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RELATION BETWEEN CREDIT LOSSES AND MACROECONOMIC FACTORS IN EUROPEAN BANKS

Master's Thesis

Finance

May 2019

UNIVERSITY OF OULU ABSTRACT OF THE MASTER'S THESIS

Oulu Business School

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Department of finance			
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Title Relation between credit losses and macroeconomic factors in European banks			
Subject Finance	Type of the degree Master of science	Time of publication May 2019	Number of pages 75

Abstract

Credit loss modelling under IFRS standards has changed towards a more forward-looking approach. The new expected credit loss model allows using all relevant information that is available without undue cost, also forward-looking information. Macroeconomic factors provide this kind of easily available information and thus they can be utilized in the credit loss modelling. Hence, I apply a large set of macroeconomic variables in order to find those ones that help to estimate future credit losses. Bank-specific features are also likely to affect credit loss changes, so they are also considered in this thesis.

On a sample of 24 European countries and 202 banks, I examine the explanatory power of changes in macroeconomic variables on consequent credit losses. The empirical analysis is based on several pooled, fixed effects and logistic regression specifications. I also use stepwise regressions based on Akaike information criteria to select a set of relevant variables in the multivariate regression specification.

The univariate regression results suggest that important macroeconomic variables explaining the changes in credit losses of the following year are the house price index, gross fixed capital formation, the nominal long-term interest rate and the term spread. Based on the multivariate regression results, inflation, unemployment and bankruptcies are the most important macroeconomic variables and bank size is the most important bank-specific variable. Small banks typically suffer from greater credit loss increases than medium and large banks, but medium and large banks are more sensitive to economic fluctuations. In addition, commercial banks are more sensitive to the changes in the house price index and unemployment than savings banks whereas savings banks are more sensitive to the changes in the number of bankruptcies.

The results documented have valuable implication for the practical implementation of the credit loss models and estimating future credit losses. The findings can be especially exploited in European banks that follow IFRS standards and apply the expected credit loss model.

Keywords

IFRS 9, ECL modelling, banking

Additional information

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1 INTRODUCTION

Credit loss modelling of banks showed its importance at the latest during the financial crisis of 2008. Credit losses are defined as the losses made by a bank arising from loans that are not repaid. The idea of the credit loss modelling is to recognize credit loss allowances in order to reflect future expected credit losses. Poorly implemented credit loss modelling can lead to overstatements of a bank's financial assets and prevents the timely information of the assets to flow to the financial markets (Barth & Landsman, 2010; Camfferman, 2015). Overstatements make the financial health of a bank look distorted. When an economy is in a recession, it is likely that these overstatements will backfire as credit losses start to increase, but insufficient allowances are made. This affects the profitability of a bank. The financial crisis showed the worst scenario of the consequences of overstatements and too low levels of allowances.

The credit loss modelling is a means to reflect credit risk through credit loss allowances. If credit risk is inaccurately estimated, it can have severe consequences, such as foster financial crises. It has been stated that credit risk was the major cause of the financial crisis of 2008 and of the European debt crisis (Gebhardt, 2016.) During the financial crisis, the incurred credit loss model of the accounting standard IAS 39 was applied. One of its major drawbacks was that it led to a delayed credit loss recognition. Due to the need for improvements in accounting standards, International Accounting Standards Board (IASB) and Financial Accounting Standards Board (FASB) started to work for the common accounting principles (Financial Crisis Advisory Group, 2009). However, the cooperation was challenging and eventually IASB issued IFRS 9, that includes the expected credit loss model, without FASB in 2014 (IASB, 2014).

IFRS standards are largely used in Europe and thus, also the expected credit loss model, effective since 2018, is applied in many European banks. The new expected credit loss model allows using all relevant information that is available without undue cost, also forward-looking information (IASB, 2014.) The aim is to avoid a delayed recognition of credit losses which was a problem with the IAS 39 incurred credit loss model (Barth & Landsman, 2010).

Macroeconomic factors are easily available information that provide also forward-looking information. Thus, they can be exploited in the credit loss modelling. This study covers an extensive set of macroeconomic factors that are possible predictors of future credit losses. The aim is to identify which of them are useful in the expected credit loss modelling for banks in Europe. Thus, the first research question that I aim to tackle is: which macroeconomic factors are important for the credit loss modelling in European banks? The bank-specific features may also have an impact on the changes in credit losses and thus, are also considered. Especially, I want to examine whether bank size has an impact on the changes in credit losses. Thus, the second and third research questions are: are there differences between banks with different size and do other bank-specific features matter in estimating future credit losses? It is also interesting to examine whether there are differences between the credit loss changes in savings and commercial banks. The fourth research question is: does it matter whether a bank is a commercial or a savings bank in estimating the future credit losses?

Macroeconomic factors reflect the state of an economy. Thus, they also reflect the systematic banking credit risk (Castro, 2013). Several studies find a relation between macroeconomic factors, defaults and credit risk. For instance, Kalirai and Scheicher (2002) study the relation between credit risk through credit loss allowances and macroeconomic factors in Austrian banks and find that industrial production, stock market, the short-term interest rate and business confidence affect credit loss allowances. Virolainen (2004) examines the possible macroeconomic factors determining the corporate sector default rates in Finland and finds that GDP, interest rates and corporate indebtedness have a significant relation with corporate defaults. Jakubik and Schmieder (2008) study credit risk and macroeconomic factors in Czech Republic and Germany and find variables that determine credit risk in both countries. Defaults and credit risk are closely related to credit losses. Thus, they should have the same determinants, such as certain macroeconomic factors. Prior literature of the relation between macroeconomic factors, defaults and credit risk is reviewed in detail in section 3.

The macroeconomic factors considered in this study are mainly based on the studies by Boss (2002) and Kalirai and Scheicher (2002) who divide macroeconomic factors into distinct groups. The groups in this study are cyclical indicators, price stability indicators, private sector indicators, stock market indicators, interest rate indicators and other indicators. Cyclical indicators are real GDP and industrial production. Price stability indicators include inflation, narrow money (M1) and the house price index. Stock market variables are the STOXX Europe 600 index, and the Dow Jones Industrial Average (DJIND) index. Interest rate indicators include short- and long-term nominal and real interest rates and the term spread. Other indicators are exports and the exchange rate.

Bank-specific variables included are inefficiency, leverage, solvency, size and profitability. Prior literature indicates that these bank-specific variables have a relation with non-performing loans and hence, they should have a relation with credit losses. For instance, Berger and DeYoung (1997) explain the relation between non-performing loans and inefficiency in U.S. commercial banks whereas Chaibi and Ftiti (2015) study the determinants of non-performing loans including both macroeconomic and bank-specific variables in France and Germany similarly as Louzis, Vouldis and Metaxas (2012) in the Greek banking sector. In addition to inefficiency, leverage, solvency, size and profitability, I also examine whether a type of a bank i.e. whether a bank is a savings or a commercial bank, matters or not. Salas and Saurina (2002) study credit risk in Spanish commercial and savings banks and find that non-performing loans are more sensitive to the business cycles in commercial banks than in savings banks. Hence, it is expected that credit losses are also more sensitive to the macroeconomic factors in commercial banks than in savings banks.

Data consists of the annual time-series data of macroeconomic variables for 24 European countries and bank-specific variables for 202 European banks. The sample period covers 14 years from 2005 to 2018. The macroeconomic variables are retrieved from the OECD database expect the stock market indicators which are from the Worldscope database. The bank-specific variables are also retrieved from the Worldscope. Data is described in detail in section 5.

The empirical analysis is based on several pooled, fixed effects and logistic regression specifications. I also use stepwise regressions to find relevant variables for the multivariate regression specifications because selecting right explanatory variables manually from the large set of explanatory variables is difficult. All macroeconomic variables cannot be not included in the same multivariate model because some of them are highly correlated. However, if an important variable is omitted from the regression, there is a danger that estimated coefficients of included variables and the intercept become biased and inconsistent. This leads to biased forecasts and inappropriate inferences (Brooks, 2014, p. 179.) However, including highly correlated variables in the same regression can lead a situation where multicollinearity is present (Brooks, 2014, pp. 170–171). If there is perfect multicollinearity, all coefficients cannot be estimated. If there is a near multicollinearity, coefficients will have high standard errors, the regression is sensitive to small changes and the confidence intervals are wide. Consequently, the significance tests might yield incorrect inferences (Brooks, 2014, p. 172.) Thus, it is justifiable to exclude some of the macroeconomic variables from the multivariate regression to avoid multicollinearity in the model. Methods are described in detail in section 6.

Results are represented in section 7. Based on the univariate regression results the house price index, gross fixed capital formation (GFCF), the nominal long-term interest rate and the term spread are important determinants of the credit loss changes of the following year. The results suggest that the change in the house price index and the change in GFCF are negatively related to the change in credit losses. Both the change in the nominal long-term interest rate and the change in the term spread have positive relation with the change in credit losses. This is intuitive because interest rates and the term spread represent the borrowing costs (Ang, Gorovyy, & Van Inwegen, 2011; Kalirai & Scheicher, 2002).

The multivariate linear regression results suggest that inflation and unemployment have the strongest effects on credit loss changes for the following year. However, the coefficients of these variables are to some extent contradictory with prior literature. Inflation has a positive relation with credit losses that might arise from the decrease of the real income of households and companies. Unemployment growth has a negative relation with credit loss changes. This can be due to the high correlation of unemployment with GDP and bankruptcies in the same multivariate model, but it can also indicate that banks might grant fewer loans because the number of people that are eligible for a loan is decreased and consequently the credit losses decrease too.

Based on the multivariate logistic regression results, the growing number of bankruptcies increases the most the probability to an extreme credit loss increase to occur. Typically, the corporate loans are bigger than the loans of households and hence, the result is intuitive. If a company defaults, it is likely that credit losses increase considerably. Logistic regression results also suggest that medium solvency banks are more likely to face extreme credit loss decreases than low solvency banks.

The results suggest that bank size is an essential variable to explain credit loss changes. Small banks typically suffer from greater increases in credit losses compared to medium and large banks whereas credit losses of medium and large banks are more sensitive to the changes in macroeconomic factors. The possible explanation is that larger banks operate also in foreign countries and hence, they are more exposed to economic fluctuations. In addition, credit losses of commercial banks are more sensitive to the changes in house prices and unemployment than savings banks. Commercial banks are also less likely to face extreme credit loss decreases. However, credit losses of savings banks are more sensitive to the changes in the number bankruptcies.

As well as in this thesis, some prior studies consider both macroeconomic and bank-specific variables, but those studies concentrate typically on a few European countries. This thesis covers 24 European countries and hence, contributes prior literature. The set of macroeconomic variables is also extensive, and the aim is to identify those variables that are useful in estimating the credit losses for the following year. The results documented have valuable implication for the implementation of credit loss models and estimating the future credit losses. This is because IFRS 9 has been effective only since 2018, so it is likely that there is still a need for the improvements of banks' expected credit loss models. The findings can be especially exploited in European banks that follow IFRS standards.

The study proceeds as follows. Prior literature is presented in sections 2, 3 and 4. Section 2 focuses on the credit loss modelling of banks, section 3 reviews the existing literature related to macroeconomic factors and their possible relation with credit losses and the focus of section 4 is on the bank-specific variables and credit losses.

The data and the methodology are described in sections 5 and 6 respectively. The research results are presented in section 7 and lastly, section 8 concludes.

2 CREDIT LOSS MODELLING IN THE BANKING SECTOR

2.1 Why does credit loss modelling matter?

Accounting standards require credit risk to be reflected in the financial statements through impairments of financial assets and credit loss allowances. These allowances reduce the net income and thus a bank's equity (Gebhardt, 2016). However, too low levels of credit loss allowances will lead to overstatements of financial assets (Camfferman, 2015). Consequently, the financial health of a bank looks better than it is in reality. When an economy faces a downturn and the book value of financial asset differs from its market value, unexpected credit losses occur because they were not taken into account as allowances. This affects the profitability of a bank and endangers its capital adequacy. Hence, the forecasting of future credit losses is an important part of financial accounting in the banking sector.

Barth and Landsman (2010) examine the role of financial reporting of banks in the financial crisis of 2008. They note that loans comprise a meaningful portion of the banks' total assets and hence, the reporting of loan loss allowances is a critical component for the financial health in the banking industry. During the financial crisis, the IAS 39 incurred credit loss model was applied. Barth and Landsman (2010) note that the incurred credit loss model could have potentially deprived the markets of timely information of the value of bank assets, i.e. lead to delayed credit loss recognition. Thus, credit loss formation under IAS 39 has potentially contributed to the financial crisis (Barth & Landsman, 2010).

Credit loss modelling during the financial crisis might have also led to procyclicality. According to the Financial Stability Forum (2009), procyclicality means the dynamic interactions between the financial and the real sectors of the economy and these interactions tend to amplify fluctuations in the economy and exacerbate financial instability because they are reinforcing each other. One of the shortages of the IAS 39 incurred credit loss model was that the allowances for loan losses were recognized only in the case of a loss impairment (Financial Crisis Advisory Group, 2009). Consequently, the allowances increased during economic downturns leading to the decreasing profits of banks. Thus, banks were less willing to lend and tightened lending for instance by increasing interests. This kind of banks' behaviour might have led to a credit crunch, a sudden reduction in the general availability of loans, amplifying the downtrend even more (Adzis, Tripe & Dunmore, 2016; Wall & Koch, 2000).

It has also been stated that credit risk was the actual major cause of the financial crisis and of the European debt crisis (Gebhardt, 2016). As credit loss allowances reflect credit risk, credit loss modelling plays a crucial role to capture the right perception of credit risk. If the level of risk is understated, it can have severe consequences, as an extreme example, the financial crisis. All in all, the financial crisis showed that there was a real need for improvements in the credit loss model.

2.2 Credit loss modelling in Europe

The drawbacks of the IAS 39 incurred credit loss model motivated issuing the new IFRS 9 standard. The incurred credit loss model did not take account expected credit losses that were possible after the balance sheet date and the recognition of these credit losses was restricted to the situations where was objective evidence of a loss event. The additional expected credit losses took place in the next fiscal period (Camfferman, 2015; Gebhardt, 2016.) Hence, the model led to a delayed credit loss recognition.

Due to the shortages of the incurred credit loss model that revealed during the financial crisis, the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) started to develop together converged solutions for the credit loss recognition (Financial Crisis Advisory Group, 2009). Finding a common solution was difficult, and hence the IASB and the FASB continued to develop their own credit loss models separately (IASB, 2011). Eventually, in July 2014, the IASB issued the complete version of IFRS 9 Financial instruments, which has been effective since January 2018 (IASB, 2014).

The credit loss modelling of banks in Europe follows largely IFRS standards because IFRS standards are required for domestic public companies and for listings by foreign companies in the European Union (IFRS Foundation, 2018). IFRS 9 contains the classification and measurements of financial assets, financial liabilities, and some contracts to buy or sell non-financial items (IFRS Foundation, 2017). It also includes the expected credit loss (ECL) model which allows using all relevant information that is available without undue cost, including forward-looking information, to estimate the future credit losses (IFRS Foundation, 2014). Macroeconomic factors and bank-specific characteristics provide this kind of useful and also forward-looking information and hence, they can be utilized to produce more accurate credit loss estimations.

3 MACROECONOMIC FACTORS AND CREDIT LOSSES

Macroeconomic factors and their changes describe the state of the economy. According to Salas and Saurina (2002), problem loans are closely related to economic cycles – there are always macroeconomic factors behind every financial crisis. In addition, macroeconomic factors also reflect the systematic banking credit risk (Castro, 2013).

Several studies focus on the macroeconomic determinants of defaults and credit risk. However, the relationship between default rates, credit risk and banks' credit losses is obvious (Virolainen, 2004). Hence, it is justifiable to examine the same factors as determinants of credit losses as with defaults and credit risk. This study follows largely the categorization by Kalirai and Scheicher (2002) and Boss (2002): macroeconomic variables are divided into six groups which are cyclical indicators, price stability indicators, private sector indicators, stock market, interest rate indicators and other indicators.

3.1 Cyclical indicators

Cyclical indicators include the real GDP growth and industrial production. GDP is discovered to be an important macroeconomic determinant of credit risk fluctuations in the literature (Jiménez & Mencía, 2009). Typically, GDP is negatively related to loan losses and to the probability of default. During economic downturns when GDP growth is negative, borrowers are less likely to be able to pay back their liabilities whereas during upturns, when GDP growth is positive, the loan losses decrease (Kalirai & Sheicher, 2002.)

According to Kalirai and Scheicher (2002), industrial production growth tends to lead to the GDP growth cycle. Hence, when industrial production increases, credit losses should decrease because the economy is growing. Kalirai and Scheicher find a negative relation between industrial production and credit loss allowances. Boss (2002) also finds that industrial production is an important determinant and has a negative relation with default rates. Thus, the relation between industrial production and credit losses is expected to be negative.

3.2 Price stability indicators

Inflation, money supply and house prices are included as price stability indicators. Inflation has an ambiguous relation with credit losses. One could expect that inflation has a positive relation with credit losses because when the prices increase, the costs of production increase complicating the financial situation of firms. But for instance, Jakubik and Schmieder (2008) who study the effects of macroeconomic factors on credit risk in Czech Republic and Germany, find that inflation is negatively related to firms' default rates in the Czech Republic. The reason is that inflation improves the financial situation of debtors in the short run because the real value of the debt obligation is decreased (Jakubik & Schmieder, 2008).

On the other hand, inflation reduces the real income of households and firms (Chaibi & Ftiti, 2015). This will deteriorate their ability to repay debt and therefore increasing the probability of a credit loss to occur. For instance, Rinaldi and Sanchis-Arellano (2006) find that inflation has a positive relation with non-performing loans. However, they also note that the expected relation is ambiguous. Thus, the relation between inflation and credit losses and is interesting to examine.

Monetary aggregates, for instance M1, M2 and M3, measure the amount of money circulating in an economy. They are usually presented as end-of-month national currency stock series (OECD, 2012). Boss (2002) and Kalirai and Scheicher (2002) include the monetary aggregate, narrow money (M1), in their studies. It consists of currency and overnight deposits circulating in an economy (OECD, 2012). Including M1 as a monetary aggregate is due to its potential relation with inflation (Kalirai & Scheicher, 2002). Both Boss (2002) and Kalirai and Scheicher (2002) find that M1 is statistically significant in explaining credit risk. In both studies the relation between M1 and credit risk is negative and hence, the relation between M1 and credit losses should also be negative. Thus, if the amount of the currency and overnight deposits increases, credit losses should decrease.

House prices also represent the price stability. Those banks that grant more mortgage loans may have higher exposure to housing prices. House prices might not affect only the defaults of households but also corporate defaults. Vlieghe (2001) examines aggregate corporate default rate in the UK and finds that property prices are a significant determinant of corporate failures in the short run. This might be due to the important role of property as a collateral also in corporate loans. In the short-run, the coefficient is negative which means that as the property prices increase, the defaults decrease (Vlieghe, 2001.) Hence, the relation between house prices and credit losses could be negative. However, if the house prices increase, it also means that more debt is needed to buy a new house. Thus, the relation between house prices and credit losses might not be negative though, but positive if, for instance, the income level does not increase with the house prices. The consequence could be that banks grant larger loans but the ability to repay is not any better than before.

3.3 Private sector indicators

Private sector indicators include unemployment, household consumption, household income, gross fixed capital formation (GFCF), bankruptcies and indebtedness of private sector. Unemployment reflects the state of households – unemployment affects the ability to repay debts (Kalirai & Scheicher, 2002). Hence, one could expect the relation between unemployment and credit losses to be positive. High unemployment occurs during bad economic states similarly as low output growth and low economic activity (Bali, Brown & Caglayan, 2014). Thus, it is likely that unemployment has a correlation with GDP. Virolainen (2004) finds that it is problematic to include unemployment rate because it has strong collinearity with GDP. Hence, it is important to detect multicollinearity and high correlations between variables before including them into the same regression.

Jakubik and Schmieder (2008) find that unemployment is the most important macroeconomic driver for household defaults in the Czech Republic: it has a positive and significant relation with household defaults. If a household defaults, it naturally causes a credit loss for a bank. Unemployment affects also the household income and if the household is over-indebted, it is highly likely that this household defaults due to a lower income stream in the case of unemployment (Jakubik & Schmieder, 2008.) Intuitively, household consumption is positively related to income and hence, household consumption and household income should both have a negative relation with loan defaults and credit losses (Kalirai & Scheicher, 2002).

In this study, by following Kalirai and Scheicher (2002), investment is measured as gross fixed capital formation (GFCF) which is the acquisition and creation of assets by producers for their own use, minus disposals of produced fixed assets (OECD, 2019). According to Kalirai and Scheicher (2002), companies invest more when the economic outlook is favorable. During economic upturns, credit losses typically decrease and hence, it is expected that corporate investments are negatively related to credit losses. This assumption is supported by the findings by Festić, Kavkler and Repina (2011): the GFCF lowers the non-performing loans to total assets in the certain economies in Central and Eastern Europe. Bankruptcies, instead, typically increase during economic downturns. Hence, bankruptcies are expected to be positively related to credit losses (Kalirai & Scheicher, 2002). Findings by Gerlach, Peng and Shu (2005) support the expected relation as they find that bankruptcies have a positive relation with the ratio of non-performing loans to total loans. Obviously, if a company goes bankrupt, there is a high risk that the company is unable to repay its debt obligations which in turn appears as an increase in non-performing loans and credit losses.

According to Fisher (1933), over-indebtedness will lead to the growing number of bankruptcies and unemployment. Thus, it would be logical that credit losses have a positive relation with indebtedness. Vlieghe (2001) notes that corporate indebtedness also influences the willingness of banks to lend. If the corporate indebtedness is high, banks would reduce lending in order to avoid additional credit losses whereas if the corporate sector is not over-indebted, banks would be more willing to lend because the increase of credit losses is less probable. Jakubik and Schmieder (2008) measure indebtedness as corporate credit-to-GDP ratio and find that this variable plays a significant role for the prediction of corporate default rates. However, this specification takes only into account the indebtedness of firms, but banks lend money to both firms and households. The private sector credit-to-GDP would wholly capture the indebtedness of the private sector.

3.4 Stock market indicators

Stock markets are related to the economic cycle. When stock markets increase, stock returns are higher to investors which lowers the probability of loan defaults (Kalirai & Scheicher, 2002). Stock market is usually in an upward trend when the corporates' financial health is better. Hence, the assumption is that corporate defaults and credit losses are negatively related to the stock market's upturn. A stock market index also reflects the future cash flows of business borrowers and the wealth of household borrowers (Krainer, 2014). Hence, using these holdings may influence the bank performance too.

Beck, Jakubik and Piloiu (2013) examine the macroeconomic determinants of non-performing loans across 75 countries during the past decade. They find that decline of stock prices influences bank asset quality, especially in countries with large stock markets relative to the size of the economy. Krainer (2014) examines the differences between a traditional demand-oriented model of bank lending and a non-traditional capital budgeting model based on stock market valuations in the Euro area. He finds that the stock market has an important role in the bank lending decisions. Castro (2013) examines the relation between macroeconomic developments and bank credit risk in Greece, Ireland, Portugal, Spain and Italy and finds that an increase in stock prices leads to a reduction in non-performing loans. However, it takes some time before the effect on credit risk is significant (Castro, 2013). Hence, the relation between the stock market and credit losses is expected to be negative and to have a lag before appearing statistically significant.

3.5 Interest rate indicators

Interest rates reflect direct costs of borrowing and hence the higher the rates, the greater the probability of default (Kalirai & Scheicher, 2002). Thus, the relation between credit losses and interest rates is typically positive. However, there might be a lag between these two: interest rates rise or fall preceding the failure rate of companies and hence preceding the change in credit losses (Liu, 2004).

The relation can be estimated for instance by regressing credit losses on the real or the nominal interest rates with different maturities, such as 3-month, 6-month and 12-month interest rates. Jiménez and Mencía (2009) use the 3-month real interest rate whereas Virolainen (2004) prefers 12-month nominal interest rates. Kalirai and Scheicher (2002) use both nominal and real interest rates to study their effect on credit loss allowances. Bali et al. (2014) apply relative T-bill rate, defined as the difference between the 3-month T-bill rate and its 12-month backward moving average. Ali and Daly (2010) use the 6-month treasury bill rate measured as market yield on US Treasury notes at 6-month constant maturity, quoted on investment basis. Thus, the preferred measures and maturities vary depending on the study.

The term spread, also known as the steepness of the yield curve, is measured as the long-term interest rate minus the short-term interest rate. Under expectations hypothesis the term spread is a forward-looking measure of the future short-term interest rates and thus reflects the future short-term borrowing costs (Ang et al., 2011). According to Kalirai and Scheicher (2002), the term spread indicates the impact of monetary policy and the economic cycle. A relatively steep yield curve is related to the fast growth of the economy. Therefore, future interest rates are expected to rise to produce inflationary pressures (Kalirai & Scheicher, 2002). The relation between the term spread and the credit losses is negative in this case. However, the future higher interest rates are related to greater costs of borrowing and like mentioned earlier, interest rates are typically positively related to the credit losses. Hence, the higher future interest rates potentially lead to greater credit losses in the future. The steep yield curve today will be flatter in the future due to high short-term interest rates. Flat yield curve indicates a recession. This dynamic nature of the term spread makes its relationship with credit losses ambiguous (Kalirai & Scheicher, 2002).

3.6 Other indicators

Other indicators include exports and exchange rates. Small open economies can be more sensitive to changes in exports (Kalirai & Scheicher, 2002). A decrease in exports is also one example of a shock to the GDP. A decreasing GDP indicates an economic downturn and is expected to be associated with increasing credit losses. Kaminsky and Reinhart (1999) also note that exports are in a lower level during banking crises compared to normal times. This strengthens the assumption of negative relation between exports and credit losses.

Exchange rates and exports are related to each other – a real exchange rate appreciation may weaken the performance of export-oriented firms and thus lead to loan defaults (Fofack, 2005). On the other hand, the appreciation of a real exchange rate can improve the repayment ability of borrowers who borrow in a foreign currency. This can lead to a decrease in the number of loan defaults (Nkusu, 2011.) Thus, the relation between exchange rates and credit losses can be either positive or negative.

Jakubik and Schmieder (2008) examine and compare the macroeconomic determinants of credit risk in the Czech Republic and Germany. They show that the real exchange rate has a significant impact on firms' default rates in the Czech Republic: the appreciation of domestic currency has a positive relation with corporate credit risk. Boss (2002) also finds that the exchange rate index from the previous period has a significant positive impact on credit defaults. These findings suggest that the appreciation of the exchange rate is related to an increase in defaults and thus also to an increase in credit losses.

4 BANK-SPECIFIC VARIABLES AND CREDIT LOSSES

In this thesis, not only the macroeconomic factors but also bank-specific variables are taken into account. Existing literature concentrates on bank-specific variables and their relation to non-performing loans and credit risk. Non-performing loans, credit risk and credit losses are closely related to each other. Thus, the bank-specific variables related to non-performing loans are likely to be related to credit losses.

4.1 Inefficiency

Berger and DeYoung (1997) investigate the effect of bank-specific variables on problem loans in US commercial banks. They formulate mechanisms, called *bad management, bad luck, skimping* and *moral hazard* that are related to efficiency and capital adequacy. Their findings suggest that a decrease in cost efficiency is related to increasing future problem loans. Podpiera and Weill (2008) end up with similar findings with Berger and DeYoung (1997) as they find that a decrease in cost efficiency leads to an increase in non-performing loans in Czech banks between 1994 and 2005.

Inefficient banks, that have problems with monitoring their internal costs, might also have problems with estimating non-performing loans. Thus, bad management of costs has a positive relation with future non-performing loans and hence with credit losses. This is called *the bad management hypothesis*. *The bad luck hypothesis* refers to a situation where an event that is beyond a bank's control can lead to a non-performing loan. Hence, a bank needs more resources to recover the non-performing loan leading to cost inefficiency. Using more resources might help to avoid credit losses in the future but the costs will increase. Thus, *the bad luck hypothesis* says that the relation is negative between credit losses and inefficiency. *The skimping hypothesis* means that a bank which spends insufficient resources to reach proper loan quality will end up with a high level of non-performing loans in the long run and the relation of credit losses and inefficiency is positive in the future. Thus, the relationship between inefficiency and non-performing loans can be positive or negative (Berger & DeYoung, 1997.)

Berger and DeYoung (1997) measure short-term efficiency as a percent of maximum cost efficiency achieved by bank based on the estimated best-practice cost frontier for the year in question. Louzis et al. (2012) examine the determinants of non-performing loans in the Greek banking sector. They use the ratio of operating expenses to operating income to measure inefficiency similarly as Chaibi and Ftiti (2015). The ratio of operating expenses to operating income is simpler, more easily available and hence more comparable than the measure by Berger and DeYoung (1997). Thus, I prefer to use the ratio of operating expenses to operating income as a measure of inefficiency.

4.2 Leverage

A capital structure is likely to affect credit risk. Highly leveraged banks tend to take more risk due to a need for producing higher returns with lower capital (Chaibi & Ftiti, 2015.) According to Chaibi and Ftiti (2015), the positive relation between banks' risk and leverage is expected because financial risk increases with leverage. Hence, if more leverage is used, it is expected that credit losses increase too.

Louzis et al. (2012) measure leverage as the ratio between total liabilities to total assets and find a positive relation between leverage and non-performing loans. Chaibi and Ftiti (2015) use the same measure and find that leverage is a significant determinant of credit risk in Germany, but not in France. Ahmad and Ariff (2007) examine the determinants of credit risk between commercial banks in emerging economies and developed economies. They do neither find a significant relation between leverage and credit risk which is contrary to theory and past evidence for different test periods (Ahmad & Ariff, 2007). Thus, prior literature shows contradictory results of the significance of leverage as a determinant of credit risk.

4.3 Solvency

Moral hazard is the well-known problem of excessive risk taking when another party is bearing the cost of risk. According to Berger and DeYoung (1997) under *the moral hazard hypothesis*, a reduction in capitalization leads to an increase in non-performing loans in the future. The reason is that thinly capitalized banks may respond to moral hazard incentives by increasing the riskiness of their loan portfolios. Thus, *the moral hazard hypothesis* is a theory of the relationship between problem loans and capital ratios, also known as solvency ratios (Berger & DeYoung, 1997).

Berger and DeYoung (1997) measure solvency as the ratio between equity capital to total assets. Louzis et al. (2012) and Chaibi and Ftiti (2015) also apply the same specification of solvency. However, the riskiness is better captured by the measure of capital weighted by risk than the equity-to-total-assets ratio that approximates the relevant capital constraint poorly under the Basel standards (Altunbas, Gambacorta, & Marques-Ibanez, 2010; Gambacorta & Mistrulli, 2004). Hence, it would be more relevant use, for instance, the Tier 1 capital ratio instead of equity capital to total assets (Bank for International Settlements, 1998). However, the Tier 1 is not always available, such as in a situation where a bank has not followed Basel standards. The equity-to-total-assets ratio, instead, should be available through different time periods and regardless of standards followed.

Berger and DeYoung (1997) find that a decrease in low-capitalized US commercial banks' capital precedes an increase in non-performing loans. Ahmad and Ariff (2007) also find that regulatory capital is a significant determinant of credit risk for banks in emerging and developed economies but for Japan, Malaysia, and Mexico there is a positive relation while for Australia and India the relation is negative. However, Louzis et al. (2012) do not find a significant relation between solvency and non-performing loans in the Greek banking system. Hence, the significance seems to be dependent on the study, the sample and the empirical model. It is also worth noting that leverage and solvency are perfectly negatively correlated if the equity-to-total-assets ratio is used as the measure of solvency. If leverage should be positively related to credit losses, then solvency should be negatively related to credit losses.

4.4 Size

Size is a commonly used bank-specific variable in the literature and often measured as logarithm of total assets (e.g. Chaibi & Ftiti, 2015; Singh & Sharma, 2016). Salas and Saurina (2002) argue that bank size and non-performing loans are negatively related because the diversification opportunities increase with size. Louzis et al. (2012) call this as *the diversification hypothesis* under which bank size is negatively related to non-performing loans. If *the diversification hypothesis* is true, size and credit losses should also have a negative relation.

According to Stern and Feldman (2004), larger banks may take excessive risk because market discipline is not imposed by their creditors due to the expectation of government protection if a bank fails. These banks are known as *too big to fail* (TBTF) banks. They use more leverage, grant risky loans and eventually face more non-performing loans (Stern & Feldman, 2004.) Stern and Feldman (2004) argue that the assumption of TBTF has played a crucial role in many banking crises in recent decades. Hence, bank size and non-performing loans should have a positive relation. Louzis et al. (2012) and Chaibi and Ftiti (2015) find this positive relation confirming that larger banks take excessive risks and have more non-performing loans (Chaibi & Ftiti, 2015). These findings suggest that the relation between credit losses and size could also be positive.

4.5 Profitability

It is intuitive that past performance is negatively related to non-performing loans. According to Louzis et al. (2012), past performance can also represent a proxy of the quality of management. They measure profitability as the return on equity similarly as Chaibi and Ftiti (2015). Both studies find that bank profitability is a significant determinant of non-performing loans. Thus, it is expected that bank profitability is negatively related to credit losses.

However, it is possible that profitability is positively related to credit losses in the short run. Rajan (1994) explains the relation between credit policies of banks and demand side conditions, and he argues that managers with short horizons aim to manipulate current earnings to convince the market of the bank's profitability. This can be done by extending the terms of loans, lending new money to insolvent borrowers and weakening the covenants in order to avoid the recognition of default (Rajan, 1994). Hence, the profitability might have a positive relation with credit losses in the short run.

4.6 Type of a bank

The types of banks considered are commercial and savings banks in this study. Commercial and savings banks have different ownership structures and business objectives. According to Salas and Saurina (2002), commercial banks are for-profit organizations owned by shareholders and they provide universal banking services whereas savings banks focus mainly on retail banking and their profits are retained or distributed in cultural and social community programs. Hence, commercial banks should have a higher portion of corporate customers and savings banks a higher portion of households as customers.

Salas and Saurina (2002) study credit risk of commercial and savings banks in Spain. They find that non-performing loans are more sensitive to the business cycles in commercial banks than in savings banks. According to Salas and Saurina, the possible explanations are that commercial banks have more corporate customers whereas savings banks have more retail customers and that commercial banks tend to concentrate more on foreign markets. Based on these findings, it is expected that credit losses are more sensitive to the macroeconomic factors in commercial banks than in savings banks.

5 DATA

The aim of this study is to examine the relation between macroeconomic factors and credit losses. The sample consists of the annual time-series data of macroeconomic variables for 24 European countries and bank-specific variables for 202 European banks. The sample period covers 14 years from 2005 to 2018. The macroeconomic variables are collected from the OECD database expect the stock market indicators which are collected from the Worldscope database similarly as the bank-specific variables.

5.1 Macroeconomic variables

This study mainly follows the categorization by Kalirai and Scheicher (2002) and Boss (2002). Thus, macroeconomic variables are divided into six groups: cyclical indicators, price stability indicators, private sector indicators, stock market indicators, interest rate indicators and other indicators.

Cyclical indicators are related to the general economic activity and are included because credit losses are expected to respond to economic cycles (Kalirai & Scheicher (2002). Cyclical indicators included are the real GDP and the industrial production index. Price stability indicators are inflation, which is measured as the consumer price index, narrow money (M1), which contains currency and overnight deposits circulating in the economy (OECD, 2012), and the nominal house price index.

Private sector indicators reflect the wealth of the private sector. They consist of harmonized unemployment rate, household final consumption expenditure as a percentage of GDP, net national disposable income, gross fixed capital formation reflecting the corporate investments, private sector debt as a percentage of GDP describing the private sector indebtedness and the number of bankruptcies measured by the index.

Stock market indicators are the STOXX Europe 600 index and the Dow Jones Industrial Average (DJIND) index. The STOXX Europe 600 index reflects the state of the stock market in Europe and the DJIND index movements in the U.S. stock market.

There are linkages between spillover effects in the global markets and hence, the movements in the U.S. are also likely to have an influence in Europe (Kalirai & Scheicher, 2002). This is the reason why the DJIND index is also taken into account.

Interest rate indicators include nominal and real long-term interest rates referring to government bonds maturing in ten years, nominal and real short-term interest rates referring to three-month money market rates and the term spread measured as the difference between the nominal long-term interest rate and the nominal short-term interest rate. Other indicators include exports of goods seasonally adjusted and the average of the annual exchange rate measured as the national currency per US dollar.

All macroeconomic variables are measured as first differences expect the stock market indicators which are simple returns. The list of the macroeconomic variables, their specifications and the expected sign of the relation between the variable and credit losses is shown in table 1. The descriptive statistics for the macroeconomic are shown in appendix 1.

Table 1. The list of the macroeconomic variables, their specifications and the expected signs of the relation between the variable and credit losses.

Variable	Notation	Expected sign	Measure
Cyclical indicators			
Real GDP	GDP	-	log differenced
Industrial production	IND_PROD	-	absolute difference
Price stability indicators			
Inflation	INF	-/+	absolute difference
Narrow money (M1)	M1	-	absolute difference
House price index	HPRICE	-/+	absolute difference
Household and corporate indicators			
Unemployment	UNEMP	+	log differenced
Consumption	CON	-	log differenced
Income	INC	-	log differenced
Gross fixed capital formation	GFCF	-	log differenced
Bankruptcies	BANKR	+	log differenced
Indebtedness	INDEBT	+	log differenced
Stock market indicators			
STOXX Europe 600	STOXXE600	-	simple returns
Dow Jones Industrial Average	DJIND	-	simple returns
Interest rate indicators			
Nominal long-term interest rate	NLTIR	+	absolute difference
Nominal short-term interest rate	NSIR	+	absolute difference
Real long-term interest rate	RLIR	+	absolute difference
Real short-term interest rate	RSIR	+	absolute difference
Term spread	TERM	-/+	absolute difference
Other indicators			
Exports of goods	EXP	-	log differenced
Exchange rate	EXC	-/+	log differenced

5.2 Bank-specific variables

Bank-specific variables consist of the credit losses, inefficiency, leverage, solvency, size, profitability and the type of a bank. Credit losses are measured as actual credit losses divided by the total assets in order to scale them with respect to the size of a bank. Inefficiency is measured as operating expenses divided by operating income. Leverage is measured as total liabilities divided by total assets whereas solvency is measured as the ratio of total equity divided to total assets. Leverage and solvency are perfectly negatively correlated due to the formalization of variables. Hence, only solvency is considered in the regressions. Profitability is calculated as net income divided by total equity, and bank size is measured as the logarithm of total assets.

Dummy variables are used to form three groups of inefficiency, solvency, size and profitability. For instance, there are low, medium and high inefficiency groups indicating whether a bank has low, medium or high inefficiency. A bank has low inefficiency if its ratio of operating expenses to operating income belongs to the lowest third among all banks' similar ratios in year t. Respectively, high inefficiency refers to the highest third of these ratios in year , and medium inefficiency is between these two groups. Groups for solvency, size and profitability are formed in a similar manner, but with size, these groups are called small, medium and large instead of low, medium and high.

The types of banks examined in this study are savings and commercial banks. Again, a dummy variable is used, and it takes the value of 1 if a bank is a savings bank and the value of 0 if a bank is a commercial bank. Table 2 shows the bank-specific variables, their abbreviations and specifications. Descriptive statistics for bank-specific variables are shown in appendix 2.

Table 2. Bank-specific variables.

Variable	Notation	Measure
Credit losses	CLs	Log difference of the ratio of actual loan losses to total assets
Inefficiency	LEFF, MEFF, HEFF	Operating expenses/Operating income; dummy variable
Solvency	LSOLV, MSOLV, HSOLV	Total equity/total assets; dummy variable
Size	SMALL, MEDIUM, LARGE	Log of total assets; dummy variable
Bank profitability	LPROF, MPROF, HPROF	Net income/Total equity; dummy variable
Type of a bank	SAV, COMM	Dummy variable

CLs = Log difference of the ratio of actual loan losses to total assets, LEFF = low inefficiency bank, MEFF = medium inefficiency bank, HEFF = high inefficiency bank, LSOLV = low solvency bank, MSOLV = medium solvency bank, HSOLV = high solvency bank, SMALL = small bank, MEDIUM = medium-sized bank, LARGE = large bank, LPROF = low profitability bank, MPROF = medium profitability bank, HPROF = high profitability bank, SAV = savings bank, COMM = commercial bank.

6 METHODOLOGY

Both univariate and multivariate regression specifications are applied in this study. Univariate regressions are used to examine the linear relationship between credit losses and each macroeconomic variable independently. To select the relevant variables for the multivariate regression specifications, I use stepwise regressions with Akaike information criteria (AIC) (Yan & Su, 2009, p. 171). The multivariate linear regressions are similar as the univariate regression specifications, but there are several explanatory variables instead of one. The multivariate logistic regressions are used to examine the relation between the extreme credit loss changes and macroeconomic variables. Bank-specific dummies are also added to the multivariate specifications. In addition, the interaction terms of macroeconomic and bank-specific variables are added into the multivariate linear specification in order to examine whether the relation between credit loss changes and the changes in macroeconomic variables depend on bank size and the type of a bank.

The empirical analysis is not based only on the pooled regressions, but also on the regressions with fixed effects that are added to both univariate and multivariate linear regression specifications to deal with unobservable heterogeneity of banks and to avoid the omitted variable bias.

6.1 Univariate regression specifications

A panel data is used to examine the effects of the macroeconomic variables on the credit losses of banks. First, I examine univariate regressions to see the relation between the change of an individual variable and the change of credit losses of the following year. Univariate regressions are linear regressions specified as:

$$\Delta CLs_{ikt} = \beta_0 + \beta_X \Delta X_{kt-1} + \varepsilon_{ikt}, \tag{1}$$

where ΔCLs_{ikt} is the log difference of credit losses divided by total assets in bank i operating in country k in year t. ΔX_{kt-1} is the log difference or absolute difference of the macroeconomic variable in country k in year $t-1$[1]. ε_{ikt} is the error term. The aim is to identify those macroeconomic variables that are useful for estimating future credit losses. As the variables are changes, it is possible to examine whether a change in a macroeconomic variable affects the next year's credit losses.

The regressions with bank fixed effects are used to account unobserved common factors that affect the credit losses but are not captured by the observable macroeconomic or bank-specific variables. The fixed effects model allows the intercept to differ across the banks but not over time. If the unobservable heterogeneity was not controlled, the correlated unobservable factors, for instance economic environment and management quality, with the variables of interest cause an omitted variable bias making the interpretation of causalities inappropriate. The fixed effects model is one way to deal with the unobservable heterogeneity by transforming both the dependent and independent variables (Gormley & Matsa, 2013.)

When the fixed effects are added to the univariate specifications, the univariate model is specified as:

$$\Delta CLs_{ikt} = \beta_X \Delta X_{kt-1} + \lambda_i + \varepsilon_{ikt}, \quad (2)$$

where λ_i is the unknown intercept for each bank.

6.2 Multivariate regression specifications

Before conducting the multivariate regression analysis, variables are standardized to have the mean equal to zero and the variance of 1. This is to make the interpretation and the comparison of macroeconomic variables easier. The standardization is done by subtracting the mean of the variable and dividing the result by the variable's standard deviation:

[1] In the case of the stock market indicators, ΔX_{kt-1} refers to simple returns in year *t-1*.

$$Z_X = \frac{X - \bar{X}}{\sigma(X)}, \tag{3}$$

where Z is the Z-score i.e. standardized value of variable, X is the variable, $\bar{X}$ is the mean of the variable and $\sigma(X)$ is the standard deviation of the variable.

6.2.1 Stepwise regressions and multicollinearity tests

The multivariate model is constructed so, that highly correlated macroeconomic variables do not end up in the same regression. Hence, the correlations of macroeconomic variables, that are shown in table 3, are inspected. According to Tabachnick & Fidell (2013, pp. 89–90), two variables that have a correlation more than 0.70, should not be included in the same multiple regression without careful consideration and hence, variables that have correlation more than |0.70|, are separated in different groups.

One might think that separating the variables in different groups can lead to a situation where an important explanatory variable is omitted from the regression. According to Brooks (2014, p. 179), if an important variable is omitted, the estimated coefficients of included variables are biased and inconsistent expect if the omitted variable is uncorrelated with all included variables. But even if there was uncorrelation between the omitted variable and included variables, the intercept would be biased making also the forecasts biased. In addition, the standard errors will be biased and consequently, inappropriate inferences of hypothesis tests would be made (Brooks, 2014, p. 179.)

Table 3. Correlation matrix for the first differences of credit losses in year t and first differences of macroeconomic variables in year t-1.

	CLs	GDP_1	IND_PROD_1	INF_1	M1_1	HPRICE_1	UNEMP_1	CON_1	INC_1	GFCF_1	BANKR_1
CLs	1										
GDP_1	-0.1	1									
IND_PROD_1	-0.03	0.83	1								
INF_1	-0.003	0.44	0.57	1							
M1_1	-0.06	0.43	0.41	0.13	1						
HPRICE_1	-0.11	0.67	0.47	0.25	0.45	1					
UNEMP_1	0.06	-0.69	-0.64	-0.37	-0.52	-0.58	1				
CON_1	0.02	-0.59	-0.58	-0.21	-0.2	-0.23	0.34	1			
INC_1	-0.06	0.88	0.74	0.33	0.37	0.6	-0.65	-0.58	1		
GFCF_1	-0.13	0.86	0.7	0.34	0.3	0.68	-0.74	-0.51	0.77	1	
BANKR_1	0.11	-0.54	-0.61	-0.23	-0.24	-0.48	0.7	0.25	-0.52	-0.64	1
INDEBT_1	0.02	0.01	-0.14	-0.03	0.12	0.28	-0.08	0.23	-0.04	0.05	0.1
STOXXE600_1	-0.03	0.54	0.68	0.38	0.16	0.4	-0.27	-0.46	0.53	0.43	-0.42
DJIND_1	-0.001	0.51	0.71	0.53	0.11	0.28	-0.29	-0.4	0.48	0.39	-0.41
NLIR_1	0.22	-0.03	0.06	0.23	0.16	0.06	-0.03	0.03	-0.1	-0.1	-0.04
NSIR_1	-0.01	0.58	0.65	0.56	0.15	0.43	-0.59	-0.3	0.44	0.55	-0.42
RLIR_1	0.06	-0.38	-0.47	-0.59	-0.17	-0.16	0.26	0.22	-0.41	-0.3	0.27
RSIR_1	-0.04	-0.1	-0.22	-0.53	-0.14	0.02	-0.03	0.08	-0.18	0.02	0.04
TERM_1	0.17	-0.49	-0.47	-0.26	-0.07	-0.29	0.45	0.27	-0.44	-0.52	0.45
EXP_1	-0.01	0.6	0.65	0.57	-0.02	0.34	-0.41	-0.34	0.47	0.47	-0.27
EXC_1	0.04	-0.27	-0.21	-0.19	0.15	-0.21	0.24	0.07	-0.2	-0.26	0.04

Table continues.

Table 3 – continued.

	INDEBT_1	STOXXE600_1	DJIND_1	NLIR_1	NSIR_1	RLIR_1	RSIR_1	TERM_1	EXP_1	EXC_1
INDEBT_1	1									
STOXXE600_1	-0.1	1								
DJIND_1	-0.21	0.89	1							
NLIR_1	0.15	0.04	0.07	1						
NSIR_1	0.1	0.44	0.51	0.27	1					
RLIR_1	0.17	-0.46	-0.51	0.49	-0.25	1				
RSIR_1	0.19	-0.33	-0.37	0.11	0.16	0.77	1			
TERM_1	0.05	-0.32	-0.35	0.64	-0.57	0.61	-0.04	1		
EXP_1	0.05	0.54	0.63	0.24	0.68	-0.23	-0.02	-0.34	1	
EXC_1	-0.15	-0.15	-0.26	-0.21	-0.48	-0.07	-0.25	0.2	-0.76	1

_1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, IND_PROD = absolute difference of industrial production, INF = absolute difference of inflation, M1 = absolute difference of narrow money, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, CON = log difference of household final consumption expenditure as % of GDP, INC = log difference of net national disposable income, GFCF = log difference of gross fixed capital formation, BANKR = log difference of the number of bankruptcies measured by the index, INDEBT = log difference of the private sector debt-to-GDP, STOXXE600 = simple return of the STOXX Europe 600 index, DJIND = simple return of the Dow Jones Industrial Average index, NLIR = absolute difference of the nominal long-term interest rate, NSIR = absolute difference of the nominal short-term interest rate, RLIR = absolute difference of the real long-term interest rate, RSIR = absolute difference of the real short-term interest rate, TERM = absolute difference of term spread defined as the nominal long-term interest rate minus the nominal short-term interest rate, EXP = log difference of exports of goods seasonally adjusted, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

However, including explanatory variables that are highly correlated in the same regression leads to near multicollinearity or even perfect multicollinearity if the explanatory variables are perfectly correlated (Brooks, 2014, pp. 170-171). According to Brooks (2014, p. 171), all coefficients cannot be estimated if perfect multicollinearity exists. If there is near multicollinearity, the R-squared of the regression is high but the coefficients will have high standard errors, the regression is sensitive to small changes and the confidence intervals are wide. Therefore, the significance tests might yield inappropriate inferences (Brooks, 2014, p. 172.) Hence, it is justifiable to attempt to tackle multicollinearity by dividing the highly correlated macroeconomic variables to different groups. In addition, fixed effects models are applied in order to avoid the omitted variable bias (Gormley & Matsa, 2013).

GDP is one of the main variables of interest, and hence industrial production, income and gross fixed capital formation are left outside the multivariate model construction. In addition, the DJIND index is excluded because it is highly correlated with the STOXX Europe 600 index to make the model construction easier.

Based on the correlations, macroeconomic variables are divided into four groups that are shown in table 4. I use stepwise regressions based on Akaike information criteria (AIC) with backward selection to find the best combination of the variables of each group (Yan & Su, 2009, pp. 171–172). This method is chosen because it is infeasible to construct all possible regressions manually when there is a large set of possible explanatory variables (Yan & Su, 2009, p. 171). The backward selection includes first all explanatory variables and starts to exclude them sequentially based on Akaike information criterion in a stepwise manner until there is no variable left to remove any more (Hebbali, 2017).

Table 4. Groups of variables that have a correlation < |0.70| with each other.

Group 1	Group 2	Group 3	Group 4
GDP_1	GDP_1	GDP_1	GDP_1
INF_1	INF_1	INF_1	INF_1
M1_1	M1_1	M1_1	M1_1
HPRICE_1	HPRICE_1	HPRICE_1	HPRICE_1
UNEMP_1	UNEMP_1	UNEMP_1	UNEMP_1
CON_1	CON_1	CON_1	CON_1
BANKR_1	BANKR_1	BANKR_1	BANKR_1
INDEBT_1	INDEBT_1	INDEBT_1	INDEBT_1
STOXXE600_1	STOXXE600_1	STOXXE600_1	STOXXE600_1
NLIR_1	NLIR_1	NLIR_1	NLIR_1
NSIR_1	NSIR_1	NSIR_1	NSIR_1
RLIR_1	RLIR_1		
		RSIR_1	RSIR_1
TERM_1	TERM_1	TERM_1	TERM_1
EXP_1		EXP_1	
	EXC_1		EXC_1

_1 refers to the lag by one year. GDP = log difference of real GDP, INF = absolute difference of inflation, M1 = absolute difference of narrow money, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, CON = log difference of household final consumption expenditure as % of GDP, BANKR = log difference of the number of bankruptcies measured by the index, INDEBT = log difference of the private sector debt-to-GDP, STOXXE600 = simple return of the STOXX Europe 600 index, NLIR = absolute difference of the nominal long-term interest rate, NSIR = absolute difference of the nominal short-term interest rate, RLIR = absolute difference of the real long-term interest rate, RSIR = absolute difference of the real short-term interest rate, TERM = absolute difference of term spread defined as the nominal long-term interest rate minus the nominal short-term interest rate, EXP = log difference of exports of goods seasonally adjusted, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

To detect possible multicollinearity, a variance inflation factor (VIF) is computed for each variable in the preferred multivariate regression. The VIF describes the amount of variance of a regression coefficient which is inflated because of multicollinearity in the model. The VIF of each variable is calculated by using formula:

$$VIF(\hat{\beta}_j) = \frac{1}{1-R^2_{X_j|X_{-j}}}, \tag{4}$$

where $R^2_{X_j|X_{-j}}$ is the R^2 from a regression of *Xj* onto all of the other predictors. As a rule of thumb a VIF that exceeds 5 might indicate that multicollinearity is a problem in the model (James, Witten, Hastie & Tibshirani, 2013.)

6.2.2 Linear regressions

The multivariate linear regressions include several explanatory variables. It allows comparing the explanatory power of independent variables and to get better parameter estimates. The multivariate linear specification is in the form of:

$$\Delta CLs_{ikt} = \beta_o + \beta_1 \Delta X^1_{kt-1} + \cdots + \beta_n \Delta X^n_{kt-1} + \varepsilon_{ikt}, \tag{5}$$

where ΔX^n_{kt-1} is the log difference or the absolute difference of the macroeconomic variable X^n in country k in year $t-1$.[2] In addition to macroeconomic variables, the multivariate specification with bank-specific dummy variables is used in order to examine the effects of inefficiency, solvency, size, profitability and the type of a bank. As a reminder, solvency and leverage are perfectly negatively correlated and thus, leverage is excluded from the regressions. The multivariate regression with bank-specific dummies is:

$$\begin{aligned} \Delta CLs_{ikt} = \beta_o + \beta_1 \Delta X^1_{kt-1} + \cdots + \beta_n \Delta X^n_{kt-1} + MEFF_i + \\ HEFF_i + MSOLV_i + HSOLV_i + MEDIUM_i + LARGE_i + \\ MPROF_i + HPROF_i + SAV_i + \varepsilon_{ikt}, \end{aligned} \tag{6}$$

where $MEFF_i$ takes the value of 1 if bank i belongs to the medium inefficiency group and $HEFF_i$ takes the value of 1 if bank i belongs to the highest inefficiency group.

[2] In the case of the stock market indicators, ΔX^n_{kt-1} refers to simple returns in year *t-1*.

Similarly, $MSOLV_i$ takes the value of 1 indicating medium solvency and $HSOLV_i$ takes the value of 1 indicating high solvency. If a bank is medium-sized, $MEDIUM_i$ takes the value of 1 and if a bank is large, $LARGE_i$ takes the value of 1. $MPROF_i$ takes the value of 1 if a bank has medium profitability and $HPROF_i$ takes the value of 1 if a bank has high profitability. SAV_i takes the value of 1 if a bank is a savings bank and 0 if a bank is a commercial bank.

In addition to including the bank-specific dummies, the interaction terms are added to the multivariate linear regression in order to examine whether the relation between credit loss changes and the changes in macroeconomic variables depend on bank size and the type of a bank. This is to examine whether the credit losses of larger banks are more sensitive to fluctuations in an economy or whether they can diversify the risk related to macroeconomic variables and also to see whether the credit losses of commercial banks are more sensitive to changes in macroeconomic variables compared to the credit losses of savings banks.

The multivariate linear specifications with fixed effects are also examined to deal with the unobservable heterogeneity of banks and to avoid the omitted variable bias (Gormley & Matsa, 2013). The specification of the multivariate linear model with fixed effects is:

$$\Delta CLs_{ikt-1} = \beta_1 \Delta X_{kt-1}^1 + \cdots + \beta_n \Delta X_{kt-1}^n + \lambda_i + \varepsilon_{ikt} \,. \tag{7}$$

6.2.3 Logistic regressions

I examine whether the macroeconomic and bank-specific variables have a relation with the extreme credit loss increases or decreases of the following year by using multivariate logistic regressions i.e. logit models. There are two different logistic regression specifications. In the first specification, the dependent variable is a binary variable of credit loss changes of bank i which gets the values of 1 and 0 each year – one if an extreme credit loss increase occurs in bank i during the year t and zero otherwise, i.e.:

$$\Delta CLs_{ikt} = \begin{cases} 1, & if\ an\ extreme\ credit\ loss\ increase\ occurs\ in\ a\ bank\ i\ at\ year\ t \\ 0, & otherwise. \end{cases} \tag{8}$$

A bank has faced an extreme credit loss increase in a specific year, if the credit loss increase belongs to the highest quartile of credit loss changes of all banks during that year. The logit model is specified as:

$$Logit\left(P(\Delta CLs_{it} = 1)\right) = \beta_0 + \beta_1 \Delta X_{kt-1}^1 + \beta_2 \Delta X_{kt-1}^2 + \cdots + \beta_n \Delta X_{kt-1}^n + \beta_{1i} D_{it}^{1i} + \beta_{2i} D_{it}^{2i} + \cdots + \beta_{ni} D_{it}^{ni}\ , \tag{9}$$

where D_{it}^{ni} refers to bank-specific dummies. The probability of the occurrence of an extreme credit loss increase is:

$$P(\Delta CLs_{it} = 1) = \frac{e^{\beta_o + \beta_1 \Delta X_{kt-1}^1 + \cdots + \beta_n \Delta X_{kt-1}^n + \beta_{1i} D_{it}^{1i} + \cdots + \beta_{ni} D_{it}^{ni}}}{1 + e^{\beta_o + \beta_1 \Delta X_{kt-1}^1 + \cdots + \beta_n \Delta X_{kt-1}^n + \beta_{1i} D_{it}^{1i} + \cdots + \beta_{ni} D_{it}^{ni}}}\,. \tag{10}$$

The second logistic regression specification is otherwise similar as the first specification, but the dependent binary variable is an extreme credit loss decrease. An extreme credit loss decrease has occurred in bank i when the credit loss change belongs to the lowest quartile of credit loss changes of all banks during the year in question. The dependent variable takes the value of 1 if an extreme credit loss decrease has occurred and zero otherwise.

7 RESULTS

7.1 Univariate regression specifications

Both pooled univariate regressions and regressions with bank fixed effects are estimated. Table 5 shows the pooled univariate regression results[3] for cyclical and price stability indicators. GDP is significant at the 1 % significance level. The sign of the coefficient is negative as expected: when an economy is growing, credit losses decrease. Kalirai and Scheicher (2002) do not find a significant relation between GDP and credit risk, but several other studies with different methodologies, for instance Chaibi and Ftiti (2015), Ali and Daly (2010) and Virolainen (2004), point out that GDP has a significant relationship with non-performing loans or defaults. Industrial production, instead, is insignificant though the sign is negative as expected.

The only significant price stability indicator of the pooled univariate regressions is the house price index with a negative coefficient. This strengthens the hypothesis that the role of property plays an important role as collateral (Vlieghe, 2001). As the value of property is higher, additional sources of collateral are less needed. On the other hand, the house price index can reflect inflation, the increasing price level. Hence, the negative relation between credit loss changes and the changes in the house price index might stem from the negative relation between credit losses and inflation: credit losses might decrease because the real value of debt will decrease as inflation occurs (Jakubik & Schmieder, 2008).

[3] All tables showing the results are created in R by stargazer v.5.2.2 by Hlavac (2018).

Table 5. Pooled univariate regression results for cyclical and price stability indicators.

	Dependent variable:				
	CLs				
	(1)	(2)	(3)	(4)	(5)
GDP_1	-0.059***				
	(0.019)				
IND_PROD_1		-0.0001			
		(0.0001)			
INF_1			-0.00004		
			(0.0004)		
M1_1				-0.0001	
				(0.0001)	
HPRICE_1					-0.0002***
					(0.0001)
Constant	0.001**	0.0003	0.0003	0.0002	0.001**
	(0.001)	(0.0005)	(0.0005)	(0.001)	(0.0005)
Observations	906	891	891	310	861
R^2	0.011	0.001	0.00001	0.004	0.013
Adjusted R^2	0.010	-0.0004	-0.001	0.001	0.011
Residual Std. Error	0.013 (df = 904)	0.013 (df = 889)	0.013 (df = 889)	0.005 (df = 308)	0.014 (df = 859)

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, IND_PROD = absolute difference of industrial production, INF = absolute difference of inflation, M1 = absolute difference of narrow money, HPRICE = absolute difference of the house price index.

The results of pooled univariate regressions for the private sector and stock market indicators are shown in table 6. Significant private sector indicators are unemployment, income, GFCF and bankruptcies. Unemployment and bankruptcies have positive coefficients whereas income and GFCF have negative coefficients. Supportive findings include Chaibi and Ftiti (2015) who find that unemployment has a significant positive relation with non-performing loans and Jakubik and Schmieder (2008) who find that unemployment is the most important macroeconomic driver for household defaults in the Czech Republic. Jakubik and Schmieder also find a significant negative relation between Czech household income and defaults. GFCF also lowers non-performing loans according to Festić et al. (2011), and the findings by Gerlach et al. (2005) support the positive relation between the increase in credit losses and the growing number of bankruptcies.

Table 6. Pooled univariate regression results for private sector and stock market indicators.

	Dependent variable:							
	CLs							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UNEMP_1	0.006^{*}							
	(0.003)							
CON_1		0.024						
		(0.034)						
INC_1			-0.026^{*}					
			(0.016)					
GFCF_1				-0.027^{***}				
				(0.007)				
BANKR_1					0.002^{***}			
					(0.001)			
INDEBT_1						0.007		
						(0.012)		
STOXXE600_1							-0.00001	
							(0.00001)	
DJIND_1								0.00000
								(0.00000)
Constant	0.0004	0.0004	0.001	0.001	0.0001	0.0002	0.0005	0.0004
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0001)	(0.0005)	(0.0004)	(0.0005)
Observations	891	902	902	902	661	891	917	917
R^2	0.003	0.001	0.003	0.017	0.011	0.0004	0.001	0.00001
Adjusted R^2	0.002	-0.001	0.002	0.016	0.010	-0.001	-0.0001	-0.001
Residual Std. Error	0.013 (df = 889)	0.013 (df = 900)	0.013 (df = 900)	0.013 (df = 900)	0.004 (df = 659)	0.013 (df = 889)	0.013 (df = 915)	0.013 (df = 915)

Significance level $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, UNEMP = log difference of harmonized unemployment rate, CON = log difference of household final consumption expenditure as % of GDP, INC = log difference of net national disposable income, GFCF = log difference of gross fixed capital formation, BANKR = log difference of the number of bankruptcies measured by the index, INDEBT = log difference of the private sector debt-to-GDP, STOXXE600 = simple return of the STOXX Europe 600 index, DJIND = simple return of the Dow Jones Industrial Average index.

Stock market indicators do not appear significant in the univariate regressions which is a contradictory result compared to the findings by Kalirai and Scheicher (2002) and Boss (2002). Under these specifications, the relation between the changes in stock market indices and the changes in credit losses is insignificant.

All the other interest rate indicators except the short-term interest rates are significant in the pooled univariate regressions whereas both exports and the exchange rate are insignificant. The results for interest rate indicators and other indicators are shown in table 7.

Table 7. Pooled univariate regression results for interest rate and other indicators.

	Dependent variable:						
				CLs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NLIR_1	0.003***						
	(0.001)						
NSIR_1		-0.0001					
		(0.0004)					
RLIR_1			0.0005*				
			(0.0002)				
RSIR_1				-0.0004			
				(0.0003)			
TERM_1					0.002***		
					(0.0004)		
EXP_1						-0.001	
						(0.004)	
EXC_1							0.007
							(0.006)
Constant	0.001***	0.0003	0.0005	0.0003	0.0004	0.0004	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Observations	899	902	887	890	897	902	906
R^2	0.046	0.00004	0.004	0.002	0.030	0.00005	0.002
Adjusted R^2	0.045	-0.001	0.003	0.001	0.029	-0.001	0.001
Residual Std. Error	0.013 (df = 897)	0.013 (df = 900)	0.013 (df = 885)	0.013 (df = 888)	0.013 (df = 895)	0.013 (df = 900)	0.013 (df = 904)

Significance level $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, NLIR = absolute difference of the nominal long-term interest rate, NSIR = absolute difference of the nominal short-term interest rate, RLIR = absolute difference of the real long-term interest rate, RSIR = absolute difference of the real short-term interest rate, TERM = absolute difference of term spread defined as the nominal long-term interest rate minus the nominal short-term interest rate, EXP = log difference of exports of goods seasonally adjusted, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

As expected, the relation between credit loss changes and changes in the long-term interest rates is positive. This is intuitive as the interest rates reflect the borrowing costs. For instance, Boss (2002) also finds a positive relation between default probability and the nominal long-term interest rate of the previous year. The term spread has also a positive coefficient. According to Ang et al. (2011), the term spread reflects the short-term borrowing costs under the expectations hypothesis. The positive coefficient of the term spread supports this hypothesis – as the short-term borrowing costs increase in the future, also the credit losses will increase in the future.

When the bank fixed effects are added to the model, the model captures factors that vary over banks but not over time. Fixed effects help to account for unobserved heterogeneity and to avoid the omitted variable bias (Gormley & Matsa, 2013). Tables 8–10 show the univariate regression results for the fixed effects models. Compared to pooled linear regression results, the results for the cyclical and price stability indicators do not differ much as the same variables, GDP and the house price index, are the only significant variables. The coefficient of the house price index remains the same, but the coefficient of GDP increases about 0.02 units and the significance level drops from 1 % to the 10 % significance level.

With the fixed effects, the only significant private sector indicator is GFCF. Hence, the bank fixed effects explain better the relation to credit losses than unemployment, income and bankruptcies. The coefficient of GFCF is still negative and significant at the 1 % significance level but slightly smaller.

Results for the interest rate indicators differ only in minor respects from the pooled regression results when the fixed effects are added. The real long-term interest rate is not significant anymore compared to the pooled regression results, but otherwise the significance levels do not change, and the coefficients differ only slightly.

Table 8. Results of univariate regressions with fixed effects for cyclical and price stability indicators.

	Dependent variable:				
	CLs				
	(1)	(2)	(3)	(4)	(5)
GDP_1	-0.037*				
	(0.020)				
IND_PROD_1		-0.00002			
		(0.0001)			
INF_1			-0.0002		
			(0.0004)		
M1_1				0.00003	
				(0.0001)	
HPRICE_1					-0.0002***
					(0.0001)
Observations	906	891	891	310	861
R^2	0.130	0.125	0.126	0.418	0.136
Adjusted R^2	0.020	0.016	0.016	0.349	0.023
Residual Std. Error	0.013 (df = 804)	0.013 (df = 791)	0.013 (df = 791)	0.004 (df = 276)	0.013 (df = 760)

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, IND_PROD = absolute difference of industrial production, INF = absolute difference of inflation, M1 = absolute difference of narrow money, HPRICE = absolute difference of the house price index.

Table 9. Results of univariate regressions with fixed effects for private sector and stock market indicators.

	Dependent variable:							
	CLs							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UNEMP_1	0.003							
	(0.004)							
CON_1		0.010						
		(0.036)						
INC_1			-0.004					
			(0.017)					
GFCF_1				-0.020***				
				(0.007)				
BANKR_1					0.001			
					(0.001)			
INDEBT_1						-0.005		
						(0.013)		
STOXXE600_1							-0.00001	
							(0.00001)	
DJIND_1								-0.00000
								(0.00000)
Observations	891	902	902	902	661	891	917	917
R^2	0.126	0.125	0.125	0.133	0.400	0.126	0.128	0.126
Adjusted R^2	0.017	0.016	0.016	0.025	0.324	0.016	0.018	0.017
Residual Std. Error	0.013 (df = 791)	0.013 (df = 801)	0.013 (df = 801)	0.013 (df = 801)	0.003 (df = 586)	0.013 (df = 791)	0.013 (df = 814)	0.013 (df = 814)

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, UNEMP = log difference of harmonized unemployment rate, CON = log difference of household final consumption expenditure as % of GDP, INC = log difference of net national disposable income, GFCF = log difference of gross fixed capital formation, BANKR = log difference of the number of bankruptcies measured by the index, INDEBT = log difference of the private sector debt-to-GDP, STOXXE600 = simple return of the STOXX Europe 600 index, DJIND = simple return of the Dow Jones Industrial Average index

Table 10. Results of univariate regressions with fixed effects for interest rate and other indicators.

	Dependent variable:						
	CLs						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NLIR_1	0.002***						
	(0.001)						
NSIR_1		-0.0003					
		(0.0004)					
RLIR_1			0.0002				
			(0.0002)				
RSIR_1				-0.0004			
				(0.0003)			
TERM_1					0.002***		
					(0.0004)		
EXP_1						-0.003	
						(0.004)	
EXC_1							0.008
							(0.006)
Observations	899	902	887	890	897	902	906
R^2	0.141	0.126	0.126	0.127	0.139	0.126	0.128
Adjusted R^2	0.033	0.017	0.016	0.018	0.031	0.017	0.019
Residual Std. Error	0.013 (df = 798)	0.013 (df = 801)	0.013 (df = 787)	0.013 (df = 790)	0.013 (df = 796)	0.013 (df = 801)	0.013 (df = 804)

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, NLIR = absolute difference of the nominal long-term interest rate, NSIR = absolute difference of the nominal short-term interest rate, RLIR = absolute difference of the real long-term interest rate, RSIR = absolute difference of the real short-term interest rate, TERM = absolute difference of term spread defined as the nominal long-term interest rate minus the nominal short-term interest rate, EXP = log difference of exports of goods seasonally adjusted, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

As a summary, GDP, the house price index, GFCF, the nominal long-term interest rate and the term spread are significant in both the pooled regressions and the regressions with fixed effects. However, GDP is significant only at the 10 % significance level in the fixed effects model whereas the rest of these variables are significant at the 1 % significance level regardless of the regression specification. Hence, based on these results, I conclude that especially the house price index, GFCF, the nominal long-term interest rate and the term spread can provide useful information of the possible changes in credit losses during the following year.

7.2 Multivariate regression specifications

7.2.1 Stepwise regressions and multicollinearity tests

The stepwise regressions and their Akaike information criteria based on the backward selection procedure are shown in table 11. The set of preferred explanatory variables for the multivariate model based on the lowest AIC, 116.303, consists of GDP, inflation, the house price index, unemployment, bankruptcies and the exchange rate.

Table 11. Multivariate regressions recommended by the stepwise backward selections based on Akaike criteria.

	Dependent variable:			
	CLs			
	(1)	(2)	(3)	(4)
GDP_1	-0.041*	-0.037*	-0.041*	-0.037*
	(0.022)	(0.023)	(0.022)	(0.023)
INF_1	0.044***	0.046***	0.044***	0.046***
	(0.013)	(0.013)	(0.013)	(0.013)
HPRICE_1	-0.031**	-0.029*	-0.031**	-0.029*
	(0.015)	(0.015)	(0.015)	(0.015)
UNEMP_1	-0.057***	-0.061***	-0.057***	-0.061***
	(0.018)	(0.019)	(0.018)	(0.019)
BANKR_1	0.046***	0.052***	0.046***	0.052***
	(0.015)	(0.016)	(0.015)	(0.016)
EXC_1		0.018		0.018
		(0.012)		(0.012)
Constant	-0.011	-0.011	-0.011	-0.011
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	661	661	661	661
R^2	0.058	0.061	0.058	0.061
Adjusted R^2	0.050	0.052	0.050	0.052
Akaike Inf. Crit.	116.686	116.303	116.686	116.303
Residual Std. Error	0.263 (df = 655)	0.262 (df = 654)	0.263 (df = 655)	0.262 (df = 654)

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

The VIF values of the preferred macroeconomic variables based on the stepwise regressions are inspected. This is to detect whether there is a danger of multicollinearity in the multivariate model. The VIF for GDP is 3.2, for inflation 1.5, for the house price index 2.0, for unemployment 2.7, for bankruptcies 2.2 and for the exchange rate 1.2. These results indicate that multicollinearity is not a problem in the preferred multivariate model as all VIF values are below 5 (James et al., 2013.)

When the bank-specific dummies are added to the model, the model specification is:

$$\begin{aligned}\Delta CLs_{ikt} &= \beta_0 + \beta_1 \Delta GDP_{kt-1} + \beta_2 \Delta INF_{kt-1} + \beta_3 \Delta HPRICE_{kt-1} + \\ &\beta_4 \Delta UNEMP_{kt-1} + \beta_5 \Delta BANKR_{kt-1} + \beta_6 \Delta EXC_{kt-1} + MEFF_i + \\ &HEFF_i + MSOLV_i + HSOLV_i + MEDIUM_i + LARGE_i + \\ &MPROF_i + HPROF_i + SAV_i + \varepsilon_{ikt},\end{aligned} \tag{11}$$

where ΔGDP_{kt-1} is the log difference of real GDP in country k at time $t-1$, ΔINF_{kt-1} is the absolute difference of inflation, $\Delta HPRICE_{kt-1}$ is the absolute difference of the house price index, $\Delta UNEMP_{kt-1}$ is the log difference in the harmonized unemployment rate, $BANKR_{kt-1}$ is the log difference of the number of bankruptcies and EXC_{kt-1} is the log difference of the national currency per US dollar.

The correlation matrix for the variables in the multivariate model is shown in table 12 in order to detect if there are high correlations between variables and to see which of the variables have the highest correlations with the dependent variable CLs. None of the correlations is above |0.7| indicating that multicollinearity is not a problem even the bank-specific variables are added. The VIF values are also below five: 3.2 for GDP, 1.6 for inflation, 2.1 for the house price index, 2.7 for unemployment, 2.4 for bankruptcies, 1.2 for the exchange rate, 1.8 for medium inefficiency, 2, for high inefficiency, 1.3 for medium solvency, 2.1 for high solvency, 3.2 for medium size, 3.4 for large size, 1.5 medium profitability, 1.6 for high profitability and 1.1 for savings banks. The most correlated variables with CLs are GDP, the house price index and bankruptcies.

Table 12. Correlation matrix for the variables in the multivariate model.

	CLs	GDP_1	INF_1	HPRICE_1	UNEMP_1	BANKR_1	EXC_1	MEFF
CLs	1							
GDP_1	-0.1	1						
INF_1	-0.003	0.44	1					
HPRICE_1	-0.11	0.67	0.25	1				
UNEMP_1	0.06	-0.69	-0.37	-0.58	1			
BANKR_1	0.11	-0.54	-0.23	-0.48	0.7	1		
EXC_1	0.04	-0.27	-0.19	-0.21	0.24	0.04	1	
MEFF	-0.02	0.01	-0.01	0.05	-0.01	0.001	-0.01	1
HEFF	-0.02	-0.05	0.002	-0.09	0.06	0.05	0.004	-0.5
MSOLV	-0.01	0.01	-0.003	-0.01	0.003	0.05	-0.01	-0.01
HSOLV	0.02	0.05	-0.005	0.04	-0.03	-0.03	0.005	0.07
MEDIUM	-0.04	-0.04	-0.01	0.01	0.02	0.02	-0.01	0.17
LARGE	-0.03	0.02	0.01	-0.03	-0.01	0.03	0.01	-0.07
MPROF	-0.02	-0.03	-0.02	0.01	0.02	0.03	0.01	0.17
HPROF	-0.04	0.14	0.01	0.06	-0.08	-0.01	-0.01	0.11
SAV	0.01	-0.02	0.01	0.02	0.004	-0.001	0.02	0.01

Table continues.

Table 12 – continued.

	HEFF	MSOLV	HSOLV	MEDIUM	LARGE	MPROF	HPROF	SAV
HEFF	1							
MSOLV	0.04	1						
HSOLV	-0.24	-0.5	1					
MEDIUM	-0.06	0.12	0.03	1				
LARGE	0.14	-0.01	-0.32	-0.5	1			
MPROF	0.12	0.03	0.02	0.17	-0.04	1		
HPROF	-0.25	-0.02	-0.03	-0.15	0.12	-0.5	1	
SAV	-0.04	0.03	-0.06	-0.09	0.07	-0.02	0.01	1

_1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar, MEFF = medium inefficiency bank, HEFF = high inefficiency bank, MSOLV = medium solvency bank, HSOLV = high solvency bank, MEDIUM = medium-sized bank, LARGE = large bank, MPROF = medium profitability bank, HPROF = high profitability bank, SAV = savings bank.

7.2.2 Linear regressions

Multivariate linear regressions are estimated with and without bank fixed effects. The results for multivariate regressions are shown in table 13. GDP is significant only in pooled multivariate regression (1) at the 10 % significance level, but it has the expected negative coefficient in all regressions. The insignificant coefficient is not surprising as Kalirai and Scheicher (2002) do neither find a significant relation between GDP and credit risk.

Inflation is significant in all regressions with a positive coefficient which means that inflation and credit losses of the following year have a positive relation. This supports the explanation that inflation reduces the real income of households and firms (Chaibi & Ftiti, 2015). Another possible explanation is that rising inflation increases the costs of production, worsening the financial situation of firms. Hence, the ability of both households and firms to repay loans deteriorates. However, Chaibi and Ftiti (2015) do not find a significant positive relation between inflation and credit risk and neither do Kalirai and Scheicher (2002). Boss (2002), instead, finds a negative relation between inflation and the default probability. Rinaldi and Sanchis-Arellano (2006) find a positive relation between inflation and non-performing loans but mention that the relation is expected to be ambiguous. Hence, the findings are to some extent contradictory. The other price stability indicator, the house price index, is only significant in pooled regressions (1) and (2) and hence, there seems to be some unobservable bank-specific factors that explain better changes in credit losses than the house price index. However, its sign is negative in all regressions which is consistent with univariate regressions.

Table 13. Multivariate regression results without fixed effects and with fixed effects.

	Dependent variable:			
	CLs			
	OLS		*felm*	
	(1)	(2)	(3)	(4)
GDP_1	-0.037*	-0.035	-0.032	-0.028
	(0.023)	(0.022)	(0.020)	(0.019)
INF_1	0.046***	0.044***	0.037***	0.035***
	(0.013)	(0.013)	(0.011)	(0.011)
HPRICE_1	-0.029*	-0.029*	-0.017	-0.014
	(0.015)	(0.015)	(0.014)	(0.014)
UNEMP_1	-0.061***	-0.059***	-0.033**	-0.029*
	(0.019)	(0.019)	(0.017)	(0.017)
BANKR_1	0.052***	0.054***	0.023	0.023
	(0.016)	(0.016)	(0.014)	(0.014)
EXC_1	0.018	0.018	0.016*	0.018*
	(0.012)	(0.011)	(0.010)	(0.010)
MEFF		-0.035		-0.031
		(0.027)		(0.030)
HEFF		-0.078***		-0.030
		(0.030)		(0.031)
MSOLV		0.015		-0.004
		(0.029)		(0.041)
HSOLV		-0.046		-0.135**
		(0.033)		(0.059)
MEDIUM		-0.099***		-0.304***
		(0.037)		(0.093)
LARGE		-0.091**		-0.235*
		(0.037)		(0.120)
MPROF		-0.045*		-0.015
		(0.025)		(0.023)
HPROF		-0.089***		-0.042
		(0.028)		(0.029)
SAV		0.052		
		(0.043)		
Constant	-0.011	0.166***		
	(0.011)	(0.045)		
Observations	661	661	661	661
R^2	0.061	0.101	0.422	0.441
Adjusted R^2	0.052	0.080	0.344	0.356
Residual Std. Error	0.262 (df = 654)	0.259 (df = 645)	0.218 (df = 581)	0.216 (df = 573)
F Statistic	7.086*** (df = 6; 654)	4.833*** (df = 15; 645)		

Table continues.

Table 13. – continued.

Significance level $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. _1 refers to the lag by one year. OLS = pooled regression, felm = regression with fixed effects, CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar, MEFF = medium inefficiency bank, HEFF = high inefficiency bank, MSOLV = medium solvency bank, HSOLV = high solvency bank, MEDIUM = medium-sized bank, LARGE = large bank,, MPROF = medium profitability bank, HPROF = high profitability bank, SAV = savings bank.

From the private sector indicators, unemployment appears significant in all regressions, but bankruptcies only in the pooled regressions. Oddly, unemployment has a negative sign. One possible explanation could be that banks do not grant loans for unemployed as easily as for employed people. As the unemployment rate increases this year, fewer loans are granted decreasing the number of total loans and possibly credit losses next year. This could be the case especially with short-term loans and for instance with credit cards. However, growth in unemployment should have a positive impact on credit losses at least in the long run. The 95 % confidence interval for unemployment has positive values in the fixed effects models and thus, the effect of unemployment is not necessarily negative but positive. Another issue is that unemployment has a correlation of -0.69 with GDP and 0.70 with bankruptcies which possibly change the effect to be negative. However, if GDP and bankruptcies were excluded, the explanatory power of the regression would drop. These regressions are also suggested by the multivariate model construction method explained in subsection 6.2.1 and the VIF values, below 5, indicate that multicollinearity should not be a problem in this model (James et al., 2013).

BANKR has a positive coefficient as expected. If a firm goes bankrupt, it is less likely to repay debt obligations. However, BANKR is insignificant in the fixed effects models. This means that unobservable factors explain better the changes in credit losses instead of bankruptcies.

EXC has a positive coefficient indicating a positive relation between credit loss changes and the changes in the exchange rate. This finding is supported by Jakubik and Schmieder (2008) and Boss (2002). Jakubik and Schmieder find that the appreciation of domestic currency has a positive relation with corporate credit risk and Boss finds that the exchange rate index from the previous period has a significant positive impact on credit defaults. Currency appreciation makes the exports more expensive which affects the financial situation of firms. This possibly leads to increasing credit losses stemming from the corporate loans. However, EXC is only significant in the fixed effects models at the 10 % significance level.

The bank-specific dummies, significant in both the pooled regression and the regression with fixed effects are MEDIUM and LARGE. Both have negative coefficients. This means that small banks typically suffer from greater increases in credit losses and have smaller decreases in credit losses. This finding supports the diversification hypothesis: larger banks can diversify better the risk than small banks (Louzis et al., 2012). The findings by Salas and Saurina (2002) support these results as they find that size and non-performing loans have negative relation in commercial banks. However, there seems to be no significant differences between savings and commercial banks as SAV is not statistically significant. It is omitted from the regression with fixed effects because it is a bank-fixed variable that does not change over time.

HEFF, MPROF and HPROF are significant only in the pooled regression. HEFF has a negative coefficient which means that high inefficiency banks face smaller increases and greater decreases in credit losses than low inefficiency banks. This result is contradictory with prior literature as Berger and DeYoung (1997) and Podpiera and Weill (2008) find that inefficiency (efficiency) is positively (negatively) related to non-performing loans. Banks having medium or high profitability face smaller increases and greater decreases in credit losses compared to low profitability banks. This is in line with prior literature. For instance, Chaibi and Ftiti (2015) find that higher profitability decreases non-performing loans.

In addition to MEDIUM and LARGE, a significant bank-specific dummy is HSOLV in the regression with fixed effects. HSOLV has a negative coefficient as expected which means that if a bank has a high solvency ratio, credit losses do not increase as much as if a bank has a low solvency ratio and if credit losses decrease, the decrease is greater in a bank with a high solvency ratio. This finding is supported by Berger and DeYoung (1997) who find that the reduction of capitalization leads to increasing non-performing loans.

When the magnitudes of macroeconomic variables are compared, the results suggest that inflation and unemployment have the strongest effects on credit loss changes consistently in all regression specifications. BANKR has also a strong positive relation, but only in the pooled regressions. Hence, I conclude that based on these findings, the changes in inflation and in unemployment are important factors in explaining credit loss changes for the next year. I also conclude that the most important bank-specific variable explaining the changes in credit losses is bank size: small banks typically suffer from greater increases in credit losses compared to medium and large banks. The difference is greater between small and medium-sized banks as the coefficient of MEDIUM is larger in both regression specifications and it remains significant at the 1% significance level also after adding the bank fixed effects.

In addition, the multivariate linear regressions with interactions between macroeconomic variables and size and also between macroeconomic variables and SAV are estimated. Interaction terms are added to examine whether the size of a bank change the effect of a macroeconomic variable on credit losses and whether there are differences in the effects of macroeconomic variables between commercial and savings banks. I focus on the interpretation of interaction terms.

The interactions between macroeconomic variables and size are presented in table 14. The interaction term HRPICE*MEDIUM is economically and statistically significant in both regressions with and without fixed effects. The coefficient is positive indicating that the effect of the house price index is greater in medium-sized banks than in the small banks. Other interaction terms of macroeconomic variables and size are not significant in the regression with fixed effects.

Table 14. Regression results with the interaction terms of macroeconomic variables and size.

	Dependent variable:	
	CLs	
	OLS	*felm*
	(1)	(2)
GDP_1	-0.054	-0.015
	(0.079)	(0.076)
INF_1	0.039	-0.013
	(0.040)	(0.037)
HPRICE_1	-0.179***	-0.105**
	(0.046)	(0.052)
UNEMP_1	-0.239***	-0.086**
	(0.044)	(0.041)
BANKR_1	0.147**	-0.039
	(0.059)	(0.059)
EXC_1	0.018	0.029
	(0.035)	(0.032)
MEFF	-0.037	-0.037
	(0.027)	(0.031)
HEFF	-0.087***	-0.030
	(0.030)	(0.032)
MSOLV	0.010	-0.011
	(0.029)	(0.041)
HSOLV	-0.072**	-0.145**
	(0.033)	(0.060)
MEDIUM	-0.126***	-0.317***
	(0.039)	(0.095)
LARGE	-0.128***	-0.251**
	(0.040)	(0.123)
MPROF	-0.044*	-0.016
	(0.025)	(0.024)
HPROF	-0.094***	-0.039
	(0.028)	(0.031)
SAV	0.028	
	(0.042)	
GDP_1:MEDIUM	0.011	-0.010
	(0.089)	(0.084)
GDP_1:LARGE	0.043	-0.008
	(0.083)	(0.080)
INF_1:MEDIUM	0.012	0.059
	(0.046)	(0.042)

Table continues.

Table 14. – continued.

	Dependent variable:	
	CLs	
	OLS	*felm*
	(1)	(2)
INF_1:LARGE	-0.007	0.048
	(0.043)	(0.040)
HPRICE_1:MEDIUM	0.179***	0.113**
	(0.054)	(0.057)
HPRICE_1:LARGE	0.159***	0.085
	(0.051)	(0.056)
UNEMP_1:MEDIUM	0.209***	0.072
	(0.055)	(0.051)
UNEMP_1:LARGE	0.222***	0.055
	(0.051)	(0.048)
BANKR_1:MEDIUM	-0.096	0.104
	(0.072)	(0.070)
BANKR_1:LARGE	-0.119*	0.061
	(0.062)	(0.062)
EXC_1:MEDIUM	-0.007	-0.013
	(0.039)	(0.036)
EXC_1:LARGE	0.007	-0.005
	(0.038)	(0.035)
Constant	0.210***	
	(0.047)	
Observations	661	661
R^2	0.153	0.452
Adjusted R^2	0.117	0.355
Residual Std. Error	0.253 (df = 633)	0.217 (df = 561)
F Statistic	4.251*** (df = 27; 633)	

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. OLS = pooled regression, felm = regression with fixed effects, CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar, MEFF = medium inefficiency bank, HEFF = high inefficiency bank, MSOLV = medium solvency bank, HSOLV = high solvency bank, MEDIUM = medium-sized bank, LARGE = large bank,, MPROF = medium profitability bank, HPROF = high profitability bank, SAV = savings bank.

In addition to the interaction term HPRICE*MEDIUM, the interaction terms HPRICE*LARGE, UNEMP*MEDIUM, UNEMP*LARGE with the 1 % significance level and BANKR*LARGE with the 10 % significance level are significant in the pooled regression. All these interaction terms, expect the BANKR*LARGE, are positive indicating that credit losses of small banks are less sensitive to the changes in house prices and in unemployment than credit losses of medium-sized and large banks. These results suggest that bank size is an important variable for explaining credit loss changes and support the hypothesis that the credit loss changes of medium and large banks are more sensitive to the changes in macroeconomic factors. Salas and Saurina (2002) find that commercial banks, that typically operate in foreign countries, are more sensitive to economic fluctuations. Hence, the possible explanation with medium-sized and large banks could be that they also operate in foreign countries and thus they are more exposed to economic fluctuations than small banks.

The interactions between macroeconomic variables and SAV are presented in table 15. HPRICE*SAV, UNEMP*SAV and BANKR*SAV are significant in the pooled regression. HPRICE*SAV and UNEMP*SAV have negative coefficients significant at the 1 % significance level. Hence, the changes in credit losses of commercial banks are more sensitive to the changes in house prices and unemployment compared to savings banks. This is a consistent result with the finding by Salas and Saurina (2002) who find that commercial banks are more sensitive to the economic fluctuations. The coefficient of BANKR*SAV is positive and significant at the 1 % significance level in the pooled regression meaning that credit losses of savings banks are more sensitive to the changes in the number of bankruptcies compared to commercial banks. None of the interactions between macroeconomic variables and SAV in the regression with fixed effects is significant.

However, it is worth noting that the commercial banks dominate the sample as the descriptive statistics for bank-specific variables show in appendix 2. The number of commercial banks in the sample is 2380 whereas the number of savings banks is 181. Hence, the results might be affected by the small number of savings banks.

Table 15. Regression results with the interaction terms of macroeconomic variables and SAV.

	Dependent variable:	
	CLs	
	OLS	*felm*
	(1)	(2)
GDP_1	-0.023	-0.031
	(0.021)	(0.020)
INF_1	0.033***	0.036***
	(0.012)	(0.011)
HPRICE_1	-0.024*	-0.012
	(0.014)	(0.014)
UNEMP_1	-0.035**	-0.027
	(0.018)	(0.017)
BANKR_1	0.027*	0.021
	(0.015)	(0.015)
EXC_1	0.020*	0.017*
	(0.011)	(0.010)
MEFF	-0.012	-0.033
	(0.025)	(0.030)
HEFF	-0.054**	-0.034
	(0.027)	(0.032)
MSOLV	0.051*	0.006
	(0.027)	(0.041)
HSOLV	-0.019	-0.134**
	(0.030)	(0.059)
MEDIUM	-0.096***	-0.302***
	(0.033)	(0.093)
LARGE	-0.067**	-0.232*
	(0.034)	(0.121)
MPROF	-0.028	-0.014
	(0.023)	(0.024)
HPROF	-0.060**	-0.042
	(0.025)	(0.029)
SAV	0.158***	
	(0.041)	
GDP_1:SAV	0.167	0.171
	(0.134)	(0.130)
INF_1:SAV	0.026	-0.029
	(0.039)	(0.037)
HPRICE_1:SAV	-0.337***	-0.129
	(0.094)	(0.100)

Table continues.

Table 15. – continued.

	Dependent variable:	
	CLs	
	OLS	*felm*
	(1)	(2)
UNEMP_1:SAV	-0.372***	-0.048
	(0.067)	(0.078)
BANKR_1:SAV	0.767***	0.166
	(0.092)	(0.107)
EXC_1:SAV	-0.058	0.026
	(0.046)	(0.045)
Constant	0.104**	
	(0.041)	
Observations	661	661
R^2	0.260	0.445
Adjusted R^2	0.235	0.354
Residual Std. Error	0.236 (df = 639)	0.217 (df = 567)
F Statistic	10.680*** (df = 21; 639)	

Significance level *p<0.1; **p<0.05; ***p<0.01. _1 refers to the lag by one year. OLS = pooled regression, felm = regression with fixed effects, CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar, MEFF = medium inefficiency bank, HEFF = high inefficiency bank, MSOLV = medium solvency bank, HSOLV = high solvency bank, MEDIUM = medium-sized bank, LARGE = large bank, MPROF = medium profitability bank, HPROF = high profitability bank, SAV = savings bank.

7.2.3 Logistic regressions

Logistic multivariate regressions are used to examine the relation of macroeconomic and bank-specific variables with extreme credit loss changes, i.e. credit loss changes in the highest quartile and extreme credit loss decreases, i.e. credit loss changes in the lowest quartile. The extreme credit loss changes are examined separately for every year of the sample period. Table 16 shows the logistic regression results.

The significant variables for the logistic regression, where the dependent variable is the extreme credit loss increase, are BANKR, MSOLV, MEDIUM and LARGE. BANKR has a positive coefficient indicating that growing number of bankruptcies increases the probability of extreme credit loss increases. This is intuitive because usually before a firm goes bankrupt, everything is done in order to save a firm and to fulfill the debt obligations. The loans of firms are also greater than the loans of households and hence, if a firm is unable to repay its debt, it is about greater credit loss increases than with households.

The significant positive coefficient of MSOLV in logistic regression (1) indicates that banks having a medium solvency ratio are more likely to face extreme credit increases compared to low solvency banks. However, this variable is significant only at the 10% significance level. Instead, MSOLV is positive and statistically significant at the 1% significance level in logistic regression (2) indicating that banks that have a medium solvency ratio are more likely to face extreme credit loss decreases compared to banks with a low solvency ratio. This is not the case with banks with a high solvency ratio. The possible explanation is that there are no additional benefits of any higher solvency ratio after reaching a medium solvency ratio. These results might also indicate that medium solvency banks have more volatile changes in credit losses than low solvency banks as MSOLV is positive and statistically significant in both logistic regressions, although only at the 10 % significance level in regression (1).

MEDIUM and LARGE have negative coefficients in logistic regression (1). This means that small banks are more likely to face extreme credit loss increases relative to their size than medium and large banks. Credit losses are scaled by total assets and hence, a possible explanation is that small banks face as much credit loss increases as medium and large banks, but the size of a bank is only smaller. These results are consistent with the results of the multivariate regressions – small banks suffer from greater increases in credit losses than medium and large banks.

In addition to MSOLV, variables EXC, HEFF, and SAV are statistically significant in logistic regression (2), where the dependent dummy variable is the extreme credit loss decrease. EXC has a negative coefficient meaning that it is less likely that an extreme credit loss decrease occurs as the domestic currency appreciates. This strengthens the finding of the positive relation between credit loss changes and exchange rate changes in the multivariate regressions. The dummy variable HEFF is positive and significant indicating that banks having high inefficiency are more likely to face extreme credit loss decreases than low inefficiency banks. This supports *the bad luck hypothesis*: higher costs might be an indication of using more resources. Consequently, additional resources help to lower the future credit losses.

Table 16. Logistic regression results.

	Dependent variable:	
	Extreme credit loss increase	*Extreme credit loss decrease*
	(1)	(2)
GDP_1	0.117	-0.123
	(0.209)	(0.216)
INF_1	-0.050	0.005
	(0.115)	(0.121)
HPRICE_1	-0.076	-0.174
	(0.143)	(0.154)
UNEMP_1	-0.231	0.106
	(0.168)	(0.177)
BANKR_1	0.334^{**}	-0.229
	(0.136)	(0.161)
EXC_1	0.125	-0.274^{**}
	(0.104)	(0.120)
MEFF	-0.342	-0.073
	(0.254)	(0.280)
HEFF	-0.194	0.486^{*}
	(0.264)	(0.285)
MSOLV	0.483^{*}	0.778^{***}
	(0.257)	(0.266)
HSOLV	-0.088	-0.011
	(0.312)	(0.335)
MEDIUM	-1.362^{***}	-0.326
	(0.314)	(0.344)
LARGE	-0.823^{***}	-0.116
	(0.310)	(0.339)
MPROF	-0.321	-0.325
	(0.234)	(0.249)
HPROF	-0.182	0.136
	(0.249)	(0.260)
SAV	-0.056	0.898^{**}
	(0.374)	(0.359)
Constant	0.083	-1.507^{***}
	(0.380)	(0.420)
Observations	661	661
Log Likelihood	-344.707	-318.129
Akaike Inf. Crit.	721.414	668.259

Significance level $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. _1 refers to the lag by one year. CLs = Log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, INF = absolute difference of inflation, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, BANKR = log difference of the number of bankruptcies measured by the index, EXC = log difference of the annual exchange rate measured as the national currency per US dollar, MEFF = medium inefficiency, HEFF = high inefficiency, MSOLV = medium solvency, HSOLV = high solvency , MEDIUM = medium-sized, LARGE = large, MPROF = medium profitability, HPROF = high profitability, SAV = savings bank.

The results suggest that savings banks are more likely to face extreme credit loss decreases compared to commercial banks as SAV is positive and significant at the 5 % significance level. However, savings banks are not less nor more likely to face extreme credit loss increases because the variable is insignificant in logistic regression (1). However, as discussed in subsection 7.2.2, the number of savings banks in the sample is small and possibly affects the results.

As a summary, medium size of a bank decreases the most the probability of the occurrence of the extreme credit loss increase whereas the growing number of bankruptcies increases the most this probability. If a bank is a savings bank, it increases the most the probability of the occurrence of the extreme credit loss decrease whereas the appreciation of domestic currency decreases the most this probability. MSOLV, i.e. a bank has a medium solvency ratio, affects also considerably the probability of the extreme credit loss decrease. Hence, the conclusion is that MEDIUM, BANKR, SAV, EXC and MSOLV are important variables in explaining extreme credit loss changes that occur during the following year.

8 CONCLUSIONS

The credit loss modelling is a means to reflect credit risk and to make the financial health of a bank look more realistic. If the credit loss modelling is poorly implemented, it can have severe consequences as the financial crisis showed in 2008. Consequently, accounting standards have been improved from the financial crisis period, and nowadays IFRS standards allow using all relevant information that is available without undue cost including forward-looking information in the credit loss modelling. Macroeconomic factors provide this kind of forward-looking information and are easily available. Thus, they can be utilized in the credit loss modelling to estimate future expected credit losses. Hence, I apply an extensive set of macroeconomic variables based on the prior literature in order to find those ones that are useful for estimating the changes in credit losses for the following year. Thus, particularly the predictive relation is examined. In addition, the bank-specific features are also likely to affect the credit loss changes, so I include the bank-specific variables in the study. Especially, I examine the impact of bank size and the impact of the type of a bank on the relation between the changes in macroeconomic factors and credit loss changes.

Prior studies focus mainly on a few countries whereas this thesis is based on the sample of 24 European countries and 202 banks from these countries. Thus, the results can be especially exploited in the credit loss modelling in European banks. As IFRS 9, including the expected credit loss model, has been effective only since 2018, it is likely that there is still a need for the improvements of banks' credit loss models. Thus, the results have valuable implication for practical implementation of the credit loss models and estimating future credit losses. However, one should note that accounting standards have changed during the sample period of 2005–2008, and it is likely that not all 202 banks of the sample have followed the same standards.

The empirical analysis is based on several pooled, fixed effects and logistic regressions. In addition, to select the relevant variables for the multivariate model, I use stepwise regressions based on Akaike information criteria (Yan & Su, 2009, pp. 171–172). The preferred macroeconomic variables based on the stepwise regression results are GDP, inflation, the house price index, unemployment, bankruptcies and the exchange rate.

Based on the univariate regression results the house price index, gross fixed capital formation (GFCF), the nominal long-term interest rate and the term spread are important determinants of the credit loss changes of the following year. The results suggest that the changes in the house price index are negatively related to the changes in credit losses and this finding is supported by Vlieghe (2001) who argues that the short-run negative relation is due to the important role of property as collateral. The changes in GFCF are also negatively related to credit loss changes in the univariate regressions which is supported by Festić et al. (2011) who find that the growth in GFCF lowers non-performing loans.

Both the changes in the nominal long-term interest rate and the changes in the term spread have a positive relation with the changes in credit losses and these results are supported by Boss (2002). The nominal long-term interest rate reflects the long-term borrowing costs whereas the term spread reflects the future short-term borrowing costs (Ang et al., 2011; Kalirai & Scheicher, 2002). Thus, it is intuitive that the changes in borrowing costs are positively related to the changes in future credit losses.

Based on the multivariate regression results, inflation and unemployment have the strongest effects on credit loss changes for the following year. Inflation has a positive relation with the increase in credit losses, but this finding is to some extent contradictory with prior literature. For instance, Boss (2002) finds a negative relation between inflation and the default probability and Kalirai and Scheicher (2002) do not find a significant relation between inflation and credit risk at all. Rinaldi and Sanchis-Arellano (2006) find a positive relation between inflation and non-performing loans but also mention that the relation is expected to be ambiguous. Unemployment has an unexpected negative relation with the credit loss changes which can be due to its high correlation with GDP and bankruptcies. However, it can also indicate that banks grant fewer loans because there are fewer people who are eligible for a loan. Consequently, the credit losses might decrease as the number of loans granted is decreased.

The growing number of bankruptcies affects the most the probability that an extreme credit loss increase occurs. Typically, corporate loans are bigger than the loans of households and hence, the result is intuitive. If a company defaults, it is likely that credit losses increase considerably. In addition, medium solvency banks are also more likely to face extreme credit loss decreases compared to low solvency banks.

Bank size is an important determinant of credit loss changes. The results suggest that small banks suffer from greater increases in credit losses compared to medium and large banks. However, credit losses of medium and large banks are more sensitive to the changes in macroeconomic factors than credit losses of small banks. The possible explanation is that larger banks operate also in foreign countries and hence, are more exposed to economic fluctuations. Credit losses of commercial banks are also more sensitive to the changes in house prices and unemployment than credit losses of savings banks. In addition, commercial banks are less likely to face extreme credit loss decreases. These findings are consistent with prior empirical evidence by Salas and Saurina (2002) who find that size and non-performing loans are negatively related in commercial banks and that commercial banks are more sensitive to economic cycles than savings banks. However, results suggest that credit losses of savings banks are more sensitive to the changes in the number bankruptcies.

It is worth noting that the commercial banks dominate the sample, and this might affect the results. Thus, further research would be warranted in this respect and the research could be extended to other types of banks than only commercial and savings banks. I also use only the changes of macroeconomic variables lagged by one year. Hence, it would be interesting to examine whether the explanatory variables with more lags are better predictors of future credit loss changes and thus, would provide valuable information for the credit loss modelling.

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APPENDICES

The appendices show the descriptive statistics for the macroeconomic variables of 24 European countries and for the bank-specific variables of 202 European banks for the sample period from 2005 to 2018.

Appendix 1. Descriptive statistics for the first differences of macroeconomic variables.

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
GDP_1	2,814	0.01	0.03	-0.2	0.01	0.03	0.1
IND_PROD_1	2,688	0.3	5.4	-23.0	-0.9	3.1	11.5
INF_1	2,688	-0.04	1.1	-5.3	-0.4	0.7	4.0
M1_1	1,120	5.8	3.7	-3.0	3.8	7.6	30.0
HPRICE_1	2,559	2.2	6.3	-38.8	-1.3	5.7	24.8
UNEMP_1	2,688	-0.01	0.1	-0.4	-0.1	0.04	0.5
CON_1	2,716	-0.002	0.01	-0.1	-0.01	0.01	0.1
INC_1	2,716	0.01	0.03	-0.2	0.002	0.03	0.2
GFCF_1	2,716	0.01	0.1	-0.5	-0.01	0.05	0.3
BANKR_1	2,050	0.03	0.2	-0.7	-0.1	0.1	1.3
INDEBT_1	2,688	0.01	0.04	-0.1	-0.02	0.03	0.4
STOXXE600_1	2,828	0.1	0.2	-0.4	-0.04	0.2	0.5
DJIND_1	2,828	0.1	0.2	-0.4	0.03	0.1	0.4
NLIR_1	2,713	-0.2	1.1	-12.4	-0.7	0.2	8.4
NSIR_1	2,709	-0.2	1.0	-5.3	-0.4	0.4	2.0
RLIR_1	2,684	-0.3	2.0	-11.8	-1.1	0.6	11.5
RSIR_1	2,678	-0.3	1.6	-7.2	-1.1	0.6	7.0
TERM_1	2,702	-0.01	1.3	-12.1	-0.6	0.3	7.6
EXP_1	2,716	0.04	0.1	-0.4	-0.005	0.1	0.4
EXC_1	2,814	0.001	0.1	-0.2	-0.05	0.05	0.3

N = number of observations, Mean = sample mean, St.Dev = standard deviation, Min = sample minimum, Pctl(25) = lower quartile, Pcrl(75) = upper quartile, Max = sample maximum. _1 refers to the lag by one year. CLs = log difference of the ratio of actual loan losses to total assets, GDP = log difference of real GDP, IND_PROD = absolute difference of industrial production, INF = absolute difference of inflation, M1 = absolute difference of narrow money, HPRICE = absolute difference of the house price index, UNEMP = log difference of harmonized unemployment rate, CON = log difference of household final consumption expenditure as % of GDP, INC = log difference of net national disposable income, GFCF = log difference of gross fixed capital formation, BANKR = log difference of the number of bankruptcies measured by the index, INDEBT = log difference of the private sector debt-to-GDP, STOXXE600 = simple return of the STOXX Europe 600 index, DJIND = simple return of the Dow Jones Industrial Average index, NLIR = absolute difference of the nominal long-term interest rate, NSIR = absolute difference of the nominal short-term interest rate, RLIR = absolute difference of the real long-term interest rate, RSIR = absolute difference of the real short-term interest rate, TERM = absolute difference of term spread defined as the nominal long-term interest rate minus the nominal short-term interest rate, EXP = log difference of exports of goods seasonally adjusted, EXC = log difference of the annual exchange rate measured as the national currency per US dollar.

Appendix 2. Descriptive statistics for the bank-specific variables.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
CLs	917	0.000	0.01	-0.1	-0.000	0.000	0.4
INEF	1,820	11.1	86.7	-841.7	2.4	8.4	2,498.1
LEV	2,140	0.9	0.8	0.002	0.9	0.9	34.2
SOLV	2,140	0.1	0.8	-33.2	0.1	0.1	1.0
SIZE	2,143	16.4	2.8	6.4	14.8	18.1	23.4
PROF	2,139	4.4	202.8	-52.9	0.03	0.1	9,376.9
SAV	2828	0.064	0.245	0	0	0	1
COMM	2828	0.84	0.365	0	1	1	1

N = number of observations, Mean = sample mean, St.Dev = standard deviation, Min = sample minimum, Pctl(25) = lower quartile, Pcrl(75) = upper quartile, Max = sample maximum. CLs = log difference of the ratio of actual loan losses to total assets, INEF = operating expenses/Operating income, LEV = total liabilities / total assets, SOLV = total equity/total assets, SIZE = log of total assets, PROF = net income / total equity, SAV = savings bank, dummy variable, COMM = commercial bank, dummy variable.