MASTER THESIS

DEVELOPING A STRESS TESTING MODEL FOR THE CREDIT RISK EXPOSURE OF A LEASING COMPANY

W.B. Merckel

Supervisors
First supervisor: Ir. Drs. A.C.M. de Bakker
Second supervisor: Dr. B. Roorda
External supervisor:

28-03-2012

PUBLIC

Summary

The goal of this thesis was to develop a stress testing model for the credit risk for the different portfolios owned by the leasing company. This research makes it possible to further strengthen the measurement and management of risks at the leasing company. In addition, trough implementing stress testing as risk measurement tool, the leasing company anticipates on stricter financial control by external auditors. To provide this model, the following research questions is answered in this thesis:

" How can a stress test be developed as risk measurement tool for the credit risk exposure of the leasing company? "

During this thesis, important literature and most recent trends in conducting stress testing at financial institutions were examined. Most research about stress testing is focused on banks and not at other financial institutions such as leasing companies. Different types of stress analyses, varieties of shocks and types of scenarios were evaluated. Based on the theoretical background and the existing credit risk models of the leasing company, a stress testing model is developed.

Confidential

The stress test can be used by management to reduce the credit risks of the portfolio in several ways. Firstly, the credit models can be changed in a progressive way, which will increase credit provisions. Secondly, the management can decide to reserve capital for possible losses in a stress scenario. Finally, the management could decide to sell contracts with a higher risk incorporated to lower the expected loss.

Preface

In 2015 I started the master Financial Engineering & Management. Since then I have learned a lot, but also endured some difficult periods. I am therefore happy and proud to finalize my study by presenting this thesis for the graduation of my master.

I had the opportunity to write this thesis at a leasing company in the Netherlands. This fulfilled my wish to do my internship at a company that is both a financial institution and a corporate business. I am grateful to my supervisor at the leasing company who introduced me to the complex leasing world. He was a great sparring partner and made time to deliver feedback and ideas for my thesis. I would like to thank all my colleges for their openness and pleasant collaboration. I could always count on their support and knowledge. I look forward to working together at this prodigious company.

I also want to acknowledge my supervisors from the University of Twente for providing their feedback and knowledge. The thorough and structural feedback of Toon de Bakker helped me improving the structure of my thesis and guided me throughout the research. I want to thank Berend Roorda for the organization and the guidance in the financial engineering track. His feedback in the last phase of my thesis was very helpful for the completion of this thesis.

Above all I want to thank all my family, friends and especially Carola who supported me during my master thesis and who were there for me during some difficult periods in my master.

Wouter Merckel
Amersfoort, March 2017

A. Table of content

B. List of figures

C. List of tables

v

D. List of abbreviations

BIS	Bank for International Settlements
CRI	Credit Risk Indicator
DNB	De Nederlandsche Bank
EAD	Exposure At Default or Exposure
EBA	European Banking Authority
ECB	European Central Bank
EL	Expected Loss
ESRB	European Systemic Risk Board
GVAR	Global Vector Autoregressive
LGD	Loss Given Default
MVAR	Mixture Vector Autoregressive
NiGEM	National institute's Global Econometric Model
PD	Probability of Default
PIT	Point-In-Time
SSM	Single Supervisory Mechanism
VaR	Value at Risk
VAR	Vector Autoregression Model
VECM	Vector Error Correction Model
WACM	Weighted Average Correlation Method

1 Introduction

In this introduction, first the leasing company and especially the risk management department will be introduced. In the next section the problem statement is given. In section four, the relevance of the research is described.

1.1 The leasing company

The leasing company is one of the biggest automotive service providers of the Netherlands. The main activities of the company are financing, leasing and providing insurance intermediation for both business and private customers

Confidential

1.2 Risk Management Department

The risk management department of the leasing company consists of six people. Their daily activities are mainly focused on work for company A and consist of modelling credit risk, residual value risk, operational risk, monthly and quarterly reporting, regulatory affairs and business continuity management.

Confidential

Company A describes in their annual report of 2016 (Company A, Annual report 2016, 2016) risks as "*the danger of loss or damage that could occur if an expected future development turns out to be less favourable than planned*". In the annual report is formulated that local risk management teams are responsible for designing the local structures for the models and procedures used for risk measurement management and for the execution of these processes and technical perspectives.

Confidential

1.3 Problem Statement

The risk management department of the leasing company wants to be progressive in using new modern risk management tools to anticipate on pressure from regulators and external auditors to conduct extensive risk controlling. With this study, the objective is to research how stress testing can be implemented at the leasing company as new complementary risk management tool for their credit portfolios. The research goal is formulated accordingly:

Research goal To develop a stress testing model for the credit risk exposure of the leasing company.

This goal is described in our main research question:

Research question How can a stress test be developed as risk measurement tool for the credit risk exposure of the leasing company?

In order to answer the main research question, five sub-questions are guiding our analysis of the main research question (see Table 1). Sub-question 1 connects this research to existing literature. The study focus on exploring which stress testing models exist and how they work. With the second sub-question is reviewed which models for calculating credit risks best meets the needs of the leasing company. Relevant data for the development is gathered (available at the leasing company) and a design for implementation is developed (sub-question 3). Sub-question 4 is used to test the model. Finally, when the model is tested, the findings are reflected and there is advised how the model can be used as risk measurement tool at the risk management department at the leasing company.

Table 1: Main research question and sub questions

Research Question	How can a stress test be developed as risk measurement tool for the credit portfolios of the leasing company?
Literature review	1. What are the main models for stress testing credit portfolios?
Analysis of model(s) of the leasing company	2. What is the best model to implement at the leasing company?
Development	3. How can this model be implemented at the leasing company?
Model evaluation	4. Does the model measure correctly what it is designed for?
Reflection	5. How can the model be used to manage risks?

1.4 Relevance

Scientific contributions – Research on stress testing of financial risk has increased since the financial crisis in 2008. This is mainly because regulators have established more and stricter regulations about how banks have to control their risks. Because stress testing is a more advanced credit risk measure, few research focuses on smaller (non-bank) financial institutions that endure credit risks. This research gives an overview of the latest trends in conducting stress testing on credit risk portfolios. In addition, it contributes to the existing literature by application on an automotive retail-financing portfolio.

Managerial contributions – Credit risk is the greatest form of risk for the leasing company. This research makes it possible to further strengthen the measurement and management of risks at the leasing company. In addition, the leasing company anticipates with this research on stricter regulations on financial control.

1.5 Limitations of report

This report will have the following limitations:

- This report is only based on the Dutch market and economy;
- This report is based on the models as they were in place in October of 2016 at the leasing company;
- Only extensions for the implementation of stress tests are researched (not revision or improvements for the existing credit risk models);
- Correlation(s) between credit, market and/or liquidity risks/other models are not included;
- Due to the confidential data that is used, only software can be used that is local available at the leasing company;

1.6 Outline

Chapter 2 of this report contains the theoretical framework. In this chapter a literature study is conducted focused on stress testing credit risk. In this section the main advantages and disadvantages of different stress testing methodologies are summarized. This section describes al theory necessary for answering the first sub question.

Chapter 3 and chapter 4 contains answers for the second and third sub questions. In chapter 3 the structure and the credit risk models of the leasing company are explained. By combining the literature described in chapter 2 and the existing models in chapter 3, in chapter 4 stress testing methods are selected and a design for the stress testing model is developed.

In chapter 5 the fourth sub question is answered by testing the model trough simulating it for all portfolios of the leasing company. The results from chapter 5 are used in chapter 6 to present the conclusion. This is followed by recommending how the stress testing model can be used as risk measurement tool for the leasing company to manage risks. In this chapter the report is concluded by presenting suggestions for further research.

2 Theoretical framework

In this chapter relevant literature on credit risk and stress testing is discussed. The structure of this chapter is shown in Figure 1. In appendix A, the literature search approach is given. This chapter is concluded with an overview of the advantages and disadvantages of the different models that are distinguished from the literature.

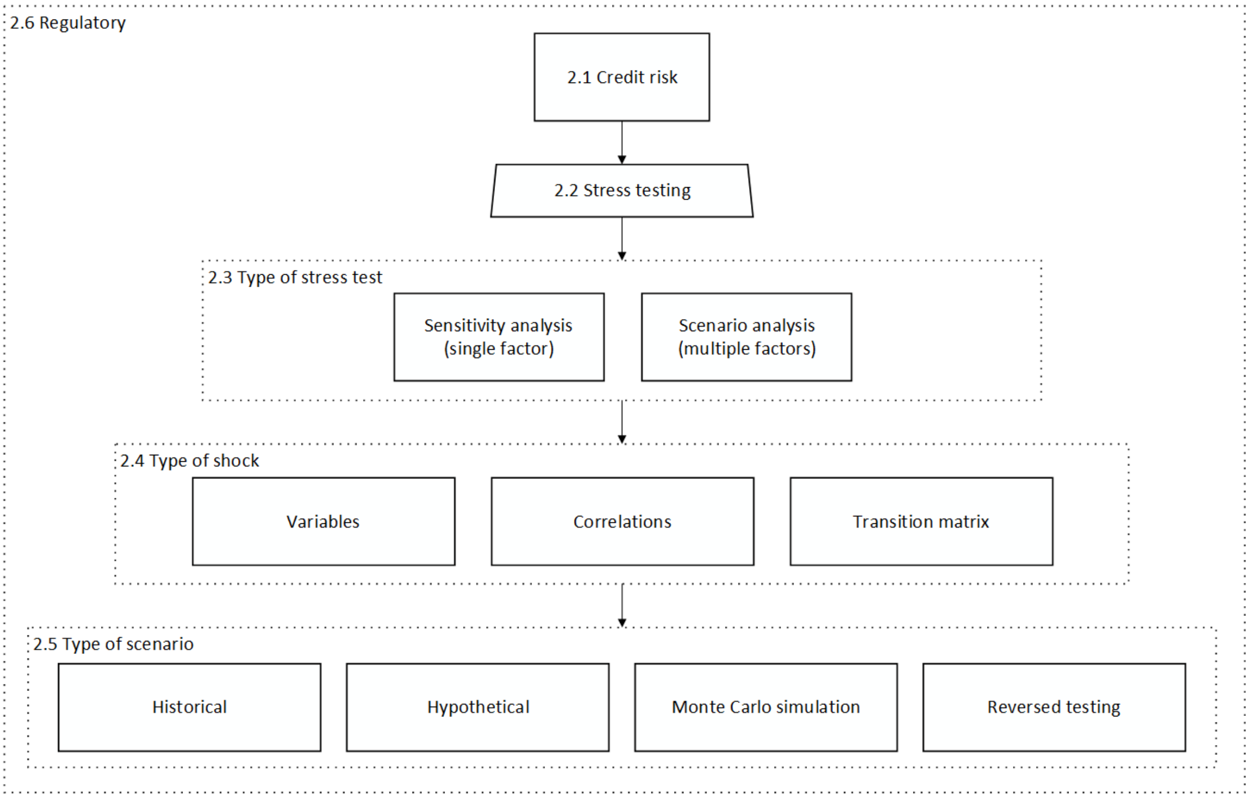

Figure 1: Research design of theoretical framework

2.1 Credit risk

For most financial institutions, credit risk is the risk that the value of a portfolio will decrease due to default or impairment because borrowers are not meeting their obligations (Henry & Kok, 2013; Blaschke, Jones, Majnoni, & Peria, 2001). It is one of the most substantial parts of total risk based capital requirements (Jimmy & Chen, 2016). Credit risk can be divided in expected and unexpected credit losses as seen in Figure 2. Expected credit losses are losses that can be estimated and where therefore provisions are made. Unexpected losses are harder to predict and therefore instead of provisions, credit risk capital can be hold to endure these losses. It is mostly defined as the maximum loss within a known confidence interval.

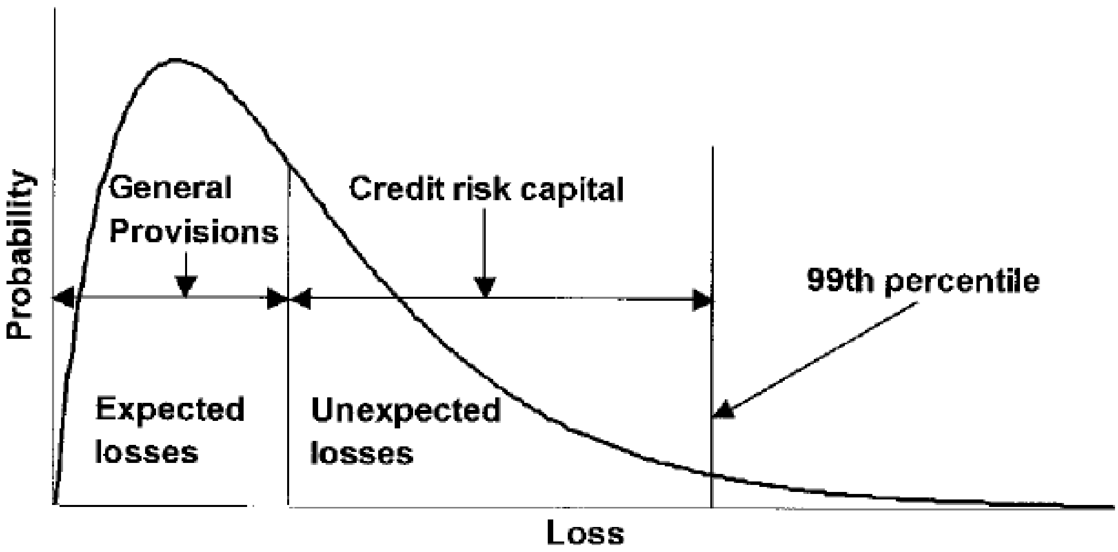

Figure 2: Probability of Losses (Blaschke, Jones, Majnoni, & Peria, 2001)

The most used indicators for the analysis of credit risk include PD, LGD and EAD (Henry & Kok, 2013; Blaschke, Jones, Majnoni, & Peria, 2001). Another common used measure is VaR, which is measured by a certain percentile of the distribution of future credit portfolio losses and exist of expected and unexpected losses (Rösch & Scheule, 2007). The expected loss of a contract can be calculated with (End, Hoeberichts, & Tabbae, 2006; End J. W., 2011):

$$EL = PD \ x \ LGD \ x \ EAD$$

To cover unexpected losses, banks are restricted to have capital cover (required risk capital) (Sommar & Shahnazarian, 2009). The greater the outcome of extreme situations, the greater the amount of required risk capital. To improve the credit risk of financial institutions Basel II and III regulations are set to guide the calculation of minimum capital requirements (Tsukahara, Kimura, Sobreiro, & Zambrano, 2016).

The regulatory framework in BASEL II and BASEL III is based on stressing of PD, EAD and LGD (Seah, So, & Thomas, 2014; Rösch & Scheule, 2007; Tsukahara, Kimura, Sobreiro, & Zambrano, 2016). PDs are stressed by a 99,9th percentile of a standard normally distributed variable and the sensitivity is based on the asset correlation. To stress the EAD and LGD scenario testing is conducted. Third, the stress testing of asset correlations is mandatory for large banks under BASEL II and BASEL III to test the impact on the PD (Rösch & Scheule, 2007).

2.2 Stress testing

Stress testing is not a new phenomenon. In the early 1990s, stress testing was used by large and internationally owned banks (Vuković, 2014). However, since the financial crisis in 2007-2008, the need to identify weaknesses in bank's capital structures is increasing (Doumpos, Zopounidis, & Fragiadakis, 2015). Stress testing describes a range of techniques that is used to assess the vulnerability of a portfolio by exploration of exceptional but plausible events as seen in Figure 3 (BIS Committee on the Global Financial System, 2005; Blaschke, Jones, Majnoni, & Peria, 2001; Mawdsley, McGuire, & O'Donnell, 2004; Henbest, 2006). Where the focus was first at market risk (80% of stress testing before the crisis), nowadays more attention is paid to credit risk (Steeve, 2012). To further strengthen the capital adequacy of banks, stress testing as supervisory control is introduced and has evolved as an important systematic risk management tool to identify financial institutions vulnerabilities (Doumpos, Zopounidis, & Fragiadakis, 2015). The outcomes of these tests are used by supervisors and bank management (Doumpos, Zopounidis, & Fragiadakis, 2015). According to the bank for International Settlements, stress testing plays an important role in (Basel Committee, 2009):

- Providing forward-looking assessments of risk;
- Overcoming limitations of models and historical data;
- Supporting internal and external communication;
- Feeding into capital and liquidity planning procedures;
- Informing the setting of banks' risk tolerance;
- Facilitating the development of risk mitigation or contingency plans across a range of stressed conditions.

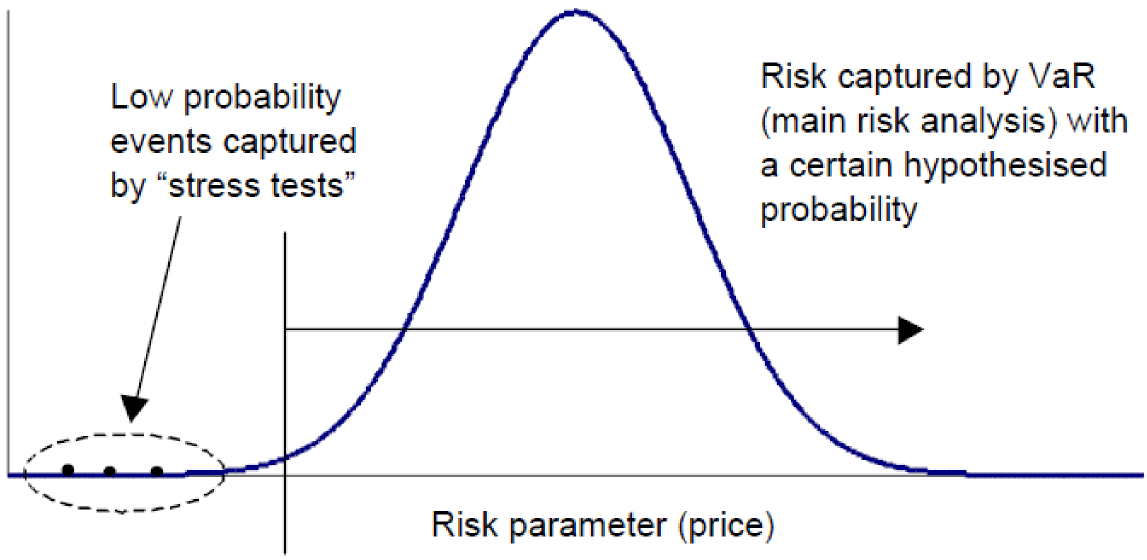

Figure 3: Stress test capturing exceptional but plausible events (BIS Committee on the Global Financial System, 2005)

A global approach for stress testing consists of five steps as given in Figure 4. The first step in designing a stress test is to define the scope of the analysis (type of test, type of shock and type of scenario) and translate this into a shock scenario. The second step is to map this scenario to relevant risk drivers in the risk model of the financial institution. The third step is to run and calibrate the model. The fourth step is interpreting the results on P&L and capital of the financial institution. The last step is to account for feedback effects of the economy and markets. This last step applies especially for system banks.

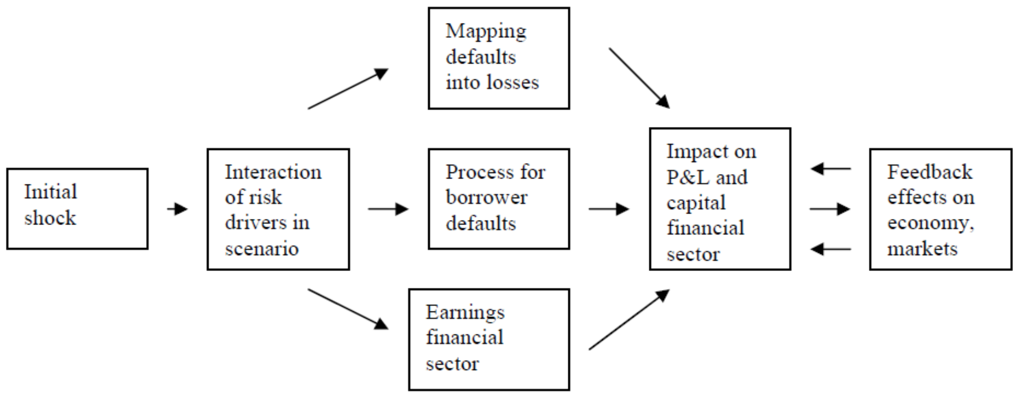

Figure 4: Stress testing framework (End, Hoeberichts, & Tabbae, 2006)

However, stress testing is based only on a few scenarios and is not expected to capture all potential risks and should only serve as one of several inputs for the capital planning process of risks (Federal Reserve, 2013). Nowadays stress testing includes the exploration of the risk profile of a firm, the allocation of economic capital, the verification of existing limits and the evaluation of business risk (BIS Committee on the Global Financial System, 2005). Banks that use internal models for meeting market risk capital requirements are obligatory to use comprehensive stress testing (Blaschke, Jones, Majnoni, & Peria, 2001).

Most stress testing is done on movements in market risks (interest-rate risk and exchange rate risk) (Mawdsley, McGuire, & O'Donnell, 2004). Second, the majority of tests focus at credit based stress testing (BIS Committee on the Global Financial System, 2005). Third stress testing is performed on liquidity and operational risks. Most of stress testing is done at portfolio level and can consist of sensitivity testing (individual risks), scenario analyses (multiple risks) or other types of stress testing (like extreme value or maximum loss) (BIS Committee on the Global Financial System, 2005; Blaschke, Jones, Majnoni, & Peria, 2001; Mawdsley, McGuire, & O'Donnell, 2004; Rösch & Scheule, 2007; Tsukahara, Kimura, Sobreiro, & Zambrano, 2016; Borio, Drehmann, & Tsatsaronis, 2014). In practice, a combination of different types of scenarios is common practice (BIS Committee on the Global Financial System, 2005). The types of shocks that can be researched using stress testing are individual market variables (prices, interest rates, etc.), underlying volatilities or underlying correlations (Blaschke, Jones, Majnoni, & Peria, 2001). Scenarios can be developed using historical data, however, using this approach may lose relevance over time as markets and institutional structures changes. Two other types of scenario creation are hypothetical and Monte Carlo simulation (Blaschke, Jones, Majnoni, & Peria, 2001). Hypothetical scenarios can be used to search for a scenario that has a great impact on a portfolio of a business. The difficulty in hypothetical analysis is creating a realistic scenario and defining the likelihood of that event occurring (Blaschke, Jones, Majnoni, & Peria, 2001). Another way of stress testing is reversed testing using scenarios to quantify how much stronger a given scenario configuration needs to be to drive a bank below a pre-defined threshold (for example a 6% Core Capital Tier 1 ratio) (Henry & Kok, 2013).

2.3 Type of stress tests

In this section, two main types of stress tests are described as seen in Figure 5.

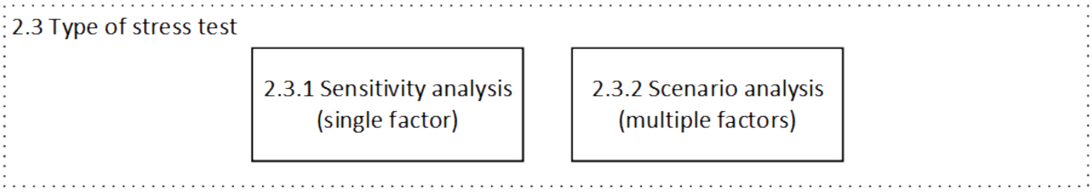

Figure 5: Layout of section 2.3.

2.3.1 Sensitivity analysis

Sensitivity analysis is the stress testing of one specific risk factor or simple multi risk factors affecting the capital or liquidity of a portfolio or a whole institution (Henry & Kok, 2013; European Banking Authority, 2015). This can be done by stress testing only one of the parameters of the PD model to research if a parameter is sensitive. Another possibility is to do a sensitivity test on PD level where underlying parameters are disregarded. The advantage of sensitivity analysis is that it is quite simple and can easily be implemented. This is however immediately a disadvantage because through the simplicity of the model it can be questioned whether the model is realistic and reliable.

2.3.2 Scenario analysis

Scenario analysis is the use of a coherent scenario for the stress testing of multiple parameters of credit risk of a financial institution (European Banking Authority, 2015). Most of the times a hypothetical (often a macro econometric) model is used for the creation of a scenario. Jones, Hilbers and Slack (2004) describe for the development of the model, important considerations such as baseline assumptions, policy responses, time horizon and which variables are assumed fixed and which are shocked. An advantage of scenario analysis is that tailor made scenarios can be designed that are specifically relevant for a financial institution. A problem when using scenario analysis is to predict the behaviour of the selected (macroeconomic) variables and predicting the likelihood of the scenario occurring (Foglia, 2008). How a macro econometric model can be designed is further discussed in 2.5.2.

2.4 Type of shock

The main type of shocks that are researched in literature are shocking of variables, shocking of correlations and shocking of the transition matrix of a model. This section is structured following Figure 6.

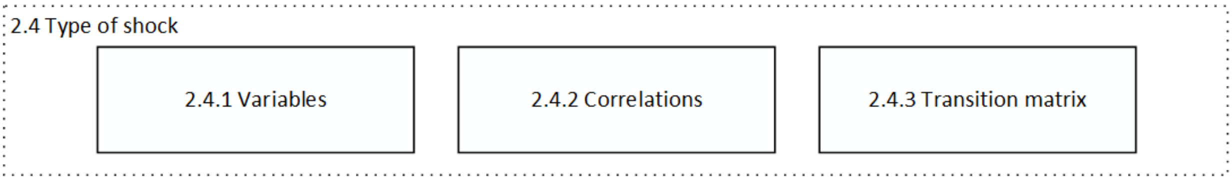

Figure 6: Layout of section 2.4.

2.4.1 Variables

Most common in stress testing credit risk is stressing the variables of the models of financial institutions. In most cases a stress scenario is mapped to the variables of the credit risk models. This is further discussed in section 2.5.

2.4.2 Correlations

Correlations are used to measure the dependence of a portfolio to identify the risk concentrations on counterparty level (Packham, Kalkbrener, & Overbeck, 2016). Not much research is done specific on stress testing of correlations in credit risk models. However, a change in correlations can have a significant influence on credit risk models (Numpacharoen, 2013). When using rating-transition models, Yang & Du (2016) state that *"it is commonly believed that borrowers with higher risk ratings are more sensitive and vulnerable to adverse shocks"*. This means that if correlations are not set right, this can influence the impact on the expected losses. Stress testing of the correlations can in this case be a way to map the vulnerabilities.

Numpacharoen (2013) describes a method to adjust the correlation matrix using a Weighted Average Correlation Method (WACM). As shown in the equation 1, this is done by setting one correlation matrix as the original correlation matrix R_{org} and choosing a second valid correlation matrix for the upper-or lower bound matrix R_{ref}. The adjustment weight w lies between zero and one and can be seen as a percentage of the degree of which the adjusted departs from the original matrix.

$$R_{adj} = (1 - w)\times R_{org} + w\times R_{ref} \tag{1}$$

Packham, Kalkbrener, & Overbeck (2016) research stress default correlations for elliptically distributed asset variables. They observe that when stressing default probabilities, asymptotic default correlations converge to a positive number in cases of heavy tails and to zero if tails are light-tailed. This behaviour is similar to tail dependency.

2.4.3 Transition matrix

In some credit models, a transition matrix is used to take into account the probability of the transfer of a certain contract to another risk state in a portfolio. The transition probabilities between states can depend on endogenous variables and macroeconomic variables (Liu, Nassar, & Guo, 2015). Liu, Nassar, & Guo (2015) propose a model where macroeconomic variables are mapped to transition probabilities using the VARMAX-L model. Shock scenarios are then used to research the effect on the transition matrix. Skoglund & Chen (2016) propose for banks a simpler Markov iteration process to produce a (stressed) forecast of losses, impairments and future balances. A macro scenario is linked to the risk parameters of the model with multifactor model derived from Merton (1974). They name as advantage of the model that the Markov iteration reduces computational time and can be efficiently implemented when using parallel computing when portfolios are large.

2.5 Type of scenarios

Most of the criticism of stress testing studies is about the type of scenario that is chosen (Havrylchyk, 2010). The different type of scenarios can create a to severe or to optimistic scenario to test the vulnerabilities of a financial institution. In Figure 7 the most used type of scenarios in stress testing are given. The different types of scenarios are discussed in the following subsections.

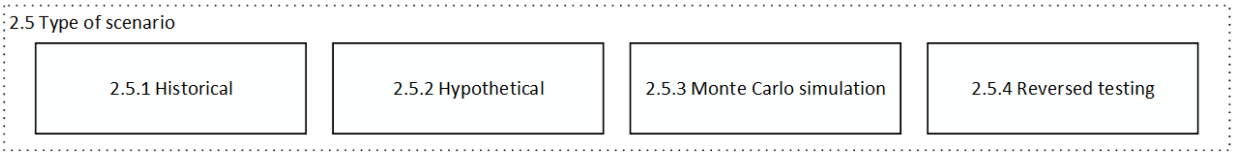

Figure 7: Layout of section 2.5.

2.5.1 Historical scenarios

There is many research done on the use of historical scenarios for stress testing (Varotto, 2012; Assouan, 2012; Jones, Hilbers, & Slack, 2004; Jakubík & Heřmánek, 2008; Breuer, Jandačka, Mencia, & Summer, 2012). Historical scenarios are by Assouan (2012) described as: *"scenarios based on historical data and rely on a crisis experienced in the past"*. The earliest banking sector stress tests where based on simple historical scenarios (Geršl, Jakubik, Konečný, & Seidler, 2012). The main advantage of using historical scenarios is that they are less sensitive against model risk, because they have occurred before (Varotto, 2012; Jones, Hilbers, & Slack, 2004). However, Varotto (2012) names as disadvantage that the history of relevant events is relatively short. This is supported by Gieseck et all. (2011) and Haldane (2009) which argue that the plausibility of events in stress testing depends on a long observation period.

2.5.2 Hypothetical scenarios

As stated in subsection 2.3.2, most of the scenario analyses are hypothetical scenarios. Hypothetical scenarios are scenarios that are plausible, but have not happened (Assouan, 2012). A disadvantage of a hypothetical scenario is that it is hard to predict the likelihood that a scenario will occur. However, an advantage is that they can be more forward-looking and flexible to formulate events that could substantially affect a financial institution (End, Hoeberichts, & Tabbae, 2006). Often scenarios are derived from a macroeconomic model using a satellite model like one as shown in Figure 8 (Geršl, Jakubik, Konečný, & Seidler, 2012). In this model the macroeconomic scenarios are designed using a DSGE (dynamic stochastic general equilibrium) model. A disadvantage of using macroeconomic scenarios is the high degree of subjective judgement. The scenario can therefore sometimes be considered weak (Bellotti & Crook, 2014). In macroeconomic scenarios, a macroeconomic shock is simulated to test what for effect this has on the balance sheet of a financial institution (Fang-Ying, 2011).

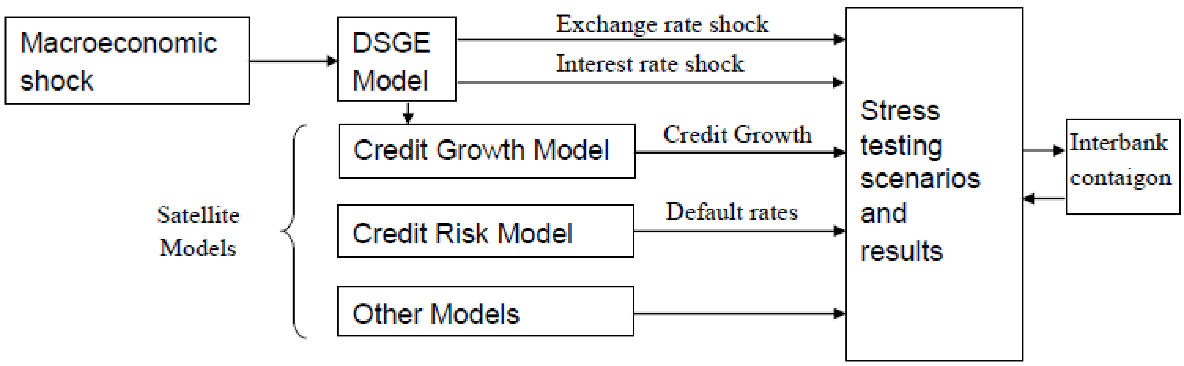

Figure 8: Satellite model (Geršl & Seidler, 2012)

To show the effect of this macroeconomic shock, macroeconomic variables are connected to risk factors of the financial institutions risk model. The most common used economic variables are: GDP growth, unemployment rate, (three-month) interest rate, export growth, inflation, property prices, domestic consumption, stock exchange indexes and interest rate spread or long-term interest rate (Gavalas & Syriopoulos, 2014; Jakubík & Heřmánek, 2008; Henry & Kok, 2013; Havrylchyk, 2010; Jiménez & Mencía, 2009). When constructing a macroeconomic scenario, it is important that a reference point in a steady state of the economic is used (Buncic & Melecky, 2013). Buncic & Melecky (2013) state that*: a through-the-cycle concept provides such a reference point, where the steady-state is represented by the average value of the macroeconomic variables over a typical business or credit cycle"*. When using a trough-the-cycle (TTC) model, changes in the credit cycle does not lead directly to chances in risk factor of the model (Topp & Perl, 2010). However most financial institutions use a Point-In-Time (PIT) model (Topp & Perl, 2010). This model try to evaluate the current credit situation or the credit situation point-in-time moment of a client by taking both cyclical and permanent effects of these client into account (Buncic & Melecky, 2013). Much research is done about the creating and linking of macroeconomic scenarios to risk models of financial institutions. In most of these models, LGD is assumed to remain constant (End, Hoeberichts, & Tabbae, 2006). In the remainder of this subsection, the main topics in the literature about creation macroeconomic scenarios are discussed.

The creation of a macro econometric model can be done in three different ways (Foglia, 2008; Vuković, 2014):

1. As a structural econometric model;
2. A vector autoregressive method;
3. Statistical approach.

A structural econometric model can be created by the business, imposed by regulators but can also be a historic scenario. To make a structural econometric model that can be used periodically, it is possible to link scenarios to certain macroeconomic parameters. An example is to link the scenarios to the National Institute's Global Econometric Model (NiGEM). With this model, which is derived from data back to 1961, several scenarios can be simulated (Duellmann & Kick, 2014).

If there is no macroeconomic model available or no feasible shocks can be generated, it is possible to use some form of regression model (VECM) (Foglia, 2008; Seah, So, & Thomas, 2014; Assouan, 2012). There can be made a distinction between models that use a causal relationship between PD and macroeconomic factors because variables are considered endogenous and a time series approach where macroeconomic factors are considered exogenous (Assouan, 2012). Many different kinds of regression models are proposed in the literature. The most used form is a Vector Autoregression Model (VAR) (End, Hoeberichts, & Tabbae, 2006; Song & Huh, 2011; Liu, Nassar, & Guo, 2015; Hoggarth, Sorensen, & Zicchino, 2005). But for example Schechtman & Gaglianone (2012) use a quantile regression model, Castrén, Dées, & Zaher (2010) use a Global Vector Autoregressive (GVAR) model, Guarda, Rouabah, & Theal (2013) use a Mixture Vector Autoregressive (MVAR) model that allow for a multi-modal distribution of residuals, Breeden (2016) uses a multiple regression model, Havrylchyk (2010) uses an univariate regression model (one dependant variable and a multivariate regression model (multiple dependent variables) and Zhang & Kang (2014) use a LOGIT regression model. To conclude this subsection, the most used regression model (VAR) is described.

Schechtman & Gaglianone (2012) describe the most structured and reduced-form of VAR for the transformation of Credit Risk Indicators (CRI_t) and add in equation 5 a stress testing flavour to the model:

$$CRI_t = \frac{1}{1+\exp(-y_t)} \quad \left(or\ y_t = ln\left(\frac{CRI_t}{1-CRI_t}\right)\right) \tag{2}$$

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \gamma_0 z_t + \sum_{j=1}^{q} y_j z_{t-j} + u_t \tag{3}$$

$$z_t = \mu + \sum_{k=1}^{m} A_k z_{t-k} + \varepsilon_t,\ m > q \tag{4}$$

$$(u_t, \varepsilon_t) \sim N(0, \Sigma), \Sigma = \begin{pmatrix} \Sigma u,u & \Sigma u,\varepsilon \\ \Sigma \varepsilon,u & \Sigma \varepsilon,\varepsilon \end{pmatrix} \tag{5}$$

Where y_t is the logit transformation of an observable $CRI_t \in [0,1]$, z_t is a vector of macroeconomic variables at time t, u_t is a normal error, homosedastic and independent with regard to past information and ε_t is a normal white noise. Equation 3 links the macro-credit to real-valued credit risk indicator(s) y_t and z_t. Two main criticisms on this model (Schechtman & Gaglianone, 2012) are that it is based on normality, which is not always the case, and that it is too restricted for the uncertainty of a macro credit risk link. They argue that it represents a limitation for the stress testing of tails of credit risks.

The third possibility for creating macroeconomic stress tests is the use of a statistical approach. Macroeconomic and financial variables can be for example modelled through a multivariate t-copula (Foglia, 2008). They name two main advantages of using the t-copula approach. The first advantage is that using a t-copula, it is possible to model the marginal and dependence structure of the multivariate distribution separately. A second advantage is that this approach shows tail dependence between the macro-financial variables. A disadvantage is that a statistical approach is backward looking. Often only scenarios are produced, that are not worse than historic events. Often statistical approaches are combined with Monte Carlo a simulation, which is further discussed in the next section.

2.5.3 Monte Carlo simulation

Many models use (some form) of Monte Carlo simulation for the creation of scenarios. Often this is in combination with historic, macroeconomic or reversed testing (Fang-Ying, 2011; Song & Huh, 2011). Bellotti & Crook (2014) and (Dunbar, 2012) use both a Monte Carlo simulation for stress testing as an alternative to a scenario-based (hypothetical/historical) approach. Bellotti & Crook (2014) use principal component analysis to derive macroeconomic factors for the probability of default model. Because the macroeconomic factors they use are uncorrelated, they can simulate independently data as economic scenarios for stress testing. Because more scenarios are developed using a loss distribution, it can be back-tested and is so less subjective than a scenario based approach. Vladimir, Surzhko, & Khovanskiy (2015) use Monte Carlo simulation to estimate changes in the rating structure using the transition matrixes of the models. Like Bellotti & Crook (2014) and (Dunbar, 2012) they use macroeconomic factors to model the probability of default using a loss distribution. Finally, Breuer, Jandačka, Mencia, & Summer (2012) use a Monte Carlo simulation to simulate different scenarios to identify the worst-case scenario.

2.5.4 Reversed stress testing

Reversed stress tests aim at finding scenarios that causes a financial business model to become unviable (Grundke & Pliszka, 2015; European Banking Authority, 2015). Henry & Kok (2013) describe that: *"reversed stress-testing as applied in the forward-looking solvency analysis framework quantifies how much stronger a given scenario configuration needs to be in order to drive a certain number of banks below a pre-defined capital ratio threshold"*. Grundke & Pliszka (2015) expect that banks have to perform reversed stress in a quantitative way. The European Banking Authority (2015) states: *"reversed stress test is used as a risk management tool aimed at increasing the institution's awareness of its vulnerabilities by means of the institution explicitly identifying and assessing the scenarios (or combination of scenarios) that result in a pre-defined outcome"*. However until now, little research and standard approaches are developed for reversed stress testing. A disadvantage of reversed stress testing is that it can be mathematically and conceptually challenging, certainly when many risks factors are included in the model. A requirement for stress testing is that all components of the credit model(s) are fully integrated. The reversed stress test modelled by Grundke & Pliszka (2015), focusses on modelling a stress test for zero-coupon bonds of banks. They use a linear factor model to identify systematic risk factors. Then principal component analysis is used to reduce the complexity of a dataset by an orthogonal linear transformation of the original data into a new orthogonal space. However, the results of this researched can be questioned, because of the limited data points that were used. Patel (2014) describes an approach where first a loss distribution of the current portfolio is determined. Subsequently with the use of a Monte Carlo simulation macroeconomic and credit risk factors are simulated to calculate a portfolio loss in different scenarios. Then Patel (2014) sort the results on the highest aggregate portfolio loss to search for vulnerable scenarios.

2.6 Regulatory

Since the introduction of the Single Supervisory Mechanism (SSM), the ECB is responsible for identifying vulnerable banks from both a bank level (micro) and system-wide (macro) perspective (Henry & Kok, 2013) in Europe. One of the methods to identify vulnerabilities in banks models is stress testing. Stress testing is already used since 2011 by the European Bank Authority (EBA). Nowadays, together they are responsible for the stress testing of banks in Europe with assets over 30 billion Euros. The EBA is responsible for coordinating the stress tests. The scenarios are developed by the European Systemic Risk Board (ESRB) and the ECB in cooperation with competent authorities, the EBA and the European Commission (European Banking Authority, 2016).

The micro and macro stress testing from a regulatory point can also be referred to as bottom-up approach (micro) and top-down approach (macro) (Vuković, 2014). The first approach is driven by the financial institutions. With this approach, regulatory authorities define macroeconomic scenarios that will affect the parameters financial models of financial institutions to test the impact on the balance sheet and/or capital adequacy ratios. Typically, these stress tests are tailor-made scenarios (Henry & Kok, 2013). An advantage of this approach is that it is more detailed. However, this becomes also a disadvantage because it makes it hard to compare different financial institutions. The second approach requires financial institutions to deliver certain financial data to the regulatory authorities. The authorities themselves are subsequently testing the banks bank-by-bank or as a system as a whole. Because this is the same for all banks under that regulatory institution, this data is not very detailed, but can be used easily to compare banks and analyse the impact on the banking system as a whole.

The design of scenarios is conducted in a four-pillar structure as seen in Figure 9. As seen in the figure, credit risk models are only a part of the total stress model. The first step in the model is to determine a set of macro-financial risks that could have an impact on financial institutions (or the whole system). Second, a satellite model is used to map the macroeconomic scenario(s) to the risk variables of a financial institution. In the third step is evaluated what for effect this has on the balance sheet of the financial company (solvency ratio, regulatory capital, etc.). In the last part, the impact is evaluated (feedback).

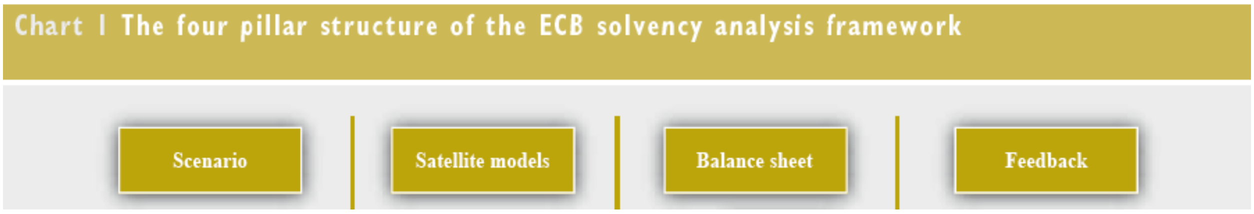

Figure 9: Four pillar structure of ECB solvency analysis framework (Henry & Kok, 2013).

The most recent regulatory stress test is conducted for banks by the EBA in the beginning of 2016. In the methodological note (European Banking Authority, 2016), EBA describes the three main steps for financial institutions in the stress test:

1. Estimating starting values of the risk parameters;
2. Estimating the impact of the scenarios on the risk parameters;
3. Computing impairment flows as the basis for provisions that affect the P&L.

The stress test in 2016 consists of a baseline and an adverse scenario for a period of 2016-2018. The main factor in the stress test is determined of the GDP growth in EU countries for a baseline and adverse scenario, as given for the Netherlands and the European Union in Table 2 (European Systemic Risk Board, 2016). The adverse scenario is based on shocks in the exchange rate, funding, house prices, foreign demand, interest rate and equity, oil and food prices and domestic demand.

Table 2: GDP growth for EU and Netherlands (European Systemic Risk Board, 2016).

	Baseline growth rates (percentages)			Adverse growth rates (percentages)		
	2016	2017	2018	2016	2017	2018
Netherlands	2.1	2.3	1.4	-1.0	-1.6	-0.4
European Union	2.0	2.1	1.7	-1.2	-1.3	0.7

Besides micro and macro stress testing, reversed stress testing is used by the ECB (Henry & Kok, 2013). It is expected that large banks have to do more reversed stress testing in the future in a quantitative way (Grundke & Pliszka, 2015).

2.7 Overview of advantages and disadvantages of stress testing models

In Table 3 a summery is given of all advantages and disadvantages for all different (sub)types of stress testing that where distinguished from the literature. Stress testing models can consist of a combination of different subtypes to develop a more reliable and/or realistic model.

Table 3: Summary of advantages and disadvantages of different (sub)types of stress testing.

	Advantages	Disadvantages
Type of stress test		
Sensitivity (single parameter)	- Simplicity of method	- Not very realistic and reliable
Scenario	- Can be tailor made	- Behaviour in future is hard to predict - Prediction of likelihood of scenarios is difficult
Type of shock		
Variables	- Can be used for all models	
Correlations	- Can have huge impact if risk models include correlations matrix	- Advanced method - Correlations not included in all models
Transition matrix	- Can have high impact if risk models include transition matrix	- Transition matrix not included in all models
Type of scenario		
Historical	- Low sensitivity for model risk because based on historic events	- History of relevant events is often short - Does not incorporate tail risk
Hypothetical	- Forward looking - Availability of relevant literature - Flexible	- Probability of events is hard to define - High degree of subjective judgement
Monte Carlo simulation	- Creation and evaluation of many different scenarios - Can be combined with other types of scenarios	- Statistical approach, depends on (a select group of) variables and their statistical distribution
Reversed testing	- Offers feedback on 'how low can we go'	- Mathematically and conceptually challenging

3 Analysis of existing models of the leasing company

In this chapter an analysis is made of the models of the --- confidential --- business lines of the leasing company, focused on the credit models that are used to calculate provisions. In the first section the activities of the business lines are given. In the second section the credit risk models of the leasing company are described. In the last section of this chapter the main financial key figures of the leasing company are presented.

3.1 Business lines of the leasing company

--- Confidential ---

3.2 Credit risk models at the leasing company

--- Confidential ---

4 Methods & data

For the design process of the stress testing model the framework as shown in Figure 10 is used which is based on the stress testing framework of End, Hoeberichts, & Tabbae (2006) and the stress testing framework of Henry & Kok (2013). In the first stage of the design, the type of stress test that is conducted is determined. In the second phase, a stress scenario for the stress test is formulated. In the third phase the effects of the stress scenario at the risk factors of the credit risk model is evaluated. In the fourth phase of the model, the interaction of the risk drivers is mapped on the portfolio at a client level. In the last phase, the results of the stress test are interpreted.

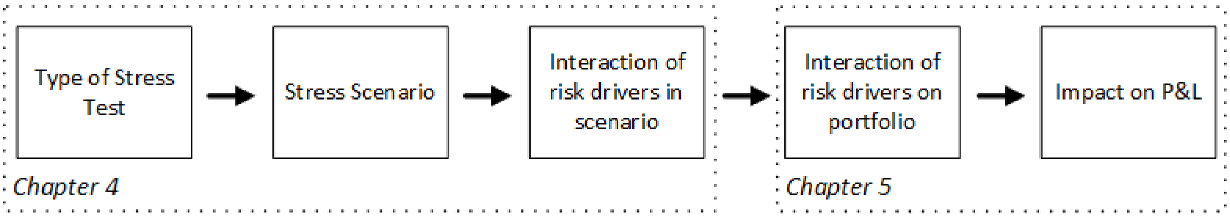

Figure 10: Stress testing framework

The model will be designed in such a way that the leasing company can easily use it periodically. In addition no specific simulation software is available at this moment at the leasing company, so the model has to be running in excel with optionally input from SPSS. The first three phases of the framework are discussed in the first three sections of this chapter. The fourth and fifth phase are discussed in the next chapter. In the fourth section of this chapter, the stress testing model is described. This chapter is concluded with a description of the used data.

4.1 Type of stress test

First the type of stress test that the leasing company fits best has to be determined. Three aspects are taken into consideration:

1. Existing credit models at the leasing company;
2. Software that can be used;
3. Existing stress test of company A;

Confidential

Secondly, the stress test has to be performed with the software that is available at the leasing company. At this moment, the Risk Management department of the leasing company uses no specific simulation applications. The model therefore has to run in excel (VBA). For more statistical analysis, the SPSS software is available.

Confidential

Considering these three aspects, only few stress tests distinguished in the literature can be used. As can be seen in Figure 1 a decision has to be made between the type of test, type of shock and type of scenario. First is determined which type of test fits best. Because it is logic that a stress scenario will affect more than one parameter when it really occurs, [redacted], it can be argued that the stress test should test multiple factors. Second is determined that the variables of the credit model will be shocked in the stress test. The types of scenarios that will be used in the model are hypothetical and historical scenarios. Hypothetical scenarios are used because they are forward-looking and flexible to formulate. A second argument for using a hypothetical method is that it connects with the yearly stress testing questionnaire of company A. However, following Guarda, Rouabah, & Theal (2013), the predictions for designed stress scenarios could break down in the face of extreme events. Therefore, in addition a historical scenario can be seen as more plausible then hypothetical scenarios. This is why in addition to hypothetical scenarios, historical scenarios are proposed.

4.2 Stress Scenario

Following Jones, Hilbers and Slack (2004), considerations have to be made about base line assumptions, policy responses and which variables of the credit model are assumed fixed and which are shocked. First, the month of the used portfolio data for stressing the credit model is defined as the baseline. Within all models we will assume that no intervention is taken. This is because the purpose of this stress test is to determine if the existing portfolios can sustain different scenarios and does not incorporate responses.

Confidential

Confidential

The next step is to describe the stress scenarios for the hypothetical and historical scenarios. The most widely used form to describe a hypothetical scenario is a macroeconomic scenario. In the stress test five different multivariate scenarios are used. Three scenarios are used from the stress test of company A that were developed in association with the Hall Institute for Economic Research (IWH) in October 2016. This not only to connect with the stress test of company A, but also because the macroeconomic parameters that are used are consistent with the variables that are suggested in the literature.

The three scenarios that are used are the two different scenarios for an economic crisis and the economic downturn scenario. Other scenarios are not incorporated because they are less relevant for the Dutch market. Furthermore, the stress test is focused on the portfolio at this moment. Therefore, multi-year scenarios are not included. The fourth scenario is based upon the most worse macroeconomic events based on the Dutch economy from the last 70 months (regression period). The fifth scenario is a historic scenario that incorporates the economic crisis of 2008/2009. All macroeconomic scenarios that will be used in the stress test are given in Table 4.

Confidential

4.3 Interaction of risk drivers in stress scenario

In this section is described how the stress scenarios interact with the risk parameters. As discussed in section 4.2, PD and LGD will change in a stress scenario and the EAD is fixed.

For the mapping of the macroeconomic scenarios to the risk parameters, a model has to be developed that will change the PD and LGD depending on the macroeconomic scenario. However, there are difficulties with modelling PD and LGD to the macroeconomic scenarios. First, the PD is not tracked historically over a very long period, which makes it hard to determine a good fit between the PD and macroeconomic factors. Second, the PD is heavily sensitive to model changes (which are yearly performed). Another problem is that LGD is fixed historic average in the credit models. Because of this, no relationship between LGD and macroeconomic variables can be determined.

Confidential

However, the default rates of the business units of the leasing company are tracked over time and are less subject to model changes. In Figure 11 the historic default rates of the different portfolios are shown. The default ratio is defined as all defaulted utilisation of a portfolio divided by the whole utilisation of a portfolio. The utilisation is the sum of all open unpaid invoices and the remaining book value of all contracts of the portfolio. A regression model will be used in chapter 5 to map the macroeconomic factors to the default rate. This approach is supported by Wilson (1997) who relates default rates to expected losses based on an economic model. This stress default ratio (dr^{*}) can be used to stress the expected loss as a substitute of stressing the PD.

However, default rates cannot be linked to the LGD because it is fixed. Therefore, a downturn LGD is developed for stressing the LGD. A downturn LGD is based on data from economic downturn periods (Company A, 2016). The approach that we use differs per business entity. This because as for each business entity different models are used over time. The models are described in chapter 5.

4.4 Stress testing model

The goal of this thesis is to develop a stress test for the portfolios of the leasing company. In this section the model and its working is described. As input for the model the monthly provisions report of the different business units is used. In this excel file all relevant data for each client is given. It consists of different important qualitative and quantitative information including PD, LGD, EAD and provisions at a client level.

The stress testing model is built in excel using VBA. The VBA code and the input sheet of the model are attached in appendix C. The model is modelled at a client basis. Therefore the computing time can become problematic. Preferable the simulation time of the model is minimized. The model has to be simulated separately for the different portfolios.

The model consists of two important sheets. The first important sheet is the in- and output sheet (called input sheet in the model). In this sheet the number of simulations, the stress default ratio and the stress LGD of the portfolio has to be specified as input of the model for each scenario. After simulating the model, in this sheet the current key figures like utilization, default rate, LGD, expected loss and number of clients are shown. For each scenario the simulated default rate, the average simulated expected loss and the increase of the expected loss relative to the current situation is given.

The second important sheet in the simulation is the debtor sheet. This sheet is used as input for the model. The input files differ slightly per portfolio. Therefore, the VBA code has to be programmed in such a way, that the model can be simulated for each portfolio without errors.

To derive a clear VBA code, different VBA subs are used. This subs are 'called' trough the main VBA sub stress test. In the stress test sub, first all information that is required for running the simulation is stored in variables. Examples are the number of clients and the different column numbers of utilisation, PD, LGD, exposure and expected loss. The VBA code is designed in such a way, that for all different portfolios the correct information is gathered. Second, all data from the input sheet is stored in a VBA array called DATA. All calculations that are necessary are conducted in this DATA array. By using an array the model time is decreased with a factor 10 compared with calculating values in the excel sheet.

For each scenario first is determined, how the increase in default rate (Δdr) in that scenario has to be distributed over all clients. The increase in Δdr is calculated by substracting the current default rate of the portfolio from the calculated stressed default rate. To map this Δdr on the portfolio, there has to be simulated an increase in the number of clients that is in default. An algorithm is used to determine a percentage of each PD class that should default in order to achieve Δdr. In Table 5 to Table 7 an example of this procedure is given. In this example Δdr is 5% which results in a total amount of utilization that should default of 60.

Table 5: Initial state

PD	Total utilization	Expected Utilization to default	distribution	Initial utilization to default
0,1%	€ 1.000	€ 1,00	4,17%	€ 2,5
10,0%	€ 180	€ 18,00	75,00%	€ 45,0
50,0%	€ 10	€ 5,00	20,83%	€ 12,5

100,0%	€ 10			
Total	€ 1.200	€ 24	100%	€ 60

The algorithm consists of three phases, an initial state, n number of iterations and a final state. In the initial state is determined from the PD which percentage of utilization is expected to default. This distribution is used to calculate the initial utilization for each PD class that should default. However, in Table 5 can be seen that in the initial state, the utilization to default in the highest PD class, is higher than the total utilization of the corresponding PD class. This could be the case not only for one, but for several PD classes. In the second phase of the algorithm this surplus is redistributed over the other PD classes to reach the stressed default rate. In this example there is a surplus of €2,5. This surplus is redistributed over the other PD classes by calculating the distribution for the remaining PD classes relative to their utilization. The calculated distribution is used to redistribute the remaining surplus over the other PD classes as can be seen in Table 6.

Table 6: Redistribution of surplus

PD	Utilization	Expected Utilization to default	distribution	surplus	Redistribution
0,1%	€ 1.000	€ 1,00	5,26%	€ 0,13	€ 2,63
10,0%	€ 180	€ 18,00	94,74%	€ 2,37	€ 47,37
50,0%	€ 10	€ 5,00			€ 10
100,0%	€ 10				
Total	€ 1.200	€ 24	100,00%	€ 2,50	€ 60,00

The second phase of the algorithm is repeated n time using a while loop until there is no more surplus. If the final state is reached, the final stressed default percentage for each PD class is calculated as can be seen in Table 7.

Table 7: Stressed default percentage of example

PD	Utilization	Final utilization to default	Stressed default percentage
0,1%	€ 1.000	€ 2,63	0,26%
10,0%	€ 180	€ 47,46	26,37%
50,0%	€ 10	€ 10	100,00%
100,0%	€ 10		
Total	€ 1.200	€ 60	

After determining the stressed default percentage for each PD class, the model is simulated n times. In the simulation for each client a random number is drawn using the random function in excel. If this number is below the stress rate of the client, the stress PD of this client will become 1. Otherwise, the stress PD is equal to the maximum of the current PD and the stress rate of the corresponding PD class. The expected loss for each client is calculated by multiplying the stress PD with the stress LGD and the exposure. For each simulation, the total expected loss and the default rate of the simulation is stored. After n number of simulations, the average default and average stress expected loss over all simulations is calculated and stored in the input and output sheet of the simulation. This procedure is repeated for all different scenarios.

4.5 Description of the data

This section contains a description of the data that is used for developing stressed values of the default rate and the stress LGD. In addition it describes which dataset is used for simulating the stress test.

4.5.1 Data for default rate and LGD

For predicting the default rate in the different stress scenarios, the monthly historic default rates of all portfolios are used. For the regression analysis, all macroeconomic data from this period from the Dutch market is used. In Table 13 in appendix D a summery is given of all data.

4.5.2 Dataset for simulation

Confidential

4.6 Financial key figures

For controlling purposes, several indicators are important for the board and the shareholders of the leasing company. In this section the two indicators that include provisions are presented in equation 14 and equation 15 for October 2016. This in order to relate in chapter 5 the results of the stress test to the key financial indicators.

$$ROE = \frac{net\ income}{equity} = \text{confidential} \tag{14}$$

$$Credit\ risk\ cost\ ratio = \frac{risk\ costs}{assets} = confidential \tag{15}$$

The most important key figure of the leasing company is the Return On Equity (ROE). The ROE is used to measure how well the company performs for their shareholders. The target of the leasing company is to acquire a yearly return on equity of at least “ - - - confidential - - - ”. Another important measure is the credit risk cost ratio. This ratio measures how much the risk costs of the company are related to the assets of the company.

Confidential

5 Results

In this chapter, all modelling results are discussed for the default rate in section 5.1, LGD in section 5.2 and the stress testing model in section 5.3. This chapter is concluded with the impact of the stress test at the key figures of the leasing company in section.

5.1 Default rate model

For the mapping of the macroeconomic factors to the default rate, a multivariate linear regression analysis is conducted. To determine the best regression, the procedure is followed that is given in appendix E. The results of the final regressions are given in Table 8. For portfolio X and portfolio Y the final regression indicates that those assumptions of multivariate linear regression are met. However, for portfolio Z the results of the regression showed that the errors of the residuals where not normally distributed. To control for this, the default rates for portfolio Z were transformed into a normal distribution by taking the logarithm of the default rates. However, in the results of portfolio Y a slight trend can still be detected in the residuals, which could be a sign for some homoscedasticity. In addition the predictive power of the model is quite low

Confidential

As seen in Table 8, overall the best regression includes lagged variables for almost all variables. This is logical, because defaults are triggered as payments if they are at least - - - confidential - - - days overdue. The results of the regression analysis are used to calculate the default rates of the different scenarios as shown in Table 9.

Confidential

If the baseline is lower than the current default rate (see --- confidential ---), the model has to be calibrated. This is the case for portfolio Y and portfolio Z. This calibration is conducted through calculating the increase (factor) of the regressed default ratio in each scenario relative to the baseline. The stressed default ratio for portfolio Y and portfolio Z are subsequently determined by multiplying each scenario with the calculated factor (1.08 for portfolio Y and 1.27 for portfolio Z). The final stress default rates for the stress testing model are given in Table 10. There is a big difference between the historic scenarios and the economic crises and economic downturn scenarios.

Confidential

5.2 LGD model

In the subsections of this paragraph, the different downturn LGD of each portfolio is discussed.

5.2.1 Downturn LGD portfolio X

--- Confidential ---

5.2.2 Downturn LGD portfolio Y

--- Confidential ---

5.2.3 Downturn LGD portfolio Z

--- Confidential ---

5.3 Stress testing results

--- Confidential ---

5.4 Financial impact

--- Confidential ---

6 Conclusion & recommendations

In the last chapter of this thesis, the main conclusions are summarized. This chapter is concluded with recommendations for further research to strengthen the risk management of the leasing company.

6.1 Conclusions

In section 2.7 of this thesis, the latest trends for stress testing credit risk portfolios are given. From the existing literature an approach is designed for developing a stress testing model focused on smaller (non-bank) financial institutions. In this report a stress testing model is designed and tested by application on an automotive retail-financing portfolio. The model can simulate how different stress scenarios affect the credit risk model of the financial institution. By using a stress testing model as risk measurement tool, events that are not incorporated in the existing credit risk models can be tested. A stress test can give valuable information of the behaviour of the portfolios in stress scenarios.

Confidential

The developed model gives insight in the vulnerabilities of the portfolios. The management of the leasing company can use this information to further strengthen the company by reducing risk. A first way is to adjust the credit risk models. If the credit models are more progressive, the stress scenarios will result in a lower impact on the change in expected loss. A second way of using this information is by reserving capital for the increase in expected losses if a stress scenarios occurs. Finally, the management could decide to sell contracts in high PD classes to reduce the credit risk.

6.2 Recommendations

Credit risk is the biggest risk at the leasing company. The developed stress test can help in further strengthen the risk management of the company. In addition, this stress test can be used for delivering stress test information for the stress testing requests that is yearly requested by shareholders and accountants from company A. The simulation is automated and therefore can be easily reported on a regular basis. We advise to run the simulation quarterly to search for vulnerabilities in the credit risk of the portfolios. In addition we advise to evaluate the scenarios of the model yearly. In the model, scenarios can be easily added or removed to reduce or expand the model. In addition the model can be developed to a point in time model. This can help the risk management department by predicting the behaviour of the portfolios point in time.

6.3 Further research

In this thesis, the model that is created is designed in such a way that it represents the best possible representation of the reality. However, in modelling there is always a gap between the developed model and reality. In this section the limitations of the model are discussed and recommendations for further research are given to further strengthen the credit risk of the leasing company.

The biggest gap between the model and the reality is probably that in the stress testing model an assumption is made that only the PD of different PD classes increases and that there is a shift from non-default status to default status. However, in a real stress situation it is expected that there is also a shift of utilization between different PD classes.

Confidential

A second limitation of this model is that it focusses only on credit risk. However, underlying assumption when calculating the exposure of a client is, that the value of the underlying asset is correctly determined. There is a possibility that the value of the underlying asset is in fact lower than expected which would result in a higher exposure than assumed. Therefore, the second recommendation is to develop a stress testing model for the residual value risk.

7 Reference list

Assouan, S. (2012). Stress testing a retail loan portfolio: an error correction model approach. *The Journal of Risk Model Validation*, 3-25.

Basel Committee. (2009). Principles for sound stress testing practices and supervision.

Bellotti, T., & Crook, J. (2014). Retail credit stress testing using a discrete hazard model with macroeconomic factors. *Journal of the Operational Research Society*, 340-350.

BIS Committee on the Global Financial System. (2005). Stress testing at major financial institutions: survey results and practice.

Blaschke, W., Jones, M., Majnoni, G., & Peria, S. (2001). Stress testing of financial systems: an overview of issues, methodologies, and FSAP experiences. *International Monetary Fund*.

Borio, C., Drehmann, M., & Tsatsaronis, K. (2014). Stress-testing macro stress testing: does it live up to expectations? *Journal of Financial Stability*(12), 3-15.

Bratton, E., & Garrido, F. (2016, 4). *Cost-to-income ratios of banks worldwide*. Retrieved from S&P Global - Market Intelligence.

Breeden, J. (2016). Incorporating lifecycle and environment in loan-level forecasts and stress tests. *European Journal of Operational Research* .

Breuer, T., Jandačka, M., Mencia, J., & Summer, M. (2012). A systematic approach to multi-period stress testing of portfolio credit risk. *Journal of Banking & Finance*, 332-340.

Buncic, D., & Melecky, M. (2013). Macroprudential stress testing of credit risk: A practical approach for policy makers. *Journal of Financial Stability* , 347-370.

Castrén, O., Dées, S., & Zaher, F. (2010). Stress-testing euro area corporate default probabilities using a global macroeconomic model. *Journal of Financial Stability*, 64-78.

Company A. (2016). *Annual report 2016.*

Company A. (2016). LGD Handbook 2016.

Company B. (2016, 10 17). *Company B*.

Doumpos, M., Zopounidis, C., & Fragiadakis, P. (2015). Assessing the financial performance of European banks under stress testing scenarios: a multicriteria approach. *Operational Research*, 1-13.

Duellmann, K., & Kick, T. (2014). Stress testing German banks against a global credit crunch. *Financial Markets and Portfolio Management* , 337-361.

Dunbar, K. (2012). Forecasting and stress testing the risk-based capital requirements for revolving retail exposures. *Journal of Banking Regulation*, 249-263.

End, J. v., Hoeberichts, M., & Tabbae, M. (2006). Modelling Scenario Analysis and Macro Stress-testing. *Netherlands Central Bank, Research Department*(119).

End, J. W. (2011). Credit and liquidity risk of banks in stress conditions: Analyses from a macro perspective. *Proefschrift*.

European Banking Authority. (2015). *Draft Guidelines on stress testing and supervisory stress testing.*

European Banking Authority. (2016). 2016 EU-Wide Stress Test - Methodical Note.

European Systemic Risk Board. (2016). Adverse macro-financial scenario for the EBA 2016 EU-wide bank.

Fang-Ying, Y. (2011). The credit risk macro stress testing of the Chinese banking system. IEEE: Chinese Control and Decision Conference (CCDC).

Federal Reserve. (2013). Capital Planning at Large Bank Holding Companies: Supervisory Expectations and Range of Current Practice. *Board of Governors of the Federal Reserve System*.

Foglia, A. (2008). Stress testing credit risk: a survey of authorities' approaches. *Bank of Italy Occasional Paper*.

Gavalas, D., & Syriopoulos, T. (2014). Bank credit risk management and migration analysis; conditioning transition matrices on the stage of the business cycle. *International Advances in Economic Research*, 151-166.

Geršl, A., & Seidler, J. (2012). How to Improve the Quality of Stress Tests through Backtesting. *Czech Journal of Economics and Finance*.

Geršl, A., Jakubik, P., Konečný, T., & Seidler, J. (2012). The Framework for Testing Banking Sector Resilience Used by the Czech National Bank. *Czech National Bank Working Paper Series* .

Giesecke, K., Longstaff, F., Schaefer, S., & Strebulaev, I. (2011). Corporate bond default risk: A 150-year perspective. *Journal of Financial Economics*, 233-250.

Grundke, P., & Pliszka, K. (2015). A macroeconomic reverse stress test. *Bundesbank Discussion Paper*.

Guarda, P., Rouabah, A., & Theal, J. (2013). A mixture vector autoregressive framework to capture extreme events in macro-prudential stress tests. *The Journal of Risk Model Validation*, 21.

Haldane, A. (2009). Why banks failed the stress test. *speech given at the 2009 Marcus-Evans Conference on Stress-Testing.* Bank of England Publications.

Havrylchyk, O. (2010). A macroeconomic credit risk model for stress testing the South African banking sector.

Henbest, J. (2006). Stress Testing: Credit Risk. *Paper presented at the Expert Forum on Advanced Techniques on Stress Testing: Applications for Supervisors.* Washington, DC.

Henry, J., & Kok, C. (2013). A macro stress testing framework for assessing systemic risks in the banking sector. *Occasional Paper series ECB*(152).

Hoggarth, G., Sorensen, S., & Zicchino, L. (2005). Stress tests of UK banks using a VAR approach. *Working paper series of Bank of England*.

Institute for digital research and education. (2017, January). Retrieved from http://statistics.ats.ucla.edu/stat/spss/webbooks/reg/chapter2/spssreg2.htm

Jakubík, P., & Heřmánek, J. (2008). Stress testing of the Czech banking sector. *Prague Economic Papers*, 195-212.

Jiménez, G., & Mencía, J. (2009). Modelling the distribution of credit losses with observable and latent factors. *Journal of Empirical Finance* , 235-253.

Jimmy, S., & Chen, W. (2016). The application of credit risk models to macroeconomic scenario analysis and stress testing. *Journal of Credit Risk* , *12*(2).

Jones, M., Hilbers, P., & Slack, G. (2004). Stress testing financial systems: What to do when the governor calls.

Kline, R. (1998). Principles and practice of structural equation modeling. *Guilford publications*.

Liu, C., Nassar, R., & Guo, M. (2015). A Method of Retail Mortgage Stress Testing: Based on Time-Frame and Magnitude Analysis. *Journal of Forecasting*, 261-274.

Mawdsley, A., McGuire, M., & O'Donnell, N. (2004). The stress testing of Irish credit institutions. *Financial Stability Report 2004*, 103-109.

Merton, R. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance*, 49–470.

Numpacharoen, K. (2013). Weighted Average Correlation Matrices Method for Correlation Stress Testing and Sensitivity Analysis. *The Journal Of Derivatives*, 67-74.

Packham, N., Kalkbrener, M., & Overbeck, L. (2016). Asymptotic behaviour of multivariate default probabilities and default correlations under stress. *Journal of Applied Probability*, 71-81.

Patel, N. (2014). An innovative approach to portfolio stress testing: Linking stress testing and portfolio credit risk. The Professional Risk Managers international Association.

Rösch, D., & Scheule, H. (2007). Stress-testing credit risk parameters: an application to retail loan portfolios. *Journal of Risk Model Validation*(1), 55-75.

Schechtman, R., & Gaglianone, W. (2012). "Macro stress testing of credit risk focused on the tails. *Journal of Financial Stability*, 174-192.

Seah, Y., So, M., & Thomas, L. (2014). Stress testing credit card portfolios: an application in South Africa. *Journal of the Operational Research Society*(65), 351-362.

Skoglund, J., & Chen, W. (2016). The application of credit risk models to macroeconomic scenario analysis and stress testing. *Journal of Credit Risk*, 1-45.

Sommar, P., & Shahnazarian, H. (2009). Interdependencies between expected default frequency and the macro economy. *International Journal of Central Banking* , *5*(3), 83-110.

Song, D., & Huh, H. (2011). Macro Shocks to the Household Lending Sector in Korea: A Study Based on Macro Stress Testing. *European Journal of Economics, Finance and Administrative Sciences*.

Sorge, M., & Virolainen, K. (2006). A comparative analysis of macro stress-testing methodologies with application to Finland. *Journal of financial stability* , 113-151.

Steeve, A. (2012). Stress testing a retail loan portfolio: an error correction model approach. *The Journal of Risk Model Validation*.

The leasing company. (2016, 10 17).

Topp, R., & Perl, R. (2010). Through-the-Cycle Ratings Versus Point-in-Time Ratings and Implications of the Mapping Between Both Rating Types. *Financial Markets, Institutions & Instruments* , 47-61.

Tsukahara, F., Kimura, H., Sobreiro, V., & Zambrano, J. (2016). Validation of default probability models: A stress testing approach. *International Review of Financial Analysis*(47), 70-85.

Varotto, S. (2012). The Great Depression scenario. *Journal of Banking & Finance* , 3133-3149.

Vladimir, S., Surzhko, D., & Khovanskiy, N. (2015). Stress-Testing Model for Corporate Borrower Portfolios. *Financial Econometrics and Empirical Market Microstructure*, 279-284.

Vuković, S. (2014). Stress Testing of the Montenegrin Banking System with Aggregated and Bank-Specific Data. *Journal of central banking theory and practice* , 85-119.

Wilson, T. (1997). Portfolio Credit Risk. *Economic Policy Review*.

Yang, B., & Du, Z. (2016). Rating-transition-probability models and Comprehensive Capital Analysis and Review stress testing: methodologies and implementation. *Journal of Risk Model Validation*, 1-19.

Zhang, N., & Kang, X. (2014). The Application of Stress Testing and Applied Technology in Credit Risk Management. *Advanced Materials Research*, 435-441.

Appendix A: Framework for literature search

To conduct a structured literature search a variation of the SPICE search strategy is used (Setting, Perspective, Intervention, Comparison, Evaluation). First relevant setting, interventions and comparisons for the research where formulated as shown in Table 11. Then synonyms and related search terms where added (for example for auto: automobile, motorcar, motorized vehicle, passenger car) which resulted in a higher number of relevant articles (see second and third column of table). New search terms where added until it delivered no more unique new articles (which was the case with the last two search terms). The total search term is displayed below the table (execution date of the is search 24 October 2016). Relevant articles were selected by reading the title and abstract. If the relevance of the article was questionable, the conclusion and results section was read. The selection of relevant articles was read completely and used to write the theoretical framework of this research.

Table 11: Review of search strategy.

Search term	Without related search terms	With related search terms
Stress testing auto loans	2	3
Credit risk models for fixed term loans	5	82
Auto loan portfolio	8	26
Stress testing credit portfolios	49	53
stress testing methods credit risks	26	31
scenario testing credit risk	56	59
stress testing credit risk using monte carlo simulation	2	5
creating scenarios for stress testing credit risk	0	54
Number of unique articles	**140**	

TITLE-ABS-KEY ("stress testing" OR "stress testing" OR stressing AND auto OR automobile OR motorcar OR "motorized vehicle" OR "passenger car" AND loans OR loan OR credit OR "fixed term loan" OR "fixed term loans" OR mortgage) OR TITLE-ABS-KEY ("stress testing" OR "stress testing" AND credit AND risk OR risks OR exposure OR exposures AND model OR models AND loans OR "fixed term loans" OR credit OR "fixed term loan" OR "fixed term loans" OR mortgage) OR TITLE-ABS-KEY (auto OR automobile OR motorcar OR "motorized vehicle" OR "passenger car" loan OR loans OR credit OR "fixed term loans" OR mortgage AND portfolio OR portfolios) OR TITLE-ABS-KEY ("stress testing" OR "stress-testing OR stressing" AND credit OR loan OR loans OR "fixed term loans" OR mortgage AND portfolios OR portfolio) OR TITLE-ABS-KEY ("stress testing" OR "stress-testing" AND methods OR overview AND credit OR loan OR loans OR "fixed term loans" OR mortgage AND risk OR risks OR exposure OR exposures) OR TITLE-ABS-KEY (scenario AND testing AND credit OR loan OR loans OR "fixed term loan" OR "fixed term loans" OR mortgage AND risk OR risks OR exposure OR exposures) OR TITLE-ABS-KEY ("stress testing" OR stress-testing AND credit OR loan OR loans OR "fixed term loan" OR "fixed term loans" OR mortgage AND risk OR risks OR exposure OR exposures AND "monte carlo" OR "monte-carlo" AND simulation OR model)

Appendix B: Stress Scenarios of company A

Table 12: Stress testing scenarios developed by the Hall Institute for Economic Research

Confidential

Appendix C: VBA code and input sheet of stress testing model

--- Confidential ---

Confidential

Appendix D: Historic data

Table 13: Historic data

	Reporting frequency	Begin	End	Number of periods	Source
GDP	Quarterly	dec-10	oct-2016	18	Statline CBS
Consumer Price	Monthly	dec-10	oct-2016	71	Statline CBS
Unemployment Rate	Monthly	dec-10	oct-2016	71	Statline CBS
Industrial Production	Monthly	dec-10	oct-2016	71	Statline CBS
Vehicle sales	Quarterly	dec-10	oct-2016	70	Statline CBS
Consumption	Monthly	dec-10	oct-2016	71	Statline CBS
3 Month interest rate	Monthly	dec-10	oct-2016	71	www.global-rates.com
Sales	Monthly	dec-10	oct-2016	71	Sales figures autoweek

Appendix E: Regression analysis

Regression guideline

The multivariate regression is based on the SPSS web book of the institute for digital research and education (2017). When conducting the multivariate linear regression, two factors are taken into account. First, the default rate that follows from the multivariate linear regressions analysis should be indeed a stressed default rate. In other words, there has to be an increase in the stressed scenarios in comparison with the baseline scenario. This means that the macroeconomic regressors should have a stressed effect. Second, the outcome of the multivariate linear regression should be tested against normality, homoscedasticity and multicollinearity, which are conditions for a good working multivariate regression model. Multivariate normality means that the errors of a multivariate regression should be normally distributed. This is checked by conducting a Kolmogorov-Smirnov test (if significance level is above 0,05, the assumption of normally distribution is questionable) and plotting a histogram and Q-Q plot. Homoscedasticity means that the variance of the residuals is homogeneous across the predicted values. If this is not the case, the data is heteroscedastic. This can be tested by plotting the standardized residuals against the predicted values. If a clear trend in the data can be detected, this can be an indication of heteroscedasticity. Multicollinearity arises if variables of the regression are near perfect linear combinations of each other. The VIF (variance inflation factor) value can be used to check for multicollinearity. If the VIF value is above 5 this is a sign of multicollinearity in the regression (Kline, 1998), if the VIF value is above 10 it is a strong sign of multicollinearity and the regression should be rejected.

In Figure 12 the procedure is graphically shown that is used to determine the best regression. First a regression is performed with no lags, 3 lags, 6 lags, 9 lags and 12 lags. This because the change of default rate can have a lagged effect with respect to the macroeconomic factors. For each macroeconomic factor the lags are selected that has the logical (depending on factor positive or negative) effect. If there is no lag with the appropriate effect for a macroeconomic factor, this factor is further ignored in the regression analysis. From the remaining lags, for each macroeconomic factor the most significant lag is determined. Thereafter, the regression is again simulated with the determined lag for each macroeconomic factor. If this regression results in a stress default ratio for all scenarios (so a higher default ratio then the baseline), this regression is used. Otherwise, the macroeconomic factor from the regression that has no plausible effect is disregarded and the regression is again simulated. This is repeated until the regression results in a stress effect. Finally, the regression is tested for normality, homoscedasticity and multicollinearity. The outcomes of the regression for the different portfolios are shown in Table 14 to Table 16. In the tables, the grey cells are the not desirable effects.

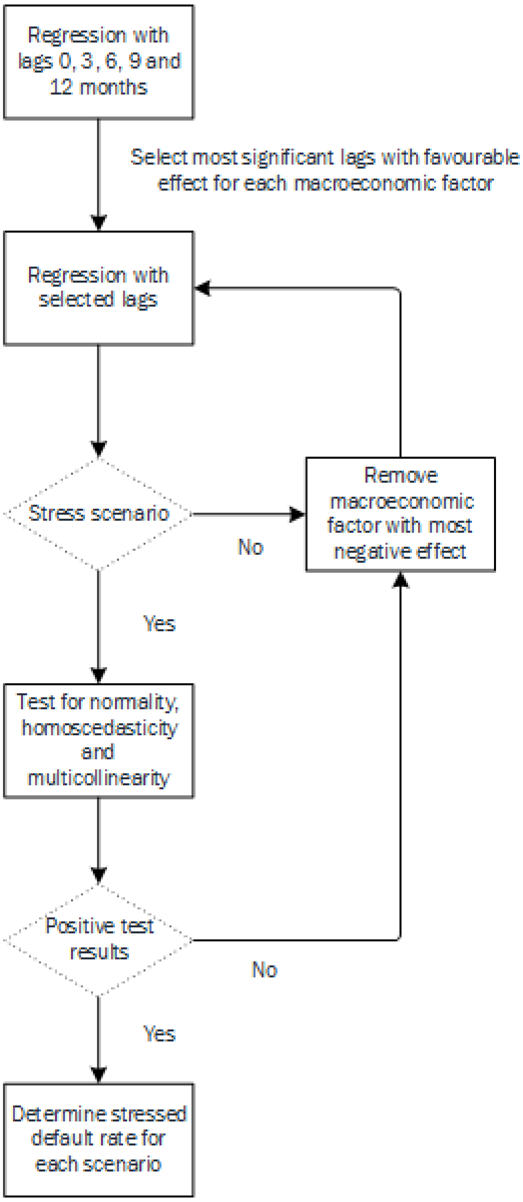

Figure 12: Regression procedure

Table 14: Regression results portfolio X

Confidential

Evaluating DEF MODEL of portfolio X

Confidential

Table 15: Regression results portfolio Y

Confidential

Evaluating DEF MODEL of portfolio Y

Confidential

Table 16: Regression results portfolio Z

Confidential

Evaluating DEF MODEL of portfolio Z

Confidential