<u>FEM21019-23 Seminar Financial Case Studies - Research Projects</u>

The following research projects will be conducted during the course FEM21019-23 Seminar Financial Case Studies:

1) Designing a pension contract in the new Dutch pension system [DNB]
2) Signal based Optimal Order Execution in the Dutch Gas Market [Eneco]
3) Embedded option spreads - revolving credit facilities [ING]
4) A sophisticated Non-Maturing Deposits Volume model [Knab]
5) A modelling contest for multi-country yield curves [Ortec Finance]
6) Probability of Default: Transforming backward-looking into forward-looking predictions [PwC]
7) Credit rating models during COVID-19 [Zanders1]
8) Credit stress testing [Zanders2]

This document provides descriptions of the research projects. These descriptions are quite general: what exactly will be investigated is not completely fixed. The references and links can be used to obtain an impression of the research topic. It is strongly recommended to glance through this material when determining your preferences.

Your preferences will be taken into account as much as possible in forming the research teams and allocating the research projects, but the seminar coordinator and case supervisors make the final verdict. To be able to take into account your preferences, please send these by email to **the coordination email (fcs@ese.eur.nl)** before **Monday December 11, 2023, 17:59h.** Project preferences should be given in the following format:

1 (favorite): project x
2 (2nd favorite): project y
…
8 (least favorite): project z

That is, a complete ranking of <u>ALL</u> eight available projects should be given. In addition, a maximum of three preferred team members may be indicated. If all team members have a mutually agreed-upon ranking of the projects, a single e-mail is sufficient (but please indicate clearly that it concerns shared preferences).

The groups and allocation of research projects will be announced on **Friday December 15, 2022**. You are then required to prepare any reading material provided on the research topic before the first meeting with your supervisors.

First meeting

The teams meet with their faculty supervisors on a weekly basis. In addition, three meetings with the firm supervisors are scheduled, as explained in detail in the course syllabus. The first meeting with the firm supervisors takes place in the week of **January 8-12, 2024**. Attendance of these meetings is compulsory. Please also note the plenary introduction meeting that will be held on **Monday January 8, 2023 at 9:00h**. Also for this meeting attendance is required.

1) **Designing a pension contract in line with the risk attitude of participants in the new Dutch pension system**

About DNB

The Dutch Central Bank (DNB), located in Amsterdam, is a central bank and supervisor and is committed to a stable and sustainable financial system, solid financial institutions and properly functioning payment transfers. To commit to a reliable financial system, it supervises banks, pension funds, insurance companies and other financial institutions.

The case is supervised by members of two departments. The “Expert Centre Financial Risk Pension Funds” department supervises pension funds and insurance companies by (amongst other things) participating in onsite visits of pension funds, their asset managers and insurance companies, assessing internal risk models for insurance companies and by performing sector-wide benchmarking projects using regulatory reporting. The “Pension policy” department is intensively involved in all policy discussions in The Hague regarding the new Dutch pension system. Many of us have a quantitative background (econometrics, physics or mathematics) just like you.

About the case

The majority of Dutch employees is currently participating in mandatory occupational pension schemes. The pension fund participants contribute to the pension fund during their working life and receive pension benefits from the time they retire until they perish. These pension premiums are invested in the financial market. In general, Dutch pension funds are a major player on international financial markets with approximately 1500 billion euros in assets in total.

The Dutch parliament has recently passed a major reform of the Dutch pension system. Within this new system, a more tailored approach is taken to the allocation of financial returns whilst keeping the collective setup. Participants bear the investment risk of their personal pension capital in a more direct way. Besides personal pension capitals, a pension fund can also hold a collective buffer, which serves as a means for intergenerational risk sharing and stabilizing benefits.

In this research project, you will investigate how the collective asset mix should be invested and how financial returns should be allocated over the different participants in order to improve the pension scheme. Stakeholders are currently exploring the design of the new Dutch pension contract. The academic community plays an important role in providing pension experts and pension board members with the necessary insights. Therefore, this case study may have a direct impact on the ongoing (policy) discussions.

Key is the risk attitude (“risicohouding”) of participants. Pension funds have to make sure that the investment risks that participants bear are in line with the investment risks that participants are willing and able to bear. In general, young employees are better capable to bear investment risks than older employees or retirees, as they look forward to many years of labor income from which to accrue pension capital. Young employees may also have more opportunities to respond to financial windfalls and setbacks by adjusting the number of working hours or by adjusting their level of savings. When including other factors than age, risk preferences can be specified even more heterogeneously.

The ultimate goal in this case is to come up with an optimal age-dependent investment strategy (optimal allocation of risk) for the individual pension capitals. Next, we investigate how different utility specifications/assumptions affect the optimal investment strategy. Furthermore, the design of the collective asset mix and the annuity choices within retirement play a role in the investment strategy.

The research project consists of the following steps:

- Choose an econometric model for the dynamics of future equity returns, inflation and interest rates. The starting point is the model in Draper (2014), commonly used in the Dutch pension sector. You can also choose your own model.
- Investigate the optimal design of the collective asset mix and how the returns should be allocated over the different members? Should young and old members get the same level of immunization regarding interest rate risk?
- How do you measure (using the output from your econometric model) whether your allocation of risk is optimal? How do you make sure that the investments risks are in line with the "risicohouding" of the different participants?

Possible directions to investigate:

- Investigate what utility functions are supported by empirical evidence. Then incorporate these in the model to determine the optimal investment policies. How does this affect the policies with respect to the stylized base case with CRRA utility (Muns and Werker, 2019)?
- Assume a group with heterogenous risk preferences and risk capacities. First determine which criteria to choose when aggregating the individual objectives (Balter and Schweizer, 2021), then investigate the optimal collective investment. Next, how much does welfare increase when grouping participants into clusters with their own investment plan?
- There are many performance measures for trading strategies. What all these measures have in common is that they attempt to numerically represent the risk aversion of the trader so that a strategy optimal for the trader's preferences can be adopted. A disadvantage is that the utility functions are not particularly intuitive and it is difficult to determine the risk parameters. Investigate how different objective functions impact the optimal investment policies.

Literature

Balter, A. G., and Schweizer, N. (2021). Robust decisions for heterogeneous agents via certainty equivalents. ArXiv Preprint 2106.13059

Bodie, Z., Merton, R.C. & Samuelson, F. (1992). Labor supply flexibility and portfolio choice in a life cycle model, *Journal of Economic Dynamics and Control*, *16*: 427-449.

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2) **Signal based Optimal Order Execution in the Dutch Gas Market**

About Eneco

Eneco Energy Trade BV (EET) is the trading department of Eneco, one the 4 large utility companies in the Netherlands. It is tasked with the purchase of natural gas for its customers and for its assets (gas fired power-plants). At EET, we would like to directly engage you to take upon a challenge to come up with the best order execution strategy. We at EET are working on building an automated trading platform, so your research is focusing on a topic rooted in a real-world application.

Research Project

Getting a trading signal (Buy/ Sell/ Hold) is one thing, but any trading strategy can easily become unprofitable due to poor execution in the market and losing substantial amounts on the bid-ask spread. In this case study, you will use your econometric and ML knowledge to come up with a strategy for trading execution, so that you will receive the best price in the market, while ensuring that the order gets executed. For example, you can buy at the current market ask price by placing a ‘market order’ or even put out a ‘limit order’ to ensure you get the price that you want. The challenge with a limit order is the uncertainty of the execution at the price you put in. There are further challenges with the other available order types.

The Data

You will work with the front-month Title Transfer Facility (TTF) data. TTF is a virtual marketplace where Gasunie, the Dutch gas transmission system operator, offers market parties the opportunity to transfer gas that is already present in the Dutch gas grid to another party. Using the TTF, gas that is brought into the Dutch grid via an entry point can change owner before it leaves the national grid at an exit point.

TTF has developed as the most liquid European gas hub over the last 5 years. It has the greatest number of market participants, trading the widest range of products over the entire forward curve and by far the largest trading volumes. Thus, TTF has become the gas pricing benchmark for North-West Europe, and several other countries across Europe use TTF to price short and long-term contracts. TTF is also used to price LNG cargoes destined for Europe using a specific indexation.

The dataset consists of:

- Open-High-Low-Close (OHLC) prices at 1 minute interval
- Top order-book data, including best bid and best ask in the market in that 1-minute interval.
- Traded volume in the interval.

Challenge

Your task is to come up with a model that puts orders in the market. In the actual market, you have several choices for the orders both on the buy and sell side and the overall execution price depends on the depth and volume in the order book. But to keep things simple, you will work with following assumptions.

- You **must** buy or sell 1 lot (5 MW) of gas within a 5-minute window.
  - You can look at the buy and sell strategies separately if that is easier.
  - A more challenging question is to execute 20 lots (100 MW) within the 5-minute interval. How would this volume be split in time and over different order types, given the uncertainty in price?

- There is infinite liquidity at the best bid and best ask in the market.
- There is no limit on the market orders within the 5-minute window. Any number of orders can be created/adjusted/cancelled during the 5 minute window at any point of time.
- Allowed order types are ‘market order’, ‘limit order’, ‘conditional limit order’.
- Your model will be evaluated based on the number of trades you miss (your order does not get executed in the 5 minutes), and the price at which you buy/sell against the best price in the 5 minutes interval. You can also design some extra evaluations metrics yourself.
- The benchmark for the project is a strategy that always puts in a ‘market order’ on the entire volume in the first minute of a 5 minutes interval. Your model should beat this benchmark in terms of total value generated by delaying the order placing or using alternative order type.

There are numerous approaches to approach this problem. The model could be a simple regression model that forecasts the bid-ask prices in the next 5 minutes and then makes the decision on order type, price and the volume based on the uncertainty (or certainty) of the forecast. It could be ML model that simply takes the given input and outputs the order type, price, and the volume. The problem can also be casted into an optimization problem and handled within a classic dynamic stochastic optimization framework or reinforcement learning framework. Perhaps, you can come with a way to look at the problem form game-theoretic point of view?

We will provide you with the data from recent volatile years, which you can split into train and validation set and choose a validation strategy that you prefer (k-fold or leave one out). We will also provide you with the test set, which you can use to evaluate the out-of-sample performance of your model.

Bonus exercise

Apart from this setup, there will also be a ‘hidden test set’, which will not be shared with you and we will evaluate your model on this hidden set on our own. Note that this hidden test is not necessarily a part of the case study, but you can write an additional section for your model’s performance on this hidden set in your final report.

References

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3) **Embedded option spreads - revolving credit facilities**

About ING Model Validation

ING's global Model Validation Interest Rate Risk in the Banking Book ("MV IRRBB") team is a diverse, dynamic & international team of around 35 highly qualified professionals of various quantitative backgrounds. We are responsible for validating the IRRBB and Assets & Liability Management models of ING, in which we independently assess whether models are fit for purpose and use.

Background

ING Wholesale Banking (ING WB) offers its clients the **Revolving Credit Facility** (RCF) product. This product gives WB clients the right to draw and/or undraw the RCF up to a specified maximum amount (limit) at any time and as many times, without penalty, during a specified period. This is called the utilization option. For the amount drawn (utilized), clients pay an interest amount consisting of a floating interest rate and fixed margin. Besides this utilization option, customers also have a **cancellation option**. The cancellation option gives customers the right to cancel the RCF at any time without penalty.

ING WB funds its RCFs on a portfolio level, based on the expected drawn amount. When customers exercise the cancellation option more or less than expected, the bank may incur a loss (cancellation option cost). The cancellation option cost is charged to customers via the **embedded option spread**, which is one of the components of the fixed margin.

Assignment

You are given the task to develop a model that calculates the embedded option spread required to cover the cancellation option cost. This should be done both historically (1 scenario) as well as statistically based on a confidence level (multiple scenarios).

The cancellation option cost is driven by four main risk drivers:

(1) The timing of cancellation
(2) Changes in interest rates (discount factors) over time
(3) Changes in FTP spreads (loss of income) over time
(4) The exposure (expected drawn amount cancelled)

Each risk driver may require different type of econometric models or assumptions. ING will provide you with a starting point for your theoretical framework in which it describes how to calculate the cancellation option cost and embedded option spread, considering input values for the risk drivers. ING will also provide you with required portfolio & market data.

4) **A sophisticated Non-Maturing Deposits Volume model facilitating the measurement of interest rate risk of a NMD portfolio**

About Knab

Knab was founded in 2012 as one of the first fully digital banks in the Netherlands. The purpose and mission statement of Knab is to make customers feel at ease when it comes to their finances, each and every day, which fits perfectly with the bank's strategy to become the bank for e-driven company of the future. Knab positions itself as bank for self-employed people in the Netherlands. This research project will be guided by the Asset and Liability Management & Methodology team of Knab. Enthusiastic and talented participants of the research project are encouraged to follow up with an application for a thesis internship.

Research project

Knab is exposed to interest rate risk in the banking book. A typical banking book product is a so-called non-maturing deposit (NMD), such as a variable rate savings product or a current account. From an interest rate risk perspective, NMDs are challenging for a bank to model and hedge as these products have the embedded optionalities: the client can immediately withdraw its deposit and the bank can change the deposit rate overnight. Thus, the timing and amount of cashflows are uncertain. Banks have models in place to estimate the cashflows of NMDs. This research project will focus on projecting the amount (volume) of Knab's Variable Rate Savings portfolio, which is one of the components that make up the cashflow projection.

Modelling the dynamics of NMD volume is challenging, as there are many variables that impact the volume development. For example, interest rates on comparable products at other banks and general macroeconomic factors influence the behaviour of clients and thus impact volume development.

You are given the task to develop a sophisticated volume model for Knab's Variable Rate Savings portfolio, which can be used by Knab to project the cashflows of this portfolio and ultimately hedge the interest rate risk. Your model will need to be substantiated from both a quantitative point-of-view (e.g., back-testing, robustness, variable selection) as well as a qualitative point-of-view (e.g., substantiation on chosen calibration horizon, selected client and/or product segmentation). Additionally, you should ideally select at least two different statistical approaches (using at least one Machine Learning approach is encouraged) and compare them. Once the project starts, you will be fully informed on further minimum requirements for Knab.

In case time allows, and as a bonus, you can implement the model in Knab's overall NMD modelling framework and project the value and duration of the Variable Rate Savings portfolio (using your developed volume model) under different interest rate scenarios.

5) **A modelling contest for multi-country yield curves**

About Ortec Finance

Established in Rotterdam in 1981, Ortec Finance is a global provider of technology and advisory services for risk and return management. Our purpose is to enable people to manage the complexity of investment decisions. We do this through delivering leading technologies and solutions for investment decision making to financial institutions around the world. Our strength lies in an effective combination of advanced models, innovative technology, in-depth market knowledge, and professional advisory services, which supports investment professionals in achieving a better risk-return ratio and thus better results. Our client base operates globally in the pension, investment management, insurance, real estate, and private wealth management markets. Ortec Finance is continuously innovating through strong ties with the academic community.

Research project

Ortec Finance uses a large-scale time series **Dynamic Factor Model** (DFM), to generate density forecasts for economic and financial variables such as inflation, interest rates and equity returns. The Ortec Finance DFM is based on an extended version of the DFM of Stock & Watson (2011). One of the most important variables to model are interest rates. Especially now, as inflation has rapidly increased in the past two years and caused central banks to act, all investing eyes are on interest rates.

Ortec Finance applies an advanced version of the classical the **Nelson Siegel** (NS) model, see e.g. Diebold & Li (2006), to construct and forecast the yield curves for many countries. The NS model uses factors, identified as level-, slope- and curvature-factors, which are modelled using (V)AR or DFM, to then forecast yield curves into the future. Our objective is to generate scenarios that describe, as realistically as possible, what might happen in the future with yield curves.

This case study is about improving the NS model by modelling the yield curves for different countries simultaneously. We empirically observe that there is a large degree of correlation and co-movement between yield curves of different countries. Previous research, such as Diebold et al. (2008) and Kobayashi (2020), identified a global yield curve and three associated global factors. The yield curve of each country would then depend on that of the **global yield curve**, usually through dependence in the country-specific factors on the global factors. In Sopov & Seidler (2010) they did something similar on the regional level, where they focused on Europe.

This case is a modelling contest by making the current model more intuitive and explainable, while still capturing the relevant stylized facts. A promising idea is to incorporate **hierarchy** and **dependency** between yield curves of different countries, by including global and/or regional factors. One could also include macro-economic variables to incorporate their effect, see for example Diebold et al. (2006).

Ortec Finance provides monthly data used as input for the yield curve and DFM model. Additionally, Ortec Finance provides a suggestion for the model set-up and estimation procedure for the DFM model in combination with their yield curve model. The students have full freedom to experiment with different models to improve the current model.

References

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Stock, J. H. & M. Watson (2011). “Dynamic factor models”. In: Oxford Handbook on Economic Forecasting.

Disclaimer

6) **Probability of Default: Transforming backward-looking into forward-looking predictions**

About PwC

PricewaterhouseCoopers (PwC) is among the leading professional services networks in the world, with offices in 152 countries and more than 328,000 people. PwC Netherlands has more than 5000 people operating from twelve offices and from three different lines of service: Assurance, Tax, and Advisory. We want our service offerings and delivery to contribute to the solution of important problems and help to build trust in society. In this way we want to add value for our clients, our people and society.

PwC's Risk and Regulatory Modelling & Data team is one of the teams within PwC that people with a quantitative background can join, consisting of 20 (approx.) colleagues with backgrounds in Econometrics, Physics, Mathematics, Quantitative Finance and Accounting. The Modelling & Data team supports clients in the financial and non-financial sector on risk management, (financial) regulations, and financial supervision.

Case Background

IFRS 9, or International Financial Reporting Standard 9, is an accounting standard developed by the International Accounting Standards Board (IASB). It provides standards for the classification and measurement of financial instruments, as well as for impairment of financial assets. One of the key requirements of IFRS 9 is the implementation of an Expected Credit Loss (ECL) model. The ECL model is used to estimate the potential credit losses that a financial institution may incur due to impairment of its financial assets. Sophisticated ECL models usually consist of several components that deal with different aspects of ECL separately. In many cases, the credit risk is quantified using three parameters: probability of default (PD), loss given default (LGD), and exposure at default (EAD). In this study case, the focus is specifically on the probability of default (PD).

A PD model is used to estimate the likelihood of a borrower defaulting on their financial obligations. PD models are typically built using econometric techniques and statistical analysis. It involves analyzing historical data on borrower defaults and identifying key factors that indicate/contribute to default risk. In the context of IFRS 9, it is important to understand the concepts of through-the-cycle (TTC) PD and point-in-time (PIT) PD.

TTC PD refers to a measure of default probability that remains relatively stable over the economic cycle. It captures the long-term average default risk of a borrower, individual loan or a portfolio of loans, regardless of the current economic conditions. TTC PD is typically based on historical data and by using it for forecasting, it assumes that the future will be similar to the past in terms of default rates. PIT PD is a measure of default probability that reflects the current economic conditions and incorporates forward-looking information. For the purposes of IFRS 9, institutions are required to use PIT PD for estimating expected credit losses. This is because IFRS 9 requires the incorporation of forward-looking information and current economic conditions in determining expected credit losses. PIT PD predictions are often obtained by transforming TTC PD predictions into PIT PD predictions using a separate macro-economic overlay.

Research Project

The present macro-economic climate is shifting rapidly and volatile. Recently, we have seen a surge in inflation rates across the globe. In this context, it is important to have robust models to estimate ECL properly. In this research project, the emphasis will be on conducting research on building accurate and robust models.

You will model and predict the PD for mortgage loans. To do this you will have to build at least two models, one backward-looking model and one forward-looking model transforming the backward-looking predictions. To develop the former, you must investigate the characteristics of mortgage loans and individual borrowers over a longer period (at least a full economic cycle). For the latter, you must investigate the relation between several macro-economic factors and the probability of default for mortgage loans. Please ensure that you provide a thorough explanation of the rationale of (not) incorporating different elements into both models, and how you choose to combine them.

To perform your research, you are encouraged to make use of two public data sets. Loan performance data that can be used to model the PD in the project is included in the Single-Family Historical Loan Performance primary data from Fannie Mae (https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-transfer/fannie-mae-single-family-loan-performance-data). The data consists of the origination and performance data for over amortizing mortgage loans with a 30-year fixed rate that originated after the 1st of January 1999 up until the second quarter of 2023. There are about 50 million loans to analyze in this dataset that have been fully documented. As this is a large dataset, you will first have to understand and deal with the corresponding potential implications, e.g., dealing with outliers, missing values, transformations, the high number of variables, and the class imbalance problem. The macroeconomic data that can be utilized to build the forward-looking model is made available by the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/).

Lastly, to evaluate the performance of the models, you will design a testing framework. Think about the type of tests that you want to conduct (e.g. to assess the accuracy, the discriminatory power, and/or the stability), and which periods in the dataset (e.g. during different states of the economy) you will use as the validation sample. For every decision that is made in the research, substantiation and rationale should be provided.

The case setup provides you quite some opportunities to pick different aspects. For example, you could use your developed models to research the behavior of PD (both TTC and PIT) throughout different periods. Alternatively, you could develop different models and compare their performance or investigate model interactions through the overlay.

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7) **Credit rating models during COVID-19**

About Zanders

We are a leading international consultancy firm focused on treasury, risk and finance. With over 300 employees and offices in 10 countries, we service corporates, financial institutions, public sector entities and NGO's with independent and quantitatively substantiated advice. Our goal is to help organizations with solving treasury, risk and finance issues, from idea until implementation. Our advice involves amongst others credit risk management and its quantification.

Research project

Credit risk can be derived from publicly available ratings published by Moody's, S&P and Fitch or from publicly traded bonds. But the majority of a banks counterparties do not have an external rating. Therefore, many banks have their own internal credit risk models, such as ratings models. These ratings are, amongst others, used to evaluate risks and calculate expected credit loss.

Rating models are often derived from observed defaults, which requires a material number of observations. Risk drivers are selected that have a predicting power for future default (eg. solvency, liquidity etc.). Calibration of models for internal portfolios with limited observations and very little defaults is difficult and often leads to unstable results. Therefore, banks revert to external, representative data for constructing their models. Developing such a model allows estimating credit ratings for other counterparties that do not have an external credit rating or publicly traded bonds.

The topic of rating models is an ever-evolving topic. The focus currently (and in previous years) is on improving modelling techniques by for example incorporating Big Data and Artificial Intelligence. But at this moment, the consequences of Covid 19 introduce new problems for Credit risk modelers. While the majority of corporate data showed an extreme downward pattern from 2020 to 2022 (reduced turnover and results), in most Western countries the number of defaults reached an all time low. The resulting mismatch between model predictions and realizations, deteriorates the performance of these models. Though model performance might recover at some point, historical data is 'polluted' forever, which poses interesting challenges for future model development. Especially, because regulators do not allow for directly omitting data.

Currently available techniques such as Regime Switching models could help us with better using the Covid 19 data and predicting ratings at a higher accuracy level. This type of models can, for example, more easily deal with changing patterns in corporate data. Other techniques such as Big Data and Artificial Intelligence allow financial institutions to identify explanatory variables and patterns that could be present in Covid 19 data but maybe not yet known to us. The obvious drawback of several sophisticated econometric models is that these models can become a "black box", which makes it challenging to understand and explain the drivers in the model. Therefore, it is necessary that whichever model is used, the resulting outcomes and risk drivers are explainable.

The challenge you are facing is to develop your own corporate rating model, that predicts the probability of default of a specific counterparty. As part of this assessment you need to advice how to work with observations during the specific Covid-19 period. Make use of **any** technique to improve the performance of your basis rating model. The techniques mentioned above are only meant to give you some examples. Please feel free to use whatever technique you deem as beneficially to model ratings, paying extra care to the data that originated during Covid 19. As we have developed a rating model already for our clients, your challenge is clear. Beat us!

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8) **Credit stress testing**

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Research project

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Rating models are often derived from observed defaults, which requires a material number of observations. Risk drivers are selected that have a predicting power for future default (e.g. solvency, liquidity etc.). Calibration of models for internal portfolios with limited observations and very little defaults is difficult and often leads to unstable results. Therefore, banks revert to external, representative data for constructing their models. Developing such a model allows estimating credit ratings for other counterparties that do not have an external credit rating or publicly traded bonds.

The topic of rating models is an ever-evolving topic and is also always subject to a changing macro-economic environment. As macro-economic changes impact the forecasts for future defaults, more focus is now placed on the stress tests that banks use for calculations. This requires a model to apply a scenario on non-frequent outcomes using non-frequent observations (defaults), which is a daunting process.

Banks are regularly provided with macro-economic scenarios from the European Banking Authority, and are required to calculate the potential evolution of credit risk metrics for these scenarios. However, Banks also need to come up with their own vision on stress scenarios and the impact of those. Therefore, they also predict their own macro-economic stress scenarios and use sophisticated modelling techniques.

Additionally, another technique that is applied to determine the impact of stress is that of reverse stress testing. With this technique Banks first model the maximum stress that is allowed in a model, such as the maximum amount of defaults in a fixed period. Then, they determine the likelihood of this maximum stress and then assess whether this scenario is likely to happen or not. This ensures that an analysis is performed which shows if a bank can weather the storm of a macro-economic crisis.

The challenge you are facing is to develop your own corporate rating model, that predicts the probability of default of a specific counterparty. This base rating model is then extended with a stress testing approach. After you have finished your model, we will provide the European Banking Authority (EBA) stress test scenarios, such that you are able to apply the stress to your models. As a last step we ask you to apply reverse stress testing to your rating model.

Please feel free to use whatever technique you deem appropriate to model ratings, paying extra care to the macro-economic stress that should be applied to your model. The challenge for you is to build such a rating model that, in combination with a stress test methodology, can be used to evaluate the potential evolution of banks credit risk portfolio.

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