Aalto University

MS-E2177
COVID-19 impact on credit loss modelling

Interim Report

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1 Project Status

Our goals for the project in the second phase were as follows:

- Set up data processing pipeline
- Test hypotheses to determine effects of ratings
- Replicate the SEB model
- Experiment with new models, different calibration methods, and clustering of companies

We have requested access to the data collected by Global Credit Data Consortium (GCD). This would allow us to gain vast amounts of information on credit rating development in different countries to allow us to fit the data appropriately. However, legal process with GCD was more complicated than anticipated, and there was a long delay in receiving the full datasets, which is a major setback for our group. In early April, GCD accepted the Aalto proposal for establishing contracts which will allow access to GCD data and we have proceeded by signing NDA contracts at the time of writing.

Concurrently, we have also recently received the internal data from SEB and guidelines for replicating their current model. Furthermore, we have also found new data sources for economic indicators from EconDB and Wharton Research Data Services that help develop new models.

With regard to the goals above, we have completed setting up a data pipeline and performing hypothesis testing using the sample data. Section 1.1, 1.2, and 1.3 will respectively discuss the data pipeline, hypothesis testing, and our approach to update the Merton-Vasicek model in more details.

1.1 Data processing pipeline

The main goal of having a data pipeline is to provide access to clean data that can be efficiently used for the purposes of the project such as hypothesis testing and calibrating of models and standardized output method for different models for accurate evaluation. More specifically, the pipeline aims to:

- Remove any corrupted data point or unnecessary data features from the raw sources
- Fit an appropriate distribution to smooth out the data in each risk rating category
- Construct year-over-year sector level rating migration matrices from credit data from SEB both GCD by resolving the differences in rating system and sector denotation from the two sources with the correct mapping
- Producing sector level economic z-factor from open sources
- Facilitate calibration and validation of models as well as storing and visualizing results

1.2 Migration probabilities and hypothesis testing

In order to capture migration between the different credit ratings and to calibrate the model, we consider the migration of companies in between different ratings. This technique allows us to quantify real-life developments of credit default risks.

SEB uses 16 different rating categories to picture the quality of loans. We model the rating categories enumerated from 1 to 16 where 1 is the best, i.e. safest risk category, and 16 means default. The default state is absorbing meaning that a defaulted company will not recover.

Mathematically, we formulate the set of risk ratings $\Omega = \{1, 2, \dots, 16\}$. Let t_0 be the initial time where all risk ratings are known and $t_1 > t_0$ the time after observation horizon. Typically we consider as the observation horizon one year.

When analyzing the migration of companies and loans, respectively, we are especially interested in the migration to the state of default. Therefore, we conducted in the project approach hypothesis testing which we will perform here for providing some important intermediate results within project approach:

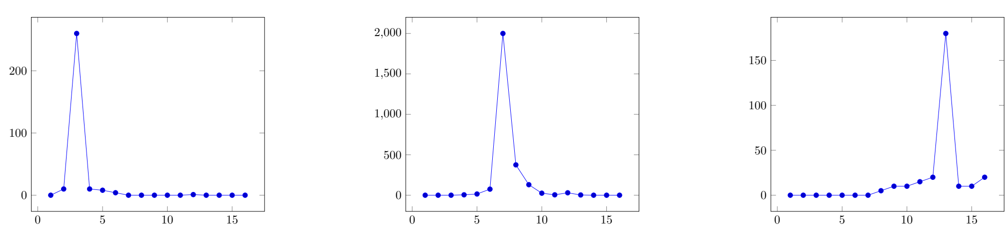
Let X define a loan and $p = 0.05$ the statistical significance level. We formulate the null hypothesis H_0 as follows:

$$H_0 : \text{Loan } X \text{ will not default during the observation horizon.}$$

With the preliminary definitions, we can now execute some sample calculations. We remark at this point that – due to the signed NDA – we are not allowed to provide real-SEB data. Instead, we perform the sample calculations from artificial data to capture the behavior of migration and hypothesis testing.

Let (Ω, Σ, P) be a statistical space where $\Sigma = 2^{|\Omega|}$ and P is a probability measure on (Ω, Σ). Furthermore, let $X : \Omega \to \Omega$ an estimator which defines a number of loans. We consider three initial states, namely $P_1 = 3, P_2 = 7$ and $P_3 = 13$. We compute the probability of companies not to default

$$P(X_{t_2} < 16 | X_{t_1} = 3) = \frac{292}{292} = 1$$
$$P(X_{t_2} < 16 | X_{t_1} = 7) = \frac{2663}{2663} = 1$$
$$P(X_{t_2} < 16 | X_{t_1} = 13) = \frac{260}{280} = 0.92857$$



(a) Migration distribution for grade 3

(b) Migration distribution for grade 7

(c) Migration distribution for grade 13

Figure 1: Sample graphs of the migration for selected initial risk ratings.

As calculated, we reject the null hypothesis for the last and accept it for the first two calculations. We identify that with lower initial risk ratings the probability to default in the observation horizon increases.

Again, we clarify that the provided calculations only monitor the system behaviour and do not use real-data sets. Nevertheless, the concept of migration – especially to default state – is one central concept in extending the current Merton-Vasicek model by distinguishing additional filtering in data as the primary economy sector of operating firms.

1.3 Approach to the Merton-Vasicek model

The Merton-Vasicek model aims to predict point-in-time (PIT) default rates of portfolios from historic through-the-cycle (TTC) default rates by incorporate a economic indicator Z and portfolio sensitivity ρ:

$$\mathrm{PIT} = \Phi\left[\frac{\Phi^{-1}(\mathrm{TTC}) + \sqrt{\rho}Z}{\sqrt{1-\rho}}\right]$$

However, the true effect of COVID-19 on the default rates is very complicated and it is easy to see the reasons for the initial model failing: As the macroeconomic effects are highly variable in different industries, the single factor Merton-Vasicek model with one macroeconomic driver is not sufficient to model these effects. The one factor Merton-Vasicek model usually uses a normalized GDP as the systemic risk z-factor. Sector level macroeconomic data is needed.

We also assume that the sector based total value added is not alone the best indicator for measuring the economic effects. Thus, our goal is to replace the single z-factor with a multi-variable function consisting of various indicators. Such economic sector level information is available under NACE sector standards on Eurostat[1]. In order to convert these sector labels into the labels used by GCD, we need to receive conversion tables from GDC. This approach will induce a multi-variable optimization problem where in addition to the sensitivity parameter, we need to optimize the weights for the model. Initially we will attempt to minimize the test error on the observed default rates. Later we will try to improve the solution by measuring the error on risk-rating level.

The de facto approach to sensitivity parameter is to use a single sensitivity parameter for all industries and for a large portfolio. We believe that the sensitivity is a less significant factor for COVID-effects and thus we will leave improving this as a secondary goal and initially we will use a single sensitivity parameter for the whole dataset. Further improvements for this require a working implementation of the sector level model for testing purposes. Possible factor for improving the results could be to fit the sensitivity to vary in different countries to represent different economic environments, and COVID-19 support measures.

2 Project Plan update for the remainder of the project

The rest of the project is divided into two main work packages visualized in figure 2

- **Modeling** with the final model as the deliverable starting from NDA with Global Credit Data
- **Reporting** with the final report as the deliverable

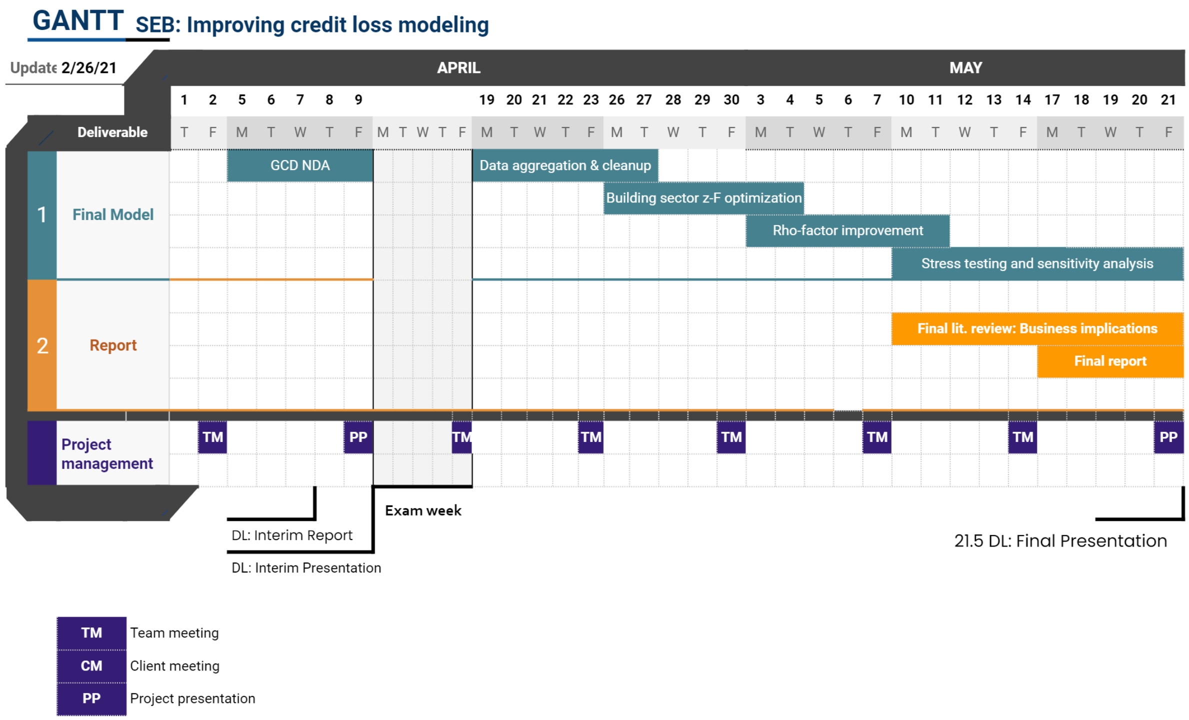


Figure 2: Project GANTT. Larger version available in the Appendix 1

- **Project management** For scheduling team client meetings

After the project plan report, the initial schedule has been adjusted and past activities have been omitted. The work packages have been simplified into two. There was a significant unexpected delay in receiving the final data. Our team has just gained permission to access the Global Credit Data data but we have not received it yet.

3 Updated Risk Management Plan

Table 1 shows the updated table over the risks of the project. At this point of the project the team has received and familiarized themselves with the client data. Since the quality of the data has been of fairly bad quality, the risk of poor data quality has been upgraded to "High". Further, The team members have worked together now for an extended period of time, and they all have shown good communication skills and they are committed finalizing the project with the best outcome for the client. Thus, the risk level of insufficient communication between team members has been lowered to "Low". Due to the increased density of other projects and exams during April the team has added increasing workload as a minor risk for the project. Overall it is possible to prepare for recognized risks.

Risk	**Probability**	**Effect**	**Impact**	**Mitigation Strategy**
Poor data quality	High	Misleading, incorrect or inaccurate results	High	Careful handling of data
Model too complex for the scope of the course	Medium	Too wide problem to solve for the allocated time	High	Focusing on explicit project goals.
Data security	Low	NDA contract violation	High	Local data management, risk assessment preceding deadlines
Insufficient communication between team members	Low	Resentment due to imbalance in workload between team members, misunderstandings	Medium	Regular communication between team members and manager and scheduling
Team member inactivity or dropout	Low	High workload for other team members	High	Good communication between the project manager and the rest of the team. Clear schedule.
Too heavy workload for team members	Low	Decreased quality of work or delay	Medium	Good planning throughout the project and limiting the area of focus.
Resulting model does not provide accurate enough results	Medium	The tool will provide low or no value for the client	High	Strive for performance

Table 1: Updated evaluation of risks

References

[1] Eurostat *NACE Rev. 2: Statistical classification of economic activities in the European Community* [*Eurostat Methodologies and Working papers*]. ISSN 1977-0375