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Attributing changes in CVA risk capital charge for OTC derivatives portfolio

Final report

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Glossary

basis point A percent of a percent (10^{-4}) which is a commonly used unit in finance when bonds are involved.

credit spread The difference of the credit level between an investment and a highly stable bond such as US government bonds.

Credit Valuation Adjustment (CVA) The market value of the counterparty credit risk.

CVA risk CVA risk measures the amount of capital a party has to have set aside due to regulation for preparation in case a counterparty defaults.

derivative A finance product that derives its price from some other product or rate.

exposure In finance field exposure indicates how much a contract is exposed if it ceases to exist.

hedging Hedging is done to protect investments by investing in another product that negatively correlates with the original asset.

maturity Contracts are formed for a certain time period, and the end period is called maturity.

OTC Over-The-Counter derivatives are not publicly traded, instead two parties make the deal between themselves.

portfolio In finance a portfolio consists of all the different contracts or investments made by an institution or individual.

tenor Indicates how much time is left to maturity.

underlying asset Underlying assets are the assets upon which a derivative's price is based.

vanilla derivative A plain derivative with no exotic features such as an interest rate swap or a foreign exchange swap.

1 Introduction

Our client is the financial services arm of a large bank. Like all its institutional peers, our client holds an ongoing portfolio of contracts directly negotiated and signed with other financial institutions or entities. Because these contracts are not undertaken through an exchange such as New York Stock Exchange or NASDAQ, they are called over-the counter (OTC) derivatives. OTC derivatives comprise a nearly 500,000 billion USD market [1].

To motivate these contracts, consider the following example. A bank has given a loan to an individual. In this market banks have to offer these loans at an interest rate which varies with the Euribor[1]. To eliminate the varying income from the varying interest, the bank wants to form a contract with another bank, such that it takes the risk from the varying interest rates. The banks form an interest rate swap, in which the other bank pays a fixed amount of cash to the original bank and it pays the varying interest to the other bank. A derivative portfolio consists of contracts such as the interest rate swap and other derivatives.

Each contract remains valid until maturity or if one of the parties involved with the contract goes bankrupt. Thus, there exists a counterparty credit risk that is calculated from the value of the contract, that is how much the contract benefits its owner. This value is called exposure. Since it is impossible to certainly predict the exposure, the expected exposure (EE) is used by simulating different scenarios where the underlying asset asset of the contract faces different situations. Taking the average of the positive simulations forms the EE curves, where curve describes the expected exposure through time. The expected exposure is used to calculate the market value of the counterparty credit risk. This is called Credit Valuation Adjustment (CVA). CVA is subtracted from the value of the contract, i.e. its price decreases.

In finance, there is plenty of regulation. Most of the regulation is formed to give boundaries to financial institutions in order not to limit the possibilities of taking advantage of the markets. One of these boundaries is capital charge, where each financial institution is required to have a certain amount of capital for worst case scenarios. Further to Financial Crisis, the required capital has increased drastically since 2008. CVA risk is used to calculate the amount of capital required to reserve when making contracts to account for that contract's counterparty credit risk. There are many alternate

[1] The Euro Interbank Offered Rate (Euribor) is a daily reference rate, published by the European Money Markets Institute, based on the averaged interest rates at which Eurozone banks offer to lend unsecured funds to other banks in the euro wholesale money market (or interbank market).

ways allowed by the regulations for banks to calculate the risk capital charge and there are many allowances for a bank to avoid holding certain portions of the capital by buying hedging investments or protections, such as other OTC trades. Because banks would rather be making more loans and investments, they do not want to hold more capital than is necessary (or regulated) for CVA risk. When the need for CVA capital goes up between one assessment date and the next, the bank would want to know what changes in market factors (e.g. interest rates, FX rates, credit spreads) accompany the rise in CVA risk capital charge. [2]-[6]

Like most banks, our client wants to attribute rises in CVA risk capital charge to market factors. At the current state, our client has practices of executing this with a top-down manner. In this project, a bottom-up method is developed by calculating the CVA risk changes at a single-counterparty level with different portfolios. The proposed model can estimate the impact of market factors on vanilla derivative portfolios. Its implementation as a software script returns visual representations and a choice for numerical outputs. The model is implemented with Python as a Jupyter Notebook. The client can further use it, develop it or extend it as required.

2 Literature review

2.1 CVA risk

The calculations associated with CVA risk are guided by the existing regulations and the interpretations of those regulations in banks. In EU Basel I-IV legislation controls a vast array of financial markets. The most important one with regards to CVA, Basel III, states that all financial institutions must reserve capital proportional to the size and riskiness of the investment portfolio they hold. The history behind this development is fairly recent, as it was not until the Financial Crisis when agents in the financial markets realized that there are a number of risks that were not accounted for, nor was the impact of the realized risks sufficiently accounted for. New legislation was established to prevent such major events occurring. Among the new legislation is Basel III, which is a framework on how to calculate the capital charge through expected exposure, but gives room for interpretation. The client provided equations they use internally, which were implemented in the model later. [2]-[4]

The regulatory postulated CVA formula is of form

$$CVA = LGD_{MKT} \sum_{i=1}^{T} \max\left\{0, \exp\left(-\frac{s_{i-1}t_{i-1}}{LGD_{MKT}}\right) - \exp\left(-\frac{s_i t_i}{LGD_{MKT}}\right)\right\} \frac{EE_{i-1}D_{i-1} + EE_i D_i}{2}, \tag{1}$$

where LGD_{MKT} is loss given default that is market implied, s_i is credit spread at tenor i, t_i is time to maturity at tenor i, EE_i is expected exposure at tenor i and D_i is the default discount factor at tenor i [7]. Credit spread, i.e. the difference of the credit level of the examined instrument and some practically risk-free investment such as an US government bond, is calculated for each contract and for each tenor.

Our client uses an approved internal method for calculating the specific risk of contracts. Differentiating equation 1 with respect to credit spread yields the first order sensitivities for credit spread movements which are of form

$$\textbf{\textit{Regulatory CS01}}_i = 10^{-4} t_i \exp\left(-\frac{s_i t_i}{LGD_{MKT}}\right) \frac{EE_{i-1}D_{i-1} - EE_{i+1}D_{i+1}}{2} \tag{2}$$

$$\textbf{\textit{Regulatory CS01}}_{\mathrm{T}} = 10^{-4} t_{\mathrm{T}} \exp\left(-\frac{s_{\mathrm{T}} t_{\mathrm{T}}}{LGD_{MKT}}\right) \frac{EE_{\mathrm{T}-1}D_{\mathrm{T}-1} + EE_{\mathrm{T}} D_{\mathrm{T}}}{2}, \tag{3}$$

where CS01 stands for credit spread sensitivity for a change of one basis point and T is maturity. Together with the sensitivities and the credit spread shifts it is possible to calculate normal and stressed value at risk (VaR) which are used to finally calculate the required capital. The approximated VaR with a 99% confidence is calculated from the average of the worst t_1 scenarios from the last two years where t_1 is some number of days based on the market conditions. The formula is of form

$$\text{VaR} = -\sqrt{10}\frac{\sum_i^{t_1}\left(\text{CS01}\cdot\text{shift}\right)}{t_1}, \tag{4}$$

where $\sqrt{10}$ comes from an additional assumption regarding the approximation of VaR. Stressed VaR is simply calculated from the average of the worst t_2 scenarios from the Financial Crisis where $t_2 < t_1$. Finally, the capital reserved for CVA risk is calculated as

$$K = \alpha\left(\text{VaR} + \text{stressed VaR}\right), \tag{5}$$

where α is a client specific coefficient that is updated from time to time based on the market situation. The actual true capital reserved for CVA risk is calculated as an average of K over sixty banking dates.

Figure 1 shows a management framework for calculating the risk capital. This framework guided the final methods used to create the model. In the end, the step from MC simulation Engine to EPE (expected exposure) was executed by the client. In addition, the correlation structure was left out, because it was difficult to estimate.

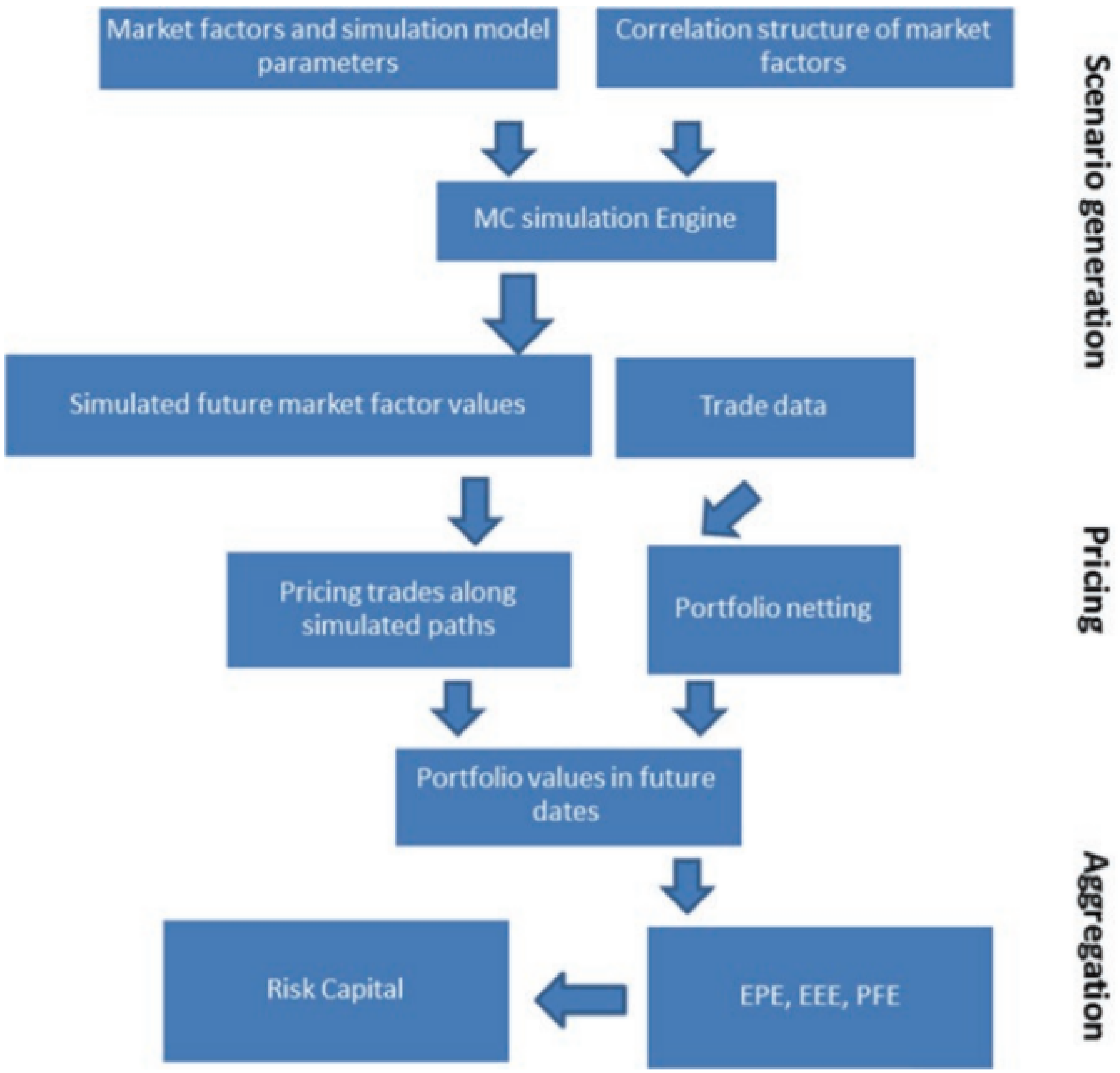

Figure 1: Three components - scenario generation, pricing and aggregation - in the counterparty risk management framework. [8]

2.2 Methods

The attribution of observed changes in a system's output to its inputs and other possible drivers is a problem not unique to our setting or even finance. The world is full of complex systems ranging from the climate to computer programs which produce more or less significant outputs, values, or measures that are changing. People want to understand what causes said changes. Thus, numerous methods have been developed to solve such problems. Most of these methods fall under sensitivity analysis, which is the study of how the uncertainty in the output of a model can be divided to different sources of uncertainty in the model input [9]. In our setting the uncertainty in the output is the changes in the CVA risk and the different sources of uncertainty in the model input are the market factors and shifts.

A very simple, straight-forward method is the one-at-a-time sensitivity analysis. It is one of the most common approaches to sensitivity analysis, the basic idea of which is that by changing one of the input factors at a time it is possible to observe what are the effects to the output. The problem of one-at-a-time sensitivity analysis is that it does not explore the input-space extensively, because it does not consider the simultaneous variation of the inputs. This means that the method cannot detect the presence of interactions between input variables [10]. Thus, one-at-a-time sensitivity analysis is effective when running the calculations is cheap, there is a limited number of inputs or possible drivers of changes in output, and when the combined effects of the drivers are limited.

A more sophisticated, analytic solution could be obtained through adjoint algorithmic differentiation (AAD). Shortly, AAD is a method that relies on the fact that any operation conducted by a computer eventually boils down to a chain of finite set of elementary operations, and can thus be differentiated using the chain rule over and over again. Algorithmic differentiation (AD) has two basic modes, forward and reverse, sometimes referred to as tangent linear and adjoint mode respectively. AAD is the reverse mode of AD, and is useful for calculating the sensitivities of a small number of outputs with respect to a large number of input parameters, while the forward mode would be useful in the opposite case [11]. The backpropagation of errors in neural networks is a special case of the reverse mode of AAD applied in machine learning [12].

While only recently picked up by the field of computational finance, AD has been successfully employed in the last 30 years in many other fields, such as computational fluid dynamics, meteorology and atmospheric sciences. Comparing to more traditional methods for computing sensitivities, AAD has two concrete advantages: reducing computational time and increasing accuracy. With AAD, the output's sensitivities to the inputs can be calculated in a single pass up to machine precision [11].

In our literature review, we did not find any established or suggested methods for solving the problem in this project. However, we found out that a financial calculation software company has actually offered a ready-made solution to our client for exactly the problem that our project is about. This solution is said to be based on AAD which suggests that it would be a suitable method for solving the problem, although no guarantees or information about the performance of the offered product were presented in the marketing material we saw. Unfortunately, using AAD to solve the problem would require source-code level access and understanding of the very calculation engine used by our client to produce the Monte-Carlo simulations, and translation of the said operations to be conducted with a library that would support applying the chain rule over the operations. Thus, AAD is mentioned as a suggestion for a more sophisticated method for solving the problem, but it was not in the project.

3 Data & Methods

To begin with building a proper framework and actual implementation the client provided a data set concerning a single-counterparty portfolio of vanilla derivatives with a CVA risk level of few hundreds of thousands of euros. During the development, the data set was pruned of unnecessary data such as information about the exact contents of the portfolio and augmented with additional necessary information such as longer historical data into the history to account for the CVA risk being calculated from the total value at risk estimations of the previous 60 banking dates. This iterative process was found very useful as it provided us with insights of the data that is actually relevant for our framework, and also how we should mold the framework to work with the available data.

The initial data set also contained the clients representative's replications of the calculations from their internal documentation needed to calculate the CVA risk from simulated expected exposure curves for a one-month time period in January and February of 2019. This information was added as a reference for constructing our own calculations as it seemed that although we were calculating everything according to the provided documentation, we could not reproduce the clients in-house calculations results. Unfortunately, these calculations could not be accurately matched either. Our reproduction of the value at risk calculations tend to fall somewhere between the true results and the clients representative's replications.

Upon reaching a state with a functioning framework and implementation, the client provided a new data set with four single-counterparty portfolios of vanilla derivatives, first of which was the same portfolio as in the initial data set. The three other portfolios had CVA risk levels in the range of one to three hundred thousand euros, and smaller daily changes in the CVA risk than the first portfolio. For these portfolios the following data was needed and provided:

- True daily CVA risk values for reference.
- True daily VaR and stressed VaR values for reference.
- The averaging period banking dates over which the CVA risk is calculated each day.
- Spread curves for each of the portfolios.
- The daily shift scenarios that were used in the true calculations.

- Simulated daily expected exposure curves for various scenarios.
- Shifts associated with all of the daily shift scenarios that were used in the true calculations.
- Projections for translating many of the above mentioned data onto same time grid.

This data was provided for the time period between the end of October 2018 and the middle of April 2019, with exact time periods varying a bit between the portfolios. This window would enable calculations starting around the beginning of 2019. Most data is true real-life data, with the exception of the additional scenarios used to identify the market factors' effects in the CVA risk. However, these scenarios come from the same calculation engine that is used to produce the real-life data.

The method selected for attributing the changes in CVA risk is one-factor-at-a-time sensitivity analysis. As the name implies, this method is based on changing one of the assumed drivers of change at a time and observing the changes in the output. This framework for the analysis is visualised in Figure 2. In short, our framework is based on going through full re-evaluation of the CVA risk calculation for each of the drivers we are interested in, and observing the changes in the results. Next, the framework is explained in detail.

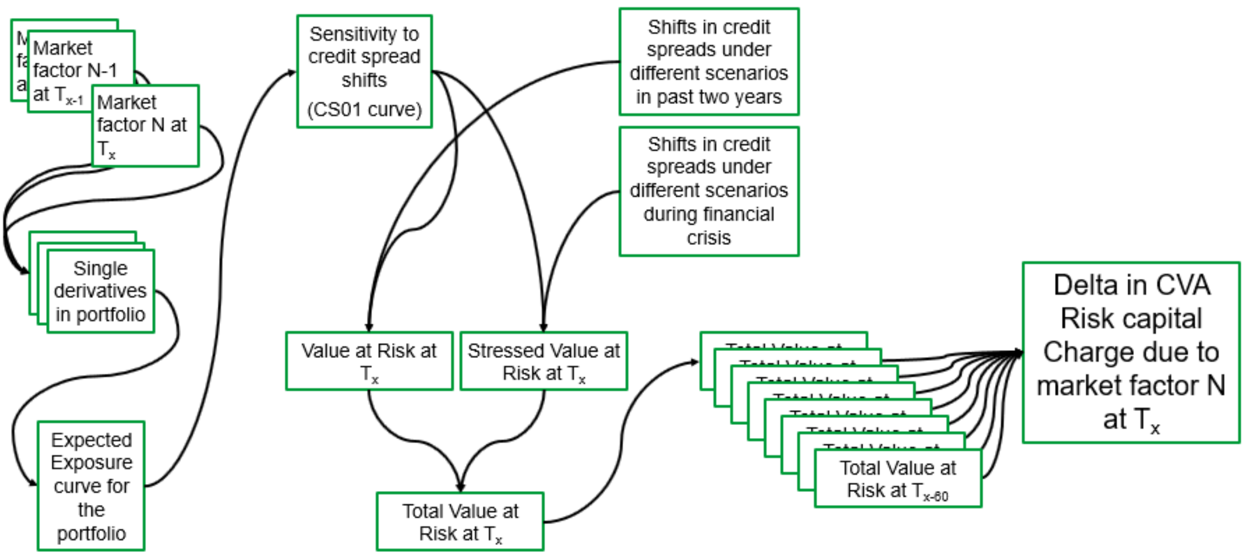

Figure 2: The calculation framework to identify the effects of market factors in the change of CVA risk.

As shown in Figure 1, the calculation of the CVA risk begins from the market factors, from which our analysis seeks to identify relevant drivers. At first, we thought about identifying these through observing the contents of portfolios, but ended up using our clients expertise instead to decide which factors will be taken into account.

After selecting the possible drivers, the Monte-Carlo simulation is conducted multiple times with two types of mixtures of market factor and portfolio content data from time T_x and T_{x-1}. The first type is a Base-scenario, where all of the market factor data is from T_{x-1}, and the portfolio contents are from T_x. This scenario is used to determine the effects of the changes in portfolio contents. The second type is a Market-factor-scenario, where all of the market factor data except one is from T_{x-1}, and the portfolio contents and the single market factor are from T_x. The difference of these second type mixtures and the Base-scenario is used to identify the effect of these market factors' changes. Additionally the Production-scenarios where all of the market factor data and the portfolio contents are from T_x are needed.

After simulating the mixture scenarios, the resulting expected exposure curves are given as input to re-evaluations of the value at risk calculation. From each scenario's simulated expected exposure curve, the value at risk measure is calculated according to the formulas in Section 2 using the shift scenarios from T_{x-1} to separate the effects of the market factors' changes and changes in shift scenarios used. To observe the combined effects of the market factors and the possible effects of left out market factors the Production-scenario where all of the market factor data and the portfolio contents are from T_x is also calculated with the shift scenarios of T_{x-1}. The changing shift scenarios effect is identified by calculating the Production-scenario where all of the market factor data and the portfolio contents are from T_{x-1} with the shift scenarios of T_x. The Production-scenarios with their correct shift scenarios are also calculated to observe the differences of our calculations and the real results. By comparing the resulting total value at risk values to each other, we obtain the attribution of change in the total value at risk between subsequent dates for the selected market factors, their combined effects, the shifts, and the combined effects of the shifts and all of the market factors. The "combined" effects will possibly also contain some unidentified drivers of change.

Now, comparing the CVA risks of two subsequent dates one must observe that the actual difference is created only by the difference of total value at risk between the furthest date into history used to calculate the CVA risk of the first date, which we will denote by T_t, and the newest date used to calculate the CVA risk for the second date, which we will denote by T_s. All other dates (excluding a few exceptions) in the averaging periods are equal and thus do not affect the change of CVA risk between the two dates. To obtain attribution for the change of CVA risks between the two subsequent dates the attributions of changes in the total value at risk are summed between T_t and T_s.

The implemented tool is written for attributing changes in a single single-counterparty portfolio's CVA risk to market factors and changes in the shift scenarios used. This same framework can potentially be used also in multiple-counterparty portfolios and over multiple portfolios, as the effects can be simply summed over the counterparties and portfolios.

4 Results

The main result of this project is the framework developed for attributing changes in CVA risk to various drivers. The concrete result is this report and a Jupyter Notebook where the parts of the framework after the Monte-Carlo simulations are implemented, that is to be delivered to the client. In this section we consider mostly the results from the calculations of the Jupyter Notebook.

Although the clients documentation and the provided replications of the documented calculations were thoroughly scrutinized, neither the true or the replication value at risk values could be exactly matched. The differences of our calculations to the real and replicated values were observed for 46 banking dates between 15th November 2018 and 12th February 2019 for the largest portfolio of counterparty 1 and means and medians of the relative errors were calculated. These measures are shown in Table 4.

Relative error	Real			Replication		
	VaR	SVaR	Total	VaR	SVaR	Total
MEAN	0,323	0,018	0,028	0,011	0,015	0,014
MEDIAN	0,318	0,015	0,030	0,007	0,014	0,013

Table 1: The mean and median proportional errors of our VaR and stressed VaR calculations (eq. 4) comparing to the true and clients replication values. The errors are calculated for 46 dates between 15.11.2018 and 12.2.2019 for the portfolio with counterparty 1.

These errors in VaR calculations are not directly translated into the attribution of changes in CVA risk, because these changes come from the differences of the VaR values between dates, not from the actual VaR values. To estimate the ability of our implementation to explain the changes, attributions for each one banking day step between 13th January and 14th February were calculated and compared to the changes in real and replicated CVA risk values of the portfolio with counterparty 1. This comparison is shown in Table 4. The values in the column "Attributed" are the summed effects of all drivers except "ReEvaluationError".

Change in CVA	Risk			
Official	Replicated	Attributed	Official not attributed	Replication not attributed
15 741	15 451	15433	1,96 %	0,12 %
15 401	15 258	15198	1,32 %	0,39 %
15 740	15 601	15619	0,77 %	0,12 %
15 925	15 652	15451	2,97 %	1,28 %
15 799	15 556	15228	3,61 %	2,11 %
15 549	15 310	15104	2,86 %	1,35 %
15 144	14 977	15070	0,48 %	0,62 %
15 454	15 289	15300	1,00 %	0,07 %
15 315	15 167	15318	0,02 %	0,99 %
15 723	15 511	15314	2,60 %	1,27 %
15 563	15 378	15335	1,46 %	0,28 %
3 896	3 563	3513	9,81 %	1,39 %
3 840	3 454	3669	4,47 %	6,20 %
3 820	3 499	3557	6,88 %	1,67 %
1 387	1 553	1525	9,91 %	1,84 %
1 258	1 383	1505	19,56 %	8,81 %
1 329	1 408	1363	2,61 %	3,18 %
4 193	3 727	3944	5,93 %	5,82 %
4 247	3 761	4059	4,43 %	7,93 %
4 872	4 224	4428	9,12 %	4,81 %
4 718	4 138	4197	11,03 %	1,45 %
4 950	4 230	4266	13,82 %	0,85 %
4 988	4 141	3983	20,15 %	3,83 %
4 502	3 798	3853	14,42 %	1,46 %
		MEAN	6,30 %	2,41 %
		MEDIAN	4,43 %	1,45 %

Table 2: The real, replicated, and attributed changes in CVA risk and the percentages of the real and replicated changes that were not explained. These values are from between 13.01.2019 and 14.02.2019 for the portfolio with counterparty 1.

The actual output of the implemented tool is an easy-to-read waterfall chart depicting the changes in the CVA risk attributed to each of the drivers. These charts with attributions between 11th and 15th March 2019 are shown for each of the provided portfolios in Figures 3,4,5, and 6. As may be observed from the figures, the key drivers of the change in CVA risk and their effects quantity can be easily observed from the charts. The most important observation is the relatively small attributions to the drivers "MarketCombined" and "MarketAndShiftsCombined", which contain the combined effects of the different market factors and combined effects of the market factors and the shifts, respectively. In addition, "MarketCombined" contains the effects of all the market factors without specific attribution and other inputs to the Monte-Carlo simulations. In addition to the combined effects of the market factors and shifts, "MarketAndShiftsCombined" will also contain the effects of any unidentified drivers which affect the calculations in the framework after the Monte-Carlo simulations of the expected exposure curves. "ReEvaluationError" is the difference of the changes in our calculations and the real changes in the CVA risk. There are more charts produced by the tool from different time periods in the Appendices.

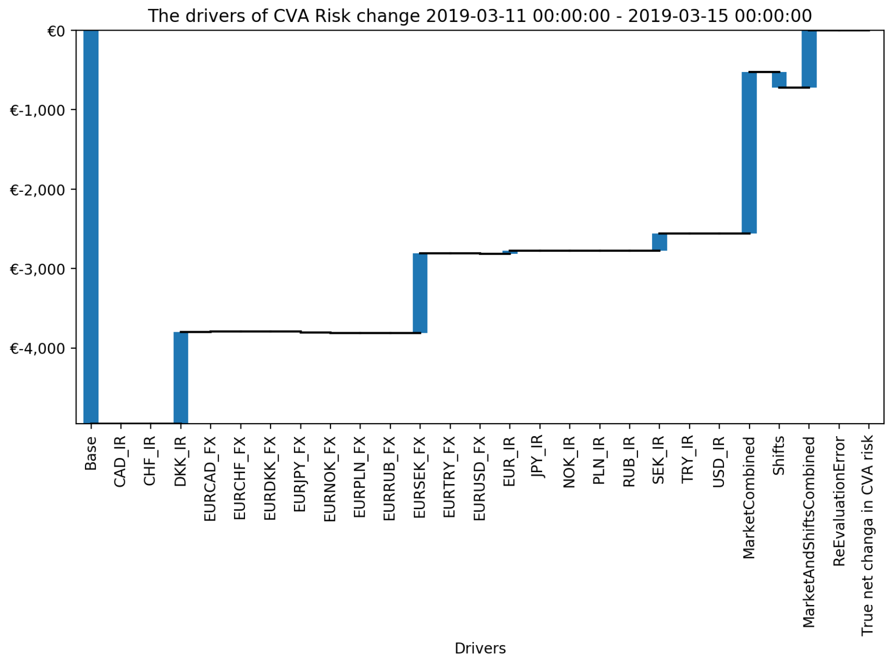

Figure 3: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 1. The bars represent the impact of drivers on the total CVA risk change, which in this case is roughly -5000 euros for base.

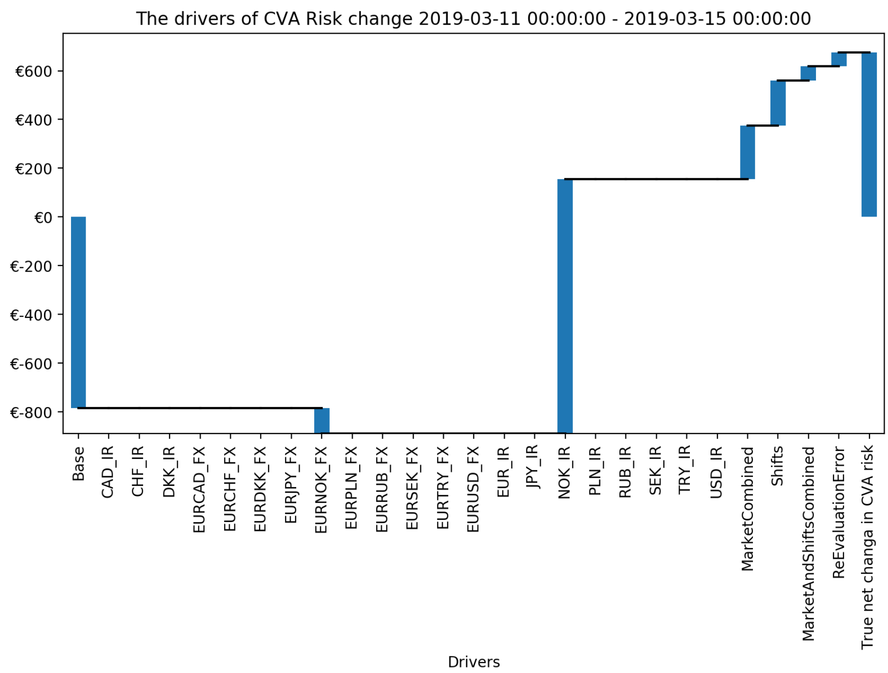

Figure 4: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 2.

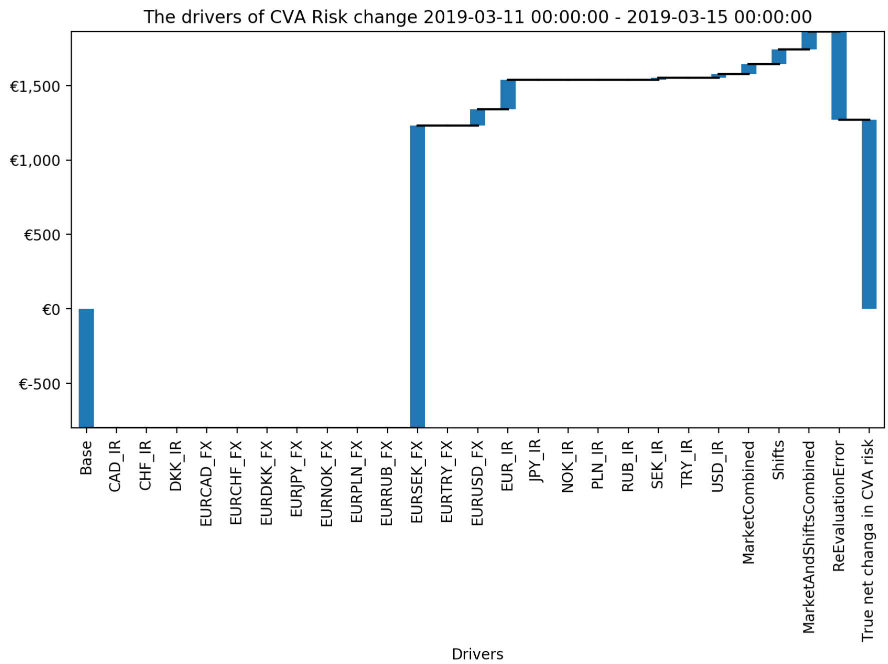

Figure 5: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 3.

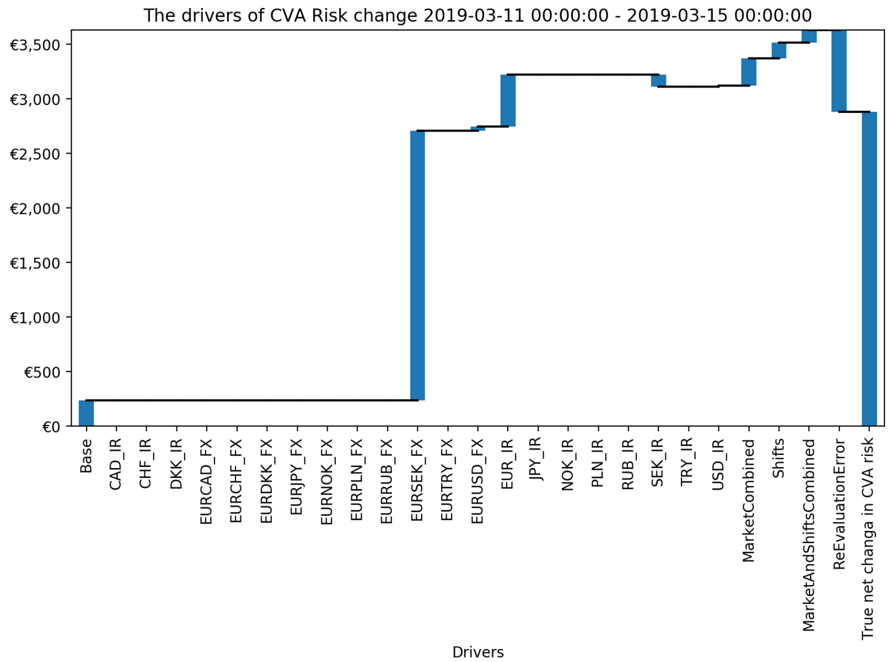

Figure 6: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 4.

The unfortunate shortfall of the tool and the framework at this point is that they only function in "normal" cases. The insight gained from the four portfolios provided by the client is that the special and exceptional case are quite frequent. The framework for attributing the changes in CVA risk between consecutive days as it is now defined is based on summing the effects on VaR of each of the drivers over the period from the day "leaving" the 60 day averaging period and the new date "entering" the averaging window. Problems arise when there are shorter periods within that period that have been - for one reason or another - left out of the official calculations. The attribution scheme is ill-equipped to handle the situation in which we do not have the shifts, or the expected exposure curves for the previous date. Just about the whole change in the VaR will be attributed to "Base" and "MarketAndShiftsCombined" drivers in such case.

5 Conclusions

The output of the project, i.e. the tool produces estimates for the impact of market factors on CVA risk. It works well with simple and coherent portfolios containing vanilla derivatives and having the input data listed in Section 3 available. The results are within reasonable limits and are realistic in a sense where changes in a certain factor also contribute to the change in CVA risk. In terms of the output of the project, the most positive result is the small attributions to the combined effects that we seem to obtain. The combined effects also include the effects of the non-recognized drivers of change, the effects of which can now be assumed small. The framework functions well for the basic cases where the averaging period is well defined and there is no out-of-calculation dates.

The literature around the subject is on the one hand abundant and on the other hand meager. Since CVA risk calculations are regulated, there is plenty of material on the subject such as Basel III regulation. Additionally, while there is literature calculating CVA risk from market factor changes, this did not bring value as it was not applicable in our client's case. Interpreting the regulations has lead to many assumptions and approximations in the official equations that are used with our client. With this in mind, our model appears to be an appropriate and sufficient approach. The best practice in this project was to rely heavily on the internal memo that was given at the beginning of the project. Nonetheless, the effort in studying the literature was not in vain as it orientated the team into the subject.

A problem with the gained results, however, is that at the moment there are not any relevant benchmark numbers to compare the results with. It is difficult to interpret how accurate the output is, because this requires relevant knowledge and experience in the field. In addition, it proved hard to come up with a method to verify the results. As the output was compared to the production value which came from the client, the difference between them was simply marked as re-evaluation error. This exposes the model for a risk where the possible error is oversimplified and the given output is taken for granted. This error is purely based on the differences of the VaR calculations that we have tried to reproduce based on the clients documentation and example replications, and should be possible to be removed from the results by finding the differences to their computations in our calculations if the client wishes to further develop the tool. On the other hand, the combined effect of cross-correlated market factors proved to be quite limited. This finding gained support from the client's side as experts in the field have found the combined effects to be minimal.

Another issue with regards the confidence of the model originates from the existing data that is used. The data includes numerous different dates related to the calculations and in some cases there are gaps between the dates. Either the data is corrupted or the dates in question have not been measured for some of the values. In any case this has the possibility to lead into situations where market factors move, but the CVA risk does not change. The model cannot handle reliably these special cases and insufficient data conditions.

The tool needs further scrutiny, improvements and development. As an experiment, it could be worthwhile to modify the framework so that instead of simulating the EE curves based on mixtures of the market factors from the last banking day and the current, the mixture would be created from data of the date leaving the 60 day averaging window that is used to calculate the CVA risk and the new date entering the window. This could eliminate the need of calculating the VaR change attributions for each date between the leaving and entering dates. Also, the calculations should be scrutinized to discard any possible errors or to correct them to reflect the actual production values' computation. As with the choice of the market variables in calculating the attributions, an expert could make a heuristic approach on determining which variables are relevant, instead of using said expert to personally evaluate each portfolio for relevant drivers. It could lead into a lighter and faster model with less noise to filter while interpreting the results. Another quite obvious addition would be the ability to increase the amount of drivers the model recognizes and calculates the CVA risk attribution for. Finally, identifying and verifying the correct behaviour or attribution in the problematic situation where there are gaps with the scenario data could result in a more reliable outcome.

To summarize, the project was a success in a sense that the outcome was desirable and acts as the first steps on calculating a bottom-up approach on the attribution of CVA risk changes to market factors. The results appeared to be reasonable and can be used as future reference when developing new methods or further iterating this one as long as the above remarks are noted.

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A Additional results

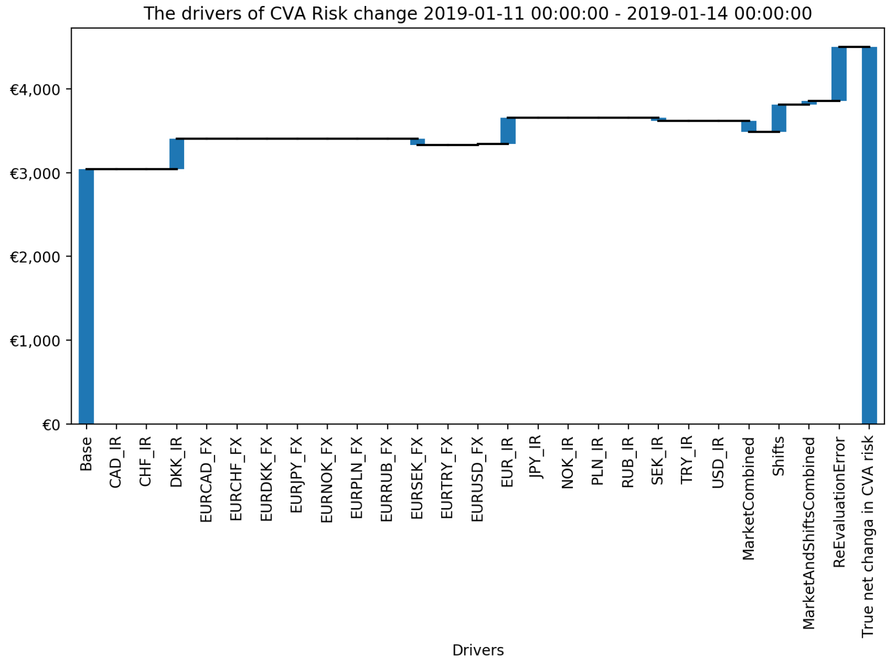

Figure 7: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 1.

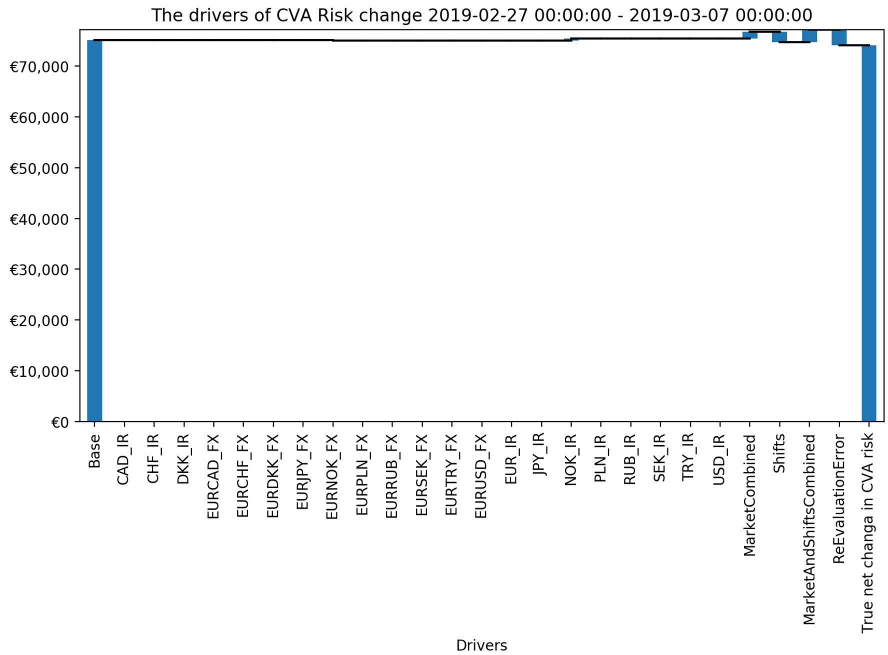

Figure 8: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 2.

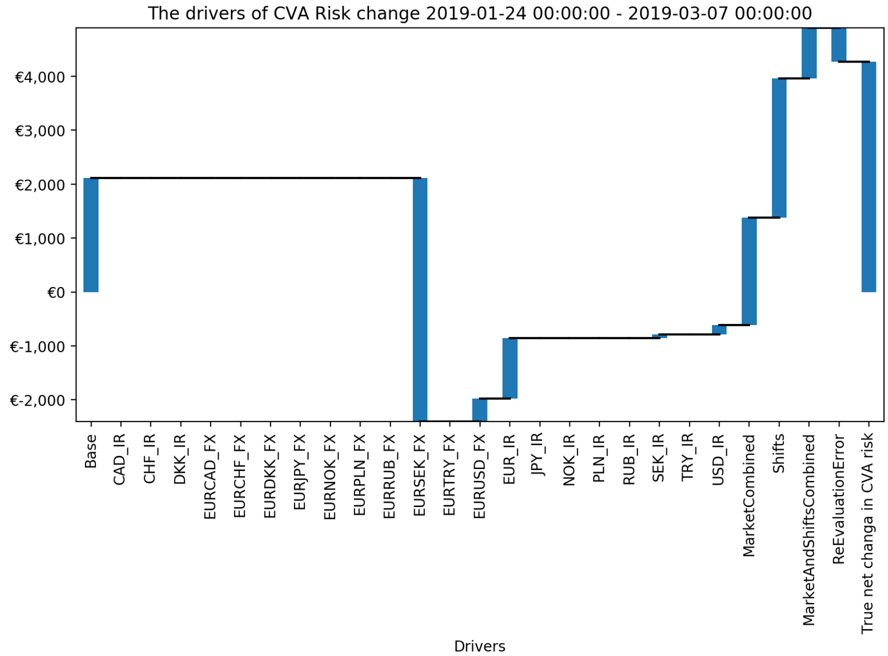

Figure 9: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 3.

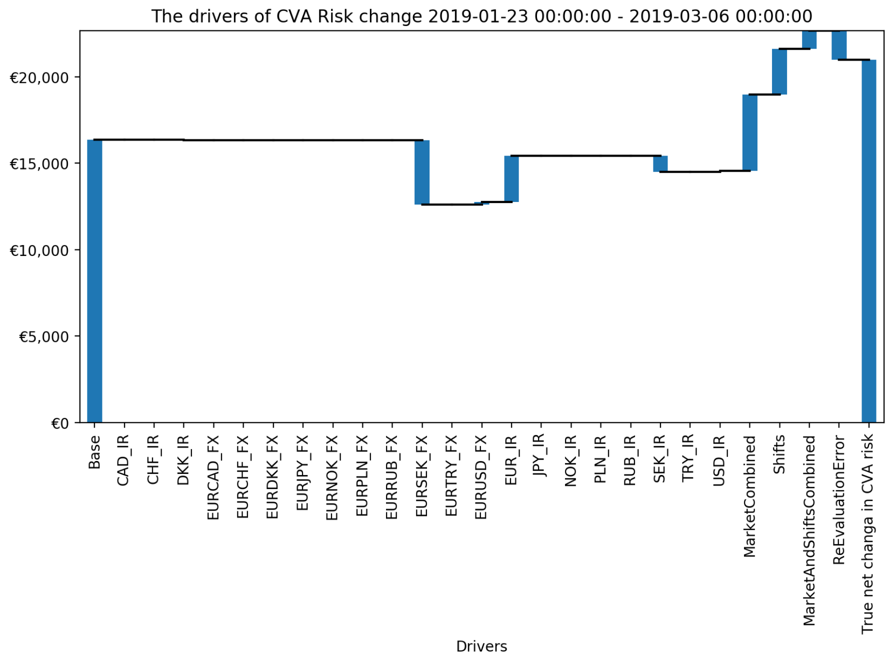

Figure 10: A waterfall chart of changes attributed to various drivers for a portfolio with counterparty 4.

B Self assessment

For our group a major problem happened right at the handover of the project plans when two of the original four members announced to retire from the project. Therefore, the project had significant changes as the number of members were cut down to half. The project plans were quickly changed to include only the two members, but the content was left untouched. Afterwards, the scope was decreased a bit to ensure the project not falling apart due to massive work amount. Basically the group reduced the approach to the problem to a more practical level instead of the original more sophisticated academic way. Since the method was approved by the client the project was successfully continued. The risks of the project decreased in time, since it became more clear week by week that some of the risks were not relevant anymore. For example once the data was received and it proved out to be in good quality, there was no risk for that. The schedule required some changes immediately after the new scope and as time passed the team observed the work load distributing unevenly between the handovers.

Comparing the project execution pace from before project plans to this moment, it would seem that the project workload was more heavy per team member at the beginning of the project compared to the end. The main reason was the frequent weekly or even biweekly meetings which were later reduced. Also, the subject of the project was heavily related to finance field which was new to every member. Studying a new field in addition to searching for relevant ways to execute the project obviously takes more time. At the end part of the project most of the work fell to one team member who was responsible for building the model at hand which in a way took the team by surprise. Obviously this could have been prevented by more active communication and commitment.

The project was successful in terms of outputs. A simple model for attributing changes in CVA risk capital charge was indeed constructed and handed over for the client. At the beginning of the project some guidelines were agreed upon between the client and the team about the simplifications the model is allowed to withstand. All in all it appears that the model works within these boundaries.

Unfortunately the results are not conflict-free. Since it was difficult to come up with ways to validate or verify the results we had to rely on identifying the possible pitfalls the model might have and based on those then identify the confidence of the output. The model and the results should be went through with an expert both in the field of finance and with a background of programming in order to understand the logic behind the script.

The team got together quite fast and got along quite well. After the group size decreased to two members, the communication worked quite well. Unfortunately already from the start of the project the workload distributed unevenly in the group which might have been one reason two members decided to leave the project. Once there were two members, one of the members had full responsibility for building the model, leaving only reporting to the other team member. Even though this was a mutual decision as the code was written by only one person, some relieving things could have been organized to ease out the script writing. For example, reading through the code every once in a while could have enforced a better and clearer language within the script. This would have lead to a more balanced understanding on the subject and a more even distribution of work hours.

The teaching staff did well throughout the course. Both professors showed interest towards the different projects and were eager to help whenever needed. At the end part of the project the team did not see any reason to ask for help, but at the beginning the help was appreciated. The assistant was also active and did thoroughly the guides and other communication. There was extra effort on guiding people to arrive to the presentations.

Our client representative was highly invested in the project which helped out really much. They were approachable and active with communication. Whenever the team needed any data or a meeting, the arrangements executed really fast. They were also eager to narrow down the scope once the group size decreased.