MASTER THESIS

THE DYNAMICS OF IFRS9 ON THE CAPITAL RATIOS OF BANKS

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The dynamics of IFRS9 on the capital ratios of banks given different economic scenarios

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Abstract

On the first of January 2018, IFRS9 accounting regulations are enforced, resulting in two main changes for banks: first, banks should hold provisions for credit losses it expects to incur, free of conservatism, and second, the amount of provisions is increased for loans substantially deteriorated since origination, of which the expected credit losses over the remaining lifetime should be estimated, incorporating all available information. The transition from through-the-cycle to point-in-time, best estimates and lifetime estimates for credit exposure is expected to have substantial impact on the financial statements of banks and consequently on the capital ratios. In this research, a hypothetical bank using the foundation approach with only corporate credit exposures is examined and the dynamics of IFRS9 on the capital ratios given different economic scenarios are analyzed. Input data is retrieved from public sources, like S&P and Moody's, and estimates are made using Markov chains and Vasicek's one-factor model. It was found that the first year of the simulation and the low quality rating grades are key factors influencing the amount of required provisions. In specific cases the effects of the point-in-time and lifetime adjustments in different economic scenarios can be seen, given the hypothetical portfolio rendered in this research.

Keywords: IFRS9, IASB, CRR, Basel regulations, BCBS, provisions, capital ratios, Vasicek's one-factor model, Markov chains, point-in-time (PIT), through-the-cycle (TTC), expected credit loss (ECL)

Contents

1 Introduction

Currently, the amount of provisions banks are required to hold for financial assets, such as loans, are defined by the international accounting framework IAS39 (IASB, 2003). However, IAS39 has been criticized for accounting for the provisions too late and the IAS39 provisions seem to be insufficient, especially during an economic downturn (e.g. BCBS, 2009; Financial Crisis Advisory Board, 2009; Financial Stability Forum, 2009; G20, 2009; Jesus & Gabriel, 2006). In an attempt to overcome these points of critique IAS39 will be replaced by a new international accounting framework, IFRS9, on the 1st of January 2018 (IASB, 2014).

Comparing IAS39 and IFRS9, two key differences are expected to substantially change the timing and amount of provisions. First, the timing of the provisions that have to be taken for impairments of financial assets will change (IASB, 2003, 2014). Following IAS39 a bank is required to hold provisions only after one or more credit loss events, as defined in IAS39, have occurred. Thereby, a bank is not allowed to incorporate any expected credit losses (ECL), no matter how likely these losses are (IASB, 2003)[1]. In contrast, according to IFRS9 a bank is required to hold provisions for all ECL based on all available information (IASB, 2014) that indicates a future loss at that point in time. So, according to IAS39 banks are required to hold provisions at the point in time that the credit loss event occurred, while IFRS9 requires banks to hold provisions assuming a default is possible for all loans.

Second, the amount of provisions that a bank is required to make for impairments of financial assets will change (IASB, 2003, 2014). According to IAS39, the amount of provisions is equal to the incurred credit losses (ICL) after a credit loss event (IASB, 2003). In contrast, according to IFRS9 the amount of provisions is equal to the ECL. The ECL is calculated with different time horizons, depending on the loan's credit quality, or stage. There are three stages defined in IFRS9 (IASB, 2014). Stage 1 contains all loans that are performing and which have not increased in credit risk since origination. For these loans the ECL should be calculated on a one-year horizon. Stage 2 consists of all loans that are performing loans, but which have suffered an increase in credit risk since origination. Regarding loans in stage 2, the ECL should be calculated over the remaining lifetime of each loan. Stage 3 consists of all non performing loans, i.e. defaulted loans, for which the ECL should be calculated over the remaining lifetime. The increased time horizon of IFRS9 is expected to result in a higher amount of provisions compared to IAS39, as the ECL increases when a longer time horizon is examined (Rhys et al., 2016).

A change in the timing and amount of provisions has a direct and an indirect effect on the balance sheet of banks. On the one hand, the asset side of the balance sheet is directly affected as the provisions lower the net value of the loans (BCBS, 2005). On the other hand, the equity side of the balance sheet is indirectly affected by the decreasing amount of retained earnings. The net

[1] An exception is made for losses which are IBNR (Incurred But Not Reported), which are loans losses that have not occurred at balance sheet date. However, from historical data from the portfolio, the bank knows that these credit loss events will occur in the near future.

result is lower, because the change in provisions should be accounted for in the income statement as costs. In the absence of a change in provisions, there are no provision costs deducted from the net result and therefore more retained earnings can be accounted for on the balance sheet (Harisson & Sigee, 2017; Rhys et al., 2016).

As the balance sheet changes, the capital ratios will be affected. Capital ratios aim to prevent banks of going into default or bankruptcy in case of an unexpected loss by requiring banks to maintain their capital at a certain capital ratio at all times (European Parliament, 2013). Capital ratios are constituted by the Basel Committee for Banking Supervisory (BCBS) in the Basel Accords (BCBS, 2006). However, these accords are not legislative for banks. The CRR, the capital requirements regulation is the regulation empowering the Basel Accords in the EU (European Parliament, 2013). The CRR defines the regulation for capital requirements of banks, such as the capital ratios. Furthermore, the CRR provides guidelines to discipline banks by proposing measures that can be used if the capital requirements are not met. An example of a measure to discipline banks is that banks are not allowed to pay dividend to its shareholders as long as the capital requirements are not met (BCBS, 2010; European Parliament, 2013). Another example is that banks have to repair the capital gap between the required amount of capital and the realized amount of capital, as a result the bank will have to retain more capital (BCBS, 2006; European Parliament, 2013).

With the measures of the CRR in mind, it is relevant for banks to have insight in the dynamics of IFRS9 on the capital ratios during different economic scenarios in order to prevent capital ratios to drop below the capital requirements. For instance, during an economic downturn, a bank's capital is more likely to be low due to unexpected losses (Catarineu-Rabell et al., 2005). As a result, a bank's capital ratios may not meet the capital requirements. If the capital requirements are not met, banks are required to increase capital. As the capital that banks are required to hold limits banks to lend new loans, banks want to meet the capital requirements. In order to meet the capital ratios at all times, banks need to understand the dynamics of IFRS9 on the capital ratios.

The objective of this research is to:

> "*analyze the dynamics of IFRS9 on the capital ratios of banks, by analyzing different economic scenarios.*"

This research contributes to academic literature by quantifying the effects of IFRS9 and the quantitative interaction of IFRS9 with the capital ratios.

The practical relevance of this research is to provide insight in the dynamics of IFRS9 in order to be able to understand the dynamics of the capital requirements during different economic scenarios. Furthermore, regulators benefit from the results of this research as the results can be used as a quantitative evaluation of the impact of IFRS9 on the capital ratios, in order to examine whether IFRS9 meets its objective. Finally, audit firms will be provided with insight in the dynamics of IFRS9 which enables them to evaluate their client's models.

The research is limited to portfolios consisting solely of loans, with a corporate exposure. A bank using the foundation approach is examined. More on the limitations of this research are discussed in Chapter 3.

With the research objective in mind, the following three research questions are answered:

1. How does IFRS9 influence a bank's capital ratios?
2. How can the influence of IFRS9 on the capital ratios given different economic scenarios be quantified?
3. What are key factors influencing the amount of provisions a bank is required to hold?

The first research question is discussed in Chapter 2. In Chapter 2 the consequences of IFRS9 on capital ratios are discussed, based on regulatory documents and literature. In Chapter 3 the model is built in order to quantify the consequences of IFRS9 on the capital ratios. The main challenge is to convert the through-the-cycle probability of default to a point in time probability of default. Also, in Chapter 3, the second research question is answered. In Chapter 4 the model is applied and the results of the model are presented. Also, different economic scenarios are simulated, e.g. the economic downturn scenario. In Chapter 5, the results are discussed and the key factors influencing the amount of provisions are identified, answering research question three. Also, recommendations for further research are done. In Chapter 6, the research is concluded with the answers to the research questions. A list of abbreviations can be found in the glossary after the references.

2 Literature Review

To be able to investigate the dynamics of IFRS9 on the capital ratios of banks given different economic scenarios, a literature review is conducted. The literature review starts with an overview of the regulations. The regulations section elaborates on the background of IAS39, IFRS9 and the CRR in order to show the procedures provided by the regulatory institutions, BCBS and IASB[2], and the variables and parameters a bank needs to constitute. These variables and parameters have been researched extensively in the current body of knowledge, resulting in multiple methods to calculate the variables. These methods are evaluated in the literature subsection.

2.1 Regulations

IAS39 and IFRS9 affect the CRR via the balance sheet. The balance sheet can be seen as the interplay between IAS39 and IFRS9 and the CRR. IAS39 and IFRS9 provide a guideline for banks on how to account for loans on the balance sheet, while the CRR impose a way to calculate the capital ratios from the balance sheet. The interplay is examined in twofold. First, the impact of IAS39 and IFRS9 on the balance sheet is examined. Second, the dynamics of a changing balance sheet on the capital ratios are explained.

As mentioned in the introduction, the balance sheet is influenced by the amount of provisions a bank is required to hold as a consequence of impairments. A key difference between IAS39 and IFRS9 is that IFRS9 anticipates on impairments before the actual loss has incurred, while IAS39 accounts per loan for impairments only after one or more credit loss events occurred. When one or more credit loss events have occurred the bank should hold provisions for the incurred losses and no future losses can be accounted for, no matter how likely the expected impairments are about to happen. The credit loss events consist of a list of subjective events, e.g. substantial financial problems of one of the parties or payments a certain period past due (IASB, 2003), for which every bank has a slightly different definition.

If a credit loss event occurred, a bank is required to hold an amount of provisions equal to the incurred credit loss (ICL). Provisions for ICL or defaulted loans are called specific provisions. Another type of provisions made for non-defaulted assets are called general provisions (European Parliament, 2013). General provisions are, in normal circumstances, inapplicable for ICL.

The ICL is the difference between the asset's carrying amount and the present value of the estimated future cash flow, discounted at the financial asset's original effective interest rate (EIR). All these variables are known by banks or directly computable. In contrast to IAS39, IFRS9 aims to hold provisions for the ECL. The ECL has to be calculated on a certain time horizon depending on the loan's stage. Three stages are distinguished in IFRS9, as explained in the introduction. Stage 1 should be calculated over a one-year horizon, while stage

[2] The IASB is the abbreviation of the International Accounting Standards Board, a regulatory institution responsible for setting regulations on how financial assets should be accounted for and the IASB is author of IAS39 and IFRS9.

2 and stage 3 should be calculated over a time horizon equal to the remaining lifetime of the loan. The time horizon in the calculation of a loan's ECL is the differentiating factor among stages.

Besides the differentiating factor, there are several common factors to calculate the ECL. It is market practice to calculate the ECL with the probability of default (PD), loss given default (LGD) (LGD equals 1-RR, where RR is the recovery rate) and exposure at default (EAD), however these variables are facultative. Multiplying PD, LGD and EAD results in the ECL. Since PD, LGD and EAD are facultative to use, there is no method defined in IFRS9 to calculate PD, LGD and EAD (these are discussed in Section 2.2). However, PD, LGD and EAD should be best estimates (IASB, 2014). According to IFRS9, a best estimate is free of conservatism and incorporates all available information (IASB, 2014). By incorporating all available information, the variable should be adjusted in such a way that the estimation of the variables include both the micro-economic factors (e.g. obligor's creditworthiness, likelihood to repay) as well as the macro-economic factors (e.g. GDP, unemployment rate). So, by incorporating both the future loss as well as all micro- and macro-economic factors, it can be expected that the ECL is likely to be higher than the ICL during or when expecting an economic downturn (e.g. Harisson & Sigee, 2017; Rhys et al., 2016; Rouault, 2014).

ICL and ECL determine the bank's amount of provisions, which influences the balance sheet in a direct and an indirect way. Directly, the change in the amount of provisions is added to the cost side of a bank's income statement and lessened from the asset value on the balance sheet. Note that the provisions for loan loss impairments are held on the balance sheet and that these provisions should be equal to the required amount of provisions after a certain year. So, if the required amount of provisions after a certain year is higher than the amount of provisions already on the balance sheet, the shortfall of provisions should be accounted for at the cost side of the income statement. However, for illustrative purposes, in this research, it is assumed that the amount of provisions on the balances sheet at the reporting date is zero.

The reporting date is the point in time at which the financial statements are based. For instance, if the reporting date is the 31st of December 2015 this means that the income statement is based on the year 2015 and the balance sheet is based on the 31st of December 2015. The reporting date in this research is the point in time at the start of the simulation, where the provisions and capital ratios should be determined given a portfolio and an economic scenario. Given different economic scenarios, this research aims to quantify the differences in the amount of provisions, while making the assumption that the existing amount of provisions at reporting date are zero.

Indirectly, if provisions are zero for a certain year, the bank has a certain amount of net result, depending on the bank's performance for that year. If the change in the amount of required provisions is greater than zero, the bank has a lower net result. The net result of a bank at the end of the year is added to the retained earnings, which is an equity reserve on the balance sheet. The balance sheet is therefore indirectly affected by provisions on the amount of equity.

The amount of equity can be divided into multiple equity categories, which are displayed on a bank's balance sheet in so called balance sheet items, e.g. retained earnings or common shares. Adding up specific balance sheet items result in regulatory capital amounts. Three regulatory capital amounts are defined by the CRR, who defines a list of balance sheet items comprising these regulatory capital amounts (Appendix A). These regulatory capital amounts are the common equity tier 1 capital (CET1), tier 1 capital (T1) and tier 2 capital (T2) (European Parliament, 2013). T1 is the sum of the CET1 and additional tier 1 capital (AT1).

From Appendix A it can be seen that CET1 includes retained earnings, which is indirectly influenced by the provisions and thereby provisions affect the regulatory capital amounts. The regulatory capital amounts are variables used to calculate the capital ratios as follows (BCBS, 2006; European Parliament, 2013):

$$\text{CET1 ratio} = \frac{CET1}{RWA} \geq 4,5\% \tag{1}$$

$$\text{T1 ratio} = \frac{T1}{RWA} \geq 6\% \tag{2}$$

$$\text{Total capital ratio} = \frac{T1 + T2}{RWA} \geq 8\% \tag{3}$$

In order to calculate the capital ratios, the regulatory capital amounts must be divided by the risk-weighted assets (RWA). According to the BCBS (2006) and European Parliament (2013), the RWA can be calculated by two methods: the standardized approach (SA) and the internal rating based (IRB) approach. The IRB approach can be subdivided in the Foundation (F-IRB) approach and the Advanced (A-IRB) approach.

For the SA a risk weight scheme is developed, in which various types of obligors are subject to a certain risk weight (European Parliament, 2013). The risk weight multiplied by the loan's exposure less the specific provisions held for the ICL or ECL (BCBS, 2017), is the loan's RWA. The sum of all financial assets' RWAs is the bank's RWA. Appendix B provides a general overview of the risk weights per obligor and for cash. Following the IRB approach, a direct way to calculate the RWA is not available as the IRB approach does not have a risk weight scheme. Instead of a risk weight scheme, BCBS (2010) and European Parliament (2013) state that the capital requirements are 8% of the RWA. The RWA can be determined indirectly by calculating the capital requirements, using the following formula:

$$\text{RWA} = 12,5 \cdot K \cdot EAD \tag{4}$$

Where EAD is not allowed to be lessened by the specific provisions nor the general provisions (BCBS, 2017) and K denotes the capital requirements. The capital requirements are defined by the ASFR model (BCBS, 2005), which is a model providing the formulas and an explanation on the capital requirements. The capital requirements aim to be a buffer against unexpected losses as a result of rare loss events. The amount of this buffer is determined taking the worst case default rate (WCDR) with 99,9% certainty using Vasicek's model (Vasicek, 2002), which equals unexpected losses plus expected losses, deducted by the expected losses, which are covered with provisions. This is illustrated in Figure 1.

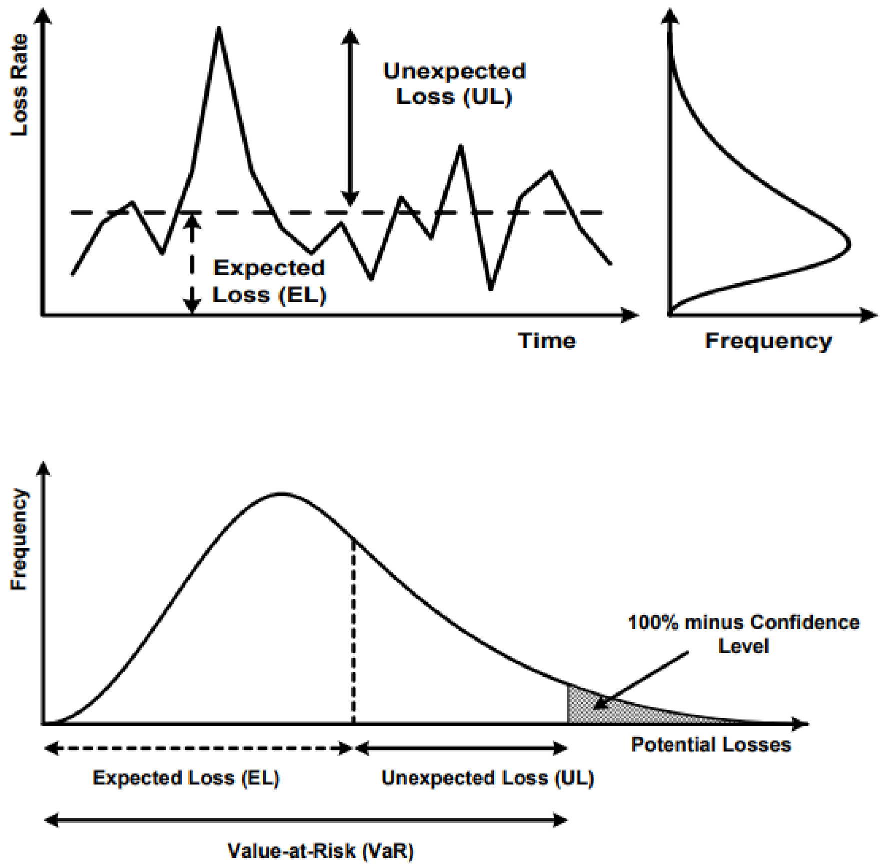

Figure 1: Relationship between the expected loss (EL), unexpected loss (UL) and value at risk (VaR) related to the capital requirements at banks (BCBS, 2005).

Calculating the RWA for the IRB approach requires PD, LGD and EAD, which should be estimated by banks. However, there are certain regulations to be considered regarding the estimation of PD, LGD and EAD. Banks following the A-IRB approach should estimate PD, LGD and EAD. Banks following the F-IRB approach should estimate the PD, while LGD is provided by the CRR. Adjustments regarding the LGD are necessary in order to take collateral into account with the so called (specific) haircuts, but these haircuts are not taken into account in this research. Furthermore, the estimates should be conservative and based on a one-year horizon.

Additionally, there are two relevant requirements of the CRR regarding the capital ratios. First, T2 is limited to the amount of T1 and can therefore in the calculations never exceed T1 (BCBS, 2010; European Parliament, 2013). Second, if there is a mismatch between one-year's ECL and the amount of provisions, there is a distribution of the excess or shortfall affecting the capital ratios (BCBS, 2010; European Parliament, 2013). If the amount of provisions are lower than the one-year ECL, 50% of the shortfall is deducted from the T1 and 50% of the shortfall is deducted from the T2. If the amount of provisions excess the one-year ECL, the excess is added to T2, with a maximum of 1,25% of the RWA for banks using the SA and a maximum of 0,6% of the RWA for banks using the IRB approach.

Summarizing the above, the IAS39 and IFRS9 and CRR set general guidelines on how to manage provisions and capital ratios, respectively. However, although these guidelines incorporate calculations of variables and parameters such as T1 and RWA, some variables and parameters need to be estimated by banks, more specifically PD, LGD and EAD.

2.2 Literature

Further details on the estimation of the PD, LGD and EAD are examined in this section. According to the IRB approach, banks are required to use the PD, LGD and EAD to calculate the unexpected loss as defined by the ASFR model and it is expected that the same variables, although adjusted, are used to calculate the ECL following IFRS9 (Rhys et al., 2016).

Comparing IRB with IFRS9, there are several differences. One difference is conservatism in the IRB approach which means that banks add a margin of conservatism to their estimates, related to the expected range of estimation errors (European Parliament, 2013). Another difference is that IFRS9 and the IRB approach require different time horizons on which the PD, LGD and EAD need to be estimated. Following IFRS9, PD, LGD and EAD estimations need to be best estimates on different time horizons which should take all information into account (IASB, 2014). According to the IRB approach, PD, LGD and EAD are always estimated on a one-year horizon. Lastly, while the IRB entails calculating the PD, LGD and EAD through-the-cycle (TTC), IFRS9 requires PD, LGD and EAD to be calculated point-in-time (PIT) (Novotny-Farkas, 2016).

TTC estimations are based on long term averages, resulting in an estimate that is stable through the business cycle and credit cycle (Novotny-Farkas, 2016; Rhys et al., 2016). PIT estimations in contrast are based on the current state of the economy and incorporates all available information and forecasts, making PIT a more real-time estimation influenced by business cycle and credit cycle (Novotny-Farkas, 2016; Rhys et al., 2016). An estimate is not necessarily 100% TTC or 100% PIT. If estimations are not 100% TTC or PIT, the estimate is called a hybrid estimation (Carlehed & Petrov, 2012; Novotny-Farkas, 2016; Rubtsov & Petrov, 2016), which contains elements of PIT and TTC. A visual representation of TTC, PIT and hybrid estimations over time are schematically displayed in Figure 2 with PD being the variable examined.

Figure 2 implies that PIT has a cyclical behavior, which is a consequence of the incorporation of all information, like the macro-economic factors. These macro-

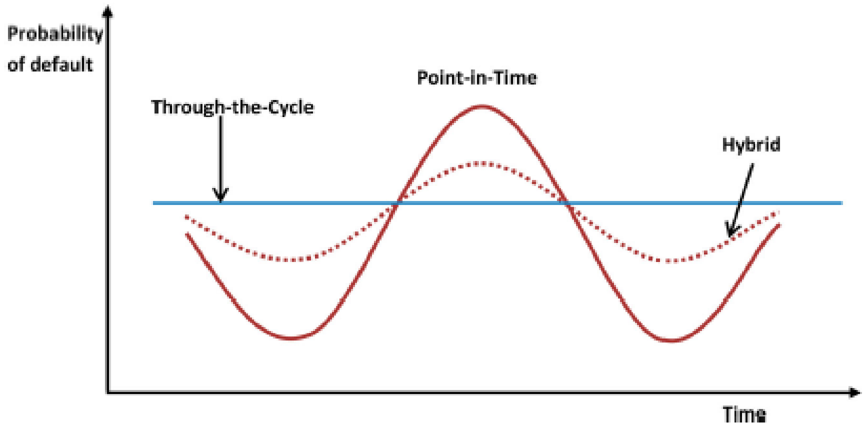

Figure 2: Schematic representation of through-the-cylce, point-in-time and hybrid probability of default over time (Novotny-Farkas, 2016).

economic factors influence the systematic credit risk, which is empirically proven by e.g. Bangia et al. (2002), Koopman & Lucas (2005), Lowe (2002), Nickell et al. (2000) and Wilson (1997a, 1997b). According to the empirical results, a PIT estimation can be seen as the more accurate method to estimate PD, LGD and EAD (Heitfield, 2004). However, a disadvantage of PIT compared to TTC is that PD, LGD and EAD will be more volatile (Maria, 2015; Rhys et al., 2016).

Volatility on the regulatory capital amounts for capital ratios is not desirable, as the BCBS fundamentally aims to minimize the influence of the state of the economy (BCBS, 2006; Gordy & Howells, 2006). If a bank would use PIT during an economic downturn, a bank is expected to have a lower net result. This lower net result effect would be strengthened if a bank is required to hold more capital due to PIT, as PIT PD, PIT LGD and PIT EAD are expected to increase (Catarineu-Rabell et al., 2005). In contrast to the volatility using PIT, TTC provides stable regulatory capital amounts. TTC does not strengthen the effect of a lower net result, because TTC PD, TTC LGD and TTC EAD are not expected to rise as they are independent of the state of the economy and based on the long term average (Novotny-Farkas, 2016). The long term average can be derived from credit rating agencies' (CRA) ratings or a bank's historical data.

2.2.1 TTC of the IRB approach

Many authors use a bank's historical data on default rates to estimate a TTC PD (e.g. Ingolfsson & Elvarsson, 2010; Vaněk et al., 2017). The main benefit is that using a bank's historical data on the default rates result in a bank specific TTC, which means that the TTC is adjusted to the bank's average portfolio risk. An average portfolio risk for big banks is, on average, more reliable than smaller banks, because of the law of large numbers. So, realizing a trustworthy estimate on a bank's TTC PD or TTC LGD using historical data is not always possible. Even when it is possible, careful examination of the data is required.

Data from e.g. 60 years ago cannot be assumed to be a good estimation for now, since the economy and working environment of banks changed over time. Considering the changing economy and working environment, a bank's historical data is more useful when there are sufficient data points and the data consist of short term or medium term historical data in such a way that the data represent the current environment in which a bank acts.

Besides a bank's historical data, CRAs rating grades can be used. A rating grade is a set of properties implying the risk attached to a loan. CRA S&P has 8 rating grades: AAA, AA, A, BBB, BB, B, CCC/C and D, where the AAA rating grade has the highest quality, implying that loans in the AAA rating grade have a(n) (almost) risk-free profile. In contrast, loans having rating grade CCC/C have a very high risk profile. The defaulted rating grade, D, contains all defaulted loans. Defaulted loans have an explicit reason that the loans are impaired. So, CRAs define a rating grade with a set of risk properties and consequently CRAs assign loans to a certain rating grade.

The CRA's rating grades are mainly TTC, as S&P (2013, p. 41) states: "The value of its rating products is greatest when its ratings focus on the long term, and do not fluctuate with near-term performance." The disadvantage of CRA's data is that the three biggest CRAs, S&P, Moody's and Fitch, rate large institutions and mainly do not assign rating grades to small and medium enterprises. However, a benefit of CRA's data is that the data is publicly available and CRAs have large databases. Research is conducted on how the CRAs assign their rating grades and rating grade migration (e.g. Altman & Rijken, 2004; Bangia et al., 2002; Nickell et al., 2000). Altman & Rijken (2004) state that CRAs only lower their rating grade when the actual rating grade is 1,25 notches lower than the current rating grade. Also, if this threshold of 1,25 notches has been met, the rating grade will be lowered (or increased) with 75% of the difference between the current and original rating grade in order to be more stable over time. So, Altman & Rijken (2004) conclude that CRAs have a time-lag and prudent credit rating grade migration property, confirming S&P's statement regarding the stability of CRA rating grades.

Two main points of critique on the CRA rating grades are discussed in the literature. First, it is found that in case of a downgrading migration, there is a higher probability for a further downgrading migration when compared to companies that experienced upgrades (e.g. Altman & Kao, 1992a,b; Bangia et al., 2002; Carty, 1997; Lando & Skødeberg, 2002; Lucas & Lonski, 1992). Second, it is argued that rating grade properties are not entirely TTC or completely independent of the state of the economy (e.g. Bangia et al., 2002; Kavvathas, 2001; Koopman et al., 2005; Koopman & Lucas, 2005; Topp & Perl, 2010; Wilson, 1997a, 1997b). Topp & Perl (2010) confirm the critique on the TTC, finding that rating grades are not 100% TTC and TTC can consequently be overestimated or underestimated.

Summarizing, the better data available would be the bank's historical data over a short term and medium term period with many data points. In absence of the bank's historical data, CRA's data provide an alternative when examining the properties of the rating grades. The rating grades contain limitations on migration probabilities and the business cycle, which should be handled carefully when using CRA rating grades regarding TTC estimates.

2.2.2 Forward looking and PIT of IFRS9

In contrast to TTC estimates, IFRS9 requires best estimates, which take into account all available information, including e.g. business cycle, macro-economic factors and forecasts. Furthermore, the best estimate should be forward looking. Best estimates can be achieved conducting a regression between a bank's historical data or CRA's annual published data and macro-economic factors, such as GDP or unemployment rate.

Using a bank's historical data has the same benefits and disadvantages as discussed in Subsection 2.2.1 regarding TTC. An alternative is to use CRAs rating data. Annually, CRAs publish their observed rating data. Rating data contains migration matrices, amongst others. Migration matrices are matrices indicating the probability that a loan migrates from one rating grade to another rating grade over a certain time horizon.

Other rating data annually published by CRAs are default rates. Of the three biggest CRAs, publicly available default rates are published by S&P. According to S&P, the default rate indicates the amount of defaulted obligors on one or more financial obligations as a percentage of the amount of observed obligors (Vazza & Kraemer, 2017). Furthermore, recovery rates are published yearly by CRA Moody's, but these recovery rates are not publicly available. However, Moody's has published data on the period from 1920 to 2008, where Moody's defines the recovery rate as the percentage of the bid price of the defaulted loan 30 days after the defaulted expected payment as a percentage of the par value (Emery et al., 2009). Forest et al. (2015) explain the shortcomings of using CRA's default rates, as a benchmark for PD, as they found that the biggest shortcoming is a bias in the dataset. The origin of the bias is that the CRAs do not have an equal distribution of observations on e.g. industry, region or rating class (Topp & Perl, 2010).

Observations of default rates over the years are subject to time-dependent macro-economic factors. Macro-economic factors are observed and published by mostly governmental economic institutions, e.g. Eurostat, NBER or IMF. Regressing macro-economic factors from governmental economic institutions with respect to CRA's default rates provide insights in the dynamics between macro-economic factors and the default rates, as done by e.g. Pederzoli & Torricelli (2005), Rubtsov & Petrov (2016) and Vaněk et al. (2017).

The dynamics between macro-economic factors and the default rate require an examination of relevant macro-economic factor (Carlehed & Petrov, 2012). The macro-economic factor is depending on the exposure examined, for instance corporate exposure depends on GDP growth (e.g. Vaněk et al., 2016), while for retail exposure the unemployment rate is expected to have a large weight on the explanatory power (e.g. Lawrence et al., 1992). In the literature, three main methods incorporating macro-economic factors in order to convert TTC to (forward looking) PIT can be distinguished: macro-economic adjusted Markov chains (Vaněk et al., 2017), Vasicek's one-factor model (Carlehed & Petrov, 2012) and KMV-Merton model (Bharath & Shumway, 2004).

Vaněk et al. (2017) show a method to convert TTC PD to PIT PD using Markov chains based on the average characteristics over time of a rating grade. The CRA rating grades are close to TTC and can be presented in a migration matrix. The migration matrix is depending on the macro-economic factors, which results in the incorporation of macro-economic factors in the migration probabilities. The migration probabilities represent the probability of having a certain rating at a certain point in time depending on macro-economic factors.

Carlehed & Petrov (2012) use Vasicek's one-factor model to compute the PIT PD using the TTC PD, default rate and correlation by assuming that the default rate represents the current state of the economy. The current state of the economy indicates a limitation of this model, namely that PIT cannot be determined multi-period. However, Vasicek's one-factor model is an analytical approach which can be repeated per rating per year. Consequently, a single repetition of Vasicek's one-factor model per rating per year is not computational intensive compared to a Markov chain with macro-economic adjustments, which is beneficial for model running time. This benefit is used by Csaba (2017), who adjusts the migration probabilities of a two ratings Markov chain with the results of Vasicek's one-factor model. García-Céspedes & Moreno (2017) proposes an extension on Vasicek's one-factor model in order to use the model for multi-period purposes by giving a weight to the most recent default rate observation of the explanatory model and a certain weight to a random error term.

Finally, KMV corporation developed a default forecasting model, the KMV-Merton model, based on Merton's debt pricing model (Merton, 1974). Merton's debt pricing model is applied to a company's balance sheet, where the equity of a company is seen as a call option and the strike price is the face value of the company's debt (Bharath & Shumway, 2004). The face value of a company's debt, the company's underlying value and the company's volatility determine the PD. Determining the PD is difficult as the company's underlying value and the company's volatility are not observable (Bharath & Shumway, 2004). Furthermore, there are some underlying assumptions, e.g. the value of a company is following Brownian motion, as a result of using Merton's debt pricing model for the KMV-Merton model that is not representative for a company's underlying value. However, an advantage of the KMV-Merton model is that no historical data of the company is required to determine a forward looking PIT PD and the model can be useful for examining a specific company, instead of assuming that all companies have the same status in the business cycle. Since, it is out of the scope of this research to examine a specific company this model is not used any further.

Influence of IFRS9 on a bank's capital ratios

The first research question can be answered, since it is reasoned that the amount of provisions resulting from IFRS9 are expected to increase and to be accounted for earlier. These consequences on timing and amount react to the critique on IAS39 and will result, assuming everything else equal, in lower capital ratios. Next to the expected lower capital ratios another consequence is expected when applying IFRS9, namely volatility. The volatility in the amount of provisions increases when applying PIT, which will in its turn result in an increase in volatility of the capital ratios.

Summarizing, Chapter 2 shows that IFRS9 and CRR provide many guidelines to practice their regulations. However, the guidelines do not provide a method to quantify the dynamics of IFRS9 on the capital ratios, as some variables and parameters, for instance PD, are subject to a bank's own estimate. The main change for banks is to switch from only using a one-year TTC PD to also estimating a one-year PIT PD and a lifetime PIT PD. TTC PD can be determined using multiple data sources, which have advantages and disadvantages. PIT PD can be determined using three methods known in literature, of which KMV-Merton model is not suited for this research.

3 Modeling

In this chapter, a model is developed to quantify the dynamics of IFRS9 on the capital ratios by quantifying IFRS9 and the F-IRB approach. The IFRS9 and F-IRB approach are expressed in formulas and the corresponding variables and parameters are quantified. Many formulas, variables and parameters are provided by IFRS9 and the F-IRB approach, however some formulas, variables and parameters are required to be derived from methods developed in literature. This chapter consists of four subsections. First, the scope of the research is further determined. Second, the regulatory required formulas in IFRS9 and the F-IRB approach are examined. This section provides a mathematical overview on how IFRS9 influences the financial statements and how consequently the capital ratios are derived from the financial statements. Details on how to determine input variables and parameters of IFRS9 and the F-IRB approach are left out in the second section of the modeling chapter. Third, a method to determine the input variables and input parameters is examined. The section provides insight on a detailed level on how the input variables and input parameters of IFRS9 and the F-IRB approach are determined. Fourth, the input variables and input parameters required in the model are provided with a value. Also, a method to render a portfolio is examined.

3.1 Scope

As already introduced in the introduction, this research examines a hypothetical bank using the F-IRB approach and the financial assets (excluding cash) only comprise corporate loans. All corporate loans are bullet loans, meaning that the principal is paid at once at maturity and there are no other cash flows during the contract. Furthermore, it is assumed that a loan can only default once, meaning that once a loan defaults it stays in default, which results in a cure rate equal to zero. The loans in the portfolio of the examined bank have on average the same diversification (in terms of geography, industry etc.) as the observed loans underlying S&P's rating data, which is a requirement in order to make the portfolio compatible with S&P's rating data. As only S&P's rating data is available, it is also assumed that the same rating grades as S&P uses are used by the hypothetical bank. Banks normally have more rating grades than the eight rating grades S&P distinguishes. Likewise, Moody's rating grades are assumed to have the same characteristics as S&P's rating grades in this research, in order to make S&P's data compliant with Moody's data. Regarding the rating grades, it is assumed that once a corporate loan has a rating grade, the loan remains rated. The threshold of a substantial deterioration since origination in order to downgrade from stage 1 to stage 2 is assumed to be one rating grade notch. The risk weight for cash and non-financial assets are equal to zero, but can have any risk weight without influencing the effect of provisions on the capital ratios if constant.

The model simulates the capital ratios of the portfolio of a hypothetical bank given different economic scenarios at reporting date, which is the 31st of December 2016, assuming that IFRS9 has already been enforced. In this chapter the corresponding financial statements and portfolio of the hypothetical bank at reporting date are presented.

3.2 Regulatory demands

This section provides a mathematical overview of the regulatory demanded formulas to determine the amount of provisions and capital ratios. Modeling these regulatory demands is conducted in three steps. First, formulas of IFRS9 regarding provisions are modeled in order to quantify the amount of provisions at a certain point in time. Second, the influence of the amount of provisions on the financial statements are illustrated with a consolidated example and third, the capital ratios are extracted from the balance sheet following the CRR.

3.2.1 IFRS9

In this subsection, the facultative formulas of IFRS9 are modeled. Formally, IFRS9 does not require any formulas, but requires the provisions to be equal to the ECL. The ECL is generally calculated with PD, LGD and EAD, which are variables unknown by a bank and as a result a bank is required to estimate these variables. The mathematical representation of the ECL for a loan is:

$$ECL_T = \sum_{t=1}^{T} \frac{PD_t \cdot LGD_t \cdot EAD_t}{(1+EIR)^t} \tag{5}$$

Where PD_t is the probability of a default between time $t-1$ and time t. Likewise, LGD_t is the loss percentage given that a default occurs between $t-1$ and t and EAD_t is the exposure given that a default occurs between $t-1$ and t. The EIR, the effective interest rate, is the rate that discounts the future cash flow through the expected life of the loan to the principal of the loan (IASB, 2003). T is the remaining time to maturity of a loan. For a stage 1 loan, T is always equal to 1. However, for example if a stage 2 or stage 3 loan matures 5 years from now, a bank should estimate ECL_5. Estimating the ECL of portfolios requires a bank to sum all loans' ECL, which can mathematically be expressed as follows:

$$ECL_T = \sum_{n=1}^{N} \sum_{t=1}^{T} \frac{PD_{t,n} \cdot LGD_{t,n} \cdot EAD_{t,n}}{(1+EIR)^t} \tag{6}$$

Where $PD_{t,n}$ is the probability of default of loan n between time $t-1$ and time t. Likewise, $LGD_{t,n}$ is the loss percentage given that loan n defaults between time $t-1$ and time t and $EAD_{t,n}$ is the exposure given that a default for loan n occurs between time $t-1$ and time t. N is the number of loans in the portfolio.

Equations (5) and (6) are TTC and therefore formally incorrect as IFRS9 requires banks to estimate PD, LGD and EAD PIT. In order to determine PIT PD, PIT LGD and PIT EAD, a bank requires to incorporate all available information. Taking all information into account, Equation (6) can be rewritten as:

$$ECL_{T|i} = \sum_{n=1}^{N} \sum_{t=1}^{T} \frac{PD_{t|i,n} \cdot LGD_{t|i,n} \cdot EAD_{t|i,n}}{(1+EIR)^t} \tag{7}$$

$$= \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{PD^{PIT}_{t,n} \cdot LGD^{PIT}_{t,n} \cdot EAD^{PIT}_{t,n}}{(1+EIR)^t} \tag{8}$$

Where i is all information available at time t, making PD, LGD and EAD PIT and therefore compliant with IFRS9. The determination of PD^{PIT}, LGD^{PIT} and EAD^{PIT} is discussed in Section 3.3.

Summarizing, IFRS9 does not provide a mathematical framework to calculate the ECL. The ECL is in practice most likely calculated by Equation (8), as some other regulatory frameworks require unadjusted TTC PD, LGD and EAD.

3.2.2 Financial statements

In this subsection, the influence of the provisions on the financial statements is illustrated using an example regarding hypothetical financial statements. Provisions influence the income statement and balance sheet, which is illustrated in Table 1 and Table 2. The tables include one example in which a certain bank has no provisions and one in which that certain bank has provisions, for which a simple, consolidated income statement and a simple, consolidated balance sheet is presented. First, the income statement is discussed shortly, to justify the underlying assumptions. Second, the balance sheet is discussed as the balance sheet is used to extract capital ratios.

Table 1: Comparison of income statements on the influence of provisions. Parentheses refer to expenses.

(a) Hypothetical result in absence of provisions.

Income statement	
Sales	100
Consolidated expenses	(90)
Δ Provisions	0
Net result	10

(b) Hypothetical result including provisions.

Income statement	
Sales	100
Consolidated expenses	(90)
Δ Provisions	(4)
Net result	6

Table 1 represents a bank's income statement, comprising of four items: sales, consolidated expenses, change in provisions and net results, which are referred to as income statement items. These items interact as follows: sales minus consolidated expenses minus change in provisions equals the net result. Sales include the income resulting from normal business activity of a bank, e.g. coupon payments or fees. The consolidated expenses include all expenses for normal business activity, including interest expenses, tax expenses, non-cash costs other than provisions (e.g. depreciation, amortization, reservations) and adjustments (e.g. currency adjustment). Sales netted by the consolidated expenses are referred to as the Earnings Before Provisions (EBP). The EBP in this example is assumed to be equal to the free cash flow, which is justified (i) assuming that per time unit the amount of investments equals the amount of depreciation and amortization and (ii) assuming that the amount of net working capital is equal over time. These assumptions are considered necessary in order to exclude effects on the financial statements other than the change in the amount of required provisions. The change in the required amount of provisions are an expense equal to the ECL and should be deducted from the EBP to obtain the net result. The net result can be positive or negative. A positive net result is a profit, while a loss is made when the net result is negative. The net result on the income statement at reporting date is added to the retained earnings on the balance sheet, which is equity. From Table 1a and Table 1b the dynamics of the change in provisions on the consolidated income statements show that the change in provisions negatively influence the net result.

The net result, change in provisions and EBP are at the reporting date transferred to the balance sheet. A hypothetical balance sheet before and after the transfer of the income statement items are presented in Table 2, where Table 2a represents the balance sheet of a hypothetical bank shown in Table 1a and Table 2b represents the balance sheet of a hypothetical bank shown in Table 1b. $t-$ indicates the reporting date just before the income statement items are transferred to the balance sheet, $t+$ indicates the reporting date just after the income statement items are transferred to the balance sheet. The hypothetical balance sheet is divided in assets, liabilities and equity, which are referred to as balance sheet classes. The asset class is divided in three balance sheet items: non-financial assets, corporate loans and cash. The asset class can be further subdivided, but is limited to these three balance sheet items. The non-financial assets consists of assets not related to a bank's core business (e.g. office building, inventory etc.). The corporate loans could be extended with other financial assets, but since this research is limited to corporate credit exposure only corporate loans are on the balance sheet. Cash is included in this example, as this provides insight in the way banks handle EBP from the income statement to the balance sheet.

Liabilities comprise the amount a bank borrows from other money lending parties and the amount of money the bank has created as a result of its money creation capability.

Lastly, the equity part of the balance sheet is divided in shareholder's equity and retained earnings. The shareholder's equity is part of CET1, but is not affected by provisions. Instead, the amount of shareholder's equity reported on the balance sheet are a result of the par value of the outstanding shares multiplied by the number of outstanding shares and possibly some premiums. The amount of shareholder's equity can change in case of an emission of new shares, which is an event not included in the model. The retained earnings are the cumulative net results over time.

Summarizing, the financial statements are affected by the provisions as shown in the example of the financial statements. The financial statements of a bank are, as mentioned before, the interplay between IFRS9 and the CRR.

3.2.3 CRR

In this subsection the capital ratios are derived from the balance sheet following the CRR. Transferring the income statement items from the income statement at the reporting date, most likely changes the variables of the capital ratios. The capital ratios are shown in Equations (1) to (3), where the regulatory capital amounts are in the numerator. These regulatory capital amounts can be calculated from the balance sheet by adding up the relevant balance sheet

Table 2: Comparison of balance sheets with respect to the influence of provisioning. t is the point in time of reporting date, where the income statement items are transferred to the balance sheet.

(a) Balance sheet as a result of Table 1a, which shows 10 currency units free cash flow are added to cash and the net result of 10 currency units are added to retained earnings.

Balance sheet $t-$		Δ	**Balance sheet** $t+$	
Non-financial assets	100		Non-financial assets	100
Corporate loans	400		Corporate loans	400
Cash	50	$\Delta 10$	Cash	60
Total assets	550		Total assets	560
Liabilities	450		Liabilities	450
Total liabilities	450		Total liabilities	450
Shareholder's equity	60		Shareholder's equity	60
Retained earnings	40	$\Delta 10$	Retained earnings	50
Total equity	100		Total equity	110
Equity + liabilities	550		Equity + liabilities	560

(b) Balance sheet as a result of Table 1b, which shows that the retained earnings increases with 6 currency units as a result of the net result, the free cash flow adds 10 currency units to the cash position and due to provisions the corporate loans' book value is reduced by 4 currency units.

Balance sheet $t-$		Δ	**Balance sheet** $t+$	
Non-financial assets	100		Non-financial assets	100
Corporate loans	400	$\Delta(4)$	Corporate loans	396[a]
Cash	50	$\Delta 10$	Cash	60
Total assets	550		Total assets	556
Liabilities	450		Liabilities	450
Total liabilities	450		Total liabilities	450
Shareholder's equity	60		Shareholder's equity	60
Retained earnings	40	$\Delta 6$	Retained earnings	46
Total equity	100		Total equity	106
Equity + liabilities	550		Equity + liabilities	556

[a]Banks present the net value of the corporate loans on the consolidated balance sheet (e.g. ING, 2016, p. 111). In the notes on the balance sheet, banks declare the loan loss provisions (e.g. ING, 2016, p. 145).

items as shown in Appendix A. These regulatory capital amounts expressed as a percentage of the RWA are the capital ratios, which banks using the F-IRB approach should calculate according to Equation (4). Recall, Equation (4) states that the RWA is 8% of the capital requirements of a bank, or the other way around: the RWA is a multiple of 12,5 of the capital requirements. The CRR defines the capital requirements K for corporate exposure as (European Parliament, 2013):

$$K = \left[\underbrace{LGD \cdot N\left(\sqrt{\frac{1}{1-R}}G(PD) + \sqrt{\frac{R}{1-R}}G(0,999)\right)}_{\text{Value at risk 99,9\%}} - \overbrace{LGD \cdot PD}^{\text{Expected loss}} \right] \cdot \tfrac{1+(M-2,5)b}{1-1,5b} \quad (9)$$

Where $N(\bullet)$ is the normal cumulative distribution function and $G(\bullet)$ is the inverse cumulative normal distribution. The brace under the formula shows Vasicek's WCDR with 99,9% confidence, which is multiplied by LGD to obtain the value at risk with 99,9% confidence. $LGD \cdot PD$ is the expected loss (EL) on a one-year horizon. R is the default correlation coefficient, which is defined for corporate exposures as:

$$R = 0,12 \cdot \frac{1-e^{-50PD}}{1-e^{-50}} + 0,24 \cdot \left(1 - \frac{1-e^{-50PD}}{1-e^{-50}}\right) \quad (10)$$

b in Equation (9) is defined as the maturity adjustment, which is mathematically defined as:

$$b = (0,11852 - 0,05478 \cdot ln(PD))^2 \quad (11)$$

M in Equation (9) is defined as the effective maturity, which is a fixed value of 2,5 (years) for banks using the F-IRB approach. LGD is set to 45% for unsecured senior loans to corporates, sovereigns and banks and 75% for subordinated loans to corporates, sovereigns and banks (European Parliament, 2013).

In order to determine the RWA and consequently the capital ratios, a detailed examination of the portfolio is required. However, to illustrate the effect of provisions on e.g. the CET1, it is assumed for this example that the RWA is 80% of the corporate loan's carrying amount resulting in a total RWA of 320. Regarding Table 2 the CET1 at time $t+$ is equal to total equity, as both shareholder's equity and retained earnings are part of CET1. With regards to Table 2a the CET1 ratio at time $t+$ can be calculated:

$$CET1 = \frac{110}{320} = 34\% \quad (12)$$

When provisions are included, Table 2b results in a CET1 at time $t+$ of:

$$CET1 = \frac{106}{317} = 33\% \quad (13)$$

As the example illustrates, the provisions reduce CET1 since the CET1 of Table 2a at time $t+$ is greater than the CET1 of Table 2b. Also, the example illustrates that as a consequence of provisions, banks are required to hold more capital in order to meet the capital requirements.

One exception in determining the RWA should be made, namely for defaulted loans. Defaulted loans have a PD of 100%, which would imply a capital requirement of zero. However, it is desired that defaulted loans also maintain a certain amount of capital for unexpected losses (BCBS, 2005). Therefore, the CRR states that the K should be the difference between the expected LGD and the worst case LGD. In this research, the worst case LGD is the conservative LGD provided by the CRR and the expected LGD for defaulted loans is derived from ING Group N.V.'s annual report of 2016 (ING, 2016).

Summarizing, this section provided an overview on how IFRS9 can influence the capital ratios in the same order as applied in the model: first provisions are calculated, then the financial statements at reporting date and finally the capital ratios are derived. IFRS9 and the F-IRB approach provide a guideline on how to perform these steps, but banks should determine the input variables and input parameters. More specifically, the undefined input parameters, TTC PD and PIT LGD, and undefined input variables, PIT PD and PIT EAD, should be determined by banks.

3.3 Modeling variables

This section provides an approach to calculate the input variables and input parameters of the regulatory demanded formulas. More specifically the TTC PD, PIT PD, PIT LGD and PIT EAD are discussed. In order to estimate these undefined variables and parameters, a mathematical framework is elaborated upon. As TTC PD is needed to calculate PIT PD, a method to estimate TTC PD is presented first. Thereafter, a method for PIT PD, PIT LGD and PIT EAD is elaborated upon. The presented method is not the only approach to estimate the variables and parameters, however due to a lack of data, other methods cannot estimate the undefined variables and parameters or require additional assumptions to be compliant. The data required for the presented methods is available in order to run the model.

3.3.1 TTC PD

Recall that TTC PD is a long term average independent of the state of the economy. The independent averages of the state of the economy, although criticized, can be found using data from CRAs' rating grades. Per rating grade the default rate per year from 1981 to 2016 is publicly available from CRA S&P. Other CRAs, like Moody's and Fitch, do not provide the default rates per rating over the last few decades. Considering the above, this research uses S&P's default rates. If the default rates over the last few decades are available, an arithmetic average is an estimation of the TTC PD:

$$PD_g^{TTC} = \sum_{a=1}^{N} \alpha_{g,a} \cdot DR_{g,a} \tag{14}$$

Where PD_g^{TTC} is the TTC PD of rating grade g, N is the number of observed years, a is an observed year. $DR_{g,a}$ is the default rate of rating grade g of year a. $\alpha_{g,a}$ is the weight given to an observed year, in which the weight depends on the number of observations per rating grade per year. For $\alpha_{g,a}$ the following should hold:

$$\sum_{a=1}^{N} \alpha_{g,a} = 1 \tag{15}$$

The PD^{TTC} is derived using the same method as PD_g^{TTC}, but including all rating grade specific observation. The method of taking the average of the past as a predictor for the TTC PD is an approximation and therefore not an exact determination. For instance, if N is 39, then an outlier in year 40 with 1 percent point deviation from the TTC results in 0,025 percent point increase of the TTC PD (assuming an average weight α), which can be a substantial increase in high quality rating grades with just a few observed years. When more observed years are available for the estimation of the TTC PD, the deviation as a result of an outlier is smaller.

Equation (14) enables a bank to estimate all variables and parameters required to calculate the capital ratios from the balance sheet. The TTC PD is not an exact determination.

3.3.2 PIT PD

The TTC PD calculated in the previous subsection is converted to a PIT PD in this section. In order to determine the PIT PD, information regarding the current state of the economy should be incorporated in order to incorporate all information. Furthermore, the PIT PD should be forward looking. In order to do so, two relevant methods are introduced in Subsection 2.2.2: Markov chains and Vasicek's one-factor model. These two models are combined as a combination of the properties of both models enables a forward looking, multi-period PIT PD incorporating the available information. This subsection continues as follows. First, the migration matrix, which is assumed to have Markov chain properties, is introduced in order to obtain a multi-period PD. Second, adjustments to the migration matrix are made using Vasicek's one-factor model in order to obtain the forward-looking and PIT property.

Migration matrix and Markov properties
Recall that migration matrices are matrices indicating the probability that a loan migrates from a certain rating grade to another rating grade over a certain time horizon. S&P's annually published TTC migration matrix is used in this research. S&P's TTC migration matrix is assumed to have Markov chain properties. Three Markov chain properties are especially helpful for the multi-year adjustment, namely (i) Markov chains have a finite amount of states, which can be interpreted as rating grades, (ii) Markov chains govern the probability of being in a certain state, which can be interpreted as the probability of a loan being in a certain rating grade, and (iii) Markov chains can be multiplied by one another an infinite amount of times, without being dependent on the historical states. So, if the migration matrix is assumed to have Markov chain properties, the migration matrix always provides the probability of being in a certain rating grade instead of somewhere in between rating grades, no matter how many times the migration matrix is multiplied by itself or by other migration matrices with Markov chain properties and independent of historical rating grade. The result is a probability distribution of a loan being in a certain rating grade, where the probability of being in the default rating grade is a multi-period PD.

Assuming a bank using an internal rating system with r rating grades, the migration matrix P is a (r x r) matrix. This migration matrix can be denoted as follows:

$$P_{t+1} = \begin{pmatrix} p_{1,1} & \dots & p_{1,j} & \dots & p_{1,r} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{i,1} & \dots & p_{i,j} & \dots & p_{i,r} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{r,1} & \dots & p_{r,j} & \dots & p_{r,r} \end{pmatrix}$$

Where P_{t+1} is the migration matrix for the period between time t and time $t+1$. $p_{i,j}$ is the probability that a loan has rating j at $t+1$, given that at t the rating is i. As it is assumed that once a loan is rated at time t, the loan is also rated at time $t+1$. As a consequence, a row in the matrix should add up to one, mathematically:

$$\sum_{j=1}^{r} p_{i,j} = 1 \tag{16}$$

Since $p_{i,j}$ is a probability, the following boundaries hold: $0 \leq p_{i,j} \leq 1$. Furthermore, column r represents the i^{th} rating grade's PD ($p_{i,r}$), as the r^{th} rating grade is the rating grade with the lowest quality. The rating grade with the lowest quality is the default rating grade, the r^{th} column is referred to as the default column. The r^{th} row is equal in all economic scenarios and at any point in time, since it is assumed that once a loan has defaulted, it cannot migrate to another rating grade. So, P_{t+1} can be rewritten by adding an absorbing row:

$$P_{t+1} = \begin{pmatrix} p_{1,1} & \dots & p_{1,j} & \dots & p_{1,r} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{i,1} & \dots & p_{i,j} & \dots & p_{i,r} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{r-1,1} & \dots & p_{r-1,j} & \dots & p_{r-1,r} \\ 0 & \dots & 0 & \dots & 1 \end{pmatrix}$$

To find the PD of a certain loan using the migration matrix above, a status vector is used. The status vector is a vector showing the probability distribution of the rating grade of a loan after a certain period. The status vector is a (1 x r) vector and is multiplied with migration matrix P to obtain the status vector for the following period, in other words, the probability that the loan has a certain rating grade in the following period. An example, assuming $r = 2$ for a non-defaulted loan results in the following:

$$s_{t+1} = s_t \cdot P_{t+1} = \begin{pmatrix} 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} 1-PD & PD \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1-PD & PD \end{pmatrix}$$

Where s_{t+1} and s_t are the status vectors at the end of a period and the start of a period, respectively. In this example, the probability on index $\{1,2\}$ of s_{t+1} is the PD, since this is the probability that the loan is in the r^{th} state, which is the default rating grade. When examining a multi-period estimation, the following general formula holds:

$$s_{t+T} = s_t \cdot \prod_{h=1}^{T} P_{t+h} \tag{17}$$

Where the P_{t+h} is the migration matrix adjusted to the state of the economy at time $t+h$. Because Equation (17) holds, the status vector s_{t+T} contains the multi-period status probabilities and as a consequence the multi-period PD. The multi-period PD from the status vector is the cumulative PD, CPD_T, which should be adjusted to PD_t (Equation (8)). T is the time from now till the point in time the PD is cumulated to and t is the timespan from $t-1$ to t. The marginal PD is the probability of default between time $t-1$ and time t, for which the following holds:

$$PD_t = \begin{cases} CPD_T, & \text{for } t = 1 \\ CPD_T - CPD_{T-1}, & \text{for } t = 2, 3, 4... \text{ years} \end{cases} \tag{18}$$

Since P_{t+h} is adjusted to the state of the economy, it is likely that $P_{t+h} \neq P_{t+h-1}$, as the state of the economy changes over time and migration matrix P should reflect the PIT migration probabilities incorporating all available information, like macro-economic factors, according to IFRS9. Therefore, the migration matrix should be adjusted for every simulated year, which can be achieved using Vasicek's one-factor model.

Vasicek's one-factor model

Vasicek's one-factor model has the property to convert a TTC PD to a PIT PD. As a result, the TTC default column of the migration matrix can be converted to a PIT default column by applying Vasicek's one-factor model to each rating grade's PD. Vasicek's one-factor model estimates the state of the economy by applying a correlation dependent weight to the long term average, the TTC PD, and a correlation dependent weight to a macro-economic factor, the default rate. To obtain a forward looking PD, the state of the economy in the future should be estimated, which means that the future default rate should be estimated. The future default rate cannot be directly obtained from any source, so the future default rate is estimated using a regression between the default rate and a macro-economic factor.

Before deriving Vasicek's one-factor model, the general outline on how to apply Vasicek's one-factor model in the simulation is explained. The estimated correlation between the historical default rates and the historical macro-economic factor on a portfolio level is estimated first. Using this correlation, the predicted default rate and the TTC PD on a portfolio level, the state of the economy independent on the rating grade can be estimated. The state of the economy, the TTC PD per rating grade and the correlation between the historical state of the economy and the default rate per rating grade are used to calculate the PD per rating grade. As a result a PD conditional on the state of the economy is estimated, meaning that the PIT PD is estimated.

A mathematical derivation of Vasicek's one-factor model is conducted. Vasicek's one-factor model is defined as (Belkin et al., 1998):

$$X_{g,n} = \sqrt{1-\rho_g} Y_{g,n} + \sqrt{\rho_g} Z \tag{19}$$

Where $X_{g,n}$ is the value of a certain loan n in rating grade rating grade g. $Y_{g,n}$ is loan n's specific default risk and Z is the systematic risk, which is a measure of the state of the economy. Both $Y_{g,n}$ and Z are mutually independent and standard normal random variables (Belkin et al., 1998; Carlehed & Petrov, 2012). As a result $X_{g,n}$ is standard normally distributed as well. ρ_g is the correlation between Z and $X_{g,n}$, which can be obtained by a regression on a time series of a rating grade's default rate and a time series of Z, Z_t. When ρ_g is equal to one, the loan's value is fully dependent on the macro-economic factors and when ρ_g is equal to zero, the loan's value is independent on the macro-economic factors.

When the value of loan $X_{g,n}$ comes below a certain threshold B, loan n gets into default. The threshold is derived from the observed historical default rate for rating grade g, the PD_g^{TTC}. So, $X_{g,n}$ defaults when $X_g < B$, with B being the inverse cumulative distribution of the rating grade's PD TTC. So, $B = G(PD_g^{TTC})$ is the default threshold of loan n in rating grade g (Belkin et al., 1998; Carlehed & Petrov, 2012).

Given the threshold, the following can be derived (Vasicek, 2002; Carlehed & Petrov, 2012):

$$PD_g^{PIT}(Z_t) = P(X_{g,n} < B_{g,n}|Z_t) \tag{20}$$

$$= P(\sqrt{1-\rho_g}Y_{g,n} + \sqrt{\rho_g}Z_t < B_{g,n}|Z_t) \tag{21}$$

$$= P(Y_{g,n} < \left(\frac{G(PD_g^{TTC}) - \sqrt{\rho_g}Z_t}{\sqrt{1-\rho_g}}\right)|Z_t) \tag{22}$$

$PD_g^{PIT}(Z_t)$ is the PD per rating grade conditional on Z_t. Once the PD is conditional on macro-economic information, the PD is PIT. Since $Y_{g,n}$ is standard normally distributed, the following holds for the PIT PD (Carlehed & Petrov, 2012):

$$PD_g^{PIT}(Z_t) = N\left(\frac{G(PD_g^{TTC}) - \sqrt{\rho_g}Z_t}{\sqrt{1-\rho_g}}\right) \tag{23}$$

Z_t represents the status of the economy and therefore, it is equal for all rating grades, but dependent on time. Inverting Equation (23), the following holds (Carlehed & Petrov, 2012):

$$Z_t = \frac{G(PD^{TTC}) - G(d_t)\sqrt{1-\hat{\rho}}}{\sqrt{\hat{\rho}}} \tag{24}$$

Where $\hat{\rho}$ is estimated from the historical default rate and d_t is the default rate of a certain year t on a portfolio level. An explanation on the determination of $\hat{\rho}$ and d_t is given.

The ρ_g parameter can be solved by calculating the correlation between the default rate per year with Z_t per year (Carlehed & Petrov, 2012). Since Z_t is dependent on $\hat{\rho}$, $\hat{\rho}$ cannot be derived from Z_t. According to Carlehed & Petrov (2012), $\hat{\rho}$ can be estimated with the second moments of the $G(d_t)$. The second moment is:

$$V[G(d_t)] = \frac{\hat{\rho}}{1-\hat{\rho}} = \sigma^2 \tag{25}$$

Which implies $\hat{\rho} = \sigma^2/(1+\sigma^2)$, where σ is the standard deviation of the historical default rate if transformed to $G(d_t)$ (Carlehed & Petrov, 2012).

The future default rate d_t must be estimated, in order to estimate a forward looking PD. The future default rate is generally estimated by conducting an ordinary least square (OLS) regression (e.g. Csaba, 2017; Vaněk et al., 2017), using the historical default rate per year and a historical macro-economic factor. The macro-economic factor should be predictable. The predicted macro-economic factor is the input in the resulting OLS regression model, which results in an estimation of the future default rate.

A typical relationship between the Z_t and the historical default rate is displayed in Figure 3. There is a strong negative correlation between the Z_t and the default rate of -0,94. This is expected as the default rate is an input parameter in the determination of the Z_t.

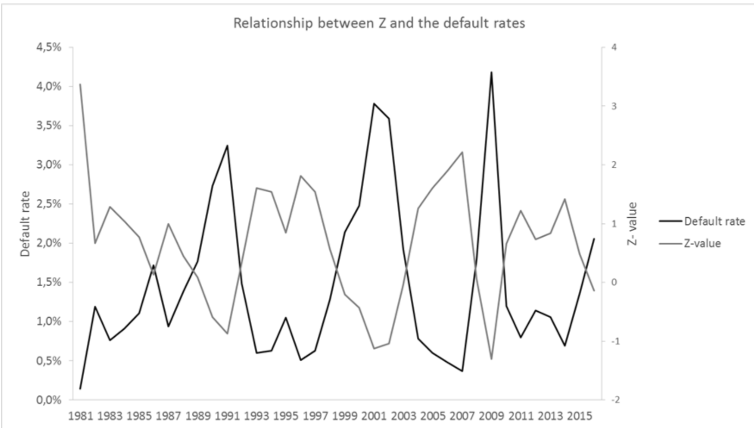

Figure 3: Relationship between the Z and the default rate from 1981 to 2016. The Z_t (Z-value) has no practical dimension and is therefore left dimensionless.

As a result, all variables and parameters are mathematically expressed in order to compute a PIT PD. Since the default rate is used for the regression, only the default column can be converted to PIT. To convert non-default columns to PIT as well, data regarding migrations on every index in the matrix is required. However, this data is unavailable, which requires this research to limit the transition to the default column. The migration matrix after Vasicek's one-factor model is applied results in the following matrix when divided in TTC and PIT:

$$P_{t+1} = \begin{pmatrix} TTC & \dots & TTC & PIT \\ \vdots & \ddots & \vdots & \vdots \\ TTC & \dots & TTC & PIT \\ 0 & \dots & 0 & 1 \end{pmatrix}$$

Adjusting the migration matrix

When only adjusting the TTC default column the sum of the row does not add up to one, as Equation (16) requires. In order to meet the requirements of Equation (16), an adjustment to the non-default columns is necessary.

Four adjustments to the non-default columns are proposed by Vaněk et al. (2017), who refers to these adjustments as alternatives. These four alternatives are presented in Figure 4 and in this research alternative II is applied. Alternative II prescribes that the effect of Vasicek's one-factor model on the TTC default column is as big as the effect of Vasicek's one-factor model on the migration probabilities to rating grades with a lower quality, referred to as downgrade migration probabilities. As a result, the non-default rating grades that represent remaining on or upgrade of loan quality, both referred to as upgrade migration probabilities, are subject to a twofold of the effect of Vasicek's one-factor model on the default column. Furthermore, alternative II incorporates the fact that the downgrade migration probabilities near the rating grade at $T = 0$ (the rating grade at $T = 0$ is referred to as the diagonal) are subject to a bigger impact of the changing default column. Therefore, during an economic downturn the downgrade migration probability is bigger than the TTC downgrade migration probability and during an economic upturn the relative upgrade migration probability increases.

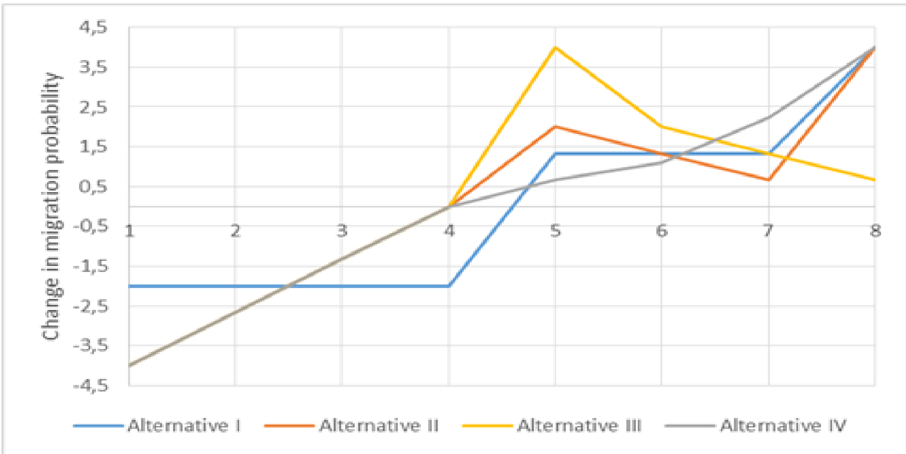

Figure 4: Schematically, the four distribution scenarios considered in this research displaying the change in migration probability per rating grade. Rating grade 4 is the current rating grade. The default column is adjusted by 4 probability units. Alternative II is used in this research, where the changes in absolute terms are higher around the diagonal than at the worst quality default rate, without rescaling the predicted PD. Alternative I is an equal distribution, alternative III rescales the predicted PD and alternative IV concentrates the impact around the tails.

Alternative II as described above is one of the four proposed distributions by Vaněk et al. (2017). Vaněk et al. (2017) do not provide an empirical proof regarding the proposed alternatives in its research. This research attempts to provide an explanation on the redistribution. This subsection continues by discussing the four proposed alternatives.

First, the expected dynamics of the downgrade migration probabilities are discussed. These dynamics hold true for all alternatives. Consider the TTC migration matrix for a rating grade, where a certain percentage of the loans with that rating grade downgrades to a lower rating grade due to various reasons (e.g. the obligor has less business than expected or the obligor had an unexpected loss). The various reasons for a loan to decrease in quality are expected to happen more frequently during an economic downturn, as the obligors are expected to have less resources available to repay their loans and as a consequence the PIT default column is expected to be higher than the TTC default column. So, when the PIT default column is higher than the TTC default column, it is assumed that the downgrade migration probabilities increase. Vice versa, various reasons for a loan to decrease in quality are expected to happen less frequently during an economic upturn, as the obligors are expected to have more resources available to repay their loans and the PIT default column is expected to be lower than the TTC default column. So, when the PIT default column is lower than the TTC default column, it is expected that the downgrade migration probabilities decrease.

Second, the expected dynamics on the upgrade migration probabilities are discussed. These dynamics hold true for all alternatives. It is expected that once the economy is in an economic upturn, the probability of repayment increases due to e.g. an increase of available resources to repay the loan. As a consequence the probability of repayment increases and the upgrade migration probabilities increase. If the economy is an economic downturn, the opposite is expected to happen and the upgrade migration probabilities decrease. So, it is expected that the upgrade migration probabilities decrease during an economic downturn and it is expected that the upgrade migration probabilities increase during an economic upturn.

Third, the distribution of the impact on the migration probabilities among rating grades is discussed. The behavior is explained separately for each alternative. Figure 4 schematically presents the four alternative distributions that are discussed on their implications.

Alternative I

Alternative I redistributes changes in the default column equally in absolute terms. Compared to the TTC migration matrix, this redistribution results in a relatively low weight on the remain probability and a relatively higher weight on the rating grades near the default rating grades. This results in a distribution that becomes more equal once the PIT default column highly deviates from the TTC default column, which practically means that given that the economy is in an economic downturn, the downgrade migration probability is getting relatively more equal. Regarding the upgrade migration probabilities, the highest rating grade becomes relatively less equal to the remain probability. This implies, in practice, that if the economy is in a downturn, the probability of a loan to upgrade to the highest rating grade is substantially deteriorated, but not impossible to achieve. The possibility to be able to migrate to the highest loan quality implies that micro-economic factors still have an impact and the loan's quality is fairly independent of the macro-economic factors and the state of the economy. The probability distribution of the upgrade probability migrations is less likely then the alternatives discussed next, so alternative I is not applied in this model.

Alternative II
Applying alternative II results in a distribution where the downgrade migration probabilities near the diagonal and the upgrade migration probabilities near the tail are affected most substantially. In practice this means that the diagonal is subject to the smallest change in relative terms. As a result the shape of the probability distribution function changes, where the upgrade migration probability becomes concentrated around the diagonal and the downgrade migration probability becomes more concentrated around the diagonal as well. This implies, in practice, that rating grades migration probabilities are substantially dependent on the macro-economic factors. Micro-economic factors have an insignificant impact on the migration probability as it is unlikely to migrate to the tails of the distribution. For example, when an obligor is performing well during an economic downturn it is unlikely that the loan upgrades to the highest quality, because the macro-economic factors have a higher weight. As a result alternative II states that once the PIT default column is higher than the TTC default column, the upgrade migration probabilities become substantially smaller and the downgrade migration probabilities increase substantially near the diagonal, but affects the near default columns generally insubstantially.

Alternative III
Alternative III applies an equal distribution for the upgrade migrations probabilities as alternative II. The difference between alternative II and alternative III is with respect to the downgrade migration probabilities. Alternative III reflects the difference between the PIT default column and TTC default column on the downgrade migration probably of the rating grade one notch lower than the diagonal, while all the other downgrade migration probabilities of alternative II reflect the rating grades more than one notch lower. As a result, the relative downgrade migration probability remains, which is an argument in favor. Practically, this implies that during an economic downturn, the downgrade migration probability increases more than the default column. As a result, the default column is less substantially dependent on the macro-economic factors, while the downgrade migration probabilities are more substantially dependent on the macro-economic factors. An argument against is that the default column is no longer adjusted as a result of the regression, meaning that the regression should be adjusted in order to apply this proposed alternative. Since adjusting the regression is out of the scope of this research, this alternative is not suited to be applied in the model.

Alternative IV
Alternative IV applies an equal distribution for the upgrade migrations probabilities as alternative II and alternative III. Regarding the downgrade migration probabilities alternative IV applies more weight to the tails. This implies in practice that an economic downturn results in a high probability of either remaining at the diagonal or a non-default rating grade near default. As a result, a higher volatility in the rating grades is expected, which is an argument against alternative IV. Alternative IV provides a likely distribution if the correlation between the macro-economic factor and the default rate is high.

All alternatives have arguments in favor and against on their implications. Even different assumption or different economic scenarios can favor one alternative above another. Empirical prove is needed to decide which alternative is best suited in practice, which is not conducted in this research. In this research, alternative II is reasoned to be best suited and is further discussed on its mathematical implications.

Mathematically, method alternative II can be denoted as follows. First, the difference between the portfolio's PIT PD and the portfolio's TTC PD is denoted as D.

$$D_{i,r} = PD^{PIT} - PD^{TTC} \tag{26}$$

Furthermore, define y as:

$$y_i = \frac{\Delta_{t+h} \cdot D_{i,r}}{2(r-1)} \frac{2i-1}{r-1} \tag{27}$$

Where Δ_{t+h} is the time $D_{i,r}$ is computed for (e.g. $\Delta_{t+h} = 1$ if one one-year migration matrix is used for $D_{i,r}$). r is the total number of rating grades a bank distinguishes and i is the row number of the index of which the migration probability is determined. Alternative II computes for all TTC probabilities an adjusted value, where the upgrade migration probabilities and downgrade migration probabilities are computed differently. For the upgrade migration probabilities the following holds:

$$p'_{i,j} = p_{i,j} + \frac{y}{r-i-1} \cdot \frac{2(r-j-1)+1}{r-i-1} \text{ for } i,j < r \text{ and } j > i \tag{28}$$

For the downgrade migration probabilities the following holds:

$$p'_{i,j} = p_{i,j} - 2\frac{y}{i} \cdot \frac{2(i-j)+1}{i} \text{ for } i,j < r-1 \text{ and } j \leq i \tag{29}$$

$$p'_{i,j} = p_{i,j} - \frac{y}{i} \cdot \frac{2(i-j)+1}{i} \text{ for } i = r-1 \text{ and } j \leq i \tag{30}$$

Where j is the column number of the migration matrix. Since negative probabilities are practically impossible, $p'_{i,j}$ is floored at 0. As a result of the computations above, a row is still not necessarily compliant with Equation (16). In order to be compliant with Equation (16), a correction term is used. The correction term is defined for a given i and $j = 1, ..., r$ as follows:

$$p^{corr}_{i,j} = p_{i,j} \cdot \frac{1}{\sum_j p_{i,j}} \tag{31}$$

With these adjustments the PIT migration matrix can be computed and used for matrix multiplications to calculate the PIT PD. A numerical example for the adjustment related to alternative II is presented in Figure 5. Appendix C presents a numerical example for alternative I to IV.

Summarizing, the TTC matrix is known from S&P's data and adjusted to be suitable for the model. Using Vascicek's model, the default column of the TTC matrix is converted to PIT, which requires adjustments to the non-default columns. The non-default columns are adjusted in a systematic way.

	1	2	3	4	5	D
1	-4	0.875	0.625	0.375	0.125	2
2	-9	-3	3.333	2	0.667	6
3	-11.11	-6.667	-2.222	7.5	2.5	10
4	-12.25	-8.75	-5.25	-1.75	14	14
5	-6.48	-5.04	-3.6	-2.16	-0.72	18

Figure 5: Changes in the migration matrix as a result of alternative II on a 6 rating grade model. The source does not define the units of changes, but these can be for instance percentages or basis points. Source: Vaněk et al. (2017).

3.3.3 PIT LGD

After the PIT PD is derived, the PIT LGD is required in order to calculate the provisions of IFRS9. LGD can be converted to PIT by taking collateral into account with haircuts. However, haircuts are excluded from the scope of this research and therefore PIT LGD is assumed to be a TTC LGD. The TTC LGD of the F-IRB approach could be applied. However, the F-IRB approach is based on a certain level of conservatism, therefore it is not a best estimate as IFRS9 requires. In an attempt to remove this conservatism, the average of the LGD per rating grade of Moody's data from 1982 to 2008 (Emery et al., 2009) is used for two reasons. First, Moody's data uses observed LGD to which no margin of conservatism is added and second, Moody's data is based on a global exposure. Moody's global exposure is assumed to be compliant with S&P's global exposure and it is assumed that the hypothetical bank examined in this research has an exposure equal to S&P's exposure. The LGD related to defaulted loans is not provided by Moody's, instead ING group N.V.'s[3] (ING, 2016) LGD related to defaulted loans is used. As a result, a TTC LGD per rating grade with much less conservatism than the TTC LGD of the F-IRB approach is applied in the estimation of the amount of provisions required by IFRS9.

3.3.4 PIT EAD

Additionally to the PIT PD and PIT LGD, the PIT EAD is required to compute the provisions of IFRS9. Recall, it is assumed that all loans are bullet loans, meaning that the principal is paid in the last year till maturity. The principal is the the minimum amount of the TTC EAD defined by Basel II, article 474 and is, considering the bullet loans, used for PIT EAD as well. However, in the last year till maturity of the loan, the principal is repaid. So, at the start of the last year till maturity, the EAD is 100% of the principal and at maturity the EAD is 0% of the principal. It is consequently assumed that on average EAD is 50% of the principal in the last year till maturity. So, in order to have a best estimate, the PIT EAD in the last year till maturity is 50% of the principal.

To further improve the accuracy of the EAD, a bank can incorporate for instance off-balance sheet items and the chance of prepayment. However, these adjustments are not incorporated in the model by assuming that the examined

[3]Rabobank and ABN Amro do not provide the LGD in such detail as ING group N.V., therefore only ING group N.V.'s data is used.

bank has no off-balance sheet items, does not accept prepayments or any other occasions for a different repayment pattern as a bullet loan.

To summarize, the TTC PD is determined as well as the TTC migration matrix. The TTC migration matrix is determined using S&P's data and consequently this TTC PD per rating grade is derived. For every year in an economic scenario, the migration matrix must be adjusted from TTC to PIT. Hence, the migration matrix has three properties required by IFRS9 as a result, namely that it is forward looking, multi-period and PIT. Assumptions regarding the PIT EAD and PIT LGD are made in order to compute provisions.

3.4 Data

Before the model can be used, the values of the variables and parameters need to be determined. In this section the values of the variables and parameters are determined, which is separated in four parts. First, all variables and parameters not specific to a loan are given a value. Second, an overview of different economic scenarios are presented. Third, the hypothetical balance sheet from Table 2 is adjusted to a balance sheet suitable for this research. Lastly, the different required properties of a loan are examined and a method to render a portfolio is explained.

3.4.1 Variables and parameters

In this subsection, all variables and parameters discussed before are provided with values. First, the TTC migration matrix is made suitable for this research. Also, values required to adjust the TTC migration matrix to a PIT migration matrix are presented.

The one-year TTC migration matrix, the average global migration matrix since 1981 is published yearly by S&P and displayed in Table 3. Unless mentioned differently, all data is obtained from S&P (Vazza & Kraemer, 2017).

Table 3: S&P average migration table, average from 1981 to 2016, weighted by the number of observations per year.

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**	**D**	**NR**
AAA	87,05%	9,03%	0,53%	0,05%	0,08%	0,03%	0,05%	0,00%	3,17%
AA	0,52%	86,82%	8,00%	0,51%	0,05%	0,07%	0,02%	0,02%	3,99%
A	0,03%	1,77%	87,79%	5,33%	0,32%	0,13%	0,02%	0,06%	4,55%
BBB	0,01%	0,10%	3,51%	85,56%	3,79%	0,51%	0,12%	0,18%	6,23%
BB	0,01%	0,03%	0,12%	4,97%	76,98%	6,92%	0,61%	0,72%	9,63%
B	0,00%	0,03%	0,09%	0,19%	5,15%	74,26%	4,46%	3,76%	12,06%
CCC/C	0,00%	0,00%	0,13%	0,19%	0,63%	12,91%	43,97%	26,78%	15,39%

An adjustment is required in order to use the migration matrix since S&P uses the non-rated (NR) rating grade. The NR rating grade is a grade where a company was rated, but not rated in the successive year due to insufficient information or the absence of a request by the party (Vazza & Kraemer, 2017). Since it is assumed that once rated, a loan will remain rated, the NR percentages will be redistributed pro rata to the seven non-default rating grades, which results in in Table 4.

Table 4: TTC migration table based on the global S&P data from 1981 to 2016, weighted on the number of observations per year.

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**	**D**
AAA	89,91%	9,33%	0,55%	0,05%	0,08%	0,03%	0,05%	0,00%
AA	0,54%	90,43%	8,33%	0,53%	0,05%	0,07%	0,02%	0,02%
A	0,03%	1,85%	91,97%	5,58%	0,34%	0,14%	0,02%	0,06%
BBB	0,01%	0,11%	3,74%	91,23%	4,04%	0,54%	0,13%	0,19%
BB	0,01%	0,03%	0,13%	5,50%	85,19%	7,66%	0,68%	0,80%
B	0,00%	0,03%	0,10%	0,22%	5,86%	84,44%	5,07%	4,28%
CCC/C	0,00%	0,00%	0,15%	0,22%	0,74%	15,26%	51,96%	31,65%

From Table 4, the TTC migration matrix can be presented by adding the absorbing state due to the assumption that loans can default only once:

$$P_{t+1} = \begin{pmatrix} 0,8991 & 0,0933 & 0,0055 & 0,0005 & 0,0008 & 0,0003 & 0,0005 & 0,0000 \\ 0,0054 & 0,9043 & 0,0833 & 0,0053 & 0,0005 & 0,0007 & 0,0002 & 0,0002 \\ 0,0003 & 0,0185 & 0,9197 & 0,0558 & 0,0034 & 0,0014 & 0,0002 & 0,0006 \\ 0,0001 & 0,0011 & 0,0374 & 0,9123 & 0,0404 & 0,0054 & 0,0013 & 0,0019 \\ 0,0001 & 0,0003 & 0,0013 & 0,0550 & 0,8519 & 0,0766 & 0,0068 & 0,0080 \\ 0,0000 & 0,0003 & 0,0010 & 0,0022 & 0,0586 & 0,8444 & 0,0507 & 0,0428 \\ 0,0000 & 0,0000 & 0,0015 & 0,0022 & 0,0074 & 0,1526 & 0,5196 & 0,3165 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

The required parameters to convert TTC to PIT and the required parameters to calculate the amount of provisions are displayed in Table 5. Table 5 shows the parameters independent of time and economic scenario, namely the TTC PD per rating grade and the corresponding correlation. The correlation is derived from the default rate per year per rating grade from 1981 to 2016 with the Z value of Vasicek's one-factor model. Also presented in Table 5 is the LGD used in IFRS9 calculations. The LGD of IFRS9 is determined using Moody's historical data. Moody's published the historical LGD of loans till 5 years before default per rating grade on corporate exposure (Emery et al., 2009). The average of the five years per rating grade provided by Moody's is the LGD used in IFRS9 calculations. For the default LGD the average of ING group N.V.'s default LGD is taken on corporate portfolio level and on corporate credit risk exposure, resulting in a LGD of 39%. Furthermore, the EIR should be determined as Equation (8) requires. The EIR has a risk free rate of 0,05% for the AAA loans and a fixed risk premium per rating grade of lower quality. In assigning the risk premiums, there is a difference between subordinated loans and unsecured senior loans. Unsecured senior loans have a risk premium is 0,75% per rating grade and subordinated loans have a risk premium of 0,90% per rating grade. The risk premiums per rating grade are arbitrary determined. Table 5 also presents the average and standard deviation of the macro-economic factor, the real GDP growth. Finally, the intercept and coefficient from the regression are presented in Table 5.

Table 5: All data is based on the timespan from 1981 to 2016, except for the intercept and coefficient real GDP growth which is based on the timespan from 2002 to 2016. The TTC PD is obtained from Vazza & Kraemer (2017). St. dev. is the abbreviation of standard deviation. *** indicates p-value $< 0{,}01$.

Variables	Average	AAA	AA	A	BBB	BB	B	CCC/C	D
TTC PD (%)	2,23	0,00	0,02	0,06	0,19	0,80	4,28	31,65	1
Correlation (ρ)	0,026	0	0,017	0,016	0,047	0,098	0,122	0,121	0
LGD	0,437	0,620	0,456	0,423	0,437	0,429	0,377	0,364	0,39
EIR unsecured senior loans		0,0005	0,0080	0,0155	0,0230	0,0305	0,0380	0,0455	0,0530
EIR subordinated loans		0,0005	0,0095	0,0185	0,0275	0,0365	0,0455	0,0545	0,0635
Real GDP growth (%)	3,51								
St. dev. real GDP growth (%)	1,25								
Intercept (β_0)	0,0385***								
Coefficient real GDP (β_1)	-0,6144***								

The intercept and coefficient are determined using an OLS regression. An OLS regression is conducted in order to determine an expression, which predicts default rates conditional on economic scenarios. The expression has the following mathematical expression:

$$DR_t = \beta_0 + \beta_1 \cdot GDP_t + \epsilon \tag{32}$$

Where DR_t is the default rate between time t and time $t-1$, β_0 is called the intercept, β_1 is the coefficient of the GDP_t. GDP_t is the real GDP growth between time t and time $t-1$. Finally, ϵ is a random standard error term as the OLS regression is an estimation. ϵ has an expected value of zero as a result it is solely used to describe the observed default rates.

The observed default rate is regressed over the according year's real GDP growth, where the timespan is from 2002 to 2016 for two reasons. First, the average before 2002 is substantially higher than the average from 2002 to 2016. In this research it is believed that the midterm historical data is more predictive than longterm historical data, as explained in Section 2.2. Second, the standard error is much lower in the 2002 to 2016 timespan, but the remaining data points are sufficient for more than one full business cycle. The data regarding the real GDP growth is obtained from the IMF (IMF, 2017). The real GDP growth is the GDP growth, corrected for inflation. As a result the real GDP growth is solely representing the economic growth.

The real GPD growth as independent regression variable is validated on its explanatory power with respect to the default rate. As mentioned before, the literature commonly uses the GDP as a predictive macro-economic factor with respect to default rates (e.g. Carlehed & Petrov, 2012; Vaněk et al., 2017) . The real GDP used in this research is validated on whether the default rate lags behind the real GDP growth on a lag from zero to three years. When no lag is applied in the regression analysis the regression shows the best explanatory value as the R^2 has the highest value (see Table 6). Graphically, the default rate and real GDP growth show a negative correlation of -0,86 (Figure 6).

Summarizing, the TTC matrix is presented, along with the LGD and parameters required for Vasicek's one-factor model. Also, the regression to predict the future default rate is presented.

Table 6: R^2 with different time lags of the default rate with respect to the real GDP growth.

Lag (years)	0	1	2	3
R^2	0,66	0,16	0,08	0,04

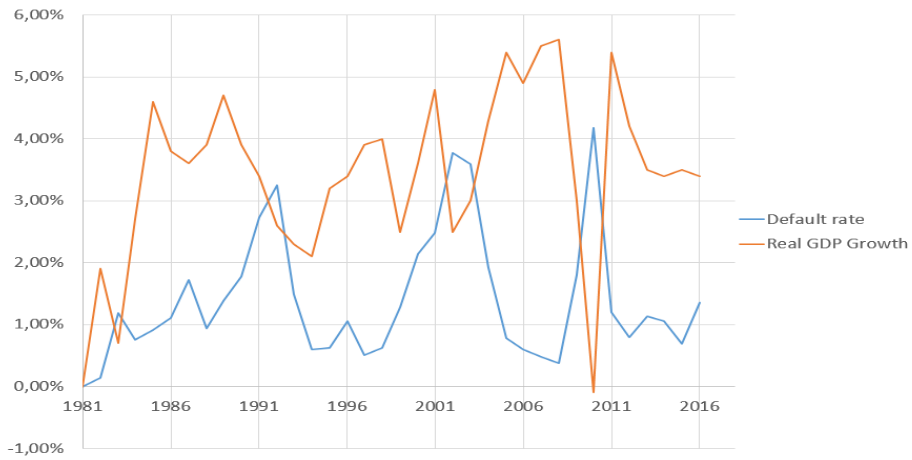

Figure 6: Default rate versus the real GDP growth from 1981 to 2016.

3.4.2 Economic scenarios

In this subsection economic scenarios are presented with respect to the real GDP growth in order to predict the future default rate as input variable of Vasicek's one-factor model. Without further adjustments to the regression related to lags between the default rate and the real GDP growth, several economic scenarios are composed. One economic scenario shows the most likely real GDP growth development for the next six years, according to the IMF. These six forecasted years are presented in Table 7 and a column displaying the index (2016 = 100) is added. Table 7 also presents other economic scenarios which are simulated in the model, comprising one upturn, one base and three downturn scenarios.

Table 7: Overview of the economic scenarios regarding the real GDP growth which are simulated in the model. 2017 to 2022 are the forecasted years with according real GDP growth figures. All numbers are in percentages except for the index (2016 = 100).

	Index	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
IMF	124,1	3,5	3,6	3,7	3,7	3,7	3,8
Upturn	130,6	3,5	3,9	4,4	4,8	5,2	5,6
Base	122,9	3,5	3,5	3,5	3,5	3,5	3,5
Downturn 1	114,3	2,3	2,2	2,3	2,2	2,3	2,2
Downturn 2	107,6	2,6	2,0	1,5	1,0	0,4	-0,1
Downturn 3	107,2	1,5	0,5	-0,1	0,5	1,5	3,1

In the upturn scenario, the real GDP linearly accelerates to the highest growth percentage (5,6%) observed in the years between 1981 and 2016. Assuming the growth rate is normally distributed with mean 3,5% and standard deviation 1,25%, the probability of a real GDP growth of 5,6% in a certain year is 4,7%[4]. Also a base scenario is ran, in which the average growth rate of 3,5% remains constant for the next six years. Furthermore, three downturn scenarios are presented. The downturn 1 scenario is a stable growth rate around one standard deviation below the mean. The probability of a growth rate lower than one standard deviation below the mean is less than 19%, assuming normal distribution. As a result, the downturn 1 scenario represents not particularly a positive real GDP growth, nor a big downturn. The downturn 2 scenario is a linearly decelerating real GDP to the worst observed real GDP growth rate between 1981 and 2016, which is -0,1%. Finally, the downturn 3 scenario is rendered in which in three years the real GDP decelerates to a growth of -0,1% and then recovers linearly to the 3,1% real GDP growth of 2016. This last economic scenario simulates the real GDP growth if a bank expects a crash and a quick recovery afterwards.

Since only a part of the loans in the portfolio is assessed over all six years, the weight of the first year of the simulation is expected to have a high weight on the amount of provisions for two reasons. Stage 1 loans, stage 2 loans and stage 3 loans are dependent on the first year of the simulation, 2017, while only stage 2 loans and stage 3 loans are dependent on the years after 2017. Also, when the maturity date of a loan is before 2022, it does not depend on all years in the economic scenario. As a result, a minor part of the stage 2 and stage 3 loans depends on year 2022. In order to validate this proposition regarding the weight on the first year, four extreme economic scenarios, are constituted as sensitivity scenarios. The yearly real GDP growth rate in the sensitivity scenarios represent either the highest real GDP growth since 1981 or the lowest real GDP growth since 1981. Furthermore, the years between 2018 and 2022 in the sensitivity scenarios are equal per sensitivity scenario. The first year of each sensitivity scenario, 2017, can deviate from the years between 2018 and 2022, emphasizing the impact of the first year. This results in four possible economic scenarios, which are presented in Table 8.

Table 8: Overview of the sensitivity scenarios regarding the real GDP growth which are run through the model. 2017 to 2022 are simulated years with according real GDP growth figures. All numbers are in percentages except for the index (2016 = 100).

	Index	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Sensitivity 1	131,2	-0,1	5,6	5,6	5,6	5,6	5,6
Sensitivity 2	99,4	-0,1	-0,1	-0,1	-0,1	-0,1	-0,1
Sensitivity 3	105,1	5,6	-0,1	-0,1	-0,1	-0,1	-0,1
Sensitivity 4	138,7	5,6	5,6	5,6	5,6	5,6	5,6

Sensitivity 1 and sensitivity 2 have the lowest real GDP growth in the first

[4]In fact, the distribution is not normally distributed, especially not at the tail of a distribution.

year observed since 1981. The sensitivity 1 scenario continues with the highest growth rate since 1981 for the next five years and the sensitivity 2 scenario continues with the lowest growth rate since 1981 for the next five years. Sensitivity 3 and sensitivity 4 have the highest real GDP growth in the first year since 1981. The sensitivity 3 scenario's real GDP continues on the lowest real GDP growth since 1981 and sensitivity 4 scenario's growth continues growing with the highest real GDP growth since 1981.

The economic scenarios presented in Table 7 and Table 8 are referred to as PIT scenarios. PIT scenarios are economic scenarios in which the provisions are estimated according to IFRS9, which is a PIT estimation. Furthermore, an optimistic economic scenario is an economic scenario with a higher index in 2022 (2016 = 100) than the base scenario. Optimistic scenarios comprise of the IMF, the upturn, the sensitivity 1 and the sensitivity 4 scenario. In contrast to optimistic economic scenarios, pessimistic economic scenarios are economic scenarios with a lower index in 2022 (2016 = 100) than the base scenario. Pessimistic economic scenarios comprise of the downturn scenarios, the sensitivity 2 and the sensitivity 3 scenario.

Lastly, three TTC scenarios are presented in order to compare with the PIT scenarios of Table 7 and Table 8. These TTC scenarios are not realistic and are in practice never used by banks. However, the TTC scenarios are provided in order to show the TTC to PIT adjustments and the adjustments with regards to conservatism. An economic scenario where no provisions are required is presented, the no-ECL scenario. Also, an economic scenario where the amount of provisions is equal to the one-year TTC ECL, the one-year TTC scenario. The last economic scenario is a TTC scenario, including the lifetime estimation for stage 2 and stage 3 loans, the multi-year TTC scenario.

With the presented economic scenarios, the default rate can be predicted, meaning that all variables and parameters required to calculate the amount of provisions based on the requirements of IFRS9 are determined. The EAD has not been mentioned, as it is independent of the rating grade and dependent on the loan. Loan parameters are discussed in Subsection 3.4.4.

3.4.3 Financial statements

In this subsection, the financial statements are composed in order to be able to determine the capital ratios. The capital ratios are derived from the balance sheet. The balance sheet and income statement over 2016 of the three biggest Dutch banks (ING, Rabobank and ABN Amro) are analyzed, averaged and rounded to be the financial statements at reporting date. The resulting financial statements at the end of the simulation provide a realistic balance sheet of mid-sized banks with an international orientation, for which it is assumed that lending is core business. The resulting financial statements are presented in Table 9, where the income statement is the result of year 2016 and the balance sheet is the bank's balance sheet at reporting date, the 31st of December 2016, before the income statement items are transferred to the balance sheet.

Considering Table 9 and Appendix A the retained earnings and shareholders

Table 9: Balance sheet and income statement in EUR millions. The balance sheet represents the 31st of December 2016 and the income statement represent the results of the year 2016. The balance sheet and income statement do not consist of more items than displayed in the balance sheet and income statement.

Balance sheet	
Non-financial assets	150.000
Corporate loans	440.000
Cash	50.000
Total assets	640.000
Liabilities	600.000
Total liabilities	600.000
Shareholders capital	16.000
Retained earnings	22.000
Other reserves	2.000
Total equity	40.000
Equity + liabilities	640.000

Income statement	
Sales	35.000
Consolidated expenses	(25.000)
Δ Provisions	
Net result	10.000

capital sum up to the CET1. There are no AT1 items on the balance sheet, since the largest part of the AT1 are e.g. regulatory deductions or cocos, which require a detailed assessment of the regulations and the portfolio with more types of financial assets than solely loans. For T2 detailed information of equity and liabilities is required, since important instruments of T2 are "subordinated liabilities treated as quality capital". In order for subordinated liabilities to be treated as quality capital, detailed information of the portfolio and liabilities is required. It is therefore assumed that T2 is not subject to any adjustment, except for the excess or shortfall between the amount of provisions and the one-year TTC ECL, as is defined by the IRB approach.

Next to the determination of the regulatory capital amount from the balance sheet, an incomes statement is required. Regarding the income statement, the dynamics are explained. The income statement from Table 9 is the same in every economic scenario. Per economic scenario, the amount of provisions are assessed based on the corporate loans portfolio. The provisions and net result are transferred to the balance sheet at reporting date, resulting in the balance sheet at reporting date.

The financial statements are presented, which incorporate the provisions of IFRS9 at reporting date. From the financial statements the capital ratios can be derived.

3.4.4 Portfolio

This subsection expels on the corporate loan portfolio of the hypothetical bank, for which the hypothetical bank is required to hold provisions. The portfolio as rendered is in the books of the bank at reporting date. The method to render the portfolio is explained. Subsequently, the properties per loan required to extract the remaining undefined variables and parameters are examined and presented.

The portfolio is determined stochastically, in which the properties discussed in this subsection can be seen as a profile and not as predetermined ratio in the portfolio. A stochastic portfolio is used for two reasons. First, it is easier to render with modeling software. Second, banks usually have an optimal portfolio risk policy. However, it is barely possible to follow this portfolio risk policy exactly, meaning that in reality banks also need to handle deviations from their optimal portfolio risk policy.

The stochastic portfolio is rendered as follows. The portfolio is rendered loan by loan until the sum of the principal is equal to 440.000, which is the amount of corporate loans on the balance sheet (Table 9). Also, per loan a number of properties are required in order to determine all variables and parameters in the model. The parameters and required properties per loan are explained.

In order to determine the EAD, the principal is required. With respect to PD, the stage of the loan, the rating grade at reporting date and the remaining time to maturity at reporting date are required. Furthermore, the LGD for the F-IRB requires a property of the loan in order to apply a 45% LGD for unsecured senior loans or 75% LGD for subordinated loans. These properties are summarized in Table 10 and explained below.

Table 10: Overview of required properties to be defined in generating a hypothetical portfolio.

Property	**Range**	**Purpose**	**Units**
Principal	[1, 2.000]	EAD	EUR million
Maturity	[1,6]	PD	Years
Rating grade	g = {AAA, AA, A, BBB, BB, B, CCC/C, D}	PD	
Stage	s = {1, 2, 3}	PD	
Seniority	S ={unsecured senior, subordinated}	LGD	

The principal of the loan is rendered in a range from 1 to 2.000 EUR million. Furthermore, it is assumed that all loans are multiples of millions and that the distribution of the principal in the portfolio is uniform. Second, the remaining time to maturity of the loan at reporting date is required. Since the economic scenarios cover the next six years, the remaining time to maturity cannot exceed six years at reporting date in order to avoid further assumptions. Also the loans can only mature on full years and half years, leaving a set of 12 maturity dates. The maturity dates have a uniform distribution. The distribution of the rating grades follows ING Group N.V.'s lending portfolio of 2016. As a consequence the hypothetical portfolio has a realistic distribution. Table 11 provides the probability distribution of a loan being in a certain rating grade.
The determination of a loan's stage is determined once at reporting date and remains unchanged throughout the entire simulation. IFRS9 has three stages with different characteristics, with all defaulted loans in stage 3 and all non-

Table 11: Probability distribution of loans being in a rating grade. The table shows the probability distribution and the cumulative probability distribution.

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**	**D**
Probability	0,071	0,119	0,189	0,27	0,265	0,055	0,016	0,015
Cumulative	0,071	0,190	0,379	0,649	0,914	0,969	0,985	1

default rating grades in either stage 1 or stage 2. Stage 3 is therefore a property of all loans in rating grade D. For non-defaulted loans, a substantial deterioration since origination is required in order to downgrade from stage 1 to stage 2. Origination date is unknown in this research. Therefore, a substantial deterioration is assumed to be one rating grade notch. So, in order to downgrade from stage 1 to stage 2, the downgrade migration probability should be determined.

This downgrade probability depends on the time of origination to the reporting date, where a longer time between origination and the reporting date generally means a higher probability to downgrade to stage 2. To determine the expected share of stage 2 loans at reporting date, more information and assumptions are required. More specifically, the time a loan is already in the portfolio should be known. Once this is known, the annual historical migration matrices are required in order to determine the cumulative probability per rating grade for a loan to be downgraded to stage 2. Both data requirements in order to determine the exact share at reporting date are not available.

In order to overcome this lack of data, the following method is used. For the non-defaulted rating grades the probability of being in stage 2 is assumed to be equal to the sum of the migration probabilities indicating a downgrade to a certain rating grade as a percentage of the probability that a loan remains, upgrades or downgrades to that certain rating grade. The result is the downgrade probability to a certain rating grade on a one-year horizon. As it is not assumed that all loans are exactly one year in the portfolio at reporting date, it is assumed that 20% of the downgraded loans in higher quality rating grades downgraded more than once prior to reporting date. For example, rating grade BB is examined:

$$S_2^{BB} = \frac{P(\text{downgraded to BB})}{P(BB)} + 0,2 \cdot S_2^{BBB} \tag{33}$$

Where S_2^g is the probability that a loan in rating grade g is in stage 2 at reporting date. $P(\text{downgraded to BB})$ can be derived from the one-year TTC migration matrix, by the sum of the probabilities above the diagonal in column BB. $P(BB)$ is the sum of the column representing the probabilities remaining in BB, upgrading to BB and downgrading to BB, which can be derived from the TTC migration matrix. The resulting probability distribution of S_2^g is displayed in Table 12, which should be interpreted as the probability that a loan at reporting date is in stage 2.

An arbitrary 20% of downgraded loans, is assumed to downgrade again. The probabilities in Table 12 denote that prior to reporting date the loans in the portfolio could have been downgraded to stage 2. As mentioned before, as a

Table 12: Probability distribution of a loan being in stage 2 at reporting date.

	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**
Probability	0,0000	0,0916	0,1029	0,0803	0,0629	0,0906	0,1211

result of a lack of data, the expected share of stage 2 loans per rating grade in the portfolio at reporting date can not be determined. However, an example is provided on how to perform a calculation on the expected share of stage 2 loans in a certain rating grade. The example uses the TTC migration matrix and it is assumed that a loan is no longer than six years in the portfolio prior to reporting date. For the six years, the TTC migration matrix is multiplied by itself and the following is computed for every rating grade per year:

$$S_2^g = \frac{P(\text{downgraded to g})}{P(G = g)} \tag{34}$$

This results in the marginal stage 2 probability density distribution as presented in Table 13.

Table 13: Distribution of stage 2 probability density distribution per rating grade per year. YE is the abbreviation of year-end. Averages are unweighted.

	YE1	**YE2**	**YE3**	**YE4**	**YE5**	**YE6**	**Average**
AA	0,092	0,072	0,058	0,047	0,038	0,032	0,057
A	0,085	0,070	0,059	0,049	0,041	0,034	0,056
BBB	0,060	0,052	0,046	0,040	0,036	0,032	0,044
BB	0,047	0,042	0,038	0,034	0,032	0,030	0,037
B	0,078	0,060	0,052	0,047	0,044	0,040	0,053
CCC	0,103	0,135	0,149	0,137	0,107	0,076	0,118
Average	0,077	0,072	0,067	0,059	0,050	0,041	0,052

Table 13 shows per rating grade the probability that a loan is downgraded to stage 2 on different time horizons. For instance, YE3 means that the origination of the loan is three year before the reporting date, so the probabilities in the YE3 column represent the probability that a loan in a certain rating grade is in stage 2 at reporting date. When conducting an OLS analysis between the probability density distribution as used in the portfolio rendering process and the cumulative distribution of the probability to downgrade to stage 2, the implied average time of a loan in the rendered portfolio can be estimated. The estimation results in an average time of a loan in the portfolio of 1,17 years prior to reporting date, assuming that the historical six one-year migration matrices are equal to the TTC migration matrix.

Next the seniority per loan is determined. It is assumed that the seniority of the loans, which is either unsecured senior or subordinated, depends on the rating grade. The lower the rating grade, the higher the probability to be a subordinated loan. The cumulative normal distribution function with a mean of 4 (corresponding to the BBB rating) and a standard deviation of 1 (corresponding to one rating grade notch) for non-defaulted loans, is used as the probability density function for the probability of a loan being a subordinated loan. Additionally, rating grade AAA has a 100% probability of being unsecured senior loan and the CCC rating grade has 100% probability of a loan being a subordinated loan. For defaulted loans, the following method is used to compute the probability of the loan to be subordinated. First, the probability of being in a certain rating grade is multiplied by the PD of that rating grade. Next, the results are pro-rata scaled up in such a way that the sum of these results equals one, which can be interpreted as the weight of a certain rating grade in the number of defaulted loans in the portfolio. For instance, if the result for rating BBB is 2%, this practically means that 2% of all defaulted loans had a rating grade BBB one year prior to default. Finally, the probability that a defaulted loan had a certain rating grade prior to default is multiplied by the probability of being a subordinated loan per rating grade. This results in a 92,4% probability that a defaulted loan is a subordinated loan.

Summarizing, the data section presents the values to be used as input for formulas required by IFRS9 and the CRR. Also several economic scenarios are presented, which are simulated. The dynamics of the income statement at the balance sheet at reporting date are explained. Furthermore the portfolio rendering process is explained in order to render a portfolio containing all properties required to determine variables and parameters. All results are rendered using free modeling software R and Microsoft Excel.

4 Results

This chapter presents the capital ratios as calculated from the model in order to analyze the dynamics of the capital ratios given different economic scenarios. The capital ratios resulting from the different economic scenarios are further analyzed by presenting the underlying variables, more specifically the variables required for IFRS9 and the F-IRB approach. The variables required for IFRS9 and the F-IRB approach are presented after examining the composition of the portfolio rendered, as the composition of the portfolio defines the input data of the model.

4.1 Portfolio composition

It is important to understand the composition of the portfolio, as the model uses the portfolio as input data to determine the capital ratios given different economic scenarios. This section presents the composition of the portfolio. The portfolio is stochastically rendered according to certain predetermined probability density distribution, as presented in Subsection 3.4.4. As a result the portfolio's composition can differentiate marginally from the probability density distribution. Especially, the potential deviations from the probability density distribution in the portfolio require an examination in order to understand potential unexpected observations.

Recall, the portfolio is rendered loan by loan until the sum of the principal is equal to the desired 440.000 EUR million of corporate loan exposure as stated on the balance sheet of Table 9. The portfolio consists of 433 loans as a result. Table 14 provides an overviews of the properties of the rendered portfolio which is used to compute the capital ratios for all economic scenarios.

Table 14: Overview of composition and key properties of the portfolio rendered. All data is rounded. The principal is in EUR million.

	Portfolio	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**
Loans	433	34	41	86	137	102	21	5	7
Share in portfolio	100%	8%	9%	20%	32%	24%	5%	1%	2%
Stage 2 loans	35	0	5	8	13	8	1	0	0
Share of stage 2	8%	0%	12%	9%	9%	8%	5%	0%	0%
Total principal	440.000	31.591	47.563	79.590	135.171	110.749	24.631	6.625	4.080
Average principal	1.016	929	1.160	926	987	1.086	1.173	1.325	583
Average maturity	3,5	4,1	3,5	3,4	3,5	3,5	3,8	3,1	1,9
Subordinated	45%	0%	2%	16%	42%	86%	100%	100%	100%

Of the 433 loans, the share of the AA and BB rating grade loans is slightly lower than Table 11 implies and the share of rating grade BBB is higher than Table 11 implies. The share of BBB loans, which is the biggest rating grade class, is 5 percent points higher than expected according to the probability density distribution in rendering the portfolio. Another deviation from the expected average is the amount of stage 2 loans in the CCC rating grade, but the rating grade consists of only 5 loans and therefore the expected amount of stage 2 loans is 0,5. From Table 14 it can be seen that the average principal for CCC loans is above average and the principal of the defaulted loans is below average. The final deviation to be mentioned is the subordinated row, where it is expected that the defaulted rating grade contains one unsecured senior loan in stead of solely consisting of subordinated loans.

Summarizing, the rendered portfolio has some deviations from the probability density distributions underlying the portfolio rendering process. However, in general the rendered portfolio is a representative portfolio with respect to the probability density distribution.

4.2 Model results

Knowing the composition of the portfolio, the results of the model regarding the capital ratios in different economic scenarios is presented. For each economic scenario in Table 7 and Table 8, the model sequentially computes the amount of provisions, the financial statements and the capital ratios. This section starts by presenting the amount of provisions and capital ratios and continues by presenting the underlying data.

The amount of provisions per economic scenario and the corresponding capital ratios derived from the end-of-the-year 2017 balance sheets are presented in Table 15. Table 15 shows the amount of provisions, the different regulatory capital amounts and the capital ratios. The total capital ratio is lower than the T1 ratio, which is lower than the CET1 ratio. Furthermore it can be seen that the total capital ratios of all economic scenarios converge to 12%.

Table 15: Overview of the capital ratios as a result of the economic scenario analysis. All data is rounded. All numbers are in EUR million. TC is the abbreviation of total capital and prov is the abbreviation of provisions.

	Prov	**CET1**	**CET1 ratio**	**T1**	**T1 ratio**	**TC**	**TC ratio**
No-ECL	0	48.000	13,7%	48.000	13,7%	48.000	13,7%
IMF	1.488	46.512	13,3%	44.415	12,6%	41.779	12,0%
Upturn	1.434	46.566	13,3%	44.172	12,6%	41.779	12,0%
Base	1.500	46.500	13,3%	44.139	12,6%	41.779	12,0%
Downturn 1	1.943	46.057	13,2%	43.918	12,6%	41.779	12,0%
Downturn 2	1.946	46.054	13,2%	43.916	12,6%	41.779	12,0%
Downturn 3	2.335	45.645	13,1%	43.712	12,5%	41.779	12,0%
Sensitivity 1	2.590	45.410	13,0%	43.594	12,5%	41.779	12,0%
Sensitivity 2	2.997	45.003	12,9%	43.391	12,4%	41.779	12,0%
Sensitivity 3	1.356	46.644	13,3%	44.211	12,6%	41.779	12,0%
Sensitivity 4	945	47.055	13,5%	44.417	12,7%	41.779	12,0%
One-year TTC	6.221	41.779	12,0%	41.779	12,0%	41.779	12,0%
Multi-year TTC	6.854	41.146	11,8%	41.146	11,8%	41.779	12,0%

From Table 15 it can be seen that the TTC scenario requires the highest amount of provisions. From the PIT scenarios, excluding the sensitivity scenarios, the upturn scenario requires the least amount of provisions. The highest amount of provisions is required for the downturn 3 scenario. The amount of provisions do not have a strict relationship with the indices representing the real GDP growth over six years, as graphically displayed in Figure 7 where the R-squared of the relationship is 0,28. Comparing Figure 7 with Figure 8, which plots the amount of provisions against the first year's real GDP growth rate, a R-squared of 0,91 is observed.

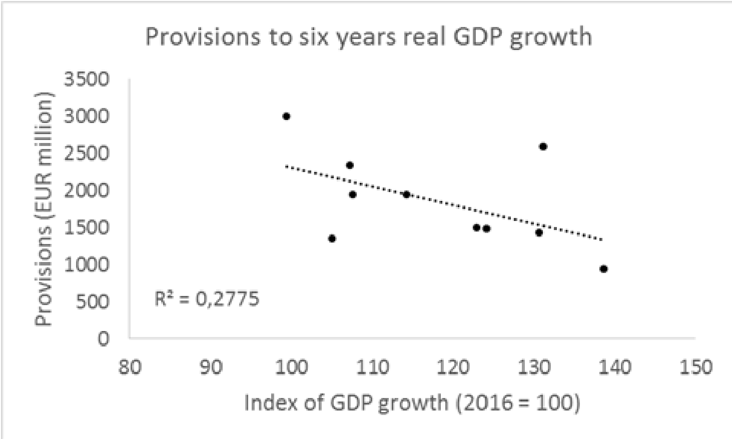

Figure 7: Relationship between economic scenarios of six years of real GDP growth with the amount of provisions required for the portfolio. $R^2 = 0,28$. The IMF, upturn, base, downturn and sensitivity scenarios are taken into account.

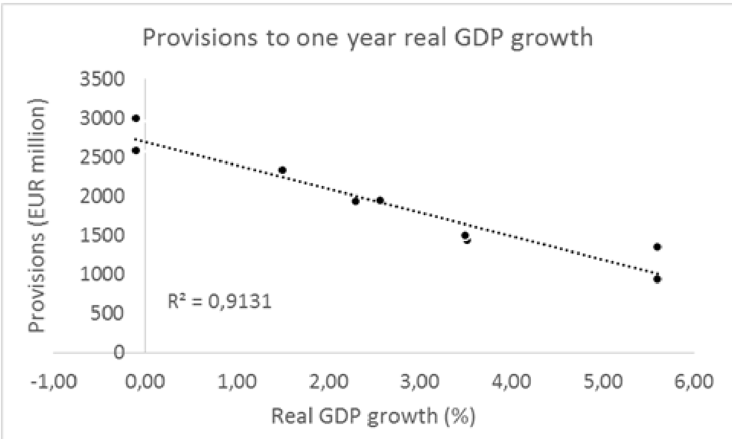

Figure 8: Relationship between economic scenarios of one year of real GDP growth with the amount of provisions required for the portfolio. $R^2 = 0,91$. The IMF, upturn, base, downturn and sensitivity scenarios are taken into account.

Per capital ratio, the difference between the different economic scenarios and the no-ECL scenario can be derived from Table 15. These relative differences with respect to the CET1 ratio are between -1,5% in case of the sensitivity 4 scenario and -5,8% in case of the sensitivity 2 scenario. Regarding the T1 ratio, the relative differences are between -7,3% in case of the sensitivity 4 scenario and -9,5% in case of the sensitivity 2 scenario. With respect to the total capital ratio, the difference is -12,4% in all economic scenarios.

An analysis per economic scenario is conducted to calculate variables per rating

Table 16: Differences between the no-ECL capital ratios and the capital ratios per scenario. TC is the abbreviation of total capital.

	CET1 ratio	**T1 ratio**	**TC ratio**
IMF	-2,9%	-8,0%	-12,4%
Upturn	-2,9%	-8,0%	-12,4%
Base	-2,9%	-8,0%	-12,4%
Downturn 1	-3,6%	-8,0%	-12,4%
Downturn 2	-3,6%	-8,0%	-12,4%
Downturn 3	-4,3%	-8,8%	-12,4%
Sensitivity 1	-5,1%	-8,8%	-12,4%
Sensitivity 2	-5,8%	-9,5%	-12,4%
Sensitivity 3	-2,9%	-8,0%	-12,4%
Sensitivity 4	-1,5%	-7,3%	-12,4%

grade and the results are presented in Table 17. Table 17 contains the percentage of provisions per rating grade, the average amount of provision held per loan per rating grade and the total amount of provisions per rating grade. The first column of Table 17 contains the result for the portfolio as a whole per economic scenario.

The amount of provisions per economic scenario is the same as the amount of provisions in Table 15, but in Table 17 the amount of provisions is also presented per rating grade. To compare the amount of provisions per rating grade, the average amount of provisions per loan is presented in the rows with average prov. A more independent, comparable measure within an economic scenario is presented in the EL row, which is the product of PD and LGD and therefore independent of the EAD of the loan.

Additionally to the results in Table 17, the results regarding the RWA and implied risk weight are displayed in Table 18. These parameters are independent of the economic scenario[5]. The implied risk weight increases as the rating grade quality decreases. The implied risk weight should be read as: the risk weight a bank using the SA should use to obtain a RWA equal to the RWA resulting from the model. Mathematically, the implied risk weight is derived by dividing Equation (4) by the EAD.

Examining the PIT results in Table 17, it can be seen that the relative amount of provisions as well as the absolute amount increases per rating grade towards the default rating grade. The total amount of provisions hold for the CCC and D loans as a share of the total amount of provisions is presented in Table 19.

The amount of provisions regarding the one-year TTC scenario is higher than the amount of provisions regarding any PIT scenario. To explain the difference between the PIT scenarios and the one-year TTC scenario, the data underlying the TTC ECL and PIT ECL is required. Table 20 shows the effect of the

[5]Note that although the parameters are independent of all economic scenarios, the parameters are specific for the rendered portfolio. When using a different portfolio, the parameters should be reassessed.

Table 17: Overview of the results per economic scenario per rating grade. EL is equal to the product of PD and LGD. Prov is the abbreviation of provision.

(EUR millions)	**Portfolio**	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**
IMF									
EL	0,77%	0%	0,01%	0,02%	0,06%	0,21%	0,79%	8,21%	34,57%
Average prov	3,44	0,0	0,09	0,11	0,42	1,44	5,13	56,18	125,89
Total prov	1.488	0,0	4	10	58	147	108	281	881
Upturn									
EL	0,75%	0%	0,01%	0,02%	0,05%	0,17%	0,78%	8,16%	34,57%
Average prov	3,31	0,0	0,07	0,10	0,33	1,09	5,05	55,81	125,89
Total prov	1.434	0,0	3	9	45	111	106	279	881
Base									
EL	0,77%	0%	0,01%	0,02%	0,07%	0,22%	0,79%	8,21%	34,57%
Average prov	3,46	0,0	0,10	0,12	0,44	1,53	5,13	56,18	125,89
Total prov	1.500	0	4	10	61	156	108	281	881
Downturn 1									
EL	0,92%	0%	0,02%	0,03%	0,12%	0,47%	1,65%	10,97%	34,57%
Average prov	4,49	0,0	0,15	0,18	0,83	3,21	10,66	74,99	125,89
Total prov	1.943	0	6	16	114	328	224	375	881
Downturn 2									
EL	0,92%	0%	0,02%	0,03%	0,13%	0,49%	1,44%	10,44%	34,57%
Average prov	4,49	0,0	0,18	0,19	0,94	3,54	9,29	71,36	125,89
Total prov	1.946	0	7	16	128	361	195	357	881
Downturn 3									
EL	1,06%	0%	0,03%	0,04%	0,19%	0,74%	2,33%	12,32%	34,57%
Average prov	5,44	0,0	0,21	0,24	1,31	5,20	14,99	84,17	125,89
Total prov	2.355	0	9	21	179	530	315	421	881
Sensitivity 1									
EL	1,20%	0%	0,02%	0,05%	0,20%	0,95%	3,80%	14,26%	34,57%
Average prov	5,98	0,0	0,12	0,22	1,05	5,31	24,4	97,32	125,89
Total prov	2.590	0	5	19	144	541	513	487	881
Sensitivity 2									
EL	1,30%	0%	0,04%	0,06%	0,28%	1,23%	3,80%	14,26%	34,57%
Average prov	6,92	0,0	0,27	0,32	1,85	8,09	24,40	97,32	125,89
Total prov	2.997	0	11	27	253	825	513	486	881
Sensitivity 3									
EL	0,68%	0%	0,02%	0,02%	0,09%	0,30%	0,03%	1,26%	34,57%
Average prov	3,13	0,0	0,17	0,12	0,83	2,91	0,17	8,65	125,89
Total prov	1.356	0	7	10	114	297	4	43	881
Sensitivity 4									
EL	0,58%	0%	0,00%	0,00%	0,01%	0,01%	0,03%	1,26%	34,57%
Average prov	2,18	0,0	0,02	0,02	0,04	0,09	0,17	8,65	125,89
Total prov	945	0	1	2	5	9	4	43	881
One year TTC									
EL	1,41%	0 %	0,01%	0,03%	0,11%	0,56%	3,21%	23,74%	75,00%
Average prov	14,14	0,0	0,11	0,29	1,09	6,08	37,61	314,50	437,15
Total prov	6.221	0	5	25	149	621	790	1.573	3.060
Multi-year TTC									
EL	1,56%	0%	0,02%	0,04%	0,19%	0,97%	3,42%	23,74%	75,00%
Average prov	15,83	0,0	0,26	0,40	1,85	10,58	40,20	314,50	437,15
Total prov	6.854	0,0	11	34	254	1.079	844	1.573	3.060

Table 18: Overview of the RWA and the according implied risk weights per rating grade. RWA is in EUR millions.

	Portfolio	AAA	AA	A	BBB	BB	B	CCC	D
RWA	349.597	0	5.426	19.413	73.529	146.931	58.505	27.433	18.360
Implied risk weight	0,795	0,0	0,11	0,24	0,54	1,33	2,38	4,14	4,5

Table 19: The required total amount of provisions of the CCC rating grade and D rating grade as a share of the total amount of provisions.

	AAA to B	CCC to D
IMF	0,22	0,78
Upturn	0,19	0,81
Base	0,23	0,77
Downturn 1	0,35	0,65
Downturn 2	0,36	0,64
Downturn 3	0,45	0,55
Sensitivity 1	0,47	0,53
Sensitivity 2	0,54	0,46
Sensitivity 3	0,32	0,68
Sensitivity 4	0,02	0,98

EAD on the amount of provisions, when the one-year TTC scenario is compared to the base scenario. The base scenario is chosen, as the base scenario represents the average real GDP growth rate and the TTC PD is defined as the long term average, implying that the base scenario simulates the same economic scenario as the TTC scenario. The one-year TTC scenario has on average a 4,2 times higher amount of provisions per loan than the base scenario. The average amount of provisions per loan divided by the loan's according EAD results in the product of PD and LGD. The one-year TTC scenario has an average 1,8 times higher product of PD and LGD than the base scenario.

Table 20: Overview of the average amount of provisions per loan per rating grade in a TTC scenario and a PIT scenario. Also the average product of PD and LGD per loan per rating grade in a TTC scenario and a PIT scenario is displayed. The TTC scenario is the one-year TTC scenario and the PIT scenario is the base scenario.

	Portfolio	AAA	AA	A	BBB	BB	B	CCC	D
Average prov TTC	14,14	0	0,11	0,29	1,09	6,08	37,61	314,50	437,15
Average prov PIT	3,46	0	0,07	0,10	0,33	1,09	5,05	55,81	125,89
TTC/PIT ratio	4,2	-	1,1	2,4	2,5	4,0	7,3	5,6	3,5
EL TTC	1,41%	0%	0,01%	0,03%	0,11%	0,56%	3,21%	23,74%	75%
EL PIT	0,77%	0%	0,01%	0,02%	0,07%	0,22%	0,79%	8,21%	34,57%
TTC/PIT ratio	1,8	-	1,0	1,6	1,6	2,5	4,1	2,9	2,2

After an adjustment of the EAD, the product of PD and LGD is higher in the TTC scenario than in the PIT scenario. In order to analyze the differences in the product of PD and LGD, the PD of the one-year TTC scenario is compared to the PD of the base scenario in Figure 9. The same overview is presented for LGD in Figure 10, where the LGD for the one-year TTC scenario is averaged by weighting the share of the loan's seniority per rating grade.

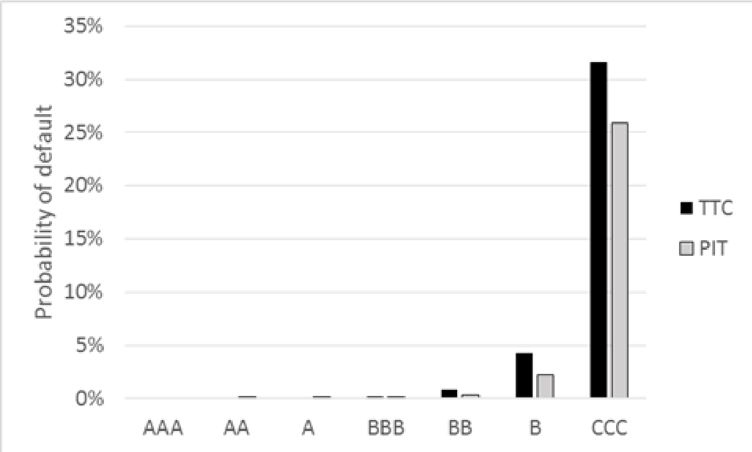

Figure 9: Relationship between the TTC PD and PIT PD of the base scenario. The low quality rating grade's TTC PD is higher than the low quality rating grade's PIT PD.

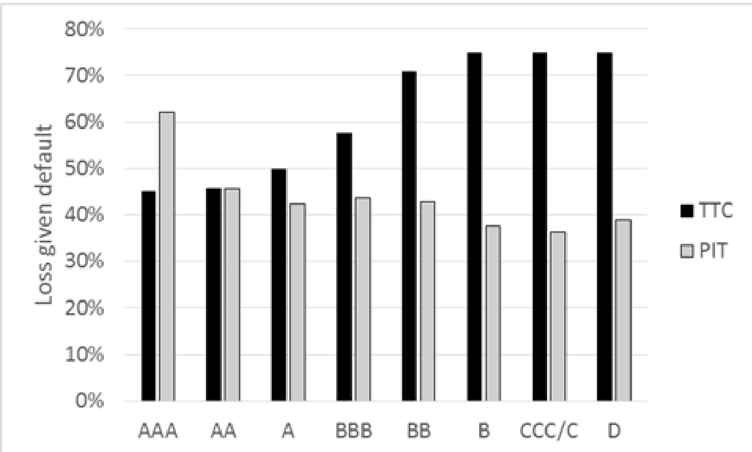

Figure 10: Relationship between the LGD for the TTC scenario and the LGD for the base scenario. The low quality rating grade's TTC LGD is higher than the low quality rating grade's PIT LGD.

As Vasicek's one-factor model adjusts the PD, an evaluation on the PD is conducted. An overview of the cumulative average PIT PD per scenario and the cumulative average TTC PD over the years is presented in Figure 11. As expected, Figure 11 shows that generally the optimistic scenarios have a lower PD. The PD is averaged weighted to the amount of loans per rating grade in the portfolio. The cumulative average TTC PD shows that the TTC PD is likely overstated as it is expected that the TTC PD is close to the base scenario instead of the downturn 1 scenario.

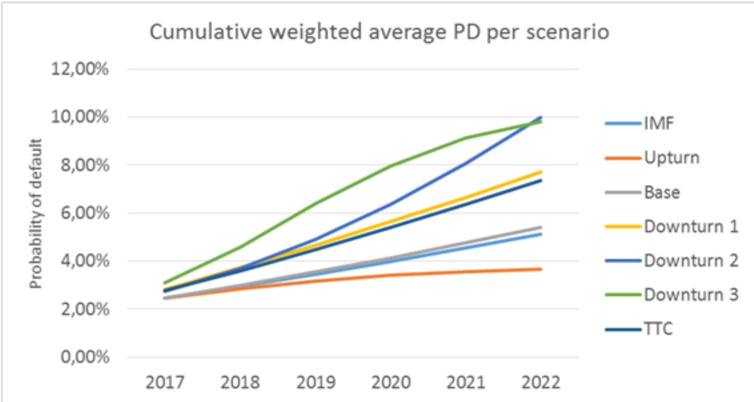

Figure 11: Weighted cumulative average PD per scenario over time.

Per rating grade in the portfolio, the cumulative average PD can be computed as well. The cumulative average PD per rating grade over time is presented in Figure 12. As expected, Figure 12 shows that the low quality rating grades require a higher PD than the high quality rating grades. Consequently, it can be seen that Vasicek's one-factor model did not result in an unexpected result.

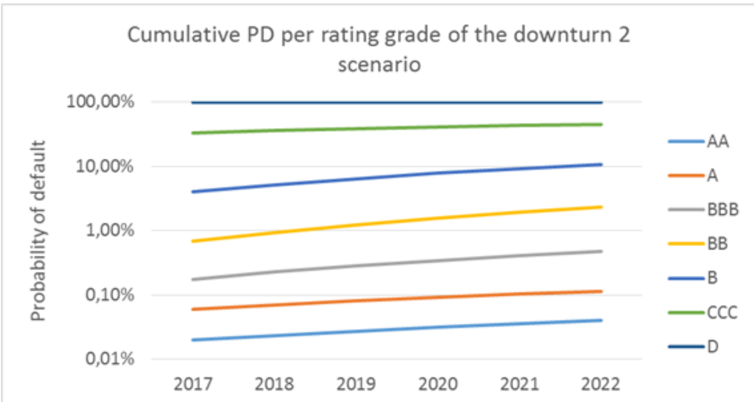

Figure 12: Weighted cumulative average PD per rating grade over time of the downturn 2 scenario. Note that the y-axis is a logarithmic scale.

Summarizing, the provisions, regulatory capital amounts and capital ratios are determined per scenario. Furthermore, the provisions and RWA are specified per rating grade per scenario. Also, the PD, LGD and EAD underlying the other results are examined. With the presented results, the key factors influencing the amount of provisions can be identified.

5 Discussion

In this chapter the results are interpreted and discussed. First, the results are discussed. Thereafter, a reflection on IFRS9 is shortly discussed. Lastly, the model is critically examined and suggestions for improvements of the model are proposed.

5.1 Results

The results presented in Table 15 are discussed. Comparing the IMF, upturn and base scenarios with the downturn scenarios, the downturn scenarios have a lower CET1 ratio. The CET1 ratio is expected to be lower, since this economic scenario is more pessimistic. However, regarding the total capital ratio, all economic scenarios converge to 12%. The converging total capital ratios are due to the shortfall of the amount of provisions with respect to the one-year TTC ECL. Recall that the CRR requires that 50% of this shortfall is deducted from T1 and 50% of this shortfall is deducted from T2. As a result the following happens in calculating the total capital ratio:

$$\text{TC ratio} = \frac{CET1_{T=0} + (EBP - prov) + T1 + T2}{RWA} \tag{35}$$

$$= \frac{CET1_{T=0} + (EBP - prov) + 0,5(prov - ECL) + 0,5(prov - ECL)}{RWA} \tag{36}$$

$$= \frac{CET1_{T=0} + (EBP - prov) + (prov - ECL)}{RWA} \tag{37}$$

$$= \frac{CET1_{T=0} + (EBP - ECL)}{RWA} \tag{38}$$

Where $CET1_{T=0}$, EBP, ECL and RWA are equal in all economic scenarios. So, if the one-year TTC ECL excesses the provisions for a certain year, the required amount of provisions becomes effectively equal to the CET1 at time $T = 0$, plus the EBP minus the one-year TTC ECL. In other words, the effective minimum amount of provisions for the total capital ratio is equal to the one-year TTC ECL. As the total capital is floored at an amount of the one-year TTC ECL, it can be seen as contradicting IFRS9 as IFRS9 wants banks to hold provisions calculated PIT.

Comparing the economic scenarios independently, the IMF, upturn and base scenario result in similar capital ratios. The downturn scenarios result independently in similar capital ratios as well, only the downturn 3 scenario has a slightly lower CET1 ratio and T1 ratio. All these economic scenarios presented in Table 7 do have substantial different indices after six years, but comparable first year real GDP growth rates (Table 7). In order to explain the similar capital ratios, four sensitivity scenarios are applied to the model in order to analyze the effect of the first year on the amount of provisions. In Subsection 3.4.2 it was hypothesized that the first year of the economic scenario has a relatively high weight in determining the amount of provisions of the portfolio. The portfolio composition, presented in Table 14, shows that 90% of the loans in the portfolio are categorized in stage 1, which means that 90% of the portfolio's loans is independent of the years after the first year of the economic scenarios. Also, the average maturity is 3,5 years, meaning that on average not all years affect the ECL of the loans equally. So, the portfolio composition indicates that the first year can be a key factor influencing the amount of provisions.

The weight of the first year on the amount of provisions can be explained by comparing Figure 7 and Figure 8. Figure 7 presents the relationship between the index of the real GDP (where 2016 = 100) and the amount of provisions required to hold for the portfolio. The relationship between the amount of provisions and the index after six years is low, but the relationship regarding the real GDP growth rate of the first year of the economic scenario and the amount of provisions is substantially higher, as presented in Figure 8. This relationship between the real GDP growth rate of the first year and the provisions confirms the hypothesis that the first year has a substantial explanatory power on the amount of provisions and consequently on the CET1 ratio.

The low explanatory power of the index after six years on the amount of provisions can be explained by analyzing the required amount of provisions of the four sensitivity analyses (Table 8). The first year of the sensitivity 1 scenario and the sensitivity 2 scenario is the lowest real GDP growth since 1981. Although, after six years the index of the sensitivity 1 scenario is 32% higher than the index of the sensitivity 2 scenario, the amount of provisions of the sensitivity 1 scenario is only 14% less than the amount of provisions of the sensitivity 2 scenario. Also, the sensitivity 1 scenario has a 80% higher amount of provisions than the upturn scenario, despite the index being only 0,5% higher than the index of the upturn scenario. The same pattern holds for the sensitivity 3 scenario and the sensitivity 4 scenario. So, the resulting amount of provisions are insubstantially related to the index, which means that the index has a low explanatory power. Summarized, within this research, the first year of each economic scenario is a key factor influencing the amount of the provisions, while the index after 6 years is not. Further research is required in order to determine whether the first year is a key factor influencing the amount of provisions if the remaining time to maturity of the loans increases or decreases.

Next to the identification of the first year as a key factor influencing the amount of provisions, another key factor influencing the required amount of provisions are the loans in the CCC and the D rating grade. The CCC and D rating grades have a share of at least 46% of the total amount of provisions for any PIT scenario, as presented in Table 19. During an optimistic economic scenario, this share is higher than during a pessimistic economic scenario. The other six rating grades together result in an insubstantial factor influencing the amount of provision.

The identified key factors influencing the amount of provisions are the first year and the CCC and D loans. However, in a certain case in Table 17 the lifetime adjustment of IFRS9 is a key factor influencing the amount of provisions. For example, examining the EL of BB and B from the sensitivity 3 scenario (presented in Table 17), an unexpected result shows the potential effect of the lifetime adjustments. The higher quality rating grade, BB, has a substantially higher EL than the lower quality rating grade, B. The reason underlying this result can be found when examining the loans in the portfolio with rating grade BB and B. The BB rating grade contains 8 stage 2 loans and the B rating grade contains 1 stage 2 loan. The loan in rating grade B has a maturity in 1,5 years and is therefore mostly exposed to the first year, while the stage 2 loans in the BB rating grade have maturities up to six years, resulting in a factor 19 higher EL for the BB rating grade. These results confirm that the lifetime adjustment potentially is a key factor influencing the amount of provisions.

Besides the lifetime adjustments, the PIT adjustment increases the EL when examining the EL of the BB rating grade of the sensitivity 3 scenario and the EL of the BB rating grade of sensitivity 4 scenario. It can be seen from Table 8 that the sensitivity 4 scenario is a more optimistic economic scenario than the sensitivity 3 scenario, while the loans in the BB rating grade are the same in both sensitivity scenarios. The sensitivity 4 scenario, which is an optimistic economic scenario, results in a factor 19 less EL, confirming that the PIT adjustment potentially is a key factor influencing the amount of provisions as well.

A critical examination on the values of the variables and parameters underlying the provisions is conducted. By comparing the amount of provisions, it is found that the one-year TTC scenario requires a higher amount of provisions than the PIT scenario with the highest amount of provisions. The high amount of provisions for the TTC scenario is unexpected as a TTC scenario is a long term average, resulting from averaging many optimistic and pessimistic economic scenarios. As it can be seen in Table 17 the total amount of provisions of the one-year TTC scenario starts to deviate more from the total amount of provisions of the PIT scenarios as the quality of the rating grades worsens. This deviation can be explained by examining the PD, LGD and EAD as these are generally higher in the one-year TTC scenario than in the PIT scenarios. The one-year PD, LGD and EAD per rating grade of two economic scenarios are compared in Figure 9, Figure 10 and Table 20, respectively.

Looking at the lower quality rating grades, the TTC PD used for the one-year TTC ECL is higher than the PIT PD used in the base scenario. The TTC PD is not provided by the regulator, but should be estimated by the bank. In this research the TTC PD is derived from the default column of S&P's TTC migration matrix. S&P's TTC migration matrix contains a NR rating grade for loans that are not rated in the successive year, which is assumed to be impossible in this research. In order to remove the NR rating grade from S&P's TTC migration matrix, the NR rating grade is pro rata distributed to all other rating grades. As a result of the distribution of the NR rating grade, all migration probabilities are increased. The migration probabilities in the default column, the TTC PD per rating grade, are possibly overestimated as a consequence. It can be argued that the NR rating grade should not be distributed pro rata, as conducted in this research. Further research is required in order to propose a better distribution of the NR over the other rating grades, or a reassessment using historical data from a bank is required in order to improve the TTC PD.

The PIT LGD used is a best estimate based on Moody's and ING group N.V.'s historical data. The TTC LGD used for the one-year TTC ECL is provided by the CRR, which is a conservative measure. Since the TTC LGD for subordinated loans is substantially higher than the TTC LGD for unsecured senior loans and PIT LGD. As a result, the average TTC LGD per rating grade increases as the share of subordinated loans per rating grade increases. In this research, the share of subordinated loans per rating grade increases as the rating grade quality decreases. So, the average TTC LGD is higher as the rating grade quality decreases, while the PIT LGD remains rather stable as the rating grade quality decreases. So, the lower the quality of the rating grade, the more the PIT LGD and TTC LGD start to deviate from each other (Table 14 and Figure 10). As the best estimate LGDs are based on historical data and the average LGD of the one-year TTC scenario is based on an arbitrary determined share of subordinated loans per rating grade, the share of subordinated loans in the rendered portfolio is most likely overestimated.

Assuming that TTC PD and TTC LGD are overestimated, as reasoned before, it is likely that the RWA is overestimated as well. The RWA depends on the TTC PD and TTC LGD. As a result the implied risk weights per rating grade is substantially higher than the risk weights usually applied if the modeled portfolio was subject to the SA (see Appendix A). The substantial higher implied risk weight of the F-IRB approach compared to the SA is another argument that the TTC PD and TTC LGD are overestimated. Consequently, if the risk weights are higher, the capital ratios are underestimated.

The TTC EAD is higher than the PIT EAD. Recall that TTC EAD is equal to the principal till maturity, while the PIT EAD is equal to the principal till one year before maturity. The last year till maturity of the PIT EAD is 50% of the principal as the considered loans are bullet loans. As can be seen from Table 20, the EAD explains a large share of the deviation of PIT from the TTC. If other types of loans are used in the portfolio, a different pattern is expected.

5.2 Reflection

Based on the results of this research, a reflection on the dynamics of IFRS9 is given. Due to IFRS9, banks are required to have enough provisions for expected impairments. When a bank foresees a pessimistic economic scenario next year or next few years, a bank will naturally try to minimize this pessimistic economic scenario as less provisions should be hold as a consequence. However, a bank is required to hold provisions based on best estimates, which increases the likelihood that banks hold a sufficient amount of provisions for the next year(s). A bank is better prepared for the upcoming next year(s) and as a consequence IFRS9 overcame the points of critique of IAS39: banks hold more provisions, before the losses are incurred.

However, three points of critique may follow on how IFRS9 is designed and IFRS9's potential effectiveness. Firs, holding provisions based on best estimates may imply the bank's outlook on the economic scenario. For instance, when a bank discloses the amount of provisions, they imply a certain economic scenario. The market can reflect a prudent attitude of the bank and markets can go down if the economic scenario is pessimistic. As a result the real economy may be reluctant to invest, which drives the implied economic scenarios further down. Consecutively, a bank on its turn is required to hold more provisions as the economic scenario worsens, even if nothing actually changed yet. As a consequence a bank need to revise its best estimate and as a result a bank might be required to hold more provisions.

Second, one can question the ability to predict the next economic downturn. If the next downturn suddenly arises, for instance due to a default or bankruptcy of a system bank, a bank is unable to prepare for such a downturn with provisions. In this specific example, a bank has the timing of the provisions equal to the IAS39.

Third, a bank may be reluctant to lend money with a long time to maturity, as a lot of research on economic scenarios is required. An economic scenario for 20 years from now is unlikely to be predicted accurately. To overcome this difficulty a bank can converge the TTC approach again, which arises the question to what extend the PIT estimation is still a PIT estimation and what would be the minimum amount of "PIT-ness" required by the regulator.

5.3 Limitations and further research

In order to limit the scope of this research, several assumptions are made to simplify the model or to overcome a lack of data. Some of these assumptions can be seen as limitations of this research. Most limitations are the result of a lack of data available in this research. One limitation is the unavailability of migration matrices over the years, which are need to use Vasicek's one-factor model. Consequently, Vasicek's one-factor model could not be used to convert the whole migration matrix from TTC to PIT. Instead, an adjustment lacking a(n) (empirical) prove is used in this research, however this adjustment is reasoned to be the most suitable adjustment. Further research can study the alternatives of Vaněk et al. (2017) or use the historical migration matrices to increase the validity and accuracy of the migration matrix in order to prove that the applied alternative is suitable to redistribute the effects of Vasicek's one-factor model.

Another limitation of this research is the accuracy of the TTC PD, as the default column was increased to distribute the NR rating grade of S&P's TTC migration matrix. The NR rating grade is pro rata distributed over the rating grades, however this might not be the appropriate distribution. The distribution of PD is analyzed and the deviation is expected to have a limited effect on the results. Further research may use historical data of a portfolio to increase the accuracy of the TTC PD or a more appropriate redistribution of the NR rating grade over the other rating grades can be investigated.

Next to the accuracy of the TTC PD, a limitation of the research is the accuracy of the PIT LGD and TTC LGD. The LGD can take collateral into account, which is left out in this research. As a result, the LGD is less accurate and fixed per rating and over time. By using the a ING group N.V.'s LGD in this research, an implied amount of collateral is taken into account. In order to improve this accuracy, historical data or a certain amount of knowledge on the collateral is required in further research.

A limitation in this research, is the assumption that a loan can default only once, meaning that the cure rate is zero. Cure rates occur when a loan is in default, say the payment is over 90 days past due, and pays according to the contract after all, say the payment is fulfilled 120 days past due. Once the loan is cured, it can re-default. The PD is possibly lower if a re-default would be taken into account and consequently the amount of provisions is overestimated in this research. Further research can improve the accuracy of the model by taking a re-default into account.

Another limitation of this research is that the model is build in order to handle corporate loans, but is not suited for other financial assets. Other financial assets require adjustments to formulas and the horizon of six years might be inappropriate for other financial assets. For instance, a mortgage portfolio has some differentiations in the calculation of the RWA and a horizon of just 6 years is too short in an average mortgage portfolio. As a consequence, an economic scenario should be established in order to simulate the years after the 6 years simulated in this model, for instance by approaching the TTC for the years after the first 6 years. Approaching the TTC parameters might be necessary as a result of a lack of reliable predictions with regards to the long term future. When modeling a portfolio with a longer average time to maturity, the impact of the first year is likely to be substantially less. In contrast, a six year horizon might be to long. When applying the model to shorter term loans like credit card debt (mostly paid within one year) the model will have to be adjusted to a payment intervals shorter than half years. As no other financial assets than corporate loans are used, this research is not limited by the six years horizon. Further research can investigate the dynamics of IFRS9 on the capital ratios with respect to other financial assets with different time horizons.

5.4 Implications

This research contributes to the literature by combining models to a new model. The model is build so that the model can be applied using publicly available data, which ensures the reliability of this research and enables other researchers to replicate this research. Furthermore, the model used in this research is the next step in a process to a quantify IFRS9 and this quantification identifies key factors influencing the amount of provisions. The identification of the key factors influencing the amount of provisions can be used to validate whether IFRS9 overcame the points of critique of IAS39.

Practically, the model used in this research contributes to risk management departments of banks. Smaller banks with a lack of available data can use the method to obtain missing data and consequently use the model used in this research to overcome this lack of data. In general, risk management departments of banks can use this research to avoid or respond to key factors influencing the amount of provisions.

6 Conclusion

The objective of this research is to analyze the dynamics of IFRS9 on the capital ratios of banks, by analyzing different economic scenarios. The research objective is achieved and the three research questions related to the research objective of banks are answered.

First, the capital ratios are affected by IFRS9 as the amount of provisions changes. IFRS9 influences the income statement by requiring banks to hold provisions for ECL. As a consequence the balance sheet is affected at the end of the year and consecutively the capital ratios are derived from the affected balance sheet. Within this research, a CET1 ratio, T1 ratio and total capital ratio of 13,7% is expected if no provisions are required to hold. When the amount of provisions required by IFRS9 are hold, the capital ratios are within this research regarding the CET1 ratio between 1,5% and 5,8% lower, regarding the T1 ratio between 7,3% and 9,5% lower and regarding the total capital ratio 12,4% lower. A positive change in the required amount of provisions of IFRS9 negatively influence the capital ratios.

For the second research question the quantitative influence between different economic scenarios are examined. Economic scenarios which are pessimistic, generally require a higher amount of provisions than economic scenarios which are optimistic. As a consequence of the higher amount of provisions, a lower net result is realized, lowering the amount of retained earnings. The retained earnings lower the amount of CET1 and as a consequence the capital ratios. However, the relationship of a pessimistic economic scenario with high provisions does not apply to all cases as there is no strict relation between the amount of provisions and the real GDP index after six years. This is due to the years representing a pessimistic economic scenario in the first few years, where the amount of provisions is higher when the years expected to be in downturn are in the near future. The exact quantitative method on how the interaction between IFRS9 and the capital ratios are achieved in this research is expelled in Chapter 3 and the results are explained in Chapter 4.

Finally, to answer the third research question on the key factors influencing the amount of provisions, several key factors are identified. The foremost key factor influencing the amount of provisions is the first year. The first year has a substantial higher explanatory power than the other simulated years. Furthermore, the amount of provisions is mostly held for loans in low quality rating grades, like CCC and D. The loans in rating grades CCC and D make up at least 46% of the total amount of provisions in this research. Also a substantial effect of PIT and lifetime adjustments were seen in specific cases. However, the PIT and lifetime adjustments do not always stand out substantially in order to observe the effects of these adjustments.

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Glossary

A-IRB	Advanced (internal rating based)
ASFR	Asymptotic single factor risk
AT1	Additional tier 1 capital
BCBS	Basel Committee for Banking Supervisory
CET1	Common equity tier 1 capital
CRA	Credit rating agency
CRR	Capital requirements regulations
EAD	Exposure at default
EBP	Earnings before provisions
ECL	Expected credit loss
EIR	Effective interest rate
EL	Expected loss
F-IRB	Foundation (internal rating based)
GDP	Gross Domestic Product
IAS39	International Accounting Standard 39
IASB	International Accounting Standards Board
IBNR	Incurred but not reported
ICL	Incurred credit loss
IFRS9	International Financial Reporting Standard 9
IRB	Internal rating based
LGD	Loss given default
NR	Not rated
OLS	Ordinary least square
PD	Probability of default
PIT	Point-in-time
RR	Recovery rate
RWA	Risk weighted assets
SA	Standardized approach
T1	Tier 1 capital
T2	Tier 2 capital
TTC	Through-the-cycle
VAR	Value at risk
WCDR	Worst case default rate
YE	Year-end

Appendix A

The following definitions of the Tier 1 capital and Tier 2 capital are retrieved from the Basel II document (BCBS (2006)) and still applicable in Basel III (BCBS (2010)). Comment equity tier 1 (CET1) plus additional tier 1 (AT1) equals the tier 1 capital (T1).

Paragraph 52:
Common Equity Tier 1 capital consists of the sum of the following elements:

- Common shares issued by the bank that meet the criteria for classification as common shares for regulatory purposes (or the equivalent for non-joint stock companies);
- Stock surplus (share premium) resulting from the issue of instruments included Common Equity Tier 1;
- Retained earnings;
- Accumulated other comprehensive income and other disclosed reserves;
- Common shares issued by consolidated subsidiaries of the bank and held by third parties (i.e. minority interest) that meet the criteria for inclusion in Common Equity Tier 1 capital. See section 4 for the relevant criteria; and
- Regulatory adjustments applied in the calculation of Common Equity Tier 1.

Retained earnings and other comprehensive income include interim profit or loss. National authorities may consider appropriate audit, verification or review procedures. Dividends are removed from Common Equity Tier 1 in accordance with applicable accounting standards. The treatment of minority interest and the regulatory adjustments applied in the calculation of Common Equity Tier 1 are addressed in separate sections.

Paragraph 54:
Additional Tier 1 capital consists of the sum of the following elements:

- Instruments issued by the bank that meet the criteria for inclusion in Additional Tier 1 capital (and are not included in Common Equity Tier 1);
- Stock surplus (share premium) resulting from the issue of instruments included in Additional Tier 1 capital;
- Instruments issued by consolidated subsidiaries of the bank and held by third parties that meet the criteria for inclusion in Additional Tier 1 capital and are not included in Common Equity Tier 1. See section 4 for the relevant criteria; and
- Regulatory adjustments applied in the calculation of Additional Tier 1 Capital

The treatment of instruments issued out of consolidated subsidiaries of the bank and the regulatory adjustments applied in the calculation of Additional Tier 1 Capital are addressed in separate sections.

Paragraph 57:
Tier 2 capital consists of the sum of the following elements:

- Instruments issued by the bank that meet the criteria for inclusion in Tier 2 capital (and are not included in Tier 1 capital);
- Stock surplus (share premium) resulting from the issue of instruments included in Tier 2 capital;
- Instruments issued by consolidated subsidiaries of the bank and held by third parties that meet the criteria for inclusion in Tier 2 capital and are not included in Tier 1 capital. See section 4 for the relevant criteria;
- Certain loan loss provisions as specified in paragraphs 60 and 61; and
- Regulatory adjustments applied in the calculation of Tier 2 Capital.

Appendix B

The tables below show a generalized and summarized overview of the risk weights applicable to different obligors and cash. The exact obligor categories and risk weights can be found in the CRR (European Parliament (2013)), article 114 to 134.

Table 21: The risk weights applicable for different obligors according to the CRR.
*Includes: credit card, overdraft, auto loans, personal finance and small business.

Risk weight	**Obligor/Asset**
0%	Cash, BIS, IMF, ECB, EC and MDBs
35%	Claims secured by residential property
75%	Claims on retail products*
100%	Claims secured by commercial real estate, other assets

Table 22: Risk weights for sovereigns.

Credit assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Below B-	Unrated
Risk weight	0%	20%	50%	100%	150%	100%

Table 23: Risk weights for corporates.

Credit assessment	AAA to AA-	A+ to A-	BBB+ to BB-	Below BB-	Unrated
Risk weight	20%	50%	100%	150%	100%

Table 24: Risk weights for banks and securities companies.

Credit assessment	AAA to AA-	A+ to A-	BBB+ to B-	Below B-	Unrated
Risk weight	20%	50%	100%	150%	100%

Appendix C

Numerical example of the alternatives as proposed by Vaněk et al. (2017).

	1	2	3	4	5	D
1	-4	0.5	0.5	0.5	0.5	2
2	-6	-6	2	2	2	6
3	-6.67	-6.67	-6.67	5	5	10
4	-7	-7	-7	-7	14	14
5	-3.6	-3.6	-3.6	-3.6	-3.6	18

(a) Changes in the migration matrix as a result of alternative I on a 6 rating grade model. Source: Vaněk et al. (2017).

	1	2	3	4	5	D
1	-4	0.875	0.625	0.375	0.125	2
2	-9	-3	3.333	2	0.667	6
3	-11.11	-6.667	-2.222	7.5	2.5	10
4	-12.25	-8.75	-5.25	-1.75	14	14
5	-6.48	-5.04	-3.6	-2.16	-0.72	18

(b) Changes in the migration matrix as a result of alternative II on a 6 rating grade model.Source: Vaněk et al. (2017).

	1	2	3	4	5	D
1	-4	1.44	1.12	0.8	0.48	0.16
2	-9	-3	5.25	3.75	2.25	0.75
3	-11.11	-6.667	-2.222	11.11	6.667	2.222
4	-12.25	-8.75	-5.25	-1.75	21	7
5	-6.48	-5.04	-3.6	-2.16	-0.72	18

(c) Changes in the migration matrix as a result of alternative III on a 6 rating grade model. Source: Vaněk et al. (2017).

	1	2	3	4	5	D
1	-4	0.125	0.375	0.625	0.875	2
2	-9	-3	0.667	2	3.333	6
3	-11.11	-6.667	-2.222	2.5	7.5	10
4	-12.25	-8.75	-5.25	-1.75	14	14
5	-6.48	-5.04	-3.6	-2.16	-0.72	18

(d) Changes in the migration matrix as a result of alternative IV on a 6 rating grade model. Source: Vaněk et al. (2017).

Figure 13: Numerical example of changes in the migration probabilities for a 6 rating grade model. Units are not specified, but can be, for instance percentages or basis points. Source: Vaněk et al. (2017).

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