t . We then simulate 10 000 paths $t + 10$ days ahead and find the discount factors for different tenors to create term structures as before. From the term structure we draw zero rates for the different tenors and create a confidence interval. Then we repeat this process at date $t + 10$ days until we have looked at the entire data set. Finally, we look at how often our real zero rate is not within our confidence interval. The tenors we evaluate are $[7D, 2W, 1M, 3M, 6M, 1Y, 2Y, 5Y, 10Y]$ and the percentiles $[1\%, 5\%, 25\%, 75\%, 95\%, 99\%]$.

To further validate our interest rate simulation we will analyse spreads using backtesting as well. The spreads are based on the same historical dataset. A spread is the difference between two zero rates with different tenors. For example a spread with tenor $10Y - 5Y$ is derived as following:

$$spread_{10Y-5Y}(t) = r_{10Y}(t) - r_{5Y}(t), \quad (38)$$

where $r_\tau(t)$ is the zero rate for tenor τ . Using the simulated zero rates, from the same simulation as for backtesting zero rates, we create a spread for each simulation by taking the difference between the two zero rates with the specified tenors. The confidence interval for the simulated spreads are calculated and compared with the real spread. The spreads we will look at are the following $[10Y - 5Y, 10Y - 2Y, 5Y - 6M]$ and we will use the same percentiles as we use for zero rates.

Because we have few samples of zero rates, we cannot assume that only 1% of the samples will be outside of the confidence interval. We assume a binomial distribution as a sum of a Bernoulli process, where a 1 represent the sample to be outside and 0 if it is within the interval. Below a table of the number of exceptions that will be allowed for 84 samples at 99% confidence level is presented. The colors represent if the number of exceptions were expected or not. A green color means that it is within the interval of expectation, yellow means that it is more exceptions than expected but not too far off. Red means that we have more exceptions than expected for the distributions. This type of table is called a traffic light table.

0	0,429889
1	0,794643
2	0,947545
3	0,989761
4	0,998396
5	0,999791
6	0,999977
7	0,999998
8	1
9	1
10	1
11	1

Figure 4: Example of how a traffic light table works for 84 samples at a confidence interval of 99%. To the left is the number of deviations and to the right the binomial distribution of that number of deviations given the number of samples and confidence level.

As we can see from figure 4, we expect 0 – 2 exceptions, and 3 – 5 exceptions are within the scope of reasonable exceptions but slightly higher than what we expected. If the number of expectations is 6 or higher, we have too many exceptions and our model does not capture the realized rate at a 99% confidence level.

During the simulation we introduce noise to our estimations. This noise can affect our confidence interval. We assume it to have the following composition, where x_τ is the data we have got, and \hat{x}_τ is the true value, without noise.

$$\hat{x}_\tau = x_\tau + e_\tau \quad (39)$$

We assume the noise, e_τ , to be uniform distributed and for the spreads we adjust the confidence interval by removing the variance of the noise.

4.4 Method for SA-CCR

Just as we did above for the IMM-method we want to calculate the EAD, but for the SA-CCR method it is calculated using a different formula, 10. Just as for IMM, α is set to 1.4 and then we need to calculate the replacement cost (RC) and the potential future exposure (PFE).

Starting off, we read in the supervisory factors used for interest rate derivatives from the table presented in appendix 9.1. Then we start with calculating the add-ons determined by the type of derivative the instrument considered is. In our case we have only considered interest rate swaps so far, so we will use the specific add-on formula and supervisory factor for that type of derivative. To get the final add-on, we sum all the individual add-ons together.

We calculate a trade supervisory delta based on the volatility, which we use

to calculate a single trade add-on by multiplying this with the maturity factor of the trade and the adjusted notional. The trade specific supervisory delta adjustment is a parameter used to reflect the direction of the transaction, if the position of the trade is long or short, and its non-linearity. It is applied at trade level to the adjusted notional amount, which is a value used to show the value of an option [13]. Finally, doing this results in an effective notional amount.

We calculate the single trade add-on for every leg in the trade and these become our time buckets. The total add-on is then the sum of all these together. To get the currency add-on we weigh the add-ons for every leg in the time bucket by the following formula, 15. Then the sum over all of these multiplied by a supervisory factor becomes the add-on.

Once we have got the add-ons, we can calculate the replacement cost and the potential future exposure, which makes out the basis in the standardized approach. One calculates the replacement cost a bit different depending on if the transaction is margined or not. If it is an unmargined transaction the replacement cost is either the value of the derivative transactions in the netting set minus the haircut value of the net collateral held, or 0, whichever is the greatest, as seen in equation 4. If it is margined it is either one of the two above or the positive threshold before the counterparty must send the bank collateral added together with the minimum transfer amount applicable to the counterparty minus the net independent collateral amount, whichever is the greatest of those three, as seen in equation 5.

The calculation of the multiplier of the potential future exposure also varies depending on if the value of the derivative transactions in the netting set minus the haircut value of the net collateral held is greater than zero or not. If it is not, we would calculate it using the following formula:

$$\text{multiplier} = \min(1, 0.05 + 0.95 \cdot \exp((V - C)/(1.9 \cdot \text{Addon}^{\text{Aggregate}}))$$

where V is the derivative transactions in the netting set, C the haircut value of the net collateral held and the aggregated add-on. This term is then multiplied by the aggregated add-on which would result in the potential future exposure. We add 0.05 to the multiplier term because the floor is set to be five percent. If however, $V - C > 0$ the multiplier equals one and the potential future exposure would therefore just be the aggregated add-on.

Then finally to get the exposure at default amount we add the potential future exposure together with the replacement cost and multiply it by an alpha parameter set to 1.4.

5 Results

5.1 Input Data

The chosen evaluation date for these calculation is 28 February 2022. The values for the input parameters for all swaps are presented in table below.

Parameter	Value
Start date	18 June 2019
End date	29 February 2028
Notional	600 000 000
Spread in %	0
Fixed rate in %	2.0595
Fixed tenor	3M
Floating tenor	3M
Currency	SEK
Ibor-index	SEKLibor
Forward term structure	SEK 3M
Discount term structure	SEK OIS
Accrual method	Actual/360

Table 1: The input data used for one trade that is used to create the swap objects and schedule.

Parameter	First trade	Second trade	Third trade	Fourth trade
Start date	18 June 2019	18 June 2019	1 Feb 2021	14 June 2021
End date	29 Feb 2028	9 March 2029	3 Feb 2031	16 June 2031
Notional	600 000 000	600 000 000	500 000 000	500 000 000
Spread in %	0	0	0	0
Fixed rate in %	2.0595	2.053	0.443	0.785
Fixed tenor	3M	3M	3M	3M
Floating tenor	3M	3M	3M	3M
Currency	SEK	SEK	SEK	SEK
Ibor-index	SEKLibor	SEKLibor	SEKLibor	SEKLibor
Forward term structure	SEK 3M	SEK 3M	SEK 3M	SEK 3M
Discount term structure	SEK OIS	SEK OIS	SEK OIS	SEK OIS
Accrual method	Actual/360	Actual/360	Actual/360	Actual/360

Table 2: The input data used for the portfolio that is used to create the swap objects and schedule.

From the calibration we get the parameters for our Hull-White process that are presented below in the table. These are the parameters that we will use in each case throughout the report.

Current market data	a	0.02510
	σ	0.009051
Stressed +24 bp	a	0.02480
	σ	0.009058
Stressed -24 bp	a	0.02520
	σ	0.009039

Table 3: The table present the optimized parameters from both calibration of the Hull-White parameters. The calibration is done for both the stressed in-data and actual data. These parameters are used in the respective Hull-White process during our calculations.

Because the parameters are calibrated on the term structure as well as volatility surfaces the parameter will depend on whether or not we use stressed input data. The $\theta(t)$ parameter is set to the term structure that is based on the current market data. In the result presented in figure 5 the following zero rates are used to create the term structure, the forward respective the discount term structure. In the case of stress calibration, we parallel shift the zero rates ± 24 basis points. The zero rates used to create the two term structures are presented in figure 5.

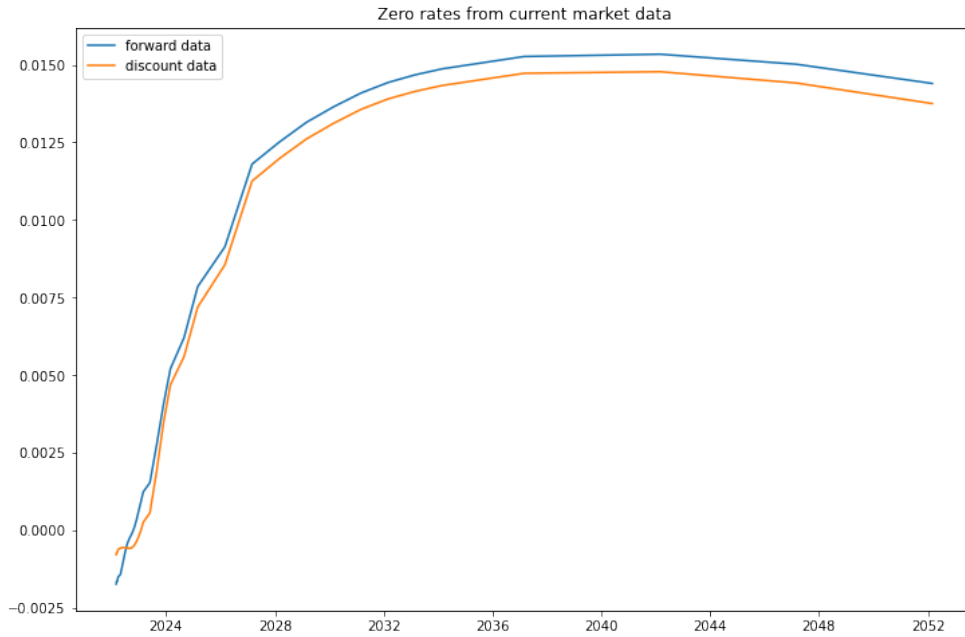


Figure 5: The plot shows the input data used. The blue line is the zero coupon rate for SEK 3M that is used as the term structure for forward rate. The orange line is the zero coupon rate for SEK overnight index that is used for discounting. Both are taken from the chosen evaluation date, 28 February 2022.

5.2 Simulation of interest rate

From the process created with the optimized parameters and term structure for forward rate and discount factor we draw 10 000 samples of short rates 30 years into the future. The first 100 simulated paths are presented in the plot below.

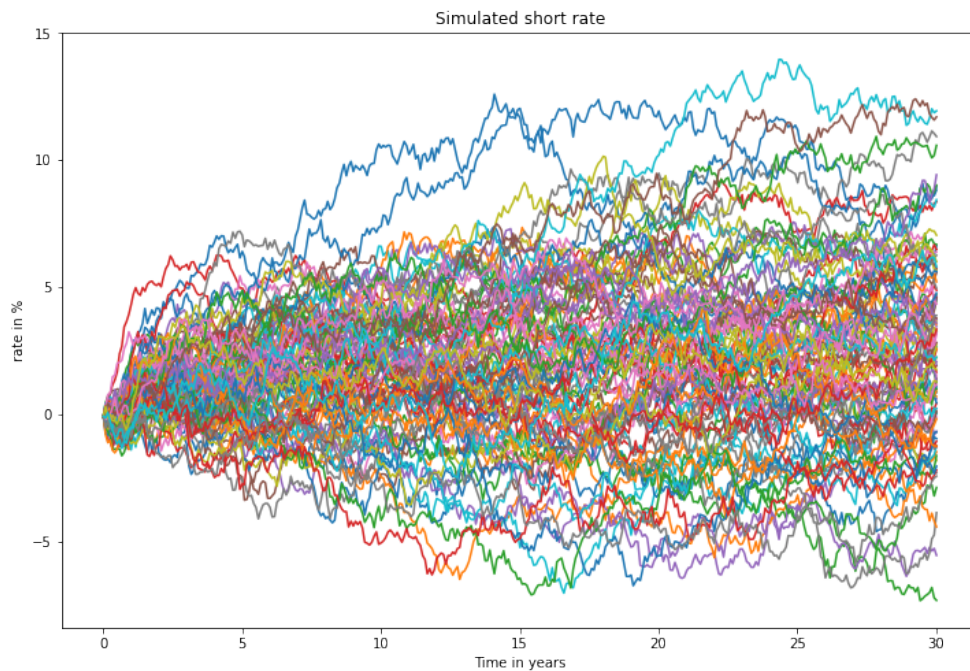


Figure 6: The plot shows the first 100 paths of the total 10 000 paths simulated. The simulated rate is drawn from the Hull-White process with the calibrated parameters.

The stress calibration was chosen as the difference between the rate at time $t = 0$ and 80% quantile at time $t = 1Y$. The difference between these two rates are 24bp. The simulated interest rate is presented below. Since we only shift the zero rates, the mean reversion $\theta(t)$ is the only part that will change.

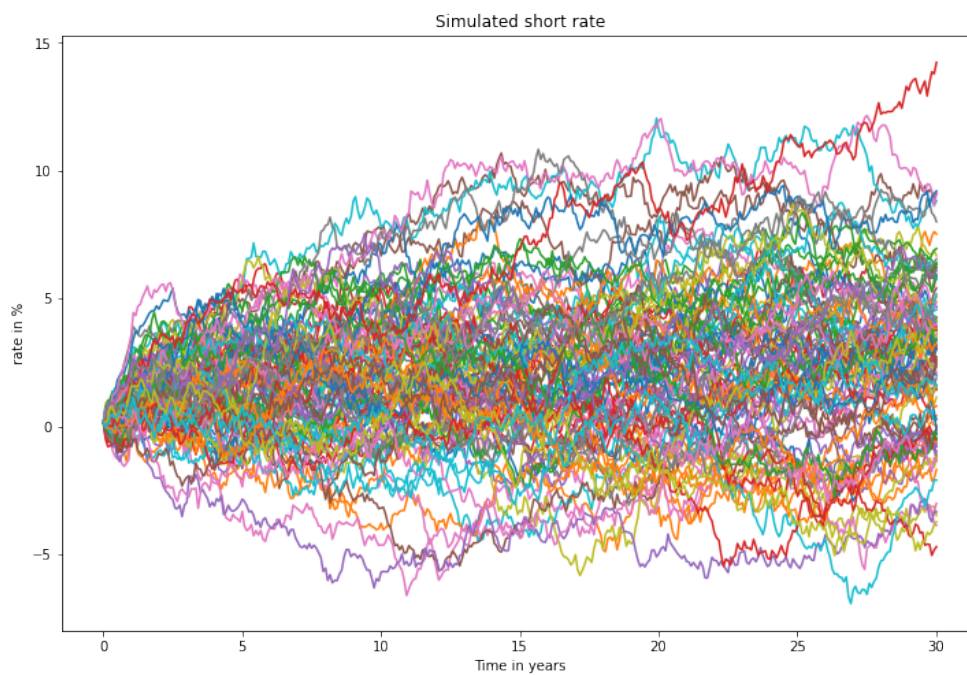


Figure 7: The plot shows the first 100 paths of the total 10 000 paths simulated. The simulated rate is drawn from the Hull-White process with the calibrated parameters and +24 basis points stressed input data.

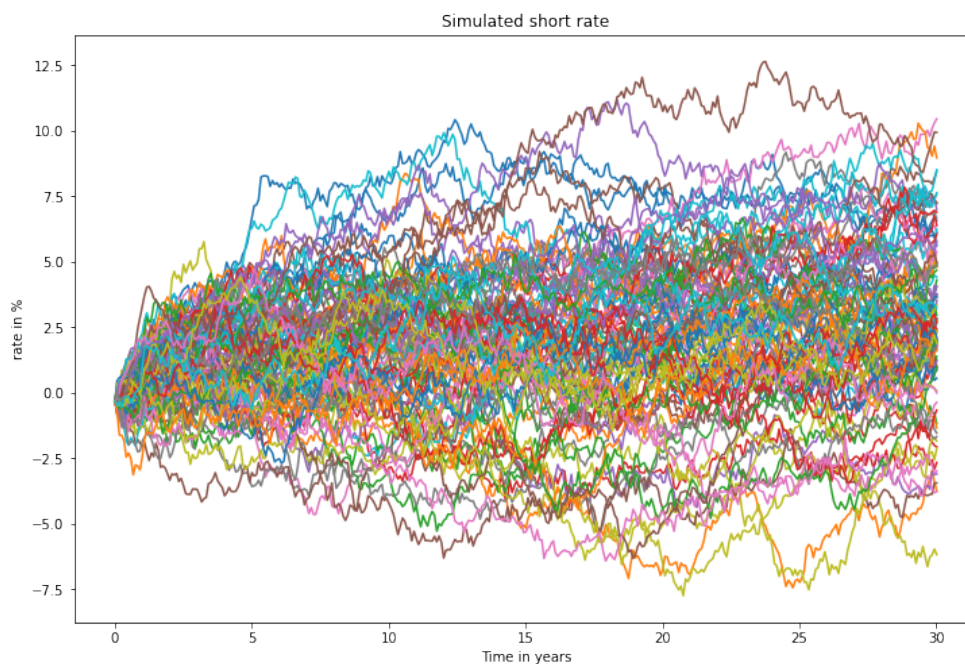


Figure 8: The plot shows the first 100 paths of the total 10 000 paths simulated. The simulated rate is drawn from the Hull-White process with the calibrated parameters and -24 basis points stressed input data.

5.3 Resulting EAD

Since we need to use the process that gives the highest EAD, the EAD will be calculated for IMM using both simulated interest rates and then evaluated. The resulting EAD from SA-CCR and both scenarios for IMM are presented in the table below. We start by looking at only one interest rate swap, and then we scale up looking at a portfolio with 4 interest rate swaps. Worth noting is that all the plots showing simulations only present the first 100 market scenarios out of the 10 000 simulated ones. This is solely done to make the plots easier to interpret and for visual aspects. The parameters and data used to produce these plots are presented above.

5.3.1 One Trade

First, we use the simulated interest rate to calculate the net present value for each path for one trade. Out of the 10 000 paths the first 100 are presented in a plot below.

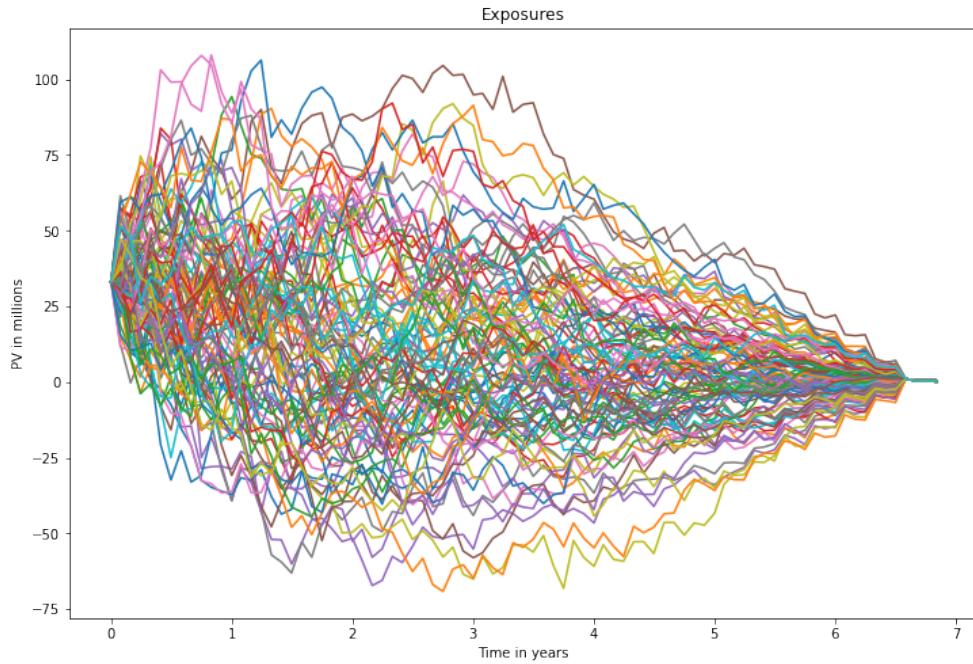


Figure 9: The figure presents the first 100 paths of the calculated exposure based on the 10 000 simulated rates paths. The exposure is calculated for one trade that is presented in table 1. All graphs start at the present value of the one trade presented in table 4 and then end after 7 years having a value of 0. The different graphs represent potential future market scenarios.

The present value for the single trade is shown in the table below.

Present value	33 179 575 SEK
---------------	----------------

Table 4: The present value at the evaluation date for one trade presented in table 1 and the input data presented in figure 5.

The resulting EAD for the two different models, SA-CCR and IMM, are presented in the table below.

Model	Resulting EAD
SA-CCR	78 316 719
IMM	49 539 399

Table 5: The resulting EAD for both IMM and SA-CCR model for one trade.

5.3.2 Portfolio

Further we want to use the same simulated paths presented in figure 6 to calculate the net present value of our portfolio. Below is the net present value netted

over the portfolio of the first 100 paths out of the 10 000 paths presented.

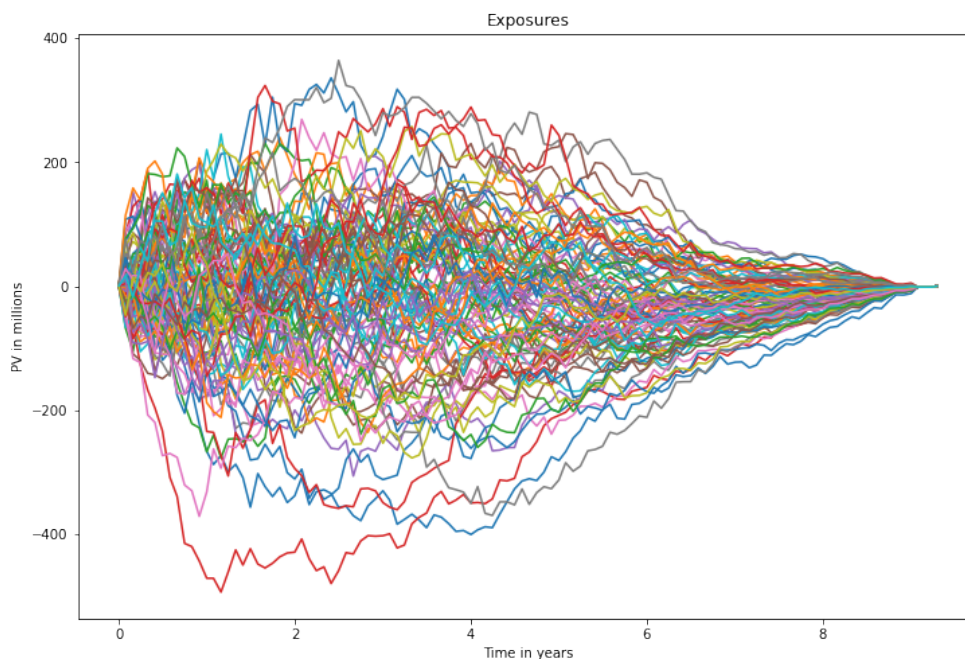


Figure 10: The figure present the first 100 paths of the netted calculated exposure for each trade based on the 10 000 simulated rates paths. The exposure is calculated for the entire portfolio that is presented in table 2. The exposures for each trade is netted over the portfolio. All graphs start at the present value of the portfolio presented in table 6 and then end after 10 years with a value of 0. The different graphs represent potential future market scenarios.

The netted present value for the portfolio is presented in the table below for the ± 24 bp stressed case and the non-stressed calibration.

Present Value	351 665
Present Value stressed with -24bp	44 015 597
Present Value stressed with +24bp	-36 554588

Table 6: Present Value of the portfolio.

Below the table over resulting EAD for the three IMM calculations and the SA-CCR model are presented. These results are for the entire portfolio, doing 10 000 simulations.

Model	Resulting EAD
SA-CCR	119 852 713
IMM	36 594 783
IMM Stressed -24bp	107 454 743
IMM Stressed +24bp	8 988 675

Table 7: The table present the resulting EAD for both SA-CCR and IMM for the entire portfolio presented in table 2. For the IMM we present the resulting EAD for calibration based on current market data and the stressed data. The values in bold are the values that we need to use in order to calculate the capital requirement later on.

In table 7 we see that the highest EAD is given by IMM calibrated on -24bp stressed input data, marked with bold text in the table. This is the resulting EAD we need to compare with the EAD from SA-CCR, also marked with bold text.

5.4 Backtesting

Further to validate our model for simulating interest rates we perform backtests. The backtesting is done on historical data of zero rates and spreads which is compared to the confidence interval from our simulated rate. The model is re-calibrated on the market data from the new evaluation date at every new simulation. We have picked plots from the backtesting for the following tenors and spreads.

$$\begin{aligned}
 \text{tenor} &= [7D, 3M, 6M, 5Y] \\
 \text{spread} &= [10Y - 5Y, 5Y - 6M]
 \end{aligned}$$

The data used for backtesting is around 3.5 years of historical data, ranging between December 2018 and April 2022. The number of data points per year is 250, since there is normally around 250 banking days per year, and therefore we in total have zero rates for approximately 840 dates. Since we validate the model every 10 days we will only be able to use 84 data points out of the dates from the dataset as validation.

5.4.1 Backtesting Zero Rate

The plots for the specified tenors for the three different confidence intervals, [75%, 95%, 99%], are presented below.

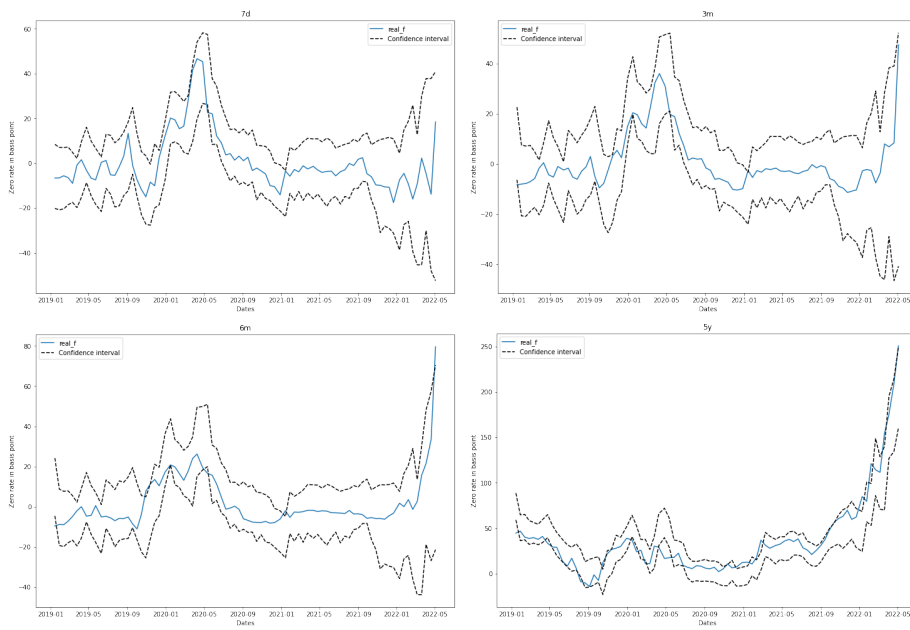


Figure 11: The plots show the backtest of the zero coupon rate with the tenors $[7D, 3M, 6M, 5Y]$ at 99% confidence level. The blue line is the realized zero coupon rate in basis points. The black dashed line represents the estimated 99% confidence interval.



Figure 12: The plots show the backtest of the zero coupon rate with the tenors $[7D, 3M, 6M, 5Y]$ at 95% confidence level. The blue line is the realized zero coupon rate in basis points. The black dashed line represents the estimated 95% confidence interval.

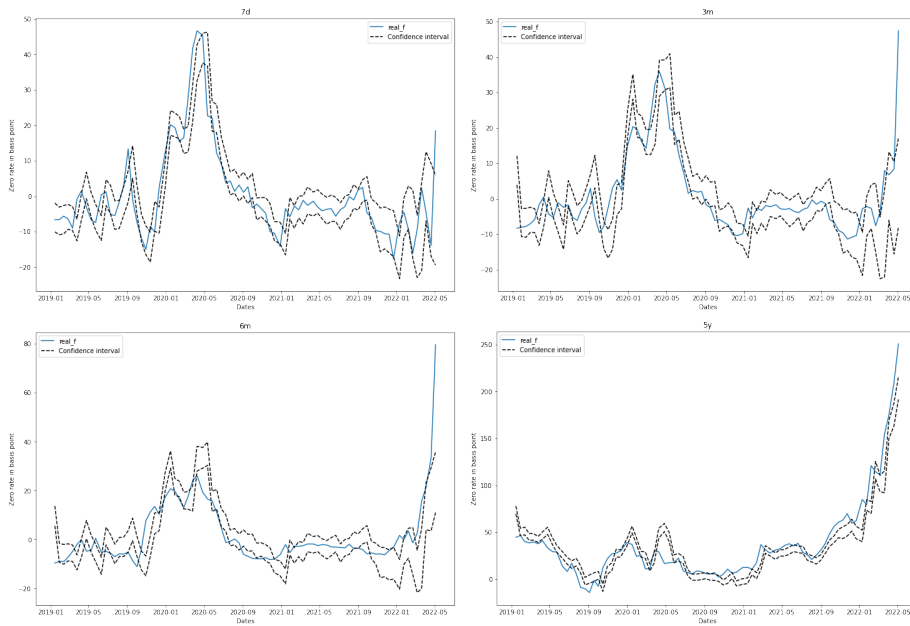


Figure 13: The plots show the backtest of the zero coupon rate with the tenors [7D, 3M, 6M, 5Y] at 75% confidence level. The blue line is the realized zero coupon rate in basis points. The black dashed line represents the estimated 75% confidence interval.

The number of exceptions from the confidence interval for the different confidence intervals for all tenors are presented below in the table.

	7D	2W	4W	2M	3M	6M	1Y	2Y	5Y	10Y
99%	1	2	2	2	3	7	7	16	21	28
95%	6	6	8	9	10	12	15	30	37	39
75%	28	29	28	29	31	39	45	54	57	63

Figure 14: The values in the table present the number of exceptions from the confidence interval for the specified confidence level and tenor. The color shows whether or not the number of deviations is accepted based on a binomial distribution of 84 data points.

If the cell in table 14 is green it means that the model were able to capture the realized zero rate in the specified confidence interval. Yellow cell means that we have more exceptions than expected from the distribution. The red cell implies that the number of exceptions is more than the given distribution allows us to have, given the confidence level. We see from the table 14 that we have only red cells for higher tenors. For the lower tenors we get fewer exceptions.

When comparing the traffic light table to the plots presented above, we see that we have some exceptions but they are spread apart from each other and they are not far from the estimated confidence interval. It seems to be able to follow the realized zero rate well but being a bit slow. Given a change in the

zero rate our model needs a few days to react to the given change. This causes some exceptions in the beginning of big fluctuations.

Comparing the figures 11, 12 and 13 for the different tenors we see that larger tenors such as '6M' and '5Y' seem to have more exceptions.

5.4.2 Backtesting Spread

Further we want to analyse how well our model can predict spreads. The specified spreads above are presented in plots below for the different confidence intervals.

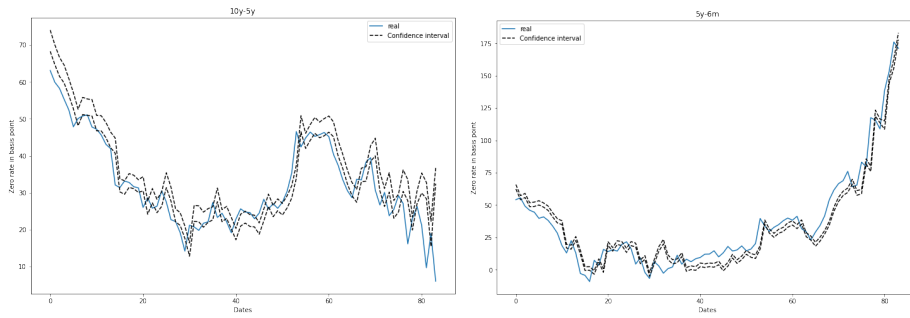


Figure 15: The plots show the backtest of spreads with the tenors $[10Y - 5Y, 5Y - 6M]$ at 99% confidence level. The blue line is the realized spread in basis points. The black dashed line represents the estimated 99% confidence interval.

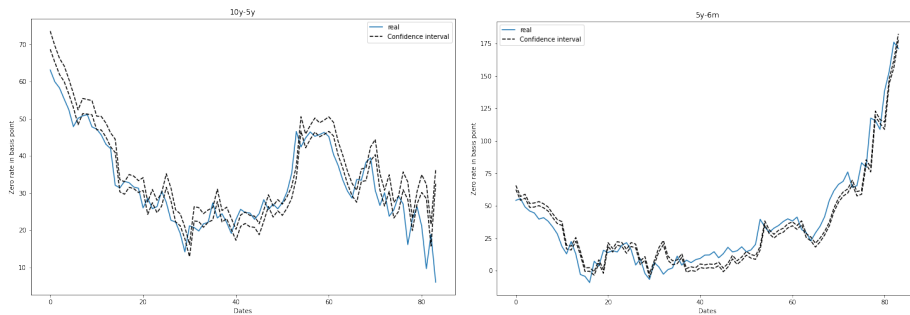


Figure 16: The plots show the backtest of spreads with the tenors $[10Y - 5Y, 5Y - 6M]$ at 95% confidence level. The blue line is the realized spread in basis points. The black dashed line represents the estimated 95% confidence interval.

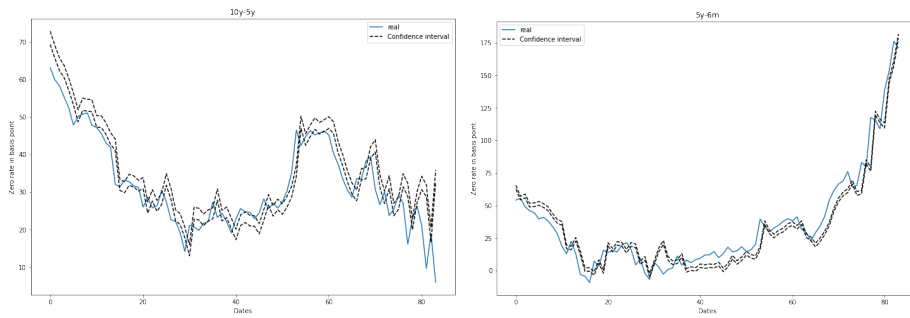


Figure 17: The plots show the backtest of spreads with the tenors $[10Y - 5Y, 5Y - 6M]$ at 75% confidence level. The blue line is the realized spread in basis points. The black dashed line represents the estimated 75% confidence interval.

The number of exceptions from the specified confidence interval for all different spread are presented below in the table.

	10Y-5Y	5Y-2Y	5Y-6M
99%	39	51	75
95%	41	54	75
75%	45	56	75

Figure 18: The values in the table present the number of exceptions from the confidence interval for the specified confidence level and spread-tenor. The color shows whether or not the number of deviations is accepted based on a binomial distribution of 84 data points.

We see that our model is substantially worse at handling spreads. This result is expected when using a one factor model and we will discuss this further in the discussion chapter of the report.

6 Discussion

6.1 Optimization of parameters

We have optimized the parameters using current implicit volatility data using a damped least square method. The resulting parameters seem to create good simulated rates. We want simulated rates that converge to our mean reversion as well as having a relatively high variance. The high variance is important to make sure that we capture the extremes. At the same time, we want realistic market scenarios that are likely to occur which implies that the variance cannot be too large either.

The speed of how fast the simulated path converges to the mean reversion, $\theta(t)$, is called the a parameter. A high a parameter will result in the simulated path quickly converging to the chosen term structure. This will cause our simulated rates to be close to each other and our ability to capture a wide range of future market scenarios will decrease.

The size of the deviation from one step to another is determined by the σ parameter. With a high σ value we can have large changes between the steps which will cause larger deviations from the chosen term structure. As mentioned above we do not want our simulations to have a too high variance, which means that both of our parameters should be quite small. Based on the resulting simulated rates in figure 6 we are pleased with the calibrated parameters. The simulated paths follow the mean reversion structure, but we still have some variance.

In reality we would calibrate the model using historical data so that our Hull-White process is analyzed under P-measure. The advantage of using a model under P-measure is that the model will variate less over time. This is because the current market fluctuations will be damped by adding historical data. Due to not using P-measure, our model will be more sensitive to current data. The reason for P-measure not being the risk measure used here is simply due to lack of time. As we will discuss in section 6.7, this is something that we would recommend to be done if one would continue this work further.

When comparing the plots for the simulated paths, both short rate and exposure, we need to be careful due to the fact that only the first 100 out of the 10 000 paths are shown in the figures. This means that we should only draw conclusions from the plots based on the overall appearance of the figures and not specific paths or extreme values.

Comparing the simulated short rates for both the stressed and non-stressed calibration we see that they look very similar. This follows from the Hull-White process being calibrated on the same implicit volatility data. The difference between the two cases is the mean reversion being shifted with ± 24 basis points. We can see the parallel shift in the mean reversion in the three figures for non-stress, figure 6, and stress calibrated, figure 7, figure 8. The difference in the figures are subtle and if we look at the calibrated parameters in table 3 we see again that the difference is very small.

6.2 Looking at EAD for the two models

The calculated present value for both the trade and the portfolio are very similar to the value that the Bank gets. The small change in the present value is due to differences in market data used in the calculations. Further in section 6.4 we will discuss the difference in data.

First comparing the EAD for one trade we see that the IMM gives a lower EAD than the SA-CCR does. The IMM gives a decrease in value at $\approx 36.75\%$. Worth noting here is that we do not look at stressed EAD for a single trade, so if doing so that could result in a higher EAD than what we are seeing right now. However, we can see a clear decrease in EAD when changing model, this is shown in the table below. Below the final EAD values are presented. These are the EAD we must use when calculating the capital requirement.

Model	One trade	Portfolio
IMM	49 539 399	107 454 743
SA-CCR	78 316 719	119 852 713

Table 8: The final EAD values that will be used for the different models.

Further we will compare the EAD for the portfolio. The scenario that gave the highest EAD, and is presented in the table above, is the IMM model calibrated on -24bp stressed input data. In all further calculations of capital requirements in this report it is the values presented in table 8 that will be used.

We see that using the IMM model would result in a $\approx 11\%$ decrease of EAD compared to what the SA-CCR gives for the portfolio. This is a substantial decrease considering the large amounts we are analysing. For this portfolio the Bank would approximately save 11% this quarter on a portfolio with a PV at approximately 350 000 SEK by changing model.

We have a portfolio that netted have a low PV. Following from this the portfolio has a relatively low exposure. One can see this as the portfolio being hedged compared to the one trade we began looking at that has a larger *PV*. This means that we have reduced the risk for the Bank by complementing the investment of derivatives with opposite stake, in this case IRS with negative PVs. The IMM model simulates possible market scenarios and analyze the exposure at the worst potential market scenario. This worst exposure is then increased with 40%, due to the α parameter, and this is our final EAD. This approach tailors the EAD to the specific underlying risk factors relevant to the portfolio. The SA-CCR model is a general template that is created to work on all types of derivatives. This model does not benefit large hedged portfolios. Our result is in line with the theory that an IMM model normally lower the capital requirements.

6.3 Backtesting

The purpose of backtesting is to show that our simulated rates manage to capture the actual rate, which we succeed with for shorter tenors. For longer tenors, longer than 6 months, our model seems to have narrow confidence intervals that do not manage to capture the realization. As mentioned in the result, the exceptions are not far outside of the confidence intervals. Further, the exceptions seem to be far apart which is a positive thing compared to if they would all have been at the same place. Even though we do have some exceptions, the plots presented in figure 11, 12 and 13 show a promising result.

Both the rates and spreads seem to have a delayed reaction to the changes in the market. We can see this by the confidence intervals being skewed to the right compared to the realization. This is normal and quite common that forecasts tend to be a bit behind real fluctuations. However, this could be caused by the a value being too high and the σ parameter being too low. A high value of a and a low value of σ will create a process that strongly follows the mean reversion. Our result may suggest that our process has a too strong mean reversion dependence. It may therefore be worth looking into altering the parameters a bit, by altering the calibration, for this reason.

The result from the spreads shows that our model is not good at capturing the realized spread. However, we were expecting this result since we are using a one factor model. To improve the result for the spreads one can consider a two factor Hull-White model or a time series model. Using for example a two factor Hull-White model instead could improve the fluctuations a bit, this would especially improve the result of the backtesting of the spreads.

The confidence intervals are very narrow, especially for the spreads, which we find to be a bit surprising. We suspect that we introduce noise into our simulation which dampens the variation between the different paths. We chose to calculate the variance of the noise for the spreads which has been added to the confidence interval, as we presented in the methodology. This increased the distance between the upper and lower limit. We still get poor results from the spreads which suggest that either we calculate the noise variance wrong, or the introduced noise was not the underlying issue.

Another aspect to take into consideration when evaluating backtesting is that the historic data used contain two stressed periods. From the data we can see two pronounced peaks at the beginning of 2020 and 2022 which corresponds to Covid-19 respectively the Russian invasion of Ukraine. It is more difficult to model and predict stressed periods which will have a substantial effect on the backtesting results and probably gives us more exceptions than if it would have been a "normal" period. The effect these stressed periods has can be seen by repeating the backtesting on data before the Covid-crash. Unfortunately, we did not have access to more data so we could not fully determine the effect of this.

6.4 The data used

Throughout the report we have used the 28th of February as our evaluation date, for all results reported above. The reason this specific date is used is solely because this is the day we first happened to get data for, and then we just continued using this date since. A date relatively far back in history was beneficial for us to use to make sure that we could present all the data without something being censured by the bank secrecy, but this specific date was just chosen at random. However, the choice of evaluation date should not affect the overall results noticeable since historical data and set rates are used etc.

We faced some challenges in obtaining the market data. We obtained two sets of data. At first, we got current market data for the chosen evaluation date. During the backtesting we used historical market data instead to be able to evaluate our model in the past. It is not routine for the Bank to access historical market data like this and therefore there were no previous methods for obtaining this. The historical data gathered from the Bank was compared against the data previously obtained, for the same date, and unfortunately they did not match.

When using the first dataset introduced, our simulated rate and PV corresponded with the Bank's result. In our model we need to use historical market data which caused our result to be different from the result from the Bank. To be able to compare and analyze the result we have only used the historical dataset in this report.

6.5 Potential sources of errors and simplifications

One of the major sources of errors found in our model is the use of Hull-White under risk neutral measures, Q-measure, instead of under P-measure. Doing the calculations under Q-measure results in the model to better follow current market changes. Because of this, our result would probably change if we used a P-measure model instead. The EAD could increase due to the P-measure not being able to follow market fluctuations as well.

The change of measurement would affect the backtesting as well. As we can see in figure 11, 12 and 13 our model follows the market fluctuations well. But it has got some delayed reactions to market fluctuations. This would probably become even worse when changing to P-measure.

As mentioned above the result presented in this report are not based on the same market data the Bank uses in their calculations. The valuation of the swaps and simulated zero rates are based on market data and because of this the results will be different depending on which data is used. This could be good to be aware of, but in this report, we are mainly interested in comparing the two models to each other and not the specific value so it should not affect the comparison of the two models too much.

Further some simplifications we made of the calculations are that we only looked at Interest Rate Swaps in SEK without any collateral agreements. This is one of the easier form of transactions from a calculation point of view. To further validate the results and compare the two models more thoroughly a wider range of transactions should be considered, including different types of transactions and for different currencies. If we would have had the time this would definitely have been one of the main aspects we would focus to expand the models for.

We did not look at any company specific netting agreements, instead we netted all counterparties by just summing the NPV for all trades. When backtesting for trades without collateral normally you would have a longer range of days than 10, which is what we have used now. But due to already a small number of data points the decision to use 10 days periods, which is normally used for secured transactions, were made for this case too. This is assumed to give a good enough validation anyway.

6.6 Fulfillment of purpose

As we expected, the IMM model gave a lower EAD than SA-CCR. We thought that we would get this outcome because IMM allows a more tailored risk measurement of the trading book. However, the IMM model is a more expensive approach for a financial institution to implement and uphold. Considering this cost, the decreased percentage of the capital held because of a change in methods, the cost of changing the method must be lower for this to really be cost efficient for the Bank. We believe that our results show promise of a lowered capital requirement and is worth further investigation.

During this project we have had some difficulties with python licenses and market data which delayed our implementation of the exposure calculations. The license for our computers supplied by the Bank could not install Quantlib, so the implementations has been done on our personal computers. Since the Bank's trading book, evaluation of counterparties, market predictions and a lot of other data are classified we have not been able to use that in our work. This meant that we needed to implement all methods from scratch. However, we have been able to compare some parts of the implementations such as the present value at the evaluation date and the simulated interest rates. On the original dataset our results have corresponded to the Bank's values. With the new historical dataset we see substantial differences in IMM.

6.7 Further research and improvements

For future work we would advise one to start by modifying the calibration method of the Hull-White process. We calibrate our model on current market data which does not fulfill the requirements of an IMM model, an IMM model needs to be calibrated on historical market data. Another aspect we would want to explore is looking at different models, other than Hull-White. A one-factor

Hull-White model is a simple model that only needs one input parameter. This limits the model's ability to correctly follow the zero rate. An alternative to a one-factor Hull-White process is a two-factor Hull-White, Cox-Ingersoll-Ross (CIR) model or a filter method such as a Nelson-Siegel term structure model.

With the new calibrated model we would analyze it by backtesting. Usually, we would not expect an improvement on the backtesting with a historical calibrated model. Neither would we expect an improvement for the spreads. Because of this, we decided to look at another method to model zero rates.

We looked at modelling the yield term structure using an arbitrage-free Nelson-Siegel term structure model that showed promise. The calibration was done with a Kalman filter where we updated the parameters based on minimizing a likelihood function. We adjust the functions to be under P-measure and add an adjustment term to make it arbitrage free. The calculations are based on the following article [14]. In the lack of time that was experienced we did not manage to analyze the model enough to present it as a result in this report.

Further, exposure calculations for different types of derivatives and currency modelling should be implemented. Adding a model for currency will introduce a new risk factor that will need to be evaluated with backtesting. These are necessary to evaluate the entire portfolio of the Bank.

As it is now, this model does not implement or take the wrong way risk into consideration in any way. This is a very important factor to consider, as described in the theory section above, so should this work be developed in the future this is something that we strongly advise to be done. As described, WWR can be represented through the stressed EPE calculation, or even through the choice of α parameter. But since all financial institutions, regardless of which capital requirement model is in use, should have procedures in place to identify and manage WWR, the lack of it in this report should not have a major impact on the decision of which model to use for the institute. However, since WWR can be represented through the stressed EPE calculation this may affect and give another result than the one presented in this report, should WWR be taken into consideration.

7 Conclusions

In the process of judging how trustworthy our built IMM model is, one of the tools used for this was backtesting. Since we chose to implement a simple short rate model, a one factor Hull-White model, we did not expect perfect result either. Looking at the plots of the confidence intervals our model seems to follow the real data quite well, there are no large deviations from the real dataset. Then, looking at the traffic light table the shorter tenors does perform quite well as predicted, and as assumed the longer tenors perform a bit worse because the longer into the future we get the harder it is to predict market fluctuations and movements.

The purpose of this project has been to see if an IMM model would lower the capital requirements of the Bank and therefore be a good investment for the Bank to start creating their own IMM model. This has been done by comparing this model with the SA-CCR one, currently used by the Bank today. Based on our result, our IMM model results in a lower EAD compared to the SA-CCR. The IMM model would decrease the EAD with approximately 11% for the entire portfolio and 36.75% for one trade. This result shows promise that our model can decrease the capital requirement for the Bank's portfolio, so based on these results we believe that changing model to an IMM model would be worth looking into.

We have concluded this report by some suggestions on how to improve and develop this work further. The major changes we would advise one to do is using a different, more precise, model for the simulation process and make sure that this is calibrated using historical data. In addition, using a bigger dataset would be beneficial since we have had to do a few adjustments due to a shortage of data points.

8 References

References

- [1] European Central Bank (ECB). *ECB guide to internal models*. URL: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.guidetointernalmodels_consolidated_201910~97fd49fb08.en.pdf. (accessed: 02.2022).
- [2] Tomas Björk. *Arbitrage Theory in Continuous Time, forth edition*. Great Clarendon Street, Oxford, OX2 6DP, United Kingdom: Oxford University, 2020.
- [3] GitHub user sa-ccr. *sa-ccr-python*. URL: <https://github.com/sa-ccr/sa-ccr-python>. (accessed: 02.2022).
- [4] Deloitte. *Capital management under the new standardised approach for counterparty credit risk*. (accessed: 01.2022).
- [5] EUR-Lex. *REGULATION (EU) No 648/2012 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 4 July 2012 on OTC derivatives, central counterparties and trade repositories*. URL: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32012R0648>. (accessed: 04.2022).
- [6] Finansinspektionen. *Kapitalkrav för svenska banker*. URL: <https://www.fi.se/sv/bank/kapitalkrav-for-svenska-banker/>. (accessed: 01.2022).
- [7] Patrick Graham. *30/360 vs Actual/360 vs Actual/365: Loan Accrual Calculations Explained*. URL: <https://propertymetrics.com/blog/30-360-vs-actual-360-vs-actual-365/>. (accessed: 03.2022).
- [8] Jon Gregory. *The xVA Challenge*. The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, United Kingdom: John Wiley Sons Ltd, 2015.
- [9] Law Insider. *Margined Transaction Definition*. URL: <https://www.lawinsider.com/dictionary/margined-transaction>. (accessed: 01.2022).
- [10] Finans Inspektionen. *Interna metoder för kapitaltäckning*. URL: <https://www.fi.se/sv/bank/sok-%20tillstand/bank%E2%80%933eller-finansieringsrorelse/interna-metoder-for-kapitaltackning/>. (accessed: 01.2022).
- [11] CFA Institute. *Financial Clearing Houses*. URL: <https://www.cfainstitute.org/en/advocacy/issues/central-clearing-houses#sort=%5C%40pubbrowsedate%5C%20descending>. (accessed: 05.2022).
- [12] Bank for International Settlements. *Calculation of RWA for credit risk*. URL: https://www.bis.org/basel_framework/chapter/CRE/50.htm. (accessed: 05.2022).
- [13] Bank for International Settlements. “The standardised approach for measuring counterparty credit risk exposures”. In: *Basel Committee on Banking Supervision* (2014).
- [14] Glenn D. Rudebusch Jens H. E. Christensen Francis X. Diebold. “The Affine Arbitrage-Free Class of Nelson-Siegel Term Structure Models”. In: *Journal of Econometrics* (2011).

- [15] Amir Khwaja. *SA-CCR: Standardised Approach Counterparty Credit Risk*. URL: <https://www.clarusft.com/sa-ccr-standardised-approach-counterparty-credit-risk/>. (accessed: 01.2022).
- [16] Yue-Kuen Kwok. *Mathematical Models of Financial Derivatives*. Department of Mathematics, Hong Kong University of Science Technology, Kowloon, PR China: Springer Berlin, Heidelberg, 2008.
- [17] Stephen J Nocedal Jorge; Wright. *Numerical Optimization (2nd ed.)* Springer, 2006.
- [18] THE EUROPEAN PARLIAMENT and THE COUNCIL OF THE EUROPEAN UNION. “REGULATION (EU) No 575/2013 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL”. In: *Official Journal of the European Union* 575 (2013).

9 Appendix

9.1 Table of supervisory factors

	Asset_Class	SubClass	Supervisory_factor	Correlation	Supervisory_option_volatility
1	IRD		0.50%	0	50%
2	FX		4.00%	0	15%
3	CreditSingle	AAA	0.38%	50%	100%
4	CreditSingle	AA	0.38%	50%	100%
5	CreditSingle	A	0.42%	50%	100%
6	CreditSingle	BBB	0.54%	50%	100%
7	CreditSingle	BB	1.06%	50%	100%
8	CreditSingle	B	1.60%	50%	100%
9	CreditSingle	CCC	6.00%	50%	100%
10	CreditIndex	IG	0.38%	80%	80%
11	CreditIndex	SG	1.06%	80%	80%
12	EQ		32%	50%	120%
13	EQIndex		20%	80%	75%
14	Commodity	Electricity	40%	40%	150%
15	Commodity	Oil/Gas	18%	40%	70%
16	Commodity	Metals	18%	40%	70%
17	Commodity	Agricultural	18%	40%	70%
18	Commodity	Other	18%	40%	70%
19					

[3]

10 Popular scientific summary

10.1 Comparing the two major models of capital requirements for financial institutions

In this work we have implemented and compared the two Basel III standard models of how to compute the capital requirement for financial institutions. These models being the Standardized Approach for Counterparty Credit Risk (SA-CCR) and the Internal Model Method (IMM). This work has been carried out working together with one of the major banks in Sweden, using their data and trades to obtain the results. The SA-CCR model is currently used by the Bank, and this model is seen as an easy way of calculating the capital requirement, but quite blunt. The IMM model offers more flexibility and is tailored to the Bank's trading portfolio, which means that potentially the usage of this model instead could save the Bank a sizeable amount of money. The result found was that the change of models could lower the capital requirement cost for the Bank by approximately 11 %.

The capital requirement means the amount of capital the institution is required to hold based on the counterparty credit risk. The counterparty credit risk meaning how large the exposure is towards the counterparty and how much risk the counterparty implies.

Since the IMM model enables more flexibility, it also comes with a great deal of responsibility and guidelines to follow. One of these is to backtest the model, which means that one uses historical data to predict the interest rate a certain time period into the future, and then compare this prediction with the actual value of that day. This shows how accurate the model created is, and therefore strengthens the result.

This work was done upon request of the Bank, to do a first investigation of if the change of methods would be beneficial for the Bank and something worth further looking into. This could potentially mean a lot of money saved by the Bank, money that would not be tied up and instead could be invested and hopefully lead to a more prosperous Bank.

References on how to implement an IMM model has been difficult to find, these models are as mentioned above quite closely linked to the transactions of the portfolio and therefore confidential information most of the times. This report can therefore be seen as a brief introduction on how to implement an IMM model, and important aspects to consider.