EVALUATION OF METHODS FOR DETERMINING THE CREDIT RISK PREMIUM FOR MORTGAGES

Public version

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DETERMINING A CREDIT RISK METHOD FOR MORTGAGE RATES

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Preface

This thesis marks the end of my study in Industrial Engineering and Management. I could not have wished for a better place than ABN AMRO Hypotheek Group to perform this research. During my internship I have not only learned much about the subject at hand, but also about my own qualities and skills.

This is why I would like to thank my external supervisor Daniël Linker in the first place, for providing a position as an intern, for creating the basis of this research and for all of the precious input. This goes as well for all of my helpful colleagues at Balance Management.

Many thanks go out to Toon de Bakker for helping me find this internship, and mostly for all the support and supervision during my project. Thanks as well to Berend Roorda for the guidance, with this project as well as during my study.

It only remains me to thanks my family and friends for their support during this journey.

Amersfoort, March 21, 2014

Management summary

ABN AMRO Mortgage Group (AAHG) is responsible for a substantial Dutch mortgage portfolio. One of the most important processes is determining the mortgage interest rate. This involves defining the cost price components of this rate. A correct assessment of the cost price leads to a fair price distribution within the different customer risk categories and a prudent measure of risk.

The credit risk element of this cost price must be calculated in a reliable way. It is therefore important that the method that leads to this risk assessment is justified on a sound basis. The central problem in this research is therefore defined as finding the best method for determining the credit risk component in the mortgage interest rate.

A framework containing four methods is identified for deriving credit risk in line with this research. The first is a tailored model developed for this research within the framework of the theoretical concept of credit risk modeling. The second is an application of the economic capital engine present at ABN AMRO called the CRAROC model, which is used for group wide credit risk estimations. Both of these models use value-at-risk calculation using a Monte Carlo simulation to derive an amount of economic capital per risk class. Analysis is done on basis of loan-to-value classes that are used in practice to provide comparability between methods.

The third method is the current methodology at AAHG, based on backtesting the risk parameters in order to adjust them accordingly. This results in weighted risk indices per risk class relative to the portfolio, a format which is used for all methods in this research.

The fourth method is the use of regulatory capital calculations from the Basel accords to create an assessment of the customer risk weight. Mortgage loans are treated as risk-weighted assets, using risk parameters that are compliant with the specifications from the regulations such as floors, caps and downturn assessments.

After analysis of the theoretical validity of the models, it seems that two models are considered reliable enough to come to the right risk price assessment. The group-wide CRAROC model has a sound methodological foundation which ties in with the risk capital theory. Both this model and the application of risk-weighted assets to derive risk indices are methods that are validated by the bank and regulators to be reliable, an aspect which weighs heavily in the choice of a method. From the risk weight indices it

is clear that the current method deviates significantly from all other methods. This further suggests that this current method cannot be considered as a reliable choice. The tailored model shows less deviation with the two validated methods, but is deemed a less developed model than the CRAROC engine, which is based on the same theoretical principles.

This leads to the recommendation to use the group-wide CRAROC engine as a reliable method of obtaining the credit risk premium for the mortgage cost price. In compliance with the credit risk modeling department an agreement can be made to derive the specific risk data, prior to the yearly determination of the cost price.

Because the risk-weighted asset calculation gives an indication of the minimum requirements to achieve sufficient capital, these calculations should also be performed to provide an assessment of the corresponding regulatory risk weight. The most prudent outcome between these two methods must be leading when determining the cost price.

Abbreviations

AAHG	ABN AMRO Hypotheken Groep
BP	Basis Point(s); 1/100th of 1%
dLGD	downturn- Loss Given Default
EAD	Exposure At Default
EC	Economic Capital
EL	Expected Loss
FTP	Funds Transfer Price
LAD	Loss At Default
LGD	Loss Given Default
LtFV	Loan-to-Foreclosure Value
LTI	Loan-to-Income
LtMV	Loan-to-Market Value
LTV	Loan-to-Value
NHG	Nationale Hypotheek Garantie: Dutch Mortgage Guarantee
NSR	Netto Schuld Rest: Net outstanding amount
PD	Probability of Default
RaRoRaC	Risk adjusted Return on Risk adjusted Capital
RP	Regulatory Profit
RVP	Rentevaste Periode: Interest fixation period
RWA	Risk Weighted Assets
WACC	Weighted Average Cost of Capital

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Chapter one - Introduction

1.1 Background

This research takes shape during an internship at ABN AMRO Mortgage Group (AAHG), a subsidiary of the ABN AMRO bank. AAHG is responsible for providing and managing several mortgage labels. At the balance sheet management department the main responsibilities consist of optimizing capital- and liquidity positions and determining the optimal balance between risk and return. One of the challenges of this department is the cost price setting of the mortgage rate. This involves finding a correct relation between taking on risk and a sustainable return of the mortgage portfolio.

A mortgage is in general the largest loan that consumers will have in their lifetime. It is a financial product with a large social impact. Currently an increasing focus is put on the way this product is put in the market and what kind of risks plays a role. An important element is the interest rate that accompanies the mortgage. This is the direct price that is paid by the consumer, and is the source of income for the loan provider. The interest rate has to include coverage for various costs that are taken on by the bank. Among these is the risk of a counterparty default, known as credit risk. This research sets out to explore the credit risk element of the mortgage cost price.

Various techniques can be identified to quantify the credit risk that a new customer adds to the portfolio. AAHG wants to gain insight in these various techniques and models to be able to implement a deliberate method to price the appropriate risk amount. By getting a thorough insight on the appropriate level of credit risk premium that must be incorporated in the mortgage rate it is possible to make coherent choices in mortgage pricing strategies. This leads to fair prices in line with risk elements and a correct assessment of risk behavior.

While the customer tariff changes more periodically, the related cost price is determined yearly at AAHG. This cost price consists of multiple elements. Figure 1 provides an illustration of how the customer tariff is structured. First of all there is the price that must be paid for funding capital, which is the Funds Transfer Price (FTP) for AAHG. This is the internal rate within the bank for funding the amount that is needed for the mortgage. It consists of the base rate of funding plus an addition for liquidity risk, related to the credit worthiness of the bank. Another addition consists of the operational costs, such as buildings and personnel. Next in line are the costs of expected losses and economic capital of the mortgage, the main subject of this research. The difference between the cost price and the customer tariff is called economic profit, which can also be a loss.

These price elements together form the interest rate, but their height differs per type of customer and product. The funding price for example is established within the portfolio based on the tenor of the contract, since the height of funding depends on the length for which money has to be attracted. In practice, classifying customer risk types is used to allocate suitable interest rates.

Central in this research is finding the right way to measure and allocate the amount of credit risk that a customer contract poses to the mortgage portfolio. This is encapsulated in the risk premium of the cost structure, which consists of the elements that pose the greatest challenge in the current situation.

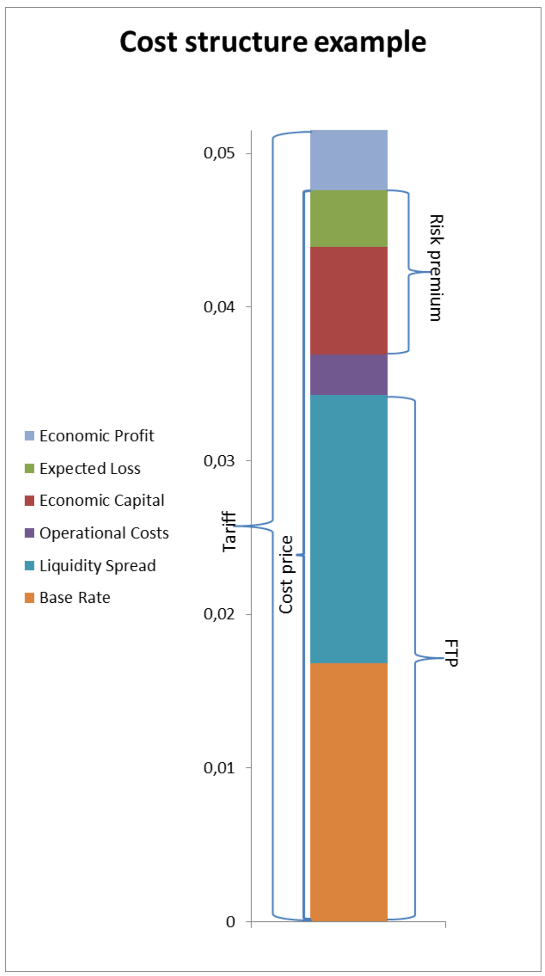

Figure 1: Construction of customer tariff. Numbers are illustrative.

1.2 Problem identification and research questions

The cost price allocation is important for several reasons. AAHG focuses on the interest of its customer, concerning risk and return. It is important that the price distribution among the categories is honest and prudent. A correct assessment of the cost price plays a role in the influencing of the desired distribution of volume in the mortgage portfolio. On basis of risk-return requirements and competition aspects it can be desirable to increase and/or decrease the input and/or output of customer volume in certain LTV classes. This is achieved by strategic price setting.

There are multiple methods and models to be considered which are able to determine the risk element of the cost price. Pricing methods often consist of models originating from various business lines, and it is not seldom that these processes are referred to as 'a black box'. What is wanted is a univocal approach of determining the height of this premium over the various product classes. This research is aimed at creating an insight in the methods for determining credit risk pricing, and making a deliberate decision for a model that fits AAHG. This leads to the following main research question:

What method should AAHG use for determining the credit risk component in the mortgage interest rate?

It is useful to break this goal down into several sub-questions. These component parts make it possible to create structure in the research.

- *What methods can be used at AAHG for deriving the credit risk in the cost price?*

The first requirement of this research is establishing the framework of methods that can be used to derive the credit risk premium. To come to the best method, it is necessary to create a theoretical framework. It contains the theoretical basis of deriving credit risk and the possible methods along with the criteria that they are subject to. Chapter two provides this theoretical framework which contains an overview of available relevant literature which offers insights in the subject and the theoretical basis of the found methods.

- *How do these methods compare to each other*

To come to a well-founded answer to the main problem, the methods need to be compared on a structured basis. Each method will yield a comparable output in the form of risk weight indices which provides the basis of the quantitative comparison. Chapter three contains an analysis of each method in which the characteristics of the models will be described, and comparable risk premium outputs will be derived. Chapter four provides a structured comparison of these aspects. This combines in to a comparison on:

- justification and validation of the theoretical elements
- model outcomes in the form of risk indices

Finally the main research question will be answered in chapter five, which will contain the conclusion and recommendations. This chapter includes a reflection on the research questions, summarization of the approach and recommendations for future research.

1.3 Scope of the project

The focus lies specifically on the credit risk element in this research, to determine how it takes shape and forms a correct reflection of the risk that is taken on. The desired level of this research is to be able to determine the required risk addition per risk class.

The context in which this risk price takes shape is researched in detail, particularly the regulatory and economic capital models. This environment will be mapped so that the process of determining the risk can be applied to a framework. With this framework we can build further on drawing conclusions about the risk/return relationship.

One delimitation of the project is that the probability of default, (downturn) loss given default and exposure at default (respectively PD, (d)LGD, EAD) parameters will be treated as a given, and the calculations and methods to derive these elements will not be explored in this project. These parameters are updated on a regular basis by the Credit Risk Modeling department as a result of comprehensive testing, monitoring and validation. Due to the complexity and required expertise of these models it is not practical to revise these when the goal and timeframe of this project are taken into account.

Another focus point from a practical motive is the loan-to-value (LTV) distinction as risk element. A customer can be classified by various risk elements, but this research will use LTV as the main classification element. A study performed by Qi and Yang (2003) shows that LTV is the single most important predictor for residential mortgage LGD. Since regulatory capital is linearly related to LGD, LTV is argued to be the best way of segmenting risk. Furthermore mortgage pricing happens along LTV classes with most financial institutions, which means that this is a company-relevant reason for showing results in this format. Another practical reason is the availability of LTV figures within the data. Other risk elements such as income figures are not as easily obtained or practical to use. This research will however be more flexible with the use of LTV as risk class instead of fixing solely on the limited number of segments used in practice.

Because of data availability the research will be confined to the Florius mortgage portfolio that is present at AAHG. A significant amount of historical data is available on this set of mortgage types and its customers. Furthermore this portfolio is of sufficient size and adequately reflects the mortgage market to be deemed significant. Paragraph 1.5 provides an overview of this data selection.

1.4 Research type and data collection

The type of research that will be conducted is applied research, using qualitative and quantitative elements. By collecting, analyzing and interpreting the theoretical environment the framework will take shape, and with employing mathematical techniques the risk methods will be analyzed. Applied research is the use of analysis to solve a given problem, in this case the quantitative/qualitative analysis is used to find an answer to the research question.

The following manners of research are applied:

- Researching literature and relevant documentation to create the framework of applicable and required elements
- Collection of appropriate quantitative data for the model input and analysis
- Structuring existing model applications into comparable data
- Deriving output data using the correct methodology along with interpretation

The type of data to be collected consists of the essentials of the theoretical framework. Through literature and available data and knowledge at AAHG a complete insight of regulations and requirements of capital structures will be gathered. Analysis of documents and materials along with gathering knowledge from key figures within AAHG will envelop this part of research.

1.5 Data

The data that is used in this research originates from the available mortgage portfolio data at AAHG. The following illustration sheds light on the structure of labels that are managed within AAHG, from which the used data originates.

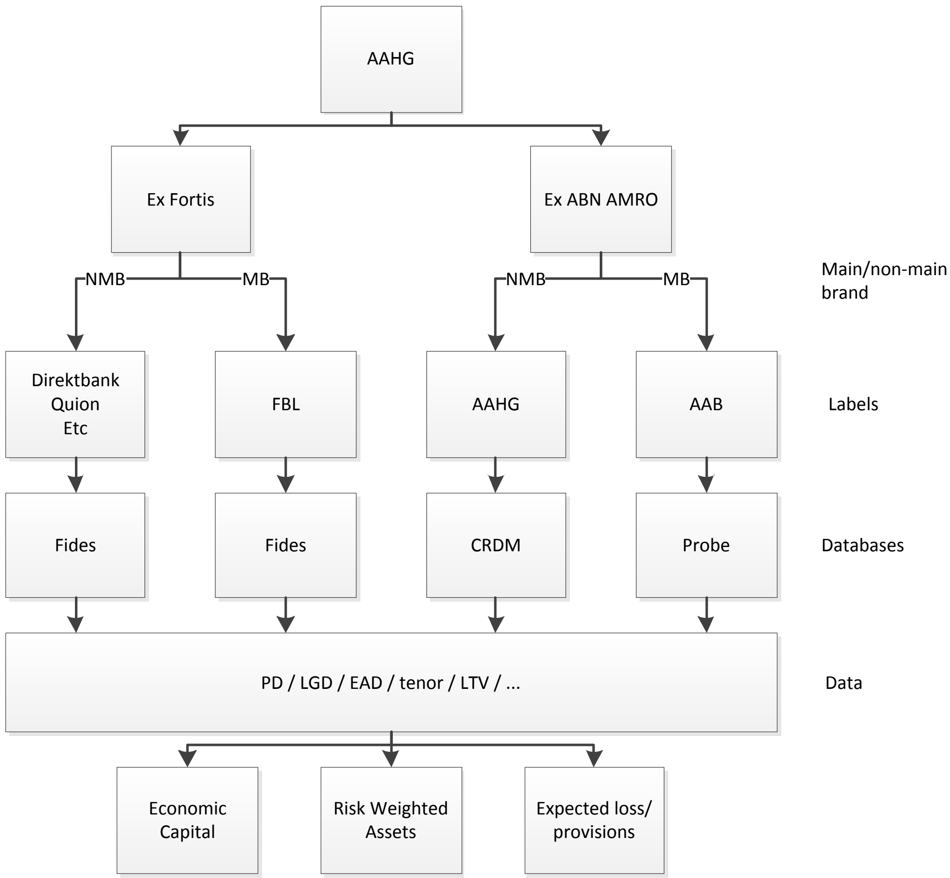

Figure 2: AAHG structure

A distinction is made between the former Fortis and ABN AMRO labels, respectively EX-F and EX-A. Both these parts have a distinction between their main- and non-main brands. Non-main brands are often white labels, products which are fully supported and managed but do not originate internally.

Active labels:

- ABN AMRO brand (including rebranded FortisBank label)
- Florius
- MoneYou

Passive labels:

- Direktbank
- MNF
- WoonNexxt
- Fortis ASR

For this report the available data consists of the Florius portfolio per June 1 2013. This dataset is chosen because of the completeness, availability and most important because this portfolio is used for the current pricing methodology. It is deemed by the decision makers to be a representative selection for the entire mortgage portfolio so that results can be translated to decision making for the other products. Using this dataset for all models in this research will furthermore provide comparability among the different methods.

The portfolio has the following properties:

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Each record in this dataset consists of a loan part. A loan can exist out of multiple parts for which different mortgage conditions can be applied, such as different mortgage types. The loan parts in the dataset share the same PD, LGD and LTV class, but differ in EAD and net outstanding amount.

Chapter two – Theoretical framework

The following section will provide an account of theoretical information and literature related to the topic at hand to provide methodological insight. The techniques and methods described here will provide guidance to give answer to the research questions in the given context, and provide the justification for the use of the techniques that are used to derive results.

2.1 Risk

When using the concept of risk in the scope of financial institutions, the definition of financial risk is often the appropriate one; the uncertainty of a return and the potential for financial loss. Financial risk can be defined by multiple types of risk. The main categories are market risk, operational risk and credit risk (Hull, 2007).

The relevant type of risk for this research is credit risk, the risk that a counterparty will default on its obligations. In that case a loss incurs depending on the exposure. The height of risk depends on the probability of default (PD) and the loss given that a default occurs (LGD). The counterparty in the context of this research is the home owner taking out a loan, and the mortgage contract with such a customer can be seen as the asset. The PD and LGD of this mortgage asset are influenced by numerous elements.

AAHG follows the definition of default compliant with Basel regulations: “The obligator is past due for more than 90 days on any material credit obligation to the banking group or the bank considers that the obligator is unlikely to pay in full its credit obligation without recourse by the bank to actions such as realizing security.” (BCBS, 2006).

To establish the risk-costs for a specific mortgage there are several factors that play a role. The most important is the ratio between the mortgage amount and the value of the security, the loan-to-value ratio (LTV). An important caveat is the difference between the foreclosure value of the security, and the current free-market value. Since 2013 the large banks have to use the actual free-market value instead of the foreclosure value that was usual until then. Since in practice most of the data uses the foreclosure value to calculate the LTV ratio, this report is structured in that fashion to avoid confusion. In the remainder of this report when LTV is used this will be an unequivocal term with loan-to-foreclosure-value. Table 1 provides the LTV classes that are used in this research to provide comparable results.

LTV Classes	NHG	LTV <=60%	60%< LTV <= 75%	75% < LTV <= 100%	100% < LTV <= 110%	110% < LTV <= 125%	LTV >125%

Table 1: Loan-to-foreclosure-value classes in practice

Note that the LTV >125% class is not used in all figures. Customer tariffs starting with this amount do not exist since this is the maximum legal tariff to start a loan. During the tenor of the contract this can however become a possibility when the underlying value decreases.

This ratio between the loan and the security is essential for the risk that the mortgagee takes on. If the mortgage can no longer be paid, the difference between the remainder of the loan and the market value could result in an 'underwater' situation, in which a remaining debt occurs. The mortgage provider takes a part of this credit risk, when a debt has to be redeemed if the customer is unable to pay off. To adjust for these scenarios a risk increment is included in the mortgage rate.

To illustrate the differences between the LTV classes, figure 3 gives an example of the customer tariffs for a specific product. A Florius mortgage with a variable interest fixation period has the price structure in this illustration (derived 20-12-2013 from https://www.florius.nl/). Each specific type of mortgage product with the according fixed interest period provides a price structure in this fashion.

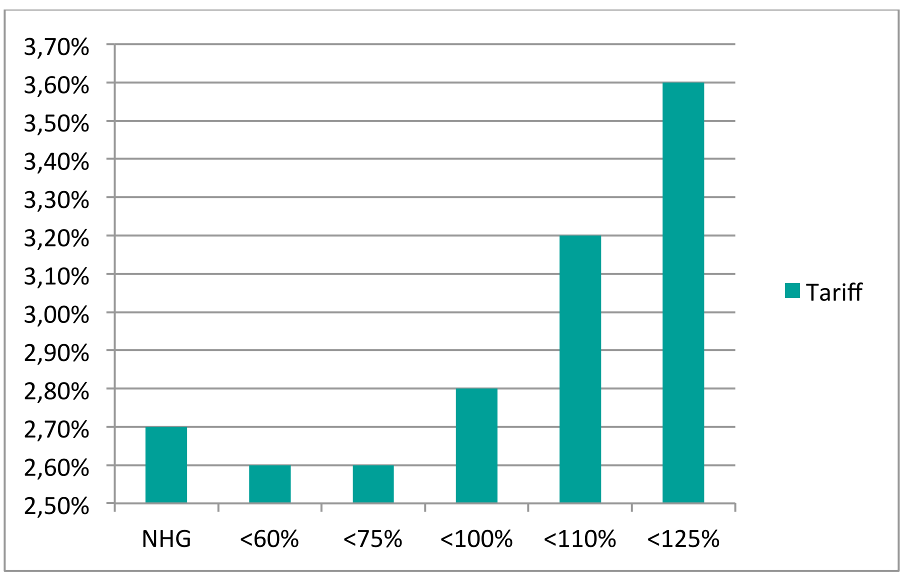

Figure 3: An example of the customer tariff per LTV class for a variable Florius mortgage product

The column on the far left of figure 3 consists of mortgages with the Dutch Mortgage Guarantee ('Nationale Hypotheek Garantie', NHG), a guarantee by an external party backed by the Dutch government that protects against the risk of default. In case of default of the homeowner, the NHG is liable for the remaining debt in certain cases (Hassink, 2003). This is a substantial decrease of the lenders' risk. Apart from decreasing the probability of remaining debt the foundation managing the NHG also helps the homeowner preventing repayment issues in an early stage when problems arise. All this makes it possible for a lender to give NHG clients a discount on the mortgage interest rate. Note that NHG contracts still have different possible LTV classes. It is depicted here among the LTV classes because in practice the NHG tariff is fixed, regardless of LTV.

An influencing factor of the interest rate height is the period for which this rate can be fixed (rentevaste periode, RVP). The customer can choose to fix the rate for a certain period to ensure more certainty of payments. Usually a higher fixation period will mean a higher price as the cost for this certainty. When the base interest rate rises, this will create a favorable situation, but the opposite is of course also true. Because the provider of the mortgage pays a funding rate to attract capital, a higher charge for a higher fixation period is required. At the end of the period new agreements are made with the mortgagee concerning the interest rate, and a possibility to revise the mortgage occurs. The risk elements with regards to this period are captured in the FTP price, which is not in the scope of this research.

A possible indicator of risk is the loan-to-income ratio (LTI). It is the factor of height of the loan versus the income of the homeowner. If a larger part of the income is used to pay for the mortgage, the homeowner could be confronted with financial distress in an earlier stage than a homeowner with a lower ratio. The LTI ratio is used when determining the acceptable maximum height of the mortgage amount. Since in general the income rises and the loan decreases during the lifetime of a mortgage, this ratio tends to become lower over time. This explains why there is a high LTI concentration among young homeowners, which forms a more vulnerable group. LTI is not widely used in practice, due to the difficulty of acquiring up-to-date income data.

A dimension that is often focused on next to risk and return is customer interest. The focus on this aspect is a recent trend, brought forth by the increasing critique on the financial system. This forces banks to centralize customer interests in their strategy to retain customers and restore trust. This creates a challenge to find a balance between proper risk management, earning a healthy profit and creating the most value for the customer.

It is clear that holding on capital is necessary due to regulated restrictions and internal models. These capital demands involve a certain cost element. Different types of capital have a different cost, so in order to assign a price to the extra amount of required capital that an asset required a firm often determines a so-called hurdle rate. At AAHG the hurdle rate is determined by calculating the weighted average cost of capital (WACC) over the firm's capital. WACC is calculated by taking the weighted average of the cost of equity and the cost of debt, based on the proportion of debt and equity.

Taking into account the amount of equity and debt capital with the according costs this leads to a hurdle rate of 9.33% at the relevant date, which will be used for the relevant calculations in this research.

2.2 Banking supervision

Due to an increasing demand on financial institutions to manage their riskiness to protect themselves and their customers, regulations are in place to impose an amount of capital that needs to be held to sustain possible losses. The Basel accords provide the supervisory regulation framework recommendations, which are implemented by the banking industry and enforced by financial supervisors. The documentation used in this report consists of the currently used Basel II framework agreed to in 2004, as well as the Basel III framework which is currently under implementation. Revised versions appeared in 2006 and 2011 respectively (BCBS 2006, 2011).

Risk bearing assets, in this case the mortgage portfolio, need to be backed by a minimum amount of required capital. By means of Risk Weighted Assets (RWA) this required capital is calculated for the entire mortgage portfolio. To cover for this capital, each new security needs to include a risk premium in the interest rate at the right proportion.

The first Basel accords where mainly focused on keeping on capital for credit risk. Under this framework the amount of required capital is basically 4% of the mortgage portfolio.

Capital can be divided into two tiers as core measure of a bank's financial strength in accordance with the Basel accords:

- Tier 1: shareholders' equity and disclosed reserves
- Tier 2: undisclosed reserves, revaluation reserves, general provisions, hybrid instruments and subordinated term debt

Together they form the bank capital that counts toward the regulatory capital requirement.

Basel II was developed to account for multiple types of risk. The following structure (figure 4) took form in this second set of recommendations, which is still valid with a couple of enhancements under Basel III.

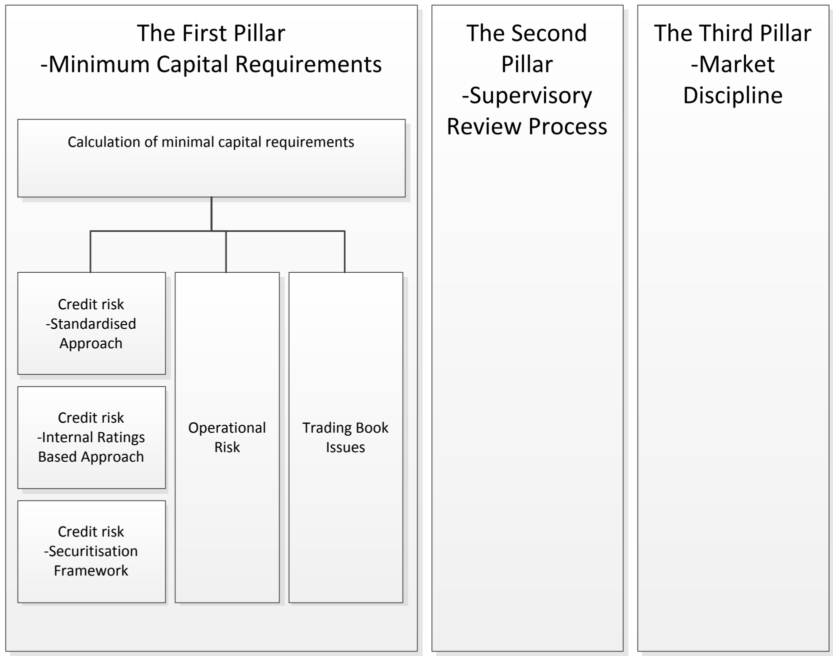

Figure 4 Basel framework schematic

The three pillar concept extends each of the concepts of Basel 1 with multiple types of risk and more possibilities for regulators to implement policy rules and standards.

2.2.1 The first pillar

Different types of assets yield different risk profiles. These profiles are standardized by the recommendations set out within the Basel framework. The definition of regulatory capital used in this report is the minimum capital required by the regulator, identified with the capital charges in the approach of the Basel accords (Elizalde and Repullo, 2006).

Risk weighted assets (RWA's) are defined by multiplying the value of the asset with a certain risk weight that the asset bears. Under Basel II pillar 1 it states that total capital to be held is calculated as 8 percent of risk weighted assets:

$$0.08 \times (Credit\ Risk\ RWA + Market\ Risk\ RWA + Operational\ Risk\ RWA)$$

Credit risk weighted assets are calculated as 12.5 times the capital required, using information about default probability and the fraction of loss in case of a default. Specifically for residential mortgage exposure the risk weighted assets must be assigned according to the following method from the Basel II standards (BCBS, 2006, paragraph 328):

Correlation: $R = 0.15$

Capital requirement: $K = LGD * N\left[\left(\frac{1}{\sqrt{1-R}} * G(PD) + \sqrt{\frac{R}{1-R}} * G(0.999)\right)\right] - PD * LGD$

Risk weighted assets: $RWA = K * 12.5 * EAD$

Where N(x) denotes the cumulative distribution function for a standard normal random variable, and G(z) denotes the inverse cumulative distribution function for a standard normal random variable. This method is based on a reversed Merton model, where the standard normal part of the capital requirement formula return a conditional PD for a default threshold (G(PD)) and a conservative value of the systemic factor (G(0.999).

Included in the calculations for RWA are floor values for PD and LGD, due to regulations (BSBS, 2006, paragraph 266/285). PD has a minimum of 0,03%, and LGD should be at least 10%. This is one of the reasons of the discord with internal capital methods. These floors are likely to drive up the risk premium for low-risk customers, which cushions the price for high-risk customers.

Article 468 of the Basel II framework requires that LGD parameters must “reflect economic downturn conditions where necessary to capture the relevant risks”. This translates into a downturn LGD (DLGD) parameter that is used for use in the RWA calculation. AAHG derives this figure by applying stress percentages on cure rates and collateral values.

2.2.2 The second pillar

Pillar 2 under Basel II is defined as “a measure of the amount of capital that a firm believes is needed to support its business activities or set of risks”. This allows supervisors to require banks to hold extra capital if they find that its risk management framework is inadequate. Internal developed capital adequacy models have to determine how much capital is required for all bank activities. Taking all types of risk into account leads to the determination of economic capital. Section 2.3 of this research will further explain how economic capital is assessed and how this forms the basis of this requirement.

2.2.3 The third pillar

The purpose of Pillar 3 is to complement the minimum capital requirements and the supervisory review process with market discipline. Market discipline is encouraged by developing a set of disclosure requirements which will allow market participants to assess key pieces of information on the scope of application, capital, risk exposures, risk assessment processes, and hence the capital adequacy of the institution (BCBS, 2006).

2.2.4 Basel III

A new set of regulations is currently being developed to form the Basel III standard (BCBS, 2011). The main concern is improving both quantity and quality of capital to be kept. This is an addition of extra buffer capital held under Pillar 1. To act as a buffer against losses a minimum of 7% of a bank's RWA forms the core tier one capital instead of the 2% under Basel II. A counter-cyclical buffer of 0 to 2.5% can be called upon when the economy is in a tough state. In addition a firm must comply with a 3% leverage ratio between core capital and total net exposure so that a healthy relation between borrowed and owned equity exists. In addition to requirement of more high quality core capital and conservation buffers, Basel III introduces minimum liquidity standards in the form of two ratios. The liquidity coverage ratio ensures short-term resilience, defined as the amount of unencumbered, low risk assets that banks must hold to offset forecast cash outflows during a 30-day crisis. Finally a net stable funding ratio encourages banks to form a more stable structure to fund activities by measuring the proportion of long-term assets which are funded by long term, stable funding.

2.3 Economic capital

For a financial firm to be able to survive in a worst-case scenario, a certain amount of economic capital is required. Economic capital is calculated on basis of a firm's internal standards and methods. In addition to accounting and regulatory rules, a firm develops its own assessment of correct risk measurement to provide a more realistic representation of its solvency.

Economic capital is often calculated using Value at Risk techniques (VaR) with a certain confidence interval over a one-year period. Figure 5 provides an illustrative example. The probability distribution of the portfolio losses has an expected loss part, and an unexpected part. The difference between these loss parts is the economic capital which needs to be held to account for the unexpected part until a certain threshold value. This threshold value is based on the confidence level which defines to which extreme losses are accounted for.

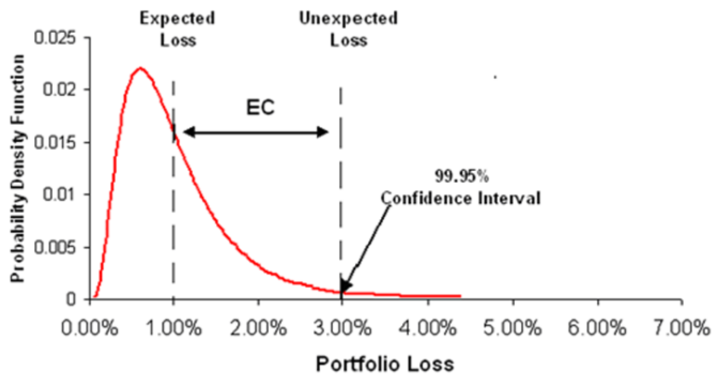

Figure 5: Economic Capital for credit risk (http://www.investopedia.com/articles/economics/08/economic-capital.asp)

Economic Capital is also an integral part of the Basel frameworks. Under Basel II's Pillar Two, it is named under the Capital Adequacy Framework as the institutions own responsibility to account for its risk appetite, forecasts, capital allocation, performance and other aspects that determine the capital requirements. Economic Capital has multiple uses within the bank, among which capital budgeting and portfolio management, but most importantly in the scope of this project is the pricing of products.

During an economic crisis it is likely that realized loss rates move along with observed default frequencies. This implies a correlation between PD and LGD. In the Basel II accords it is recommended to use a 'Downturn' LGD (DLGD), a measure of loss given default that aims to reflect economic downturn conditions where necessary to capture the relevant risks (BCBS, 2006). Several studies can be found (Dimou et al, 2003) (Miu and Ozdemir, 2005) in which it is argued that regulatory capital under the IRB approach does not sufficiently allow for correlation between PD and LGD. Downturn LGD is criticized as alternative for this correlation, and several methods are suggested.

In a research performed by Calem and LaCour-Little (2001) risk-based capital requirements are developed based on simulation of default and loss probability distributions. The data that is used as input consists of default delinquencies, including incidence and timing, original LTV, loan amount, note rate, geographic location and mortgage credit scores based on LTV and credit history. These are more augmented risk factors than the customer data that is usually available on Dutch debtors. Where possible these input factors should be taken into account.

AAHG uses economic capital assessment for both business unit-level portfolio measurement and enterprise-wide relative performance measurement. Appendix A gives an overview of uses for economic capital at AAHG. Important in line of this research is the relative risk indication per mortgage loan that EC calculation offers.

2.4 Methods

In this section the selection of possible methods will be established as part of the framework.

The first method that can be identified is the existing model present at the credit risk department of AAHG. It consists of a credit risk model that is currently used to determine the risk price. It uses historical back testing to provide relative risk weights necessary to allocate risk premium. This model has been put into question as discussed in the problem statement, and therefore will be subject to review.

Regulatory standards provide a point of reference for setting the cost price. This is why the Risk Weighted Asset methodology from the Basel standards is used as another viable method. It provides a possibility for determining the risk component by taking mortgages as balance sheet items and subjecting them to the risk weighted assets calculation. The regulatory amount of capital to be held can give an indication of relative risk weights, and is therefore another important element to give insight in the risk price.

Getting a measure of risk is not only used for mortgages but for every relevant element within ABN AMRO. This is why there is an extensive model present at the bank for determining portfolio credit risk for all the bank's corporate and consumer exposures. This group-wide model is called the CRAROC model. It calculates the expected loss and the economic capital for a portfolio, taking portfolio diversification effects into account. The possibilities to adopt this method for the specific mortgage requirements for AAHG will be explored.

This comes down to three models presently available in the organization. What remains is the possibility of constructing a new model on theoretical basis to extend the framework. This explores what the possibilities are of creating an internal model for AAHG that is tailored for the required situation. This model will be the first method to be discussed because it will be developed using the credit risk theory. This will provide insight in the workings of credit risk models in general, which will be helpful for the methods further in the research.

Figure 6 provides an overview of the model structure of the different methods and the order in which they will be discussed:

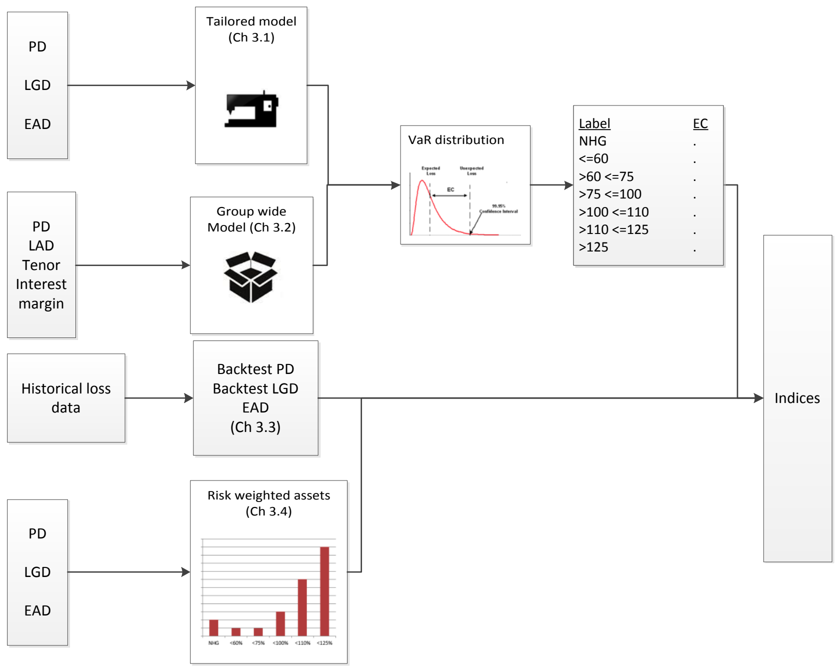

Figure 6: Outline of methods

The methods will be evaluated on basis of validity, theoretical justification and a comparison of risk premium outcomes. The underlying theory leading to the structural elements of a model needs to be sound. In order to implement a good credit risk model it is important that it is constructed on a reliable theoretical basis. Using these criteria it will be evaluated if the assumptions in the method are valid and lead to a reliable risk assessment.

The final important aspect is the comparison of the numerical risk premium result that is yielded by each method. During this research a dataset (significant for the entire portfolio) is subjected to each of the four models in order to derive comparable credit risk figures. On basis of these risk figures an assessment can be made of how the models perform compared to each other.

Chapter three – Credit risk premium methods

Four methods of determining credit risk per risk category have been identified in the theoretical framework. Each of these methods will be discussed in this chapter, after which appropriate results will be derived in line of this research.

3.1 Method 1: A tailored Economic Capital model

This paragraph provides the techniques that are used to derive an indication of the economic capital amount from historical data. A probability distribution can be approximated by using historical PD, LGD and EAD data as input for a simulation. Using this result the expected and unexpected losses can be estimated with certain confidence, leading to an economic capital calculation. By using this method with a specific selection of source data, the relationship between required economic capital and the customer elements that are influencing risk can be derived. This gives a stylized result which does not capture the bank-wide capital requirements, but gives an indication of the risk premium in the mortgage price resulting from the economic capital surcharge.

A powerful method to estimate the distribution from a dataset is to perform a Monte Carlo simulation. The method consists of drawing many random samples within a domain of possible inputs from a probability distribution. When this is used with a large enough sample size, the aggregated results will form a good approximation of the true distribution (Hazewinkel, 2001). This technique is therefore used for deriving the EC estimate. Potential losses can be simulated using the PD, LGD and EAD data from the customer as input. For every iteration of the Monte Carlo simulation every customer is checked whether it is in a simulated default by comparing the PD with a random number. If this is the case, the method generates an appropriate loss-given-default times the associated exposure at default, which is taken as the potential loss. The total loss over all customers is summed up in every iteration and forms the output data. This output data, given that the simulation size is sufficient, gives an approximation of what the distribution of potential losses is.

A histogram of the output can be created to visually construct this approximation. Discrete intervals of the data form the x-axis and the frequency of occurrence of potential losses in these intervals form the y-axis.

Using the source data it is possible to estimate the expected and unexpected loss and the amount of economic capital. The expected loss is the mean of the distribution. The remaining unexpected loss is divided in a risk based part for which capital must be held, and a remainder part of the tail for which it is deemed unnecessary to hold capital. This is determined by the value at risk measure, with a certain confidence level. This means that this VaR measure can be derived by taking the cumulative amount of losses of the distribution up until the confidence level, in this case 99,95%. This results in the risk based Economic Capital by subtracting the amount of expected loss.

No external market factors or trends are implemented this model, and no relation exists with other business units. Therefore this model does not capture the bank-wide economic capital, but gives an indication of the impact of the input data on risk-based required capital. This is not a method to calculate company required capital but merely a method to estimate the impact of the input data on economic capital. Selections of data must be constructed in such a way that the results between methods can be compared. The simulation inputs are therefore structured by the LTV classes used in practice and in the other models that will be discussed in this research.

The software that is used to create the model is Microsoft SQL Server 2012. This program is convenient to store large datasets in tables and make sub selections of data. Appendix B shows the SQL script that is used to perform a Monte Carlo simulation on the available data. The first part of the method creates a sub-selection of data to derive the PD, LGD and EAD per customer, instead of per loan part. This results in 174.053 individual customers. This sub selection is further split up in datasets with their respective LTV class.

To simulate the losses, each individual customer per iteration is assigned its original PD and EAD from the dataset. The LGD factor will be simulated from a probability distribution based on the LGD from the dataset. The LGD in this dataset is an expectation of the losses that customers yield at default, calculated basis of realized losses. Examination of this 'model LGD' in the source data is made visible in figure 7, showing that the LGD is concentrated around several spikes.

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Figure 7: Source dataset LGD - histogram

This pattern is a result of the treatment of original loss data of the model that generates this expected LGD dataset. This is a complicated procedure with many boundary conditions, resulting in this pattern in the data. In order to be able to create a simulation distribution for the LGD values, the dataset is split up into four clusters, one for each of the spikes. The boundaries of these clusters are visually determined. Where possible the modus of the spike acts as boundary value. The boundary between group B and C is the value in between the modus 2,52 and 14,04, which is 8,28. The boundaries of the groups among with the resulting average of the values within these groups are available in Table 2.

<table>
<tr><th>Cluster</th><th>Mode</th><th>Under</th><th>Upper</th><th>Average</th></tr>
<tr><td>A</td><td colspan="4" rowspan="4">CONFIDENTIAL</td></tr>
<tr><td>B</td></tr>
<tr><td>C</td></tr>
<tr><td>D</td></tr>
</table>

Table 2 : Boundaries LGD division

The probability distribution for each LGD is assumed to take a form of the Beta distribution. This distribution is often used in practice to model the uncertain recovery value. The parameters of the distribution will be based on the original LGD of each loan. The main reasons for choosing the Beta distribution are:

- The highly skewed shape that is similar to historical loss distributions found in practice
- The range of losses can be bound between two points (0% and 100%)
- It can assume a wide range of shapes.

(BCBS, 1999).

While using the parameters from table 2, the resulting four distributions will have the same average but will have a distribution shape which allows for deviating scenarios instead of being centered around a single value.

The probability density function of the beta distribution is given by:

$$f(x, \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$$

Where B is the beta *function*, defined as:

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

The two shape parameters of the beta distribution can be estimated using the characteristics of the LGD data, using the following formulas:

$$\tilde{\alpha} = \overline{x}\left[\left(\frac{\overline{x}(1-\bar{x})}{s^2}\right) - 1\right]$$

$$\tilde{\beta} = (1-\overline{x})\left[\left(\frac{\overline{x}(1-\bar{x})}{s^2}\right) - 1\right]$$

Where $\overline{x}$ stands for the sample mean and s^2 represents the sample variance (Giese, 2005).

The sample mean is determined by the average of the LGD values for each group as in Table 2. The sample variance cannot be determined by the standard deviation of these groups, because the available dataset lacks the original volatility of the LGD values. Instead the LGD values are centered around certain values because of aggregation of estimates in the LGD model. Instead the LGD's sample variance will be regarded as that of a Bernoulli distribution. It can be assumed that the LGD value takes on either a normal or an extreme value. This can be considered a 'success' or 'failure' using the terminology of the Bernoulli distribution. A weight factor λ is introduced to the variance of the Bernoulli distribution to act as a cushion on this variance, in order to approximate a realistic value.

The variance of the Bernoulli distribution:

$$Var(X) = p(1-p)$$

We base the variance of the LGD model distribution on this variance with a weight factor λ. The derivation of the following equation is provided in appendix C:

$$s^2 = \lambda\overline{x}(1-c-\overline{x})$$

With $\lambda \in [0,1]$, where $\lambda = 0$ is the least extreme case and $\lambda = 1$ is the most extreme case (Giese, 2005).

c is the cure rate, the fraction of defaulted loans for which the eventual loss is zero. This cure rate is set at 25% based on expert opinion. $\overline{x}$ is the known sample mean of the grouped LGD's. Lambda is the weight factor determining the extremity of the volatility. Using a lambda of a comparable dataset will yield a reliable variance which will be more in line with a practical LGD. A dataset is available containing realized losses over different AAHG mortgages that have been in default.

Realized losses set:

- Average: *CONFIDENTIAL*
- Standard deviation: *CONFIDENTIAL*
- Variance: *CONFIDENTIAL*

This leads to $\lambda = CONFIDENTIAL$

This leads to the following four sets of parameters:

	Average	Variance	StDev	Alpha	Beta
A	*CONFIDENTIAL*				
B					
C					
D					

Table 3: Beta distribution parameters

To test if the beta distribution is an appropriate choice we look at the LGD distribution of the sample loss data set using the histogram in figure 8:

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Figure 8: Histogram of sample loss data LGD

This sample loss data set has an average of *CONFIDENTIAL* and a variance of *CONFIDENTIAL*. Using the parameter estimators in this section this leads to the beta distribution in figure 9:

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Figure 9: Beta distribution of sample loss data

A chi squared test is used to test whether the frequency distribution is consistent with the theoretical beta distribution. Using the 138 values from the density plot, a chi-squared test statistic of 28,21 is derived. Since the threshold value at a 0,005 significance is 98,12, the hypothesis that the beta distribution is a good fit is not rejected.

The four beta distributions derived from table 3 are translated into their inverse cumulative form in SQL tables, containing values respective to input column *n* with values from 0 to 1 with four decimal precision. This is displayed in figure 10, with input *n* on the x axis.

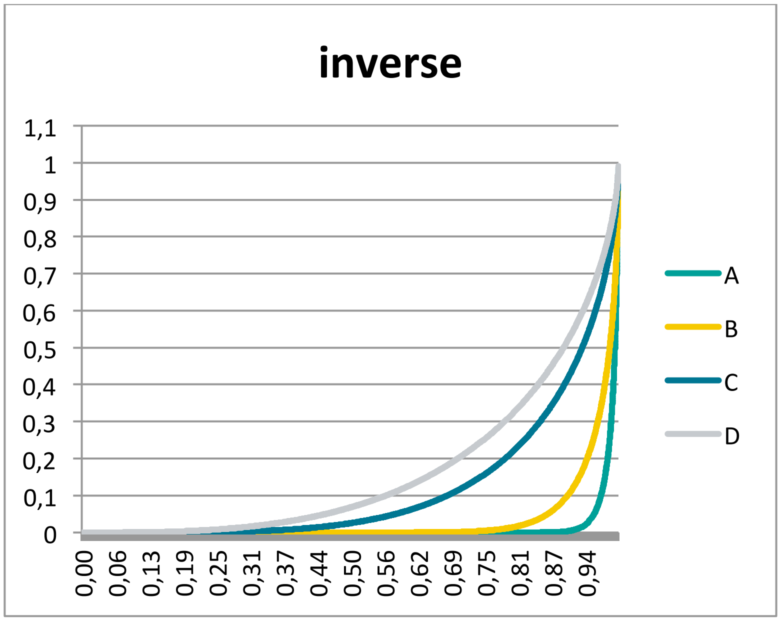

Figure 10: Inverse cumulative beta distributions for chosen parameters

The SQL beta table is linked to the script by applying a random number to the inverse cumulative distribution. The random number is rounded to four decimals, which is linked to the applicable column in the beta table with the same four decimal precision. In this way each customer defaulting in the model receives a sampled LGD with parameters based on its original LGD expectation in the source dataset aggregated per LGD cluster.

The SQL simulation consists of 100,000 iterations of simulated losses. The outcome is processed in excel by deriving histograms and statistical data per risk class. The histograms show a concentration of losses at the left of the graph, and long tails to the right containing the extreme losses.

Deriving the 99.95% value at risk figure is done by taking the cumulative weighted amount of loss up to 99.95% and extracting the corresponding value. This indicates that this amount of loss will only occur within 0.05% of possible scenarios. Using the method for each risk class with 100.000 simulations resulted in six sets of relevant data which are summarized in table 4.

<table>
<tr><th></th><th>Net outstanding amount (billions)</th><th>VaR 99.95% (millions)</th><th>Average (millions)</th><th>Economic Capital (millions)</th><th>EC/ outstanding</th><th>Index</th></tr>
<tr><td>NHG</td><td colspan="6" rowspan="6">CONFIDENTIAL</td></tr>
<tr><td><=60</td></tr>
<tr><td>>60 <=75</td></tr>
<tr><td>>75 <=100</td></tr>
<tr><td>>100 <=110</td></tr>
<tr><td>>110</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>100%</td></tr>
</table>

Table 4: Simulation model outcome per class

The value at risk figure is used to determine the required amount of economic capital by subtracting the expected loss, the average of each set. By taking the economic capital weighted with the net outstanding amount a relative risk figure is derived. This is done for each class as well as for the sum of the portfolio to derive the portfolio weight. Dividing these class figures with the portfolio weight leads to risk indices: relative risk weights as opposed to the portfolio average. These indices are relative weights with reference to the entire portfolio. For example, if an index is 50%, this means that the risk class is half as risky as the average. 200% means that a risk class is twice as risky.

It is possible to use this outcome to determine the risk component of the mortgage rate in two ways. The 99,95% VaR provides a measure of Economic Capital to be held for each risk class. When this is considered to be a right measure of required capital, it is possible to calculate the cost involved of holding this amount of capital per risk class and allocating these costs to the customer rates per class.

3.2 Method 2:Group-wide Economic Capital

This section provides the workings and outcome of the ABN AMRO group-wide method to derive economic capital for credit exposures. This is an existing method as opposed to the tailored model in the previous section. It is formally called the CRAROC model, because it is mainly used to calculate credit risk adjusted return on capital (RAROC) using the economic capital results. The method takes all group-wide exposures into account and aggregates many groups of data. It is the goal in this section to derive results relevant to the dataset used for the other methods in this research.

Components of the Credit Risk EC computations include the following data on all facilities (both corporate and consumer):

- Exposure at default (EAD)
- Default Probability (PD)
- Loss Given Default (LGD)
- Interest Margin
- Remaining tenor

Additional elements are region and industry information to determine the likelihood of joint defaults. For credit protection data about guarantees and asset securitizations are also taken into account. Portfolio losses are constructed by generating scenarios using a single factor model to compute asset returns using the before mentioned information. For both corporate and consumer exposures a simulation study yields what losses and recoveries are expected on average. These results are used to determine EC at the portfolio level and potential credit losses over a 1-year horizon.

This methodology introduces the concept of Loss At Default (LAD), which is the total incurred loss given that a default has occurred. This is equal to the exposure counterparty times the Loss Given Default.

$$LAD = EAD * LGD$$

The bank-wide methodology starts with the potential developments of the world economy. Two million potential economic scenarios are generated with regards to the losses that ABN AMRO suffers on each facility and counterparty. Due to time/data constraints, exposures consisting of small counterparties are aggregated in so called ‘LAD buckets’. The aggregation in these buckets is based on the homogeneity of the exposures in terms of the amount of loss at default, the same PD and the same product.

The resulting distribution follows the previously outlined methodology for deriving EC and EL, using Value at Risk methodology with a 99,95% confidence level. This EC is then allocated to the underlying corporate facilities and the aggregated consumer exposures. Appendix D provides insight in the economic capital per LAD bucket from the portfolio results in question.

To create a comparable insight in the relationship between risk and economic capital, this method will be performed on loan-to-value basis. Results need to be allocated to the loan to value risk classes to get in line with the other methods in this research. To achieve this, the input data will consist of aggregated LTV information. This results in group-wide EC data but with a specific EC-apportionment to these input buckets.

These results are generated by the delivering specific data to the economic capital modeling department of ABN AMRO. This methodology is developed to derive the enterprise-wide EC data, but in line of this report it is used to derive specific LTV level data. Input consists of the 1-year PD, LAD, downturn-LAD, the average tenor and the net outstanding amount per subset. The confidence level is 99.95%, which means that the most extreme scenario will only be exceeded 1/2000th of times.

Label	Net outstanding amount (billions)	Economic Capital (millions)	EC/ Outstanding	Cost of Economic Capital (millions)	EC premium (bps)	Index
NHG						
<=60						
>60 <=75			*CONFIDENTIAL*			
>75 <=100						
>100 <=110						
>110						
						100%

Table 5: Results Group-wide EC model

The next step is to translate these simulated amounts of required capital to the risk premium. Translating economic capital to customer tariff involves the cost of capital, since it would be unreasonable to account worst-case scenario losses in the cost price. Instead the cost of holding the additional required amount of capital on top of the expected loss amount should be charged on the customer. The hurdle rate of 9.33% is used for the calculations in this method (paragraph 2.1).

By multiplying the hurdle rate with the amount of economic capital for each class the gross amount of costs of economic capital per risk class is derived. These figures are translated to a weighted EC premium for the mortgage rate by dividing with the net outstanding amount.

For each class an index of the EC/outstanding compared to the portfolio total is calculated, in order to compare later methods in this report. These indices show the relative riskiness within the classes on basis of the outcome. The premium per label is divided by the premium derived over the total portfolio. For example; the method yields 27 basis points for the total portfolio by dividing the cost of economic capital with the outstanding amount. This is calculated in the same fashion for each label. 23 basis points for the NHG class leads to *CONFIDENTIAL* as its index.

Note that a customer tariff of >125% cannot be issued due to restrictions. The >110;<=125 and >125 categories from table 5 are therefore combined in this table into >110.

3.3 Method 3: The current credit risk model

The currently used method is an internally developed model by the credit risk department at AAHG (Credit Risk Analytics, CRA), using a back-test based on PD and LGD history. This method is used for internal assessment and determination of the risk price. For clarity in comparison this will be further called the 'CRA model'.

CRA makes use of historical loss data over the same portfolio that is derived to the source dataset used for the other models in this research. Using backtesting these historical results are adjusted to new PD and LGD estimations. Backtesting is looking back at realized results and compares these with the estimates to see if adjustment is necessary. This method makes use of logistic regression, a type of statistical regression. Using the loss data of customers in the portfolio, predictor variables are designed that lead to estimated PD and LGD. The portfolio indices are calculated by $\sqrt{PD} * LGD$, divided by the portfolio average. This calculation method is based on expert opinion. The choice is made to stay in line with the calculations for regulatory Risk Weighted Assets, which includes a cushioning of PD. Another consideration for choosing this formula is that the results are in line with the expectations of the outcome. If the square root is not applied to the PD the results proved too extreme for higher risk classes. Finally, the simplicity of this chosen model proved to be important for the users.

Table 6 provides the results of the CRA calculations on the applicable date.

LTV Class	Backtest PD%	Backtest LGD%	Indices $\sqrt{PD} * LGD$
NHG			
<= 60% FV			
<= 75% FV			
<= 100% FV		*CONFIDENTIAL*	
<= 110% FV			
> 110% FV			
			100%

Table 6: CRA method risk indices

Risk weight indices are derived in the same way as for the previous section. These indices are used to indicate the relative weight compared to the overall portfolio. This makes it possible to allocate the cost price elements by multiplying its required premium with the index. Appendix E gives an overview of cost price elements that can be allocated to the different price classes using these indices.

3.4 Method 4: Risk Weighted Assets

Central in this method is the risk-weight approach used in the Basel framework. This is the external capital requirement assessment that companies must follow, as opposed to the internal rating approach already covered in previous sections. The possibility of using this approach to derive relative risk weights is explored in this section.

Calculation of risk weighted assets leads to the required capital requirement relating to those assets. This means that this calculation gives an assessment of how much each asset contributes to the amount of required capital. That is why this method can be used to derive risk weight indications per risk class when calculating the RWA at LTV-class level.

Risk weighted assets are derived by following the current Basel regulations (described in paragraph 2.2). This involves using the calculation with PD and LGD as the input:

$$RWA = 12.5 * EAD * \left[LGD * N\left(\frac{1}{\sqrt{0.85}} * G(PD) + \sqrt{\frac{0.15}{0.85}} * G(0.999) \right) - PD * LGD \right]$$

In which the PD and LGD input parameters for this calculation are subject to certain minimum floor values.

The resulting RWA figures consist of a certain amount per risk class. In practice these risk classes consist of the LTV classes. The RWA amounts are used for determining the EC+EL premium per risk class, by using them to assign weighted indices. These indices provide the distribution key for the percentage amounts of credit- and operational risk, capital deductions and economic capital derived in the same way as the CRA method in the previous section.

LTV	RWA (millions)	Net outstanding amount (billions)	Risk weight	Index
NHG	*CONFIDENTIAL*			
<= 60% FV				
<= 75% FV				
<= 100% FV				
<= 110% FV				
> 110% FV				
				100%

Table 7: Risk weighted assets risk figures

These results are not in line with the expectation on the lower LTV classes. The risk weights are relatively low for these classes, since the expectation is that the 10% LGD floor in the Basel regulations would have a significant heightening effect on the risk for low LTV classes. The RWA model uses a LGD parameter that is changed to reflect downturn scenarios using stress percentages over its determining factors. This means that the LGD used in the RWA model (DLGD) is always higher than the original LGD used in the other models. This effect should be the greatest in the low LTV classes.

Appendix F provides some further insights on other risk factors using the results from this chapter.

Chapter four – Comparison between methods

A comparison between the discussed methods will be made in this chapter, providing an overview of their aspects regarding validity, theoretical justification and the risk premium results.

Figure 11 gives an overview of the resulting indices per model that are derived during this research, providing a comparison of the relative risks compared to the portfolio average.

Another possibility of providing a comparison would have been to use the amount of resulting risk premium per LTV class. In chapter 3.2, table 5 it is shown how this premium is derived using the relative risk index. The proportional relations between the classes are the same for these premiums and the risk weights. It is however better to use risk indices relative to the portfolio risk in line with this research to show how much the credit risk differs between the different LTV classes on a relative basis.

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Figure 11: Indices per risk class per method

Tailored model

The tailored model is developed at the hand of theoretical workings of an economical capital method. The results yielded from this self-developed model can be compared with the others, but more importantly creates insight in the workings of risk pricing.

This model is a stylized version of professional economic capital engines that are used in practice. It provides an indication of relation among the risk classes, but the individual outcomes per risk class cannot be deemed directly applicable. The relative results among the classes are used as an indication of their riskiness among themselves. No stress scenarios are included in the engine, which is the case with 'professional' EC engines. Stress scenarios concerning the world economy and many external factors are taken into account in these kinds of models. Because of the scope and professional level of this research, this was not a possibility to include

An eye-catching result is the difference between {<=60} and {>60<=75} for the tailored model. Where the other models exhibit small differences in risk weight for these classes, the tailored models shows a sharp increase. The risk increases significantly for customers who have a higher but still relatively low risk of >60% loan to value. It is unclear why this model shows this sharp increase between these relatively low risk classes. The input data is the same for the other models, and cannot be an explanation. An answer could be the differences between the number of data points that receive a different beta distribution resulting from the LGD grouping. But from analysis of the model LGD it seems that for the LTV<60% class: 22% in group A, 78% in group B. For the >60%LTV<=75% class: 24% in group A, 76% in group B. So this is not an explanation for the jump between the classes.

Group wide EC model

The economic capital used at ABN AMRO to calculate its economic capital requirement for all business lines was applied to the specific portfolio set used in this research. Although this engine is not specifically designed for specific asset selections such as residential mortgages, the results yielded by providing the specific data seem to be in line with the other methods.

An advantage of this model is the insight in the height of economic capital per risk class. Using value at risk theory to determine the level of economic capital for a confidence level of 99.95%, the extreme scenarios per risk class are derived. This method therefore gives a good view of the extreme losses which are possible for the mortgage environment.

A disadvantage of this method is the external aspect. A specific dataset has to be delivered to the department in question that runs the EC model. This lacks usability and insight in the process.

The model includes economic cycle factors based on simulations of the state of economy. This takes downturn scenario into account in which downturn LGD comes into play. However it must be noted that in several literary sources (Dimou et al,2003) (Miu and Ozdemir, 2005) it is stated that downturn LGD is not a correct substitute for correlation between PD and LGD.

CRA method

This model is currently used to determine the height of the cost price risk premium. Relative risk weights are determined at the hand of backtesting historical loss data. This has the limitation that past results fashion the guidance for the future. Backtesting in essence is finding a model that would have worked in the past.

The CRA method shows the greatest deviation with the group wide model when the LTV is larger than 100%. For the two highest LTV classes the model is out of line with all the other models. This would indicate that the current model yields a higher risk weight for high risk classes against the portfolio risk. An explanation can be the underlying model assumptions.

These model assumptions form one of the negative aspects of this model. The model documentation often uses arguments based on user affinity and simplicity. The choice for this methodology seems greatly based on the desire for the outcomes to lie in line with expectations. The deriving of indices by using the square root of PD times LGD is an example of an unfounded calculation other than that results fall in line with expectation.

Finally it can be put into question how much backtesting is a valid method of deriving risk measures. It is a tool which can reliably follow short term trends in loss data, but might be less robust regarding extreme scenario expectations.

RWA method

The fourth method in this research is the application of risk weighted assets for determining relative riskiness between the classes. The calculations for capital requirements for residential mortgages follow directly from the Basel II accords. This means that this method gives a good indication of relative risk weighting on basis of fixed standards. On account of regulatory purposes it can give a good indication of what extra capital is required for a new contract. It is however not a model that is tailored on the specific business situation, nor gives it room for adjustments.

The most questionable aspect is the use of caps and floors in the regulations. The PD and LGD both have a minimum factor, driving up the risk estimation for customers that should be deemed less risky. The caps on losses have the effect that categories bearing more risk receive a lower estimation, which in turn places more weight on the lower categories to subsidize for this aspect.

An explanation why the RWA model deviates can be offered by the restrictions that are present in the RWA model, in the form of caps and floors for PD and LGD. Intuitively, this would theoretically lead to relatively higher risk weights for low LTV's, and lower risk weights for high LTV's compared to models without these restrictions. The RWA model does however not exhibit higher risk indices for the lower LTV classes in relation with the other models.

This does not occur for the cap on losses that explains the smaller risk indices for the two higher LTV classes of the RWA model. It is curious however that the tailored and group wide models are more in line with the RWA model in this regard, since there are no floors or caps present in these custom models.

Chapter five – Conclusions

5.1 Conclusion and recommendation

Four models have been analyzed in order to find the best method for determining the credit risk in the mortgage cost price. The first of these models is a tailored model developed during the course of this research, in order to gain insight in the workings of credit risk models. The group-wide CRAROC model is based on the same theoretical principles on which the tailored model was developed, but proves to be more elaborate and comprehensive. The CRA methodology that is currently used to derive the relative cost price per risk class is also an internally constructed method at AAHG.

Two methods are externally validated by the regulator and internally considered as justified methods of deriving risk assessments, the group wide model (using the CRAROC engine) and the RWA calculation per Basel regulations. When evaluating the underlying model elements and assumptions, it is clear that these validated models pose the most reliable methods for deriving risk assessments. The tailored model is an attempt to apply the techniques used in the professional models, and is compliant with the regulatory model, but lacks the more advanced econometric elements of the group wide model. The current model lacks theoretical justifications for its calculation structure.

This means that on basis of theoretical justification and validity the RWA and group-wide model remain as possibilities. Compared with the RWA method the group-wide CRAROC model makes use of internal assessment of portfolio and economic factors, uses a higher confidence level and is considered a more prudent assessment of risk. It is therefore that this model is evaluated to be the most reliable method.

To provide comparability, table 8 shows the change in percentage, and the root-mean-squared deviation (RMSD) between results of the respective method and the group wide method. The RMSD is a measure of differences between actual and predicted values, applicable in this situation to compare the results. It is calculated in the following way:

$$RMSD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\theta}_i - \theta_i)^2}$$

	NHG	<=60	>60 <=75	>75 <=100	>100 <=110	>110	RMSD
Tailored							
RWA				*CONFIDENTIAL*			
CRA							

Table 8: Deviations from the group-wide model

The RWA model has the smallest deviation with the group-wide model. The CRA model appears to deviate the most by a significant number, especially for the higher risk classes. Its deviation from all the other models gives reason to disqualify this method in light of this research. The tailored model deviates close to the same range as the RWA method, but will not be taken into consideration as recommendation for the given validation reasons.

It is recommended that the CRAROC group-wide engine is used to derive the risk indices following the method and structure proposed in this research. This can take place prior to the yearly determination of the cost price at AAHG. In compliance with the credit risk modeling department an agreement can be made to derive the specific risk data in the fashion put forward in this research.

Moreover, the RWA calculation should be done simultaneously in order to comply with regulatory demands on capital to be held. The highest result must be leading in order to be prudent. The group wide model is considered to be the most reliable assessment of risk, it is more prudent and sensitive to internal risk measures. But if the (less conservative) RWA model turns out to provide more prudent risk measures, this should be leading.

5.2 – Discussion and further research

This research set out to create more insight in an appropriate method to determine the mortgage risk premium. Using relevant methodologies and theory it was possible to devise a model tailored to the mortgage portfolio present at AAHG. This process is documented in this thesis in order to provide comprehension for the decision makers on how to interpret the realization of the cost price risk element. Three other methods were identified that have the possibility to measure relevant credit risk weights. The tailored model served to provide insight in the workings of a credit risk model, and its desirable aspects

The tailored model was meant as a basic application of value at risk theory to derive comparable risk outcomes, and therefore posed some shortcomings compared to a professional calculation engine. There are several possibilities to enhance this basic method. For instance a better implementation of the

Beta distribution used to simulate the LGD factor. During this research it was not possible to receive the loss data on which the expected customer LGD of the source data was based. With this information it would have been possible to derive a more realistic estimation of the probability distribution of LGD, leading to more accurate beta distribution. It is recommended that the original loss data is retrieved for future versions of the model. It is further desirable to implement potential external factors and stress scenarios, such as the influence of the world economy and correlation between PD and LGD.

Using SQL to write a simulation tool posed some challenges, especially regarding runtime of the simulation. It would be advised to use specific simulation software, which would significantly lower runtime.

The loan volume differs between the classes. It can be argued that conclusions about the differences in risk weights per class should be weighted accordingly. It would however fall outside the scope of this research to do so. The focus of this research was the desire to be able to derive a reliable risk assessment per risk class so that decisions can be made on strategic pricing. Giving a judgment about importance on basis of volume in the classes would be detrimental to this aspect.

It can furthermore be interesting to loosen the restriction to LTV classes. A deeper exploration of the models can be done when it is possible to see the risk over a broader spectrum of risk categories. Even when this is still done on loan to value basis, it can be interesting to see how the credit risk behaves when this is calculated over more than the six LTV classes.

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Appendix A – Uses of Economic Capital

The following overview provides the different ways of utilizing economic capital (BCBS, 2009):

- It is used for measuring the marginal contribution of individual loans in credit portfolios, known as credit portfolio management.
- Another important use is risk-based pricing. When a bank has to price its product accordingly to cover all costs, it utilizes the ability to allocate economic capital.
- EC can be used for portfolio optimization, by means of measurement and performance on customer level, comprehensive view of all costs, revenues and risk. Complex aggregation of risk on customer level is possible using segmentation of customer data.
- EC can be used for customer and product profitability by analyzing the risk weighted profitability of products and customers.
- Capital adequacy assessment: EC can be used to determine the amount of required capital in accordance with ICAAP.
- Relative performance measurement: In order to assess relative performance on a risk-adjusted basis, banks calculate risk-adjusted performance measures, where economic capital measures play an important role. This is often supported by the use of key performance indicators.

Key performance indicators (KPI) are pointers for the functioning of a system and to keep track of performance (Fitz-Gibbon, 1990). Choosing the right indicator is important for a business line, since performance indicators often influence the incentive structure. They form the variables to measure company performance, so trying to optimize them should be a result of the desired conduct of business. Two KPI's are taken into special consideration at AAHG: Risk-adjusted Return on Risk adjusted Capital (RaRoRaC) and Regulatory Profit (RP). Instead of setting the focus solely on net return, risk weighting and capital to be held are taken into account in these two indicators.

$$RaRoRaC = \frac{Revenues - Expected\ Losses}{Economic\ Capital}$$

RaRoRaC is based on the need to steer on yield instead of turnover, to comply with rising capital- and liquidity demands. Both the numerator and the denominator are adjusted for risk, forming a Return on Capital indication that takes into account the cost of risk adjustments. The threshold/target for RaRoRaC is called the hurdle rate, which is the rate of return that is expected on the yield. It steers on exceeding the cost of capital in order to add value to the bank and guarantee continuity.

Regulatory Profit (RP) is a measure to determine if revenues cover the cost of the regulatory capital. This is calculated by subtracting the equity capital charge from the adjusted net profit from continuing operations. Net profit is corrected with a subordinated debt capital charge and an equity funding adjustment in order to derive a comparable adjusted figure.

$$Regulatory\ profit = Adjusted\ Net\ Profit - Equity\ Capital\ Charge$$

AAHG strives to achieve a RP of 0. In that case all required costs and requirements are covered with income.

Appendix B – SQL Script Monte Carlo simulation

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Appendix C – Derivation of simulation LGD variance

(Provided by Ir. Drs. A.C.M. de Bakker, 20-02-2014)

In the below formulas C stands for cured, NC for non-cured, c is the cure-rate.

$$LGD = cLGD_C + (1-c)LGD_{NC}$$

$$var(LGD) = var(cLGD_C) + var((1-c)LGD_{NC}) = var(0) + (1-c)^2 var(LGD_{NC})$$

λ substitution with Bernoulli derivation: $var(LGD_{NC}) = \lambda\overline{LGD}_{NC}(1-\overline{LGD}_{NC})$

$$var(LGD) = \lambda(1-c)^2\overline{LGD}_{NC}(1-\overline{LGD}_{NC})$$

$$\overline{LGD} = c\overline{LGD_C} + (1-c)\overline{LGD}_{NC} = (1-c)\overline{LGD}_{NC}$$

$$\overline{LGD}_{NC} = \frac{\overline{LGD}}{1-c}$$

$$var(LGD) = \lambda(1-c)^2\frac{\overline{LGD}}{1-c}(1-\frac{\overline{LGD}}{1-c}) = \lambda\overline{LGD}(1-c-\overline{LGD})$$

with $c \leq 1-\overline{LGD}$

This leads to the following formula for the variance per LGD-cluster, given that c is constant for all clusters:

$$var(LGD) = \lambda\overline{LGD}(1-c-\overline{LGD})$$

Appendix D – Economic capital per LAD

From the resulting group-wide calculations, the relationship between the LAD buckets and the required economic capital can be derived. The economic capital calculation method described above yields a dataset for the residential mortgage portfolio present at AAHG. In total 481 LAD buckets containing the relevant AAHG mortgage data are used as input, which result in the following corresponding risk figures. This yields a total sum of over *CONFIDENTIAL* of economic capital on residential mortgages: and a total expected loss of *CONFIDENTIAL*. Figure 12 provides the scatter plot of the data, which displays the two variables on their respective place on the axes.

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Figure 12: Scatter plot of EC and LAD

The plot seems to indicate heteroscedasticity, which means that the variance differs along the set. The pattern shown in figure 12 shows that the EC values spread out more when LAD increases. This implies that there exists regression between the two variables, but it is not consistent across all values. Estimating this relationship is complicated because the assumption of equal variance is violated.

It seems that higher loss-at-default loans exhibit a higher variance in the amount of economic capital. Apparently it is possible that a class of assets with a high LAD can exhibit extreme losses compared to an adjacent LAD class. An explanation could be that low LAD classes tend to remain stable, showing less correlation with risk.

Appendix E – Cost price premiums

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Appendix F – Risk weights per interest fixed period class

Using the results from the RWA method, some further insights can be derived on other factors than LTV, namely the interest fixed period and the Dutch Mortgage Guarantee. Figure 13 shows the effect of the interest fixed period (Rentevaste Periode; RVP) on the risk weight, per LTV class.

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Figure 13: Risk weights per RVP class

No trend is apparent from this figure, apart from a strange spike for 2 year, >125% loans. Intuitively it would seem that a higher interest fixed period would lead to higher risk, but this relation ought to be captured in the funds transfer price element. A possible correlation could exist of the RVP class with a certain customer element which is in turn correlated with the risk weight, which can explain the slight variations shown in this graph. It is however clear that a higher LTV does lead to a higher risk weight. The spike at the 2 year, >125% risk weight is treated as an outlier, supported by the fact that the number of contracts in this category is low compared to the other categories.

The next figure provides insight on the effects of the Dutch mortgage guarantee on risk weighted assets.

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Figure 14: Risk weighted assets as a percentage of the outstanding amount

The data is split up in three ways regarding NHG. The blue line excludes the NHG category altogether. The red graph includes only NHG-loans, but gives insight in the separate LTV classes present in this category. Normally no distinction between LTV classes is made for these loans since this product has a single customer tariff. This graph shows that the risk weights differ similarly as for non-NHG loans (blue). Overall, the NHG loans seem to have a lower risk weight. The green line puts all NHG loans in their respective loan to value category, as if NHG would not exist. The green graph lies (slightly) below the blue graph, indicating that NHG loans exhibit the same trend over the LTV classes with a slightly lower risk. It should be noted that the classification of NHG itself is a factor in the PD and LGD models which results in a lower risk assessment. The resulting RWA calculation is a reflection of the eventual risk that the loan portfolio bears.