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THE IMPACT OF MACROECONOMIC ENVIRONMENT ON CREDIT RISK IN COMMERCIAL BANKS

Scientific Study

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INTRODUCTION

Commercial banks meet the credit risk in every lending transaction. To reduce this risk, banks classify the debtors into different risk levels based on the set of information gathered from the clients. Such classification determines the assessed credit risk level for potential borrowers separating the default category and acceptable ones with a number of risk levels. Each risk class then gets priced at a premium which depends on the probability to repay the debt. These models measure the statistical probability that credit will be repaid and is based on the idea that it is possible to predict the future performance of loan applicants with similar characteristics to previous applicants. The credit risk assessment of customers largely relies on the availability of information. For business borrowers this information includes the financial and other data. The profitability, solvency, capital structure ratios of enterprises often are included into the credit risk assessment variables. In case of households loans banks are interested in the specific factors as employment status, income, education, personal property, marital status, past repayment history. The qualitative human credit risk assessment approaches in banks recently have almost completely been replaced by quantitative approaches. The credit records accumulated by banks are the the main background for the internal credit risk assessment models development. The lenders also share the information through the credit reference systems, but every bank makes the isolated decision. They can easily tell when the applicant is already heavily laden with debts from other lenders. Because of this, banks can avoid the irresponsible borrowers as they lend considering the information provided not only by the applicants, but also by other lenders. The most important criterion in the credit risk assessment process is to ensure that banks have the wholesome information when advancing the credits.

Before the global financial crisis, the tendency of banks‘ loan portfolio growth was observed in many countries what indicates that the debtors highly relied to a large extent in bank funding. The high credit expansion was induced by the economic growth and the further positive expectations of banks, businesses and households. But the credit slump in the aftermath of the global crisis was as hard as the growth during the credit boom. The banks faced with the problem of non-performing loans (NPLs) as many debtors became unable to meet their financial obligations when the economy deteriorated. The decrease of GDP, investments, consumption expenditures of households, the growth of enterprises bankruptcies and unemployment caused the serious problems not only for business enterprises and households, but also for banks. The quality of loan portfolio and the financial indicators of banks disimproved what indicates that in credit growth period the banks have not assessed the credit risk properly. Because the banks as the financial intermediaries play the the very important role in country‘s financial system and whole economy, the supervisors of banks also became concerned of these problems. The Basel III Accord suggests the guidelines for the consideration of macroeconomic factors in the credit risk assessment process. Banks can freely select the variables and the analysis methods striving to develop the precise internal credit risk assessment models. This objective is also common in the current scientific researches. So this study is directed for the understanding how the economic recession influences the credit risk in commercial banks. According to this the **scientific problem** can be raised – what is the main impact of the country‘s economic downturn on the debtors‘ credit risk in banks? The typical characteristics of these interrelations will be revealed in this study.

The object of this research is impact of macroeconomic changes on the credit risk in commercial banks.

The aim of this research is to reveal the main impact of macroeconomic changes on credit risk in commercial banks.

The tasks of this research:

1. To explain the economic role of commercial banks in country‘s financial system.
2. To select the main banks‘ performance measures that reflect banks‘ status.
3. To analyze the main commercial banks‘ risks that must be managed in banks.
4. To analyze the main peculiarities of credit risk management in banks.
5. To reveal the macroeconomic impact on credit risk in banks analyzing the publications of other researchers.
6. To present the Lithuanian commercial banking system.
7. To estimate the problem of non-performing loans and the changes of financial condition in Lithuanian banks.
8. To analyze the changes of commercial banks macroeconomic environment in Lithuania.
9. To develop the enterprises credit risk assessment model considering the industry sectors sensitivity to the macroeconomic changes.
10. To measure the business and households indebtedness in Lithuania and to evaluate it as factor of NPLs problem in banks.

11. To analyze the non-performing loans problem in European Union.
12. To find the dependence of non-performing loans problem on macroeconomic conditions in European Union.
13. To develop the NPLs in European Union countries prediction model.

The methods of this research consist of the analysis of scientific publications and statistical data of commercial banks and economics.

The novelty of this research. This study examines the macroeconomic factors that influence the credit risk of the Lithuanian banking system over the recent business cycle. Also the study aims to identify the determinants of non-performing loans using a cross-country modelling framework analyzing the consolidated banking and economic data of other EU countries. As the EU countries are possible non-homogeneous, the study is directed to capture the timeline of financial crisis and to evaluate the impact of it on non-performing loans in banks.

The theoretical significance of this study is that the recent scientific researches of banking were analyzed ant the main peculiarities of credit risk management considering the macroeconomic factors were generalized. The impact of business cycle fluctuations on the credit risk in banks was revealed what extends the knowledge of external factors causing the serious problems of non-performing loans in banks. The typical two-way direction relations of banking performance and the country‘s economy were estimated what are important for banks, their debtors and supervisors. This study supplements the other credit risk management researches that taken together can help to construct the sound credit risk management system that enables to keep the stability of banking sector and whole economy.

The practical significance of this study is that it contributes to the empirical statistical analysis of debtors‘ credit risk by focusing on the relationship between non-performing loans, macroeconomic and industry-specific variables in Lithuania, where the main risk of the domestic banking system relates to the weakening of its loan portfolio quality in the economic recession. The estimated interrelations can ease for bankers the understanding of the macroeconomic impact on credit risk and to develop the models that consider the business cycle fluctuations. The statistical analysis results also support the necessity of responsible borrowing because the households in this study can easily see what happened in recent financial crisis and understanding this to manage the personal finance more responsibly seeking to avoid the consequences of over-indebtedness and insolvency.

1. THEORETICAL EVIDENCE OF INTERRELATIONS BETWEEN CREDIT RISK AND MACROECONOMICS

1.1. The role of commercial banks in country‘s financial system

The commercial banks are the part of financial system that plays a fundamental role in the country‘s economy as the environment between agents who need to borrow and those who want to lend or invest and is naturally linked to all economic sectors. If the financial system does not function properly, its problems have a strong negative impact on the whole economy. For this reason the policymakers, regulators, academics and practitioners currently pay close attention to the soundness and stability of this sector (Rodriguez-Moreno, Pena, 2013). The main banks‘ deposit mobilization and credit allocation functions have important implications for economic growth and development. The significance of this intermediation process is likely to be greater in economies with thin financial markets and small non-bank sectors where a larger percentage of enterprises and individuals are likely to depend on banks for external funding (Gounder, Sharma, 2012). The banks as the financial intermediaries play a vital role in the processes of economic growth by intermediating scarce financial resources appropriately in time to productive sectors of the economy. Efficient financial intermediation has the ability of transferring their inputs into outputs that increases the volume of funds transacted in the country‘s economy. Conversely, the inefficient and uncompetitive financial institutions can increase the opportunity cost of capital in the economy, and consequently, financing of projects in such an economy is more expensive. Indeed, most of the financial intermediation in the developed ant the developing countries is carried out by commercial banks, and other financial institutions, and the financial markets play a relatively insignificant role (Reddy, Nirmala, 2013).

The commercial banks perform specific tasks in the country‘s financial system, such as the mobilizing savings, allocating resources, diversifying risks, monitoring borrowers and exerting corporate control. The development of financial system positively affects economic growth of every country. The recent empirical works suggest growth rates are higher when the legal environment enables financial systems to perform their tasks more effectively. Such facts may explain cross country differences in economic growth: countries with more sophisticated financial systems achieve higher rates of economic growth (Williams, Gardener, 2003). So, the evaluation of banks‘ performance attracts significant attention from public and financial regulators as banks are the critical institutions in most economies. Their ability to accumulate the financial resources, provide various credit operations and financial services activate financial flows that influence the growth and economic development of a country. Moreover, the banking sector is considered as a vital segment of modern economy, where the banks implement their important role and carry out specific functions (Stankevičienė, Mencaitė, 2012). As the profit seeking enterprises, the banks currently have also been increasingly focusing on customers' demands. They have also switched their business models from the sale of traditional financial products to marketing and customer orientation. Nowadays banks perform towards the relationship marketing with a focus on long-term relationships and mutual benefits with customers. The long-term, stable, and cooperative relationships with customers enable the financial industry to provide different services for different customers so as to enhance the profitability and efficiency (Lee, Lin, Chen, 2010).

The main source of commercial bank‘s interest income is loan portfolio which is the assets in the balance-sheet and it is created when the money fund is accumulated in the process of intermediation by accepting deposits. The basic function of intermediation is a source of credit and liquidity risks for any banking institution. Further, banks are exposed to various market and non-market risks in performing their functions. These risks expose banks to events, both expected and unexpected, with the potential to cause losses, putting depositors' money at risk. Expected losses may be mitigated by a combination of product pricing and accounting loss provisions, while capital funds are expected to meet unexpected losses. Thus the primary role of capital in a banking institution is to meet the unexpected losses arising out of portfolio choice of banks and to protect the depositor's money (Jayadev, 2013). The banks typically face numerous risks, including credit, interest rate, currency, liquidity, systemic risk and other. Also compared to other industries, banking stability is very dependent on trust and reputation. Because banks are clearly important to national, and even global economic stability, the various indicators are needed to monitor the bank's performance, financial status and operational competence (Chen, Cheng, 2013).

The losses and instability in banking sector often is driven by the systemic factors. According to Rodriguez-Moreno & Pena (2013), the causes of malfunctions in banking sector can be related to multiple mechanisms such as:

- Macro imbalances (e.g. excessive credit expansion in the private or public sector).
- Correlated exposures (e.g. herding behavior).
- Contagions.

- Asset bubbles.
- Negative externalities (e.g. banks too big to fall).
- Information disruptions (e.g. freezes in the interbank market).

Given this incomplete list of possible mechanisms influencing systemic risk, it is evident that various risk measures are needed to capture its complex nature. In particular, the policymakers charged with the responsibility of ensuring financial stability should rely on a wide array of measures. These measures should warn about the imbalances within the financial sector or be able to capture the abrupt materialization of systemic risk. With regard to the potential systemic risk's detectors, the measures should be based on the aggregate market level (e.g. interbank rates and stock market indices) or at the level of individual institutions. These kinds of indicators should be underpinned by measurable patterns of systemic stability which form the basis for early warning and correcting. If a systemic risk measurement indicates that destabilizing systemic events are looming, preventive policies such as stricter financial regulation and more rigorous supervision may be justified (Rodriguez-Moreno, Pena, 2013).

The economic history of the past two decades clearly demonstrates that the origins of financial crises could be noticed by either incompetent or inefficient operations of banks (Reddy, Nirmala, 2013). One of the key lessons of the recent financial crisis was that the banking sector was too levered, not being able to absorb market and credit losses. This turned out to be very costly in terms of taxpayers' money and highly disruptive to the real economy reflected, for example, in output losses and steep rises in unemployment. The minimization of the probability of these market disruptions occurrence, and therefore financial stability enhancement, sets the ground for banks' capital requirements regulation (Antao, Lacerda, 2011). Many studies after the last crisis have pointed out that the credit boom, preceding the crisis, contribute to the vulnerability of the financial system and that is why the consequences of this crisis where so harsh. Moreover, the credit booms are some of the best indicators of financial crisis throughout the history of financial markets and the different studies proved that the credit booms reduce the financial stability in a country (Kero, 2013). The decline in loan quality did not come unexpectedly in banks of many countries. The recent empirical findings also suggest that there has been an expansion of low quality loans in banks. Many of the loans granted during the credit boom preceding the financial crisis were of such a bad quality that banks must have been aware of the poor loan quality when the loan was granted. In addition, the decrease in lending standards before the crisis has been shown to be related to the market structure in the banking sector. The loan denial rates in the subprime segment decreased more in areas with highly competitive banking markets and that the market entry of new financial institutions induced a further decrease in lending standards (Hakenes, Schnabel, 2010). The loan cyclicality effect is in line with the suggestion that in general the credit risk spreads become high in a recessionary economy. The researchers note that in a booming and prosperous economy, a firm‘s demand for capital increases, and borrowers are more solvent because of increased profitability. Therefore, banks adopt looser screening standards and lend actively. Conversely, in a recession, banks severely scrutinize borrowers and lend passively. At the same time, the loan supply affects economic development and further causes economic procyclicality. Thus, economic conditions may affect the strength of banks‘ screening practices. Usually, banks screen their borrowers loosely in a booming economy and strictly in a recessionary economy (Liu, Chen, 2012).

Addressing the procyclicality in bank lending behavior has become one of the priorities for banking regulators since the financial crisis of years 2007 – 2008. Central banks across advanced countries maintain that the financial stability is the key objective of their policy. A stable financial system is a key presumption for a healthy and successful economy, so the central banks‘ role is to ascertain the stability of the country‘s financial system (Ali, Daly, 2010). The possibility that problems in one institution may spread and disrupt the normal function of the entire system reinforces the role of capital regulation. This regulation works at least in two ways: it provides a loss absorbing fund for unexpected events and, if properly designed, introduces incentives for banks to limit the risk of their activities. Although the importance of high capital requirements for financial stability, regulation on capital has an impact on the return on equity (capital is the most expensive source of banks' funding) which potentially influences the competitive stance in the financial sector. Against this background, global harmonization of prudential supervision enhancing financial stability and ensuring a level playing field among banks in different countries is crucial (Antao, Lacerda, 2011). Bank failures generate the negative externalities for other banks in the form of a loss of confidence in the stability of the financial system as a whole, losses from interbank exposures to failed banks, and losses from assets that the failing bank is forced to sell. This is different in other industries, where competitors generally gain from the failure of another firm. These negative externalities associated with bank failures offer the main rationale for financial regulation: to prevent socially costly bank failures (Laeven, 2011). The regulation framework of Basel III merges the more advanced regulatory tools for the banks‘ implementation. In particular, the Basel Committee on Banking Supervision (BCBS) proposes to introduce a countercyclical capital buffer which will be made in banks during the periods of excessive credit growth in order to curb the credit cycle and protect the banking sector from the accumulation of financial imbalances. Also the BCBS suggests a change in loan loss provisioning behaviors toward more forward-looking provisioning practices. These measures seek to increase the cost of making loans in terms of capital and loan loss provisions during the upward phase of the business cycle. It is largely accepted that the borrowers and banks are overconfident during this phase about the investment projects and the ability to repay the loans. Banks' over optimism about borrowers' future prospects brings more liberal credit policies with lower credit standards requirements. As a consequence, during the recessions, banks face the high non-performing loans (NPLs) and specific provisions problem that requires them to tighten the further credit supply, complicating the prospects of the country's economic recovery. These variations in lending are more than proportional to the changes in economic activity, suggesting that there are changes in bank loan supply that tend to accentuate the business cycle (Bouvatier, Lopez-Villavicencio, Mignon, 2012).

Bank revenues have a time variation pattern over the business cycle. Since revenues are a major determinant of bank capital and lending capacity, the time variation may have an impact on the real economy and may potentially amplify the business cycle. Banks may have a preference for smoothing total income and thus compensate for lower volumes by charging higher margins during recessions. Furthermore, credit risk and adverse selection may be more severe problems for banks during recessions and thus require higher risk premia. Also, the loan markets may be less contestable during recessions, meaning that incumbents who resort to limit pricing may maintain higher margins without encouraging potential entrants. All of these explanations rely on banks having some market power, and that market power may itself be stronger during recessions. The countercyclical behavior of margins acts as a financial accelerator, amplifying the effects of any shocks on the macroeconomy (Andersen, Berg, Jansen, 2012).

To keep the banking system of a country stable, the activity of banks must be profitable. High bank profits may be market power or efficiency-driven. If it is the case that profits are market power-driven, then households and firms are likely to experience high cost of borrowing, credit rationing and compromised banking services, among others. More importantly, these experiences are likely to have adverse consequences for the economic growth and development, thus aggravating the social and economic conditions of the regions where the economic growth and poverty reduction policies are predominantly financed by banks and the capital markets are small or inactive. However, high profitability may also be due to greater efficiency such that the implications of market power effects on profits may be discarded (Sharma, Gounder, Xiang, 2013). One prominent feature of the studies of credit institution profit inefficiency has been an attempt to delineate the effects on inefficiency measures due to institution-specific (i.e. bad management) or environment-specific factors. Credit institutions in one country may have a relatively greater inefficiency level compared to a credit institution in another because of factors specific to the local economy (risk of problem loans, lower economic growth, etc.) or because of factors germane to the institution itself (poor-managerial practices). The potential of both of these factors to impinge on inefficiency levels is not in question (Fitzpatrick, McQuinn, 2008). According to Mamatzakis, Kalyvas & Piesse (2013) the domestic or foreign bank factor also influences the bank‘s performance efficiency. Considering the home advantage hypothesis the domestic banks can operate more efficiently than foreign banks in their own country as they are more familiar with the local business environment and institutional framework. In the alternative hypothesis of the global advantage, the foreign banks may possess enough firm-specific advantages to overcome the liability of foreignness and so even outperform local competitors in the host economy. In terms of emerging and developing economies most of the evidence supports the global advantage hypothesis (Mamatzakis, Kalyvas, Piesse, 2013).

The analysis results of this chapter allow to affirm that commercial banks have the crucial role in the country‘s financial system and the economic development. For this reason the banking sector is highly regulated to assure the banking system stability and the implementation of the financial intermediation and other financial services. Many studies have proved that macroeconomic imbalances have the very negative impact on banks‘ financial results that depend on the bank‘s internal and external factors. To measure the condition of the commercial banks the quantitative indicators are needed, so the next chapter of this study aims to analyze the main rates of commercial banks‘ performance.

1.2. The main banks‘ performance measures

The stability of the banking system depends on the efficiency level of banks, as measured by a bank’s ability to operate close to the best-practice frontiers. The issue of bank efficiency has become more important following the financial crisis and its widespread impact on the stability of the financial system. During the crisis, the banks demonstrated resilience to external shocks, which alludes to the fact that an economically efficient bank can withstand financial market turmoil better than its inefficient counterpart and can contribute more to the efficient allocation of capital and the stability of the financial system (Shamsuddin, Xiang, 2012). Studies on the determinants of bank efficiency consider both internal and external factors. The internal factors originate from a bank's balance sheet and income statement, and thus are referred to as bank-specific determinants of efficiency. The external factors are those that are beyond a bank's management and control, often reflecting the economic and legal environments that affect the operation and performance of banks. Bank-specific characteristics include total assets, equity over total assets, return on assets or equity, loans-to-total assets, non-performing loans (NPLs), costs over income and costs over total assets. The impacts of these factors on bank efficiency vary across studies, depending on the specific circumstances of the banking industry analysed (Vu, Nahm, 2013). Although banking institutions have become increasingly complex, the key drivers of their performance remain earnings, efficiency, risk-taking and leverage. While it is clear that a bank must be able to generate earnings, it is also important to take account of the composition and volatility of those earnings. Efficiency refers to the bank's ability to generate revenue from a given amount of assets and to make profit from a given source of income (European Central Bank, 2010).

According to Shamsuddin & Xiang (2012), the main groups of variables that affect the degree of bank‘s profit efficiency are:

- Bank-specific characteristics: bank size, bank capitalization, asset quality, credit risk, liquidity risk and management ability.
- Ownership features.
- Transitional indicators.
- Environmental factors including stock-market development, the growth rate of real GDP per capita, annual inflation rate and interest-rate margin.

The efficiency level of a financial institution is an important indicator of its financial health and profitability. For example, the profit efficiency of a bank can tell us how close its profitability is to the highest profitability level achieved in the industry. If a bank has profit inefficiency, it is implied that resources are not optimally used or profit-enhancing opportunities are not fully utilised by the bank (Shamsuddin, Xiang, 2012). The efficiency of banks is also related to their risk-taking and leverage. The risk-taking is reflected in the necessary adjustments to earnings for the undertaken risks to generate them. Leverage might improve results in the economic upturns but, conversely, it can also make it more likely for a bank to fail, due to rare, unexpected losses (European Central Bank, 2010).

Bikker (2010) the efficiency of banks‘ performance interrelates with the competition in the banking market. The market structure, costs and profitability are the main factors of banks‘ efficiency. More efficient banks translate lower costs into the increased profits or price reductions in order to improve their competitiveness. Finally, the higher profits enable banks to lower their prices and become more competitive in order to increase their market share. Hence competition and efficiency in banking are also highly important: high quality at low cost boosts welfare (Bikker, 2010).

In addition to the efficiency, the wide set of banking indicators, such as business model, funding strategy, market structure, stability, profitability, regulation, the quality of governance and a measure of financial globalization could explain the post incidence of the crisis both across countries (at the macro-level) and across banks (at the micro-level), and be added to the analytical toolkit available for prudential supervision. Then, the use of back-in-time variables is justified by the fact that these contain information about:

- The health of the financial system in the past.
- How the financial system evolves over time.

As a consequence, they may be useful in understanding the genesis of the banking crises (Caprio Jr., D‘Apice, Ferri, Puopolo, 2014).

The Euopean Central Bank the main measures of commercial banks performance classifies into three groups:

- Traditional measures of performance.
- Economic measures of performance.
- Market-based measures of performance.

1. Traditional measures of banks‘ performance. The main traditional performance measures are similar to those applied in other industries:

- Return on equity (ROE) = Net income / Average equity.
- Return on assets (ROA) = Net income / Total assets.
- Cost-to-income ratio = Operating expenses / Operating revenue.
- Net interest margin = Net interest income / Total assets.

ROE is an internal performance measure of shareholder value, and it is by far the most popular measure of performance, because:

- ROE proposes a direct assessment of the financial return of a shareholder’s investment.
- ROE is easily available for analysts, only relying upon public information.
- ROE allows for comparison between different companies or different sectors of the economy.

The ROE rate is a measures the returns made on the initial capital invested. The investors are interested in the return on equity for banks because the equity funds represent money given to a business without a stated return date or other repayment plan. Higher equity returns for the shareholders are always more favorable. The return on equity for banks can also be a competitive advantage seen by the investors. The large listed banks with well-employed equity capital are often very attractive for the capital investments. The higher investments into the banks allow to employ more capital and increase its regulatory requirements and financial returns.

The return on assets (ROA) indicates the percentage of net income compared to bank‘s total assets. The cost-to-income ratios reflects the bank‘s ability to generate profits from a given revenue stream. Calculating this rate the impairment costs are not included into the expenses. The net interest margin is a measure for the income generation capacity of the intermediation function of commercial banks. In the calculation of net interest margin instead of total assets the interest earning assets can be used (European Central Bank, 2010).

2. *Economic measures of banks‘ performance.* These measures take into account the development of shareholders‘ value creation and assess the economic results generated by a bank from its economic assets. The rates mainly focus on the efficiency as a most important element of bank‘s performance. There are two categories of indicators amongst the economic measures:

- Indicators related to the total return of an investment, based on the concept of an opportunity cost.
- Indicators related to the underlying level of risk associated with banks’ activity.

The most popular rate in the first category is the economic value added (EVA). This rate is calculated:

$$EVA = R_f - (W_{cc} \times C_i) - (W_{cd} \times D) \qquad (1.2.1)$$

Where R_f is the return on invested funds; W_{cc} is the weighted average cost of capital; C_i is the invested capital; W_{cd} is the weighted average cost of debt; D is the net debt. EVA takes into account the opportunity cost for shareholders to hold equity in a bank, measuring whether a bank generates an economic rate of return higher than the cost of invested capital in order to increase the market value of the company.

The second category are the indicators related to the underlying level of risk associated with banks’ activity. For a bank to be successful in its operations, managers must weigh complex trade-offs between growth, return and risk, favouring the adoption of risk-adjusted metrics. The

RAROC (risk-adjusted return on capital) is the expected result over economic capital that allows banks to allocate capital to individual business units according to their individual business risk. As a performance evaluation tool, it then assigns capital to business units based on their anticipated economic value added. This measure shares in common with the EVA that it takes into account the bank's cost of capital. But RAROC goes further because it adjusts the value-added in relation to the capital needed (European Central Bank, 2010).

3. Market-based measures of banks‘ performance. These measures characterize the capital market value of a bank compared with the estimated accounting or economic value. The most commonly used rates include:

- Total share return (TSR) is the ratio of dividends and increase of the stock value over the market stock price.
- Price-earnings ratio (P/E) is a ratio of the financial results of the bank over its share price.
- Price-to-book value (P/B) which relates the market value of shareholders' equity to its book value.
- Credit default swap (CDS) is the cost of insuring an unsecured bond of the institution for a given time period (European Central Bank, 2010).

Kumbirai & Webb (2010) also point three groups of banks‘ performance measures.

1. Profitability performance:

- Return on Assets (ROA).
- Return on Equity (ROE).
- Cost to Income Ratio.

2. Liquidity performance. Liquidity indicates the ability of the bank to meet its financial obligations in a timely and effective manner. The following ratios are used to measure liquidity:

- Liquid assets to deposit-borrowing ratio (LADST) = Liquid asset / Customer deposit and short term borrowed funds.
- Net loans to total asset ratio (NLTA) = Net loans / Total assets.
- Net loans to deposit and borrowing (NLDST) = Net loans / Total deposits and short term borrowings.

LADST indicates the percentage of short term obligations that could be met with the bank's liquid assets in the case of sudden withdrawals. NLTA measures the percentage of assets that is tied up in loans. The higher the ratio, the less liquid the bank is. NLDST indicates the percentage of the total deposits locked into non-liquid assets. A high figure denotes lower liquidity.

3. Asset Credit Quality (Credit Performance). While it is expected that banks would bear some bad loans and losses in their lending activities, one of the key objectives of the bank is to minimize such losses. Credit performance evaluates the risks associated with the bank's asset portfolio i.e. the quality of loans issued by the bank. The ratios are:

- Non-performing loans (NPLs) ratio.
- Loan loss reserve to gross loans (LRGL) = Loan loss reserve / Gross loans.

NPLs ratio indicates the proportion of non-performing loans in bank‘s loan portfolio. LRGL indicates the proportion of the total portfolio that has been set aside but not charged off. It is a reserve for losses expressed as a percentage of total loans (Kumbirai, Webb, 2010).

Ongore & Kusa (2013) analyzed the banks‘ performance indicators that are given in Table 1.2.1.

Table 1.2.1

Banks‘ performance indicators (Ongore, Kusa, 2013)

Indicator	Calculation
ROA	Total income to its total assets.
ROE	Net income after taxes divided by total equity capital.
NIM	A percentage of earns on loans in a time period and other assets minus the interest paid on borrowed funds divided by the average amount earning assets.
Capital adequacy	Total capital to total assets.
Asset quality	Non-performing loans to total loans.
Management efficiency	Total operating revenue to total profit.
Liquidity	Total loans to total customer deposit.

ROE is a financial ratio that refers to how much profit a bank earned compared to the total amount of shareholders‘ equity invested or found on the balance sheet. ROA measures the ability of the bank management to generate income by utilizing company assets at their disposal. In other words, it shows how efficiently the resources of the company are used to generate the income. Net interest margin (NIM) is a measure of the difference between the interest income generated by banks and the amount of interest paid out to their lenders (for example, deposits), relative to the amount of their (interest earning) assets. NIM measures the gap between the interest income the bank receives on loans and securities and interest cost of its borrowed funds. It reflects the cost of bank intermediation services and the efficiency of the bank. The higher the net interest margin, the higher the bank‘s profit and the more stable the bank is.

The capital is one of the bank specific factors that influence the level of bank profitability. It is the amount of own fund available to support the bank‘s business and act as a buffer in case of adverse situation. Banks‘ capital creates liquidity for the bank due to the fact that deposits are most fragile and prone to bank runs. Moreover, greater bank capital reduces the chance of distress.

Loans are the major assets of commercial banks that generate the income. The quality of loan portfolio also determines the profitability of banks. Thus, the non-performing loans ratio is the best indicator for the assets quality. The major concern of all commercial banks is to keep the amount of non-performing loans to low level. This is so because high NPLs affect the profitability of the bank. Thus, the low non-performing loans to total loans rate shows the good health of the bank loan portfolio.

The management efficiency is one of the key internal factors that determine the bank profitability. One of this ratios used to measure management quality is operating profit to income ratio. The higher the operating profits to total income (revenue) the more the efficient management is in terms of operational efficiency and income generation.

The liquidity is another factor that determines the level of bank‘s performance. Liquidity refers to the ability of the bank to fulfill its obligations, mainly for depositors. The adequate level of liquidity is positively related with bank profitability. The most common financial ratios that reflect the liquidity position of a bank are customers‘ deposit to total assets and total loans to customers‘ deposits (Ongore, Kusa, 2013).

Duchin & Sosyura (2014) describes some additional banks‘ performance ratios that are commonly used in the banks‘ practice.

Capital ratios:

- Tier-1 risk-based capital ratio = Tier-1 capital / Risk-weighted assets.
- Total risk-based capital ratio = Total risk-based capital / Risk-weighted assets.
- Equity capital ratio = Equity capital / Total assets.

Bank riskiness ratios:

- Asset quality = negative of non-current loans and leases scaled by total loans and leases.
- Liquidity = Cash / Deposits.
- ROA volatility = Standard deviation of quarterly ROA over the trailing year.

Overall credit activity ratio:

- Yield on loan portfolios = Interest and fee income from loans and leases / Total loans and leases (Duchin, Sosyura, 2014).

Caruntu & Romanescu (2008) also suggest three additional commercial banks‘ performance measures:

- Leverage multiplier = (Assets / Capital) × 100%.
- Profit rate = (Net profit / Total revenue) × 100%.
- The margin of assets utilization = (Total income / Total assets) × 100%.

The leverage multiplier is important characteristic for the banks, known also under the title of leverage effect. It measures the degree in which the attraction and using of new resources conduct to an increase of capital rentability. The indicator illustrates how many times a bank successed to multiply the invested capital by resources atraction. The leverage multiplier surpass normally the value 100 and illustrates the fact that involving of new resources is efficient for the bank, respectively when the resources cost is lower then the return costs.

The profit rate is the bank‘s profitability dimension which depends first by the ratio between bank income and expenses, and second by the structure of incomes and the costs of banking activity.

The margin of assets utilization is defined as a ratio between the total operational income and the total assets, illustrating the total incomes obtained from bank‘s assets utilization: incomes from interests, commissions, etc. (Caruntu, Romanescu, 2008).

Supplementing the rates calculated by banks, the external independent banks‘ performance evaluation is also very important. The ratings of international rating agencies reflect the banks‘ activity results and the attractiveness of banks as investments. When properly assigned by rating agencies, such as Standard & Poor’s, Moody’s, and Fitch, the ratings provide the objective opinions about the bank‘s creditworthiness, investment risk, and default probability. Usually the ratings interested parties include owners, customers, management, personnel, investors, competitors, suppliers, creditors, media, regulatory agencies, researchers, and special-interest groups (Chen, Cheng, 2013). Credit rating agencies evaluate banks, firms and governments to determine the likelihood that the issuer will repay the debt or can recover losses in the event of a default. Agencies analyze the information based on their own proprietary standards and then provide a single rating. Moody’s and Standard & Poor dominate nearly 80% of the market, Fitch accounts for nearly 15% of the market, and approximately a dozen more account for the remaining 5%. Credit ratings serve investors who want information about debt instruments but may not have the resources or ability to assess public and non-public information about the firm, bank or government issuing the debt. With the information conveyed by a rating, the investors can drastically reduce their transaction costs within the financial markets. The ratings become a public good that serves the interests of the entire financial system. As the investors and other counterparts rely on ratings their downgrades during an economic downturn could contribute to the worsening of a downturn. But if the agencies do not make these downgrades when the risks markedly increase, the misinformation can also contribute to a developing disaster what happened in the recent financial crisis (Scalet, Kelly, 2012).

The banks‘ ratings also indirectly depend on the macroeconomic conditions in a country because, as it will be proved in further chapters of this sudy, the economic environment highly influences the banks‘ financial results. The rating agencies attribute the ratings for the countries that reflect their economic conditions. These sovereign credit ratings impact the economic environment of countries in a number of ways. The primary importance of ratings is the fact that they influence the interest rates at which countries can obtain credit on the international financial markets. Second, sovereign ratings also influence credit ratings of national banks and companies and affect their attractiveness to foreign investors by directly impacting the ability of firms in that country to access global capital markets. Third, institutional investors may be contractually restricted on the degree of risk they can presume which in turn implies that they cannot invest in debt rated below an agreed level (Teker, Pala, Kent, 2013). The sovereign credit rating standards of the main rating agencies have two aspects: qualitative and quantitative. Qualitative analysis takes several factors into account: a country’s economic structure, political and policy stability, and unexpected political incidents and developments. Quantitative analysis focuses on the research of a country’s macroeconomic indicators. A sovereign credit rating is then expressed as a combination of both qualitative and quantitative consideration. Different credit rating agencies have a different understanding of sovereign credit risk, so the importance assigned to qualitative and quantitative aspects varies (Chen, Cheng, Yang, 2011).

The analysis allows to conclude that the quantitative commercial banks‘ performance measures indicate the different parameters of banks‘ activity. Ensuring the stability of country‘s financial system the calculation and monitoring of these rates are very important for banks because these measures allow to estimate the imperfections in bank‘s performance and to implement the corrective actions. These indicators and ratings depend on various factors, so in the next chapter the main risks of commercial banks will be analyzed that influence the banks‘ performance.

1.3. Commercial banks‘ risks

Risk is a major concern for all financial institutions including banks and the different types of risks accompany their business. Although banks are in the business of taking risk, banking institutions need to avoid, absorb risk or it can be transferred to other participants. In scientific literature and banking practice there is no equable classification of banks‘ risks. Jasevičienė & Valiulienė (2013) maintain that the main commercial banks‘ risks are credit, market, liquidity, operational, concentration, and other (Figure 1.3.1).

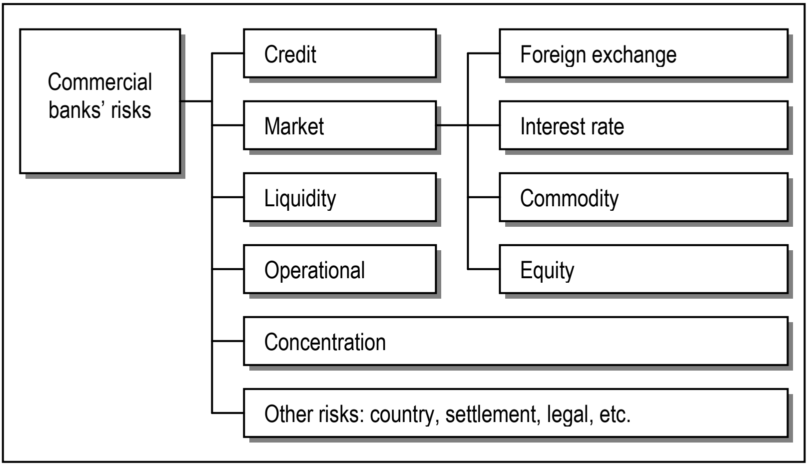


Figure 1.3.1. The main risks of commercial banks (Jasevičienė, Valiulienė, 2013)

According to National Bank of Serbia (2014), the main risks to which the banks are particularly exposed in their operations are:

- Liquidity risk.
- Credit risk.
- Market risks (interest rate risk, foreign exchange risk and risk from change in market price of securities, financial derivatives and commodities).
- Exposure risks.
- Investment risks.

- Risks relating to the country of origin of the entity to which a bank is exposed.
- Operational risk.
- Legal risk.
- Reputational risk.
- Strategic risk.

The European Banking Authority (2013) points the main risks that face the European Union banking sector in Figure 1.3.2.

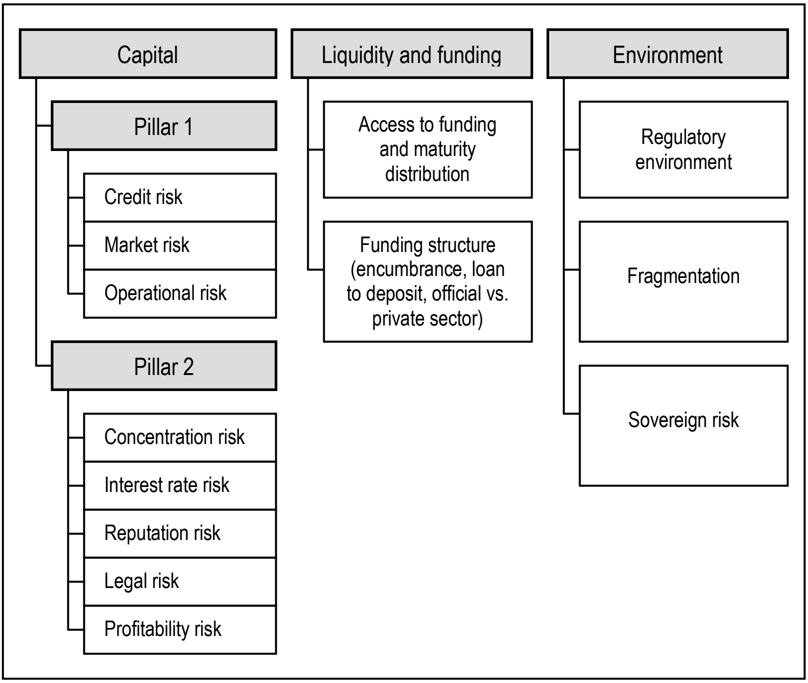


Figure 1.3.2. Main risks facing the EU banking sector (European Banking Authority, 2013)

Faure (2013) describes these main risks that must assess and manage all commercial banks:

- Interest rate risk.
- Market risk.
- Liquidity risk.
- Credit risk.

- Currency risk.
- Counterparty risk.
- Operational risk.

According to Garcia, Gimenez & Guijarro (2013) the financial institutions face these main types of risk:

- Market risk: unexpected changes in prices or rates.
- Credit risk: unexpected changes in value associated with changes in credit quality.
- Liquidity risk: the risk that the costs of adjusting financial positions will increase substantially or that a company will lose access to financing.
- Operational risk: associated to human factors: fraud, system failures, trading errors.
- Systemic risk: chain reaction crises affecting the whole market.

Al-Jarrah (2012) points that the sources of risks facing financial institutions can be decomposed into two main categories: systematic and non-systematic. The systematic or market risk is the risk that has a broad impact on all financial institutions in the market though the magnitude of the impact might not be uniform. Furthermore, the sources of systematic risk are related to variables that are outside of the bank's control. On the other hand, the non-systematic sources of risk vary and related partly to bank-specific variables. Below the analysis of the main banks' risks is given.

Credit risk is the risk of negative effects on the financial result and capital of the bank caused by borrower's default on its obligations to the bank. The credit risk severally in more detailed way will be analyzed in next chapter of this study.

Liquidity risk is the risk of negative effects on the financial result and capital of the bank caused by the bank's inability to meet all its due obligations (National Bank of Serbia, 2014). Al-Jarrah (2012) defines the liquidity risk as the potential loss to an institution from either its inability to meet its obligations or to fund increases in assets as they fall due without incurring unacceptable cost or losses. Liquidity risk for a bank is the risk of not being able to meet obligations in terms of funds demanded by clients. This applies to both sides of the balance sheet of banks, i. e. to withdrawals of deposits and to loans drawn down by borrowing clients in terms of loan commitments made by the banks. Banks are in the financial intermediation business and essentially transmute mostly short-term liquid deposits into loans and investments, which are for the most part non-liquid and have the longer terms. Banks cannot repay all deposits immediately. They rely on the position that only a certain proportion of depositors will demand their funds at the same time, and determines its liquid asset holdings (Faure, 2013). Liquidity risk is not only a source of banks' funding risk (the ability to raise cash to fund the assets), but also has a strong link to market liquidity (the ability to convert assets into cash at a given price). The originate-to-distribute model has made banks increasingly dependent on market liquidity to secure funding by issuing securities on wholesale markets and by trading credits. As a result, banks have become more vulnerable to macroeconomic and financial shocks that may engender liquidity risk (End, 2010).

Operational risk is the risk of negative effects on the financial result and capital of the bank caused by omissions in the work of employees, inadequate internal procedures and processes, inadequate management of information and other systems, and unforeseeable external events (National Bank of Serbia, 2014). Risk measurement techniques of banks now are extended to operational risk, which is the risk of losses resulting from inadequate or failed internal processes, people, and systems or from external events. It is the risk of loss arising from the potential that inadequate information system, technology failure, breaches in internal controls, fraud, unforeseen catastrophes, or any other sources of operational problems (Al-Jarrah, 2012). Operational risk has caused large losses to financial institutions. As a result, the Basel Committee on Banking Supervision mandated a new capital charge against operational risk. This forced the banks to pay attention and to measure operational risk. The most advanced methods for operational risk measurement are based on the frequency of losses over a horizon as well as the severity of losses when they happen. These two statistical distributions are combined into a distribution of losses, which is summarized by the worst loss at a high confidence level. However, the measurement of operational risk is still controversial. Data on large operational risk losses are scarcer than for other types of risk. In addition, losses may not be applicable to banks with different control environments. Even so, institutions that are now measuring operational risk find that this often leads to improvements in internal processes (Jorion, 2010).

Market risk (also called *position* risk, *trading* risk and *price* risk) is the risk of a decline in the market value of financial securities (shares, debt and derivatives) that is caused by unexpected changes in market prices and interest rates, and changes in credit spreads (Faure, 2013). Market risk exposure may be explicit in portfolios of securities and instruments that are actively traded. Conversely, it may be implicit such as interest rate risk due to mismatch of loans and deposits. Therefore, market risk is the risk that the value of on and off-balance sheet positions of a financial institution will be adversely affected by movements in market rates or prices such as interest rates, foreign exchange rates, equity prices, credit spreads and commodity prices resulting in a loss to earnings and capital (Al-Jarrah, 2012). Market risk can be divided into the interest rate and foreign exchange risk.

Interest rate risk is the risk of negative effects on the financial result and capital of the bank caused by changes in interest rates (National Bank of Serbia, 2014). This is the risk of expected earnings being influenced negatively as a result of changes in the pattern and level of interest rates (Faure, 2013). Interest rate risk, the most important type of market risk, arises when there is a mismatch between positions, which are subject to interest rate adjustment within a specified period. The bank's lending, funding and investment activities give rise to interest rate risk. The immediate impact of variation in interest rate is on bank's net interest income, while a long term impact is on bank's net worth since the economic value of bank's assets, liabilities and off-balance sheet exposures are affected (Al-Jarrah, 2012). The interest rates also are influenced by the concentration and competition in the banking market. The risk-shifting effect accounts for fewer firm defaults when loan rates decrease in a more competitive banking market. However, there is also a margin effect that reduces the interest payments from performing loans and thus bank revenues. These two effects work in opposite directions, so that the net effect on bank risk-taking and financial stability is unclear. Often the risk-shifting effect is shown to be dominated by the margin effect in competitive banking markets, such that increased competition increases bank failure risk. Also in a more concentrated banking market the risk-shifting effect can dominate and thus bank failure risk can decline with increased competition. Overall, there is a U-shaped relationship between bank competition in the market, which is measured by the number of banks, and the risk of bank failure (Jimenez, Lopez, Saurina, 2013).

Foreign exchange risk is the risk of negative effects on the financial result and capital of the bank caused by changes in exchange rates (National Bank of Serbia, 2014). The foreign exchange risk is the current or prospective risk to earnings and capital arising from adverse movements in currency exchange rates. It refers to the impact of adverse movement in currency exchange rates on the value of open foreign currency position. The banks are exposed to exchange rate risk, which arises from the maturity mismatching of foreign currency positions. In the foreign exchange business, banks also face the risk of default of the counter parties or settlement risk (Al-Jarrah, 2012). Faure (2013) this risk refers as the currency risk. Certain financial intermediaries‘ asset portfolios are made up of domestic and foreign securities. In addition to their foreign portfolios, banks also play a major role in the derivative foreign exchange markets.

Internationally, banks also have liabilities in foreign currencies. Most large banks are exposed to currency risk, which may be defined as the risk of changes in currency values unfavourably affecting the values of assets and liabilities that are denominated in currencies other than the domestic currency. Because banks, are highly leveraged, their exposure to currency risk can be devastating on their profitability and to their capital position (Faure, 2013).

A special type of market risk is the *risk of change in the market price* of securities, financial derivatives or commodities traded or tradable in the market.

Exposure risks include risks of bank's exposure to a single entity or a group of related entities, and risks of banks' exposure to a single entity related with the bank.

Investment risks include risks of bank's investments in entities that are not entities in the financial sector and in fixed assets.

Country risk is the risk of negative effects on the financial result and capital of the bank due to bank's inability to collect claims from such entity for reasons arising from political, economic or social conditions in such entity's country of origin. Country risk includes political and economic risk, and transfer risk.

Legal risk is the risk of loss caused by penalties or sanctions originating from court disputes due to breach of contractual and legal obligations, and penalties and sanctions pronounced by a regulatory body.

Reputational risk is the risk of loss caused by a negative impact on the market positioning of the bank.

Strategic risk is the risk of loss caused by a lack of a long-term development component in the bank's managing team (National Bank of Serbia, 2014).

Counterparty risk. Each party to a deal has a party on the other side of the deal which may renege on the deal or be a fraudulent party and may not perform in terms of the conditions of the deal. If a party fails to settle a deal the counterparty will do another deal which may not be as favourable and may result a loss as the unsettled deal. This risk is termed as the counterparty or settlement risk (Faure, 2013).

Systemic risk is the likelihood of experiencing a systemic failure, a broad-based breakdown of the financial system that is triggered by a strong systemic event (e.g., a financial institution failure), which severely and negatively impacts the financial markets and the economy in general (Patro, Qi, Sun, 2013). Compared to other sectors the systematic component of default plays a particularly important role in the banking industry. Due to the systemic nature of banking within the financial system there are banks whose default can potentially generate a cascade of failures. In contrast, there are other banks whose default is highly unlikely to generate a cascading failure. Traditionally, the incidence of systemic risk by banks was mostly associated to size but the recent financial crisis has shown that there are other factors having an impact on systemic risk. The individual bank default can also have adverse effects on non-financial companies. For instance, due to its impact on the supply of credit to borrowers, or via perceived increases in the future cost of financing via financial markets if there are closer connections between the banking sector and the overall financial markets (Fiordelisi, Marques-Ibanez, 2013). Systemic risk in banking systems is rooted in interbank relationships. The existing bank risk management techniques or measurements were mainly developed for individual banks, thus they are not very effective in modeling and analyzing systemic risk. The major challenge for modeling systemic risk is capturing the two risk sources:

- The insolvent bank may default on its interbank payment obligations to other banks and cause more banks to fail, thereby triggering a domino effect which is often called contagious bank failures.
- The adverse economic shock may cause significant losses in banks' correlated financial asset portfolios and result in simultaneous failures of multiple banks.

These two systemic risk sources are not independent of each other and often exist at the same time (Hu, Zhao, Hua, Wong, 2012). The systemic risk can be measured by the probability, severity, and exposure of a systemic failure. It is important to distinguish systemic risk from a systemic event and from systemic failure. Systemic risk is not systemic failure, even when such a risk is high. Whether a systemic failure happens or not depends on whether there is a sufficiently strong triggering event and whether that triggering event occurs in a high enough risk environment as to likely cause systemic failure (Patro, Qi, Sun, 2013).

The recent financial crisis triggered a paradigm shift in banking regulation from an essentially microprudential approach aiming at individual institutions to a macroprudential approach aiming at the stability of a whole financial system. From this perspective banks are considered not as isolated business entities, but as interacting institutions whose failure may produce externalities and put the system's stability at risk. A macroprudential approach to banking regulation would internalize negative external effects by imposing systemic capital surcharges so that they reflect banks' individual contributions to the risk of the whole financial system (Puzanova, Dullmann, 2013). Rodriguez-Moreno & Pena (2013) also maintain that until recently, risk management in the financial industry has usually focused on individual institution's market, credit and operational risks and ignored systemic risk. In this vein, the Basel I (1988) and Basel II (2004) Capital Accords advised risk management policy on the basis of the banks' portfolios, ignoring interconnection among banks. However, as the 2007 – 2009 crisis has shown, this bank-specific perspective is not sufficient to appropriately ensure the soundness of the financial system. This is because the risk it poses the system is greater than the sum of the risk faced by individual institutions. Nevertheless, this issue was addressed in the new Basel III (2011) Accord in which capital buffers were improved (quality and quantity) and a macro-prudential overlay proposed to deal with systemic risk (Rodriguez-Moreno, Pena, 2013).

After the analysis of banks‘ risks it can be concluded that this sector meets very high number of different risks types, so the banks‘ managers must understand their exposure and be able to manage these risks. To assure the continuity of banks‘ performance it is necessary to develop the risk management system in every bank considering the regulatory requirements. As the banks play very important role in the country‘s financial system and whole economy, the risk management actions must be directed towards the whole changing environment, because the financial problems of banks mostly depend on the improperly evaluated risk determinants. This is evident according to the recent financial crisis and the macroeconomic deterioration in many countries. While this study is concentated to the credit risk, in the next chapter the main peculiarities of this risk will be analyzed. Further, the main effects of macroeconomic changes on credit risk in banks will be revealed.

1.4. Credit risk management in banks

The Basel Committee on Banking Supervision (BCBS) defines the credit risk as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. It is usually associated with loans and securities that generate interest income, thus being the primary source of bank revenue (Gavalas, Syriopoulos, 2014). According Jasevičienė & Valiulienė (2013) credit risk is the probability that one side of transaction will not be capable to pay back according to the way stated in the contract. Also credit risk can be defined as a category of damage, which might occur due to the debtor's incapability to apply the undertakings stated in the contract or due to the reverse of the debtor's quality of creditworthiness. Credit risk arises from the potential that an obligor is either unwilling to perform on an obligation or its ability to perform such obligation is impaired (Al-Jarrah, 2012).

In a commercial bank, credit risk in lending activities is the possibility that the actual returns on a loan may vary from what the lenders expected, the difference of which represents financial loss. In other words credit risk is the risk of repayment or the possibility that an obligor will fail to perform as agreed and adversely affects capital and earnings. Credit risk is critical since the default of a small number of important borrowers can generate large losses, potentially leading to the insolvency of bank. A bank may strive towards high volume of credit by building up huge level of advances portfolio, but this growth is also accompanied by higher risk of incurring high credit losses. While the credit targets keep on pushing banks towards aggressive approach, the risk management aspect compels them to be rather conservative. To ensure proper risk management without compromising on volume of credit operations, the bank managers have to also ensure that the credit risk management framework is appropriately designed and implemented (Arora, 2012). Higher credit risk may lead to lower profitability of a bank due to a greater likelihood of uncollectible amounts owed by bank clients. In regards to corporate governance, banks should have a system of rules, procedures, and regulations to ensure that agency costs, or costs of minimizing the agency problem and, consequently, moral hazard, are as low as possible, as a way to maintain and increase the shareholders‘ value (Berrios, 2013).

The credit risk of the loan and the debtor is measured by the main indicators: the probability of default (PD), loss given default (LGD), and exposure at default (EAD).

Bank of Lithuania has defined that:

- The probability of default is a probability that the debtor will not apply the undertakings in the period of one year.
- The loss given default is the proportion (expressed in percent) of the loss due to the debtor’s failure to apply the undertaking and value of the position, which appears when undertakings are not applied.
- The exposure at default is the amount of a balance sheet items of bank or non-balance claims included in the banking book at the day of failing to apply the undertakings (Jasevičienė, Valiulienė, 2013).

Studies examining the early warning predictive signals of business default have received widespread and growing attention over last years, since such predictive signals have come to be regarded as extremely important for both the financial and non-financial sectors of any economy.

Clearly, it is of considerable importance for firms within the non-financial sectors to be aware of the probability of default amongst their competitors. However, within the financial sector, referring particularly to the banking industry, an awareness of the probability of default helps to reduce occurrences of non-performing loans and ensures the appropriate capital allocation. It also seems obvious that investors can gain from studies on predictive signals of business default, since an awareness of such signals can clearly assist them to avoid the pursuit of poor investment targets or unwise investment in questionable assets. Signals of corporate default are also undoubtedly of value to the relevant authorities, since they can assist the various bodies to monitor the relevant industries so as to avoid any potential systematic risk (Lu, Shen, Wei, 2013). Therefore, forecasting the bankruptcy of companies is an issue which nowadays is becoming increasingly important and worthwhile to analyze. In most cases, bankruptcy is a continuous process, where it is possible to distinguish several stages – from the emergence of the first signs of financial crisis, through blindness and ignorance towards the financial and nonfinancial symptoms of crisis in a firm, to inappropriate activities that lead to the final phase of the crisis, which is bankruptcy. The process of going bankrupt may even take up to 5 – 6 years. This is not a sudden phenomenon, impossible to predict. Therefore, the earlier warning signals are detected, the more time managers will have for preparing and reacting in subsequent phases of the crisis (Korol, 2013).

Managing the credit risk in banks the regulatory capital according to the BCBS requirements can be calculated by:

- The standardized approach.
- The internal ratings based approach.

In the standardized approach, to be used by less sophisticated banks, Basel II bases risk weightings for credit risk exposure on rating agencies' assessments. Basel II was implemented into EU law in 2005 as the capital requirements directive. The approach has not been changed in the Basel III proposals, nor in the EU's draft implementing Basel III. On the contrary, the reliance on the standardized approach may become even more prevalent, as the internal ratings-based approach has come under much criticism in the post-crisis context. Less known is that the UCITS III directive, governing the asset allocation of investment funds, also requires an investment grade rating for investments by money market funds. The sector has already been raising this issue with the authorities for some time, but they have yet to act (Tichy, 2011).

Under the Basel II guidelines (also incorporated in Basel III), banks are allowed to use their own estimated risk parameters for the purpose of calculating regulatory capital. This is known as the Internal-Ratings-Based (IRB) approach to capital requirements for credit risk. Only banks meeting certain minimum conditions, disclosure requirements, and approval from their national supervisor are allowed to use this approach in estimating capital for various risk exposures. The IRB approach relies on a bank's own assessment of its counterparties and exposures in order to calculate capital requirements for credit risk (Gavalas, Syriopoulos, 2014). These guidelines of the BCBS instigated commercial banks to develop internal credit evaluation models to assess the hazards of borrowers entering into default that are subsequently used as key inputs in the pricing of credit (and its derivatives) and the determination of minimum capital requirements. These models are of importance for regulators in assessing pressures in the corporate sector and for supervisors in identifying early warning signals arising from bank loan portfolios which can prove risky for banks and ultimately for the entire financial system (Bhimani, Gulamhussen, Lopes, 2013). By the IRB banks are responsible for determining PD and demonstrating the appropriateness of techniques used for measuring PD to banking supervisors. In practice, the PD models are necessary not only for regulatory capital calculation as PD models or credit scoring models can be used effectively to control risk selection, manage credit losses, evaluate new loan programs, reduce loan approval processing time, ensure that the existing credit criteria are sound and consistently applied, increase profitability and minimize acquisition costs (Genriha, Voronova, 2012).

The researchers in scientific literature distinguish three main categories of PD calculation models:

- Expert systems.
- Credit scoring models.
- Rating systems (Mačerinskienė, Ivaškevičiūtė, 2008).

The expert systems of credit risk assessment are in the system development process extracted rules that are represented as a decision table. Further this graphical representation can be readily interpreted by credit experts in the loan applicant‘s credit risk assessment process (Baesens, Setiono, Mues, Viaene, Vanthienen, 2001). An expert system is a simply system that uses a collection of membership functions and rules. The rules in an expert system are usually of a form similar to the following: if A is low and B is high then X is medium, where A and B are input variables, X is an output variable. Here low, high, and medium are the variables defined on A, B, and X respectively.

The expert system modeling can be pursued using the following steps:

- Selection of relevant input and output variables.

- Selection a specific type of inference system.
- Design and description of if – then rules.

The obtained rules by the bank's experts must be selected according to their importance. The designed expert system is based on the rules and the defined membership functions by the experts. The expert system is used as the final predicting model for credit assessment of the bank's customers. One of the advantages of this model is the combination of the knowledge of the bank's experts and the rules extracted in the system's development process (Nosratabadi, Nadali, Pourdarab, 2012). The example of expert system is given in Table 1.4.1.

Table 1.4.1

The rules of credit risk assessment expert system (Nosratabadi, Nadali, Pourdarab, 2012)

	Current ratio	Debt ratio	Net benefit ratio	Claims collection period	Credit degree of customer
1.	Medium	High	Low	Medium	Low
2.	High	Low	Medium	Medium	Medium
3.	Medium	Low	High	-	High
4.	Medium	High	-	Low	Medium
5.	High	Low	Low	High	Medium
6.	Low	Medium	Medium	High	Low
7.	-	-	High	Low	High
8.	High	Low	Medium	Medium	Medium
9.	High	Medium	High	Low	High
10.	Medium	High	Medium	Low	Medium
11.	-	High	Low	-	Low
12.	Low	Medium	Medium	Medium	Medium

Judgmental or expert-based models are established through set of formal rule-of-thumb quantitative criteria. It is an easiest way to incorporate the best practices and the knowledge of credit managers into formal automated decision rules (Nikolic, Zarkic-Joksimovic, Stojanovski, Joksimovic, 2013). But the environment is complex and it is impossible for decision makers, even highly specialized banks, to achieve full information about the objective risk properties of borrowers. Strict optimization therefore is not possible due to a lack of access to and computability of information. Thus, decision-makers develop decisional rules that abstract from the complex environment and rely on a reduced subset of information. After an evolutionary process, only those rules survive that enable the prevalent (presumably unalterable) probability distribution to be accurately approximated. The information that is required for these risk-evaluation procedures however is not easy to obtain, and problems of asymmetric information are common. It is possible that the risk exposure of a potential borrower cannot be fully identified. Consequently, it is not possible to match each borrower with the perfectly correct, risk-adjusted loan rate (Ramskogler, 2011).

The scoring models apply statistical data processing methods and historical data to obtain borrower's credit score, which can be used to allocate the borrowers to groups. There are many definitions for credit scoring, but most of them have mentioned credit scoring as a classification method, which categories customers into two main groups:

- Creditworthy customers.
- High default risk customers.

The benefits of customer credit scoring can be explained by decreasing the cost of credit analysis, easily making decisions for loan applicants and reducing customer credit risk. With a large number of customer credit cards and customer loan applications, financial institutes need to develop various kinds of credit scoring models to make better credit decisions. Therefore, new models should be developed to make more accurate predictions (Siami, Gholamian, Basiri, 2013). Credit scoring models play an important role in contemporary banking risk management practice. They contribute to the key requirement in loan approval process, which is to accurately and efficiently quantify the level of credit risk associated with a customer. The credit scoring models objective is to predict future behavior in terms of credit risk by relying on past experience of customers with similar characteristics. The level of credit risk of a borrower is associated with probability that it will default on approved loan over given time horizon, usually 1 year. The main task of credit scoring model is to provide discrimination between good and bad corporate entities in terms of their creditworthiness. Discrimination ability is the key indicator of model successfulness. The higher the discrimination power the more precise the credit scoring model will be (Nikolic, Zarkic-Joksimovic, Stojanovski, Joksimovic, 2013).

The models of this type are based on the determination of one quantitative measure for a borrower, which is obtained when customer's data is entered into statistical models. The scientists distinguish these forms of methods: linear probability model, probit model, artificial neural networks, decision tree, logit model, discriminant analysis (Mačerinskienė, Ivaškevičiūtė, 2008). According to Zhang, Gao & Shi (2014) mostly these methods have been proposed for credit scoring: logistic regression, probit regression, nearest neighbour analysis, Bayesian network, artificial neural networks, decision trees, genetic algorithm, multiple criteria decision making, support vector machine, and so on. However, Blanco, Pino-Mejias, Lara & Rayo (2013) affirm that the strict assumptions (linearity, normality and independence among predictor variables) of the traditional statistical models, together with the pre-existing functional form relating response variables to predictor variables, limit their application in the real world. For these reasons, in recent years, non-parametric statistical models, such as the *k*-nearest neighbour algorithm, support vector machines, decision tree and artificial neural network models have been successfully applied to credit scoring problems. Of these, artificial neural networks (ANNs) constitute one of the most powerful tools for pattern classification due to their nonlinear and non-parametric adaptive-learning properties. Many studies have been conducted that have compared ANNs with other traditional classification techniques in the field of credit scoring models, since the default prediction accuracies of ANNs are better than those using classic linear discriminant analysis and logistic regression (Blanco, Pino-Mejias, Lara, Rayo, 2013).

The default probability is usually obtained as a linear function from a set of economic and financial variables that provide information about different aspects of corporate clients: size, liquidity, solvency, profitability, debt, etc. A scoring or ranking model combines these variables in order to obtain an accurate assessment of default probability, thus serving to automate the evaluation process of default risk measurement within a financial institution. In order to obtain the aforementioned function, a set of explanatory variables x and a binary variable y corresponding with the company situation are related: y takes the value of 1 if the company has defaulted, and 0 otherwise. The problem can be summarized as finding a function that relates the dependent variable (default) with the set of explanatory variables (Garcia, Gimenez, Guijarro, 2013). Models constructed on the basis of financial reporting information assume that accounting statements give an objective view of the financial standing of firms. However, there is evidence that firms generally, and especially those entering into default, have incentives to dress their accounts. Non-financial information can play an important role not only in moderating the influence of financial reporting information, but also in understanding other factors driving default, especially for non-listed firms for which financial reporting information, especially in the start-up phase, may altogether not be available. Criticisms of the sole use of financial information in predicting default have led to the use of non-financial information such as age and size which are associated with stable cash flow streams. Both age and size have been found to significantly influence economic distress (Bhimani, Gulamhussen, Lopes, 2013).

For the accurate loan applicant‘s classification the data quality is very important. Data quality can be measured by many dimensions, such as accuracy, completeness, timeliness, relevance, objectivity, believability and other. Some of these dimensions (e.g., accuracy and objectivity) lend themselves to objective measurement that is intrinsic to the data itself and is independent from the context in which the data are used. There are, however, the dimensions that cannot be measured objectively. For example, relevance and believability that tend to vary with the usage context. Data relevance mostly depends on the task, because data that are highly relevant for one task may be irrelevant for another. To understand the contextual effects of data quality, it is important to take factors that pertain to the use of data into account. Also the most frequently mentioned data quality dimensions in the representation and access categories are representational consistency, easily-understandable, accessibility and security (Moges, Dejaeger, Lemahieu, Baesens, 2013). In general, for decision-makers, a high degree of informational quality entails the more efficient loan portfolio management which involves the lower costs (Dragota, Tilica, 2014).

Credit scoring models have been extensively used to evaluate the credit risk of consumers or enterprises, and they can classify the applicants as either accepted or rejected according to their specific characteristics (Zhang, Gao, Shi, 2014). Contemporary risk management practice emphasizes and promotes the use of credit scoring models for various asset classes of bank's credit portfolio. Retail banks use application and behavioral credit scoring models for automation of loan approval process for individuals. By employing process automation, the bank's staff costs are reduced, loan approval process is simplified, speeded up and more control on approval decision making process is attained (Nikolic, Zarkic-Joksimovic, Stojanovski, Joksimovic, 2013). But it is also concluded that main imperfections in individual loan evaluation using scoring models are that in creation of models characteristics of bank's borrowers who were granted a loan are used, while it is not known whether the persons (or entities) whose applications for loans were rejected would have been able to meet their obligations or not. Additionally, the size of groups of borrowers that met their obligations and failed to meet their obligations are not equal (Mačerinskienė, Ivaškevičiūtė, 2008).

The more complex compared to credit scoring models are the credit rating systems. Implementing the BCBS requirements banks must classify the loan applicants into not less than 8 risk groups (ratings). The rating objective is to set accurate ratings that inform about the probability of default over a given time horizon. With a ratings-based credit risk assessment, the rating determines the interest rate of loan and the regulatory capital hold by bank for the particular loan. The banks assign high credit ratings, leading to lower interest rates for the borrowing firm that has the lower default probability. Also banks assign low credit ratings, leading to higher interest rates for the borrowing firm with a higher default probability (Manso, 2013). Credit ratings are the assessments of the creditworthiness of debtors, and involve a hierarchical ranking process by which credit is classified into different risk categories. The banks develop their own rating scale that is very similar as of the credit rating agencies, such as Standard & Poor‘s, Moody’s and Fitch (Table 1.4.2).

Table 1.4.2

Rating scales used by Moody‘s and Standard & Poor‘s (Iyengar, 2012)

No.	Moody‘s ratings	Standard & Poor‘s ratings	Interpretation		
			Grading	Credit risk	Capacity to meet financial commitment
1.	Aaa	AAA	Highest quality	Minimal	Extremely strong
2.	Aa1	AA+	High quality	Very low	Very strong
3.	Aa2	AA			
4.	Aa3	AA-			
5.	A1	A+	Upper-medium	Low	Still strong
6.	A2	A			
7.	A3	A-			
8.	Baa1	BBB+	Medium	Moderate	Weakened
9.	Baa2	BBB			
10.	Baa3	BBB-			
11.	Ba1	BB+	Lower-medium	Substantial	Inadequate
12.	Ba2	BB			
13.	Ba3	BB-			
14.	B1	B+	Low	High	Impaired
15.	B2	B			
16.	B3	B-			
17.	Caa1	CCC+	Poor	Very high	Not likely
18.	Caa2	CCC			
19.	Caa3	CCC-			
20.	Ca1	CC+	Very low	Very near default	Vulnerable to non-payment
21.	Ca2	CC			
22.	Ca3	CC-			
23.	C1	C+	Lowest	In default	Highly vulnerable to non-payment
24.	C2	C			
25.	C3	C-			

The credit rating is a benchmark measure of default probability, namely, of a debtor failing to meet its obligations under the debt contract, and of the expected associated losses. Low ratings indicate high risk of default. Banks use credit ratings to indicate the likelihood of receiving their money back in accordance with the debt contract terms (Chen, Cheng, 2013).

In addition to the enterprises‘ PD assessment methods, the market models also are being applied. In this case the default is related to the capital structure of firms: firms default on their obligations if the market value of their assets falls below a threshold determined by the respective default model. Restricted liability creates incentives for partners to default and to shift ownership to lenders and consequently ensure a minimum limit in the settlement of their equity. This framework is the basis of the benchmark credit risk models (e.g. the JP Morgan’s CreditMetrics and Moody’s KMV). The inputs required for these models, in particular are market-based data that are available for listed firms but not for non-listed firms, what limits their applicability (Bhimani, Gulamhussen, Lopes, 2013).

The most central risk parameter of the loans is not only the previously analyzed probability of default (PD), but also the loss given default (LGD) is very important. A decade ago, the focus of academic research and banking practice was mainly on the prediction of PDs, but more recently, substantial effort has been put into modeling LGDs (Gurtler, Hibbeln, 2013). Loss Given Default is the loss incurred by a financial institution when an obligor defaults on a loan, given as the fraction of exposure at default (EAD) unpaid after some period of time. It is usual for LGD to have a value between 0 and 1, where 0 means that the balance is fully recovered and 1 means the total loss of EAD. LGD is an important value that, for several reasons, banks need to estimate accurately:

- Firstly, it can be used along with the probability of default (PD) and EAD to estimate the expected financial loss.
- Secondly, a forecast of LGD for an individual can help to determine the collection policy to be used for that individual following default. For example, if a high LGD is expected, then more effort may be employed to help reduce this loss.
- Thirdly, an estimate of LGD, and therefore of the portfolio financial risk, is an integral part of the operational calculation of capital requirements to cover credit loss during extreme economic conditions (Bellotti, Crook, 2012).

The requirements of the Basel II/III framework allow for banks to provide their own estimates of the LGD when using the advanced internal ratings based (A-IRB) approach for corporates or the IRB approach for retail exposures. In addition to the regulatory requirement, accurate predictions of LGDs are important for risk-based decision making, e.g. the risk-adjusted pricing of loans, economic capital calculations, and the pricing of asset-backed securities or credit derivatives. Consequently, banks using LGD models with high predictive power can generate competitive advantages, whereas weak predictions can lead to adverse selection (Gurtler, Hibbeln, 2013).

Taking the analyzed 3 credit risk measures (PD, LGD and EAD) together the expected credit losses are calculated as the product of the average probability of default (PD) for the loan portfolio, the exposure at default (EAD) and the loss given default (LGD). The losses stemming from the described credit risk calculations can to some extent be covered by available net income. Therefore, bank income is taken into account as the first line of defense against the losses. In particular, it is assumed that banks will use all available income to sustain their capital adequacy ratio at the same level when hit by a financial shock. If income is insufficient to fully absorb the losses emerging in the macroeconomic scenario under consideration, the losses are deducted from bank capital (Fungačova, Jakubik, 2013).

There are the particular peculiarities in the projects‘ credit risk assessment. The project finance has two sources of funds: debt and equity. Banks are the largest providers of debt capital in project finance and the financial structure of the project (leverage ratio) is very important in convincing bankers to provide capital. It implies that banks must pay particular attention to the evaluation of the credit risk of the project. The failure of the project, and the subsequent borrowers' insolvency, may damage lenders heavily.

The assessment of economic and financial feasibility of the project made by the banks should primarily evaluate the expected economic return of the project on medium and long term, rather than focusing on collaterals provided by sponsors or third parties. To assess the creditworthiness of a project is necessary to carry out a feasibility study. Preliminary test of project practicability is the first step for banks. The project should be technically feasible and economically viable. A static analysis of the project focuses on assets characteristics, tangibility and marketability of corporate assets, as well as firm's solvency ratios. In the standard corporate lending the lender has security over tangible assets. A dynamic analysis is necessary in funding project finance because lender's primary security is the future revenue stream of the project. It is a different type of analysis that focuses on the expected economic and financial returns associated with the project. In particular, a lender should deeply evaluate the degree of innovation of the project, the professional skills of people who will execute and manage the project, the capabilities, competences, and knowledge of firms involved in the project, the reaction of the target market to the introduction of new services and products (Scannella, 2013).

The real effects of bank lending depend on the agency costs of investment faced by a firm, which are negligible at times when profits and the share of internal finance are large, when uncertainty about the future and therefore information asymmetries is perceived to be low, when alternative sources of financing (other banks, non-bank intermediaries, bond markets or heavier recourse to commercial credit) are easier to find, by contrast, the premium on bank finance can increase rapidly when cash flows dryup, uncertainty increases, and non-bank financial flows fall, as is typically the case during economic downturn (Gaiotti, 2013). In lending practice the higher credit risk is associated with collateral required by banks. The rationale underlying this argument is that banks can sort the borrowers from information they have on their quality. Consequently, they charge riskier borrowers with higher rates, and simultaneously require more collateral from these borrowers. Because the collateral reduces its loss, the bank would be more inclined to demand collateral to clients with a higher credit risk. The collateral allows a reduction of the loan loss for the bank in the event of default of the loan (Blazy, Weill, 2013).

In lending practice also there is a tendency that it is more difficult to obtain credits for small enterprises. But these enterprises have some particular strengths. Small companies are known to be able to react quickly and to find creative solutions when faced with the increasing turbulence in the global markets and with the wide range of ensuing problems regarding competitiveness, social, cultural issues, and technological innovation. Small businesses are able to effectively provide products and services for market segments, which it may be too difficult, or not sufficiently profitable, for large firms to reach. The real strength of small enterprises is their essentially personal character in all aspects of company structure: ownership, management and operating systems. Owners and managers are often one and the same people and tend to be personality driven and opportunistic or instinctive in approach. The small enterprises‘ growth is a result of clear, positively motivated business intentions and actions on the part of the owner-manager, driven by the belief that the owner-manager can produce the desired outcomes (Ciampi, Gordini, 2013).

The another factor increasing the credit risk of the borrowers is their over-indebtedness. On the financing or liability side during the financial crisis many banks backed by cash collections from mortgage loans, suffered losses due to excessive risk taking by lending money to people with insufficient ability to repay. The increase in bank’s liabilities or leverage, if large and lasting enough, will trigger a financial crisis. This is complicated by having long-term assets in balance sheets, such as mortgage loans, being financed by short-term liabilities. Consequently, banks are obliged to pay cash before asset driven cash collections occur, increasing their illiquidity (Berrios, 2013).

Most households are able to manage their financial obligations and to avoid credit risks. But for the significant part of households the huge loans are actually a problem. Those who have little wealth or no safety net are vulnerable if anything unexpected occurs in the economical environment or their own economies. In general, people are considered over-indebted if they have difficulty meeting their financial commitments related to loans or the payment of bills. Over-indebtedness refers to a situation where a person or household does not have enough money to pay debt instalments and interests after other necessary expenditures have been paid. The definition of over-indebtedness presupposes that debt problems have continued for a fairly long time. According to a common European definition of over-indebtedness by the European Commission, consumers are considered to be over-indebted if they have difficulty meeting their commitments related to servicing secured or unsecured debts or payments of rent, utility or other household bills (Raijas, Lehtinen, Leskinen, 2010). The rise of the instability of a banking system becomes apparent when the level of indebtedness of an economic unit grows constantly. The influence of the external negative shocks starts to play a more crucial role. The internal dynamics of the economy is important, but the growth of instability appears exactly with the changes of external negative shock. Various countries have different levels of aggregated indebtedness, and there is no correct answer when the level of aggregated indebtedness becomes crucial for a banking system. The internal dynamics of the economy and the system of state interventions provide for its existence within definite limits. In other words, the financial markets are constantly unstable and external shocks, as the reason for the system becoming unstable, should always be taken into consideration (Fanstein, Novikov, 2011).

The causes of debtors‘ over-indebtedness are mainly related to the misundersatnding of basic economic patterns and over-confidence managing the finances. It can be argued that what went wrong is that people made the wrong decisions for a number of years, based on the assumption that asset prices would remain high and would continue to rise. The aggregate saving rate fell to zero and many people borrowed even to finance the consumption. The leverage ratios of households, firms, and institutions went up. When the whole economy in many countries went into a downward trend and the large fall in asset values occurred, people realized they were overleveraged and they had saved too little. They started saving to pay down debt and build up their assets (Allen, Carletti, 2010). The mortgage lenders often abstain from foreclosing and enforcing repayment because of low recovery rates and lengthy and costly legal procedures. Therefore individuals with negative equity have a strong incentive to default. Consistent with this view, the borrowers who have experienced a small financial shock, are more likely to default on mortgage debt than on other forms of debt (e.g., credit cards). If many borrowers with large housing price declines choose to default, also borrowers with positive net value may decide to delay payments, anticipating a possible failure of their lender. If the lender fails, their future relational value would be destroyed, and they would prefer to hold the cash until the winding-up of the bank. The downward trend in house prices during the subprime crisis was reinforced by the decision of many borrowers who exercised their implicit put options and walked away from their houses and their mortgage obligations (Trautmann, Vlahu, 2013). The risks of an economic environment are materialized if, for instance, the economy takes a downturn, unemployment increases or interest rates go up. Many consumers' economic situation is marked by short-term employment relationships providing an uncertain income. Despite positive development in the national economy, the number of low income persons can be nod decreasing. Among the different consumer groups, it is students, pensioners, unemployed people, and single parents that most often have low incomes. An irregular, uncertain, or low income makes it difficult to plan personal economy and long-term use of money. When a person's income is low or irregular, he is tempted to compensate for his scanty earnings by taking consumer credit, usually of the most expensive kind (Raijas, Lehtinen, Leskinen, 2010).

Forming the loan portfolio banks meet the problems of concentration and diversification. There are some research works on the relationship between diversification and performance of banks, however there is no consensus so far, because findings of different countries vary, with evidences supporting both opinions. On one hand, traditional banking theory suggests that banks should diversify their loans to decrease credit risk, which is also in accordance with portfolio theory. The view is due to asymmetric information, the diversification reduces financial intermediation costs. In practice, Basel Committee on Banking Supervision reported that many banking crises in the last three decades were caused by concentration, indicating that risk is highly associated with diversification. On the other hand, corporate finance theory states that firms would enjoy additional benefits resulting from reduced cost if they concentrate their activities on specific sectors which they have expertise in or are familiar with. In addition, the diversification strategy is less attractive because it also induces competition (Chen, Wei, Zhang, 2013).

Managing the credit risk the information sharing between credit institutions can reduce the possible loss caused by the debtors‘ insolvency. Theoretical and empirical research has examined various effects of credit information sharing on lenders, borrowers, and economic activity. Most of these studies document significantly positive effects of information sharing, such as an increase in the supply of credit by banks, a decrease in the costs of credit and realized default rates, and an increase in GDP growth. This finding can largely be attributed to the disciplining effect of credit information sharing around its introduction. It becomes more costly for firms to default or to be past due with payments when credit information is shared not only among current but also potential future lenders (Dierkes, Erner, Langer, Norden, 2013).

The analysis of main credit risk peculiarities has shown that the management of this risk is the concern for every bank, because the banks are enabled to develop their own credit risk assessment systems that must meet the requirements of supervising institutions. The various statistical and artificial intelligence methods are being applied for the credit risk assessment and the different sets of variables are being analyzed. The estimation of default probability of a loan applicant is usually obtained through taking into account the financial indicators, credit history of the borrower and the nature of investment. But the recent financial crisis has shown that there is another very important aspect which needs to be taken into consideration – the status of the general economy. Business cycle can have great impact on the credit portfolio of banks. This can intuitively be traced back to the relationship of business cycle and the individual firms within an industry. Also the Basel III guidelines propose the necessity to estimate the macroeconomic factors in the credit risk assessment process. So in the next chapter the impact of macroeconomic environment on the credit risk in banks estimated by other scientific researches will be analyzed.

1.5. Macroeconomic impact on credit risk in banks

The economic cycle is quite a natural phenomenon in the market economics which consists of the stages of growth, peak, recession and a bottom as the lowest point of the economic decline. In the top phase of the cycle the economics of countries is over-heated and accompanied with high gross domestic product (GDP), the low unemployment rate and the high inflation starts to cause problems. Conversely, the boom is followed by the recession phase which is closely associated with a decrease of the employment and also with a decline of the pressure on inflation (Baran, 2011). According to Kaihatsu & Kurozumi (2014), the main sources of economic fluctuations are: output growth, consumption growth, investment growth, labor, wage growth, consumption price inflation, changes in the relative price of investment, the economic policy, the loans rate, loans growth, and net worth growth.

During last two decades, the world has experienced a large number of financial crises in emerging market economies. These financial crises were not confined individual economy, but affected directly or indirectly to almost all the countries of the world. As a result, a number of international organizations, governments, and private sector institutions have begun to develop the early warning systems as a monitoring instruments to detect the possible financial crisis in advance and to alert policy makers to take the preventive actions (Yoon, Park, 2014). Each financial crisis has its own individual features, but most of them have a number of common characteristics. According to Socol (2013), the crises have the following evolution:

- The events start with an exogenous shock outside the macroeconomic system (a war, adoption, to a large extent, of a new invention, a political event, etc.).
- The extension of the bank loan results in the increase of the money supply and it supplies the economic growth. This may result in the creation of new banks, in the development of new loan instruments and in the unlimited extension of the personal loans until the moment when the phenomenon practically becomes impossible to be controlled.
- The demand increases, the prices also get increased, new profit opportunities, new companies and investors appear. The revenues increases stimulate the additional investments what further increase the revenues.
- The economic bubbles develop. The excessive trade extends from one country to another, through arbitration for goods and internationally traded assets, the capital flows or, simply, the psychological effects of transmission. The interest rates, the velocity of money and the prices, all of them continue to get increased. Some initiates profit and sell everything.
- Financial disaster. Everybody start to be aware of development of a rush for cash in order to get rid of assets and to obtain cash. This resulting in some speculative lenders‘ incapacity to return their loans. As the disaster persists, the speculators realize that

the market cannot grow more. It is the moment for them to draw back, and the rush to transform the real or financial assets into cash for a long term turns into panic.

- Crisis. The trigger may be the failure of a bank or of a big company, the revealing of a cheat or of a defalcation, or a price decrease of the initial speculation object. The prices get decreased. The bankruptcies get increased. Closeout is sometimes required, but this cannot degenerate into panic. The banks cease to grant loans for collateral assets, of which prices get decreased (Socol, 2013).

Because the economies of different countries are related, the financial crisis can also spread to other countries. The contagion is the cross-country transmission of shocks or general cross-country spillover effects. The literature includes two groups of theories explaining crisis transmission mechanisms. One group argues that the economic fundamentals of different countries are interconnected by their cross-border flows of goods, services, and capital. When a crisis originates in one country, this interdependence of economies through real and financial linkages becomes a carrier of crisis. In addition, global phenomena or common shocks such as a major economic shift in industrial countries, significant changes in oil prices or exchange rates may adversely affect the economic fundamentals of several economies simultaneously, and potentially may cause a crisis. Another group of theories argues that financial crisis spreads from one country to another due to market imperfections or the behaviour of international investors. Information asymmetries make investors more uncertain about the actual economic fundamentals of a country. A crisis in one country may give a wake-up call to international investors to reassess the risks in other countries, and uninformed or less informed investors may find it difficult to extract the informed signal from the falling price and follow the strategies of better informed investors, generating excess co-movements across the markets (Dungey, Gajurel, 2014). The recurrence of financial crises in the recent past questioned the benefits of the increasing international financial integration and challenged countries to find ways how to protect the domestic economy from the downside risks of financial openness (Steiner, 2014).

To avoid or mitigate the crisis in the country the particular factors have significant impact on it. According to Prochniak (2011), the most important economic growth determinants of the countries are investment rate (including foreign direct investments), human capital measured by the education level of the labour force, financial sector development, good fiscal stance (low budget deficit and low public debt), economic structure (high services share in GDP), low interest rates and low inflation, population structure (high share of working age population), development of information technology and communications, high private sector share in GDP and favourable institutional environment: economic freedom, progress in market and structural reforms (Prochniak, 2011).

In the literature there is an important distinction between the kinds of factors that can affect banking credit risk:

- Factors influencing the unsystematic credit risk.
- Factors influencing the systematic credit risk.

The factors influencing the unsystematic credit risk are the specific factors of borrowers:

- The individual borrower‘s specific characteristics like the individual personality, financial solvency and capital, credit insurance.
- The companies‘ specific characteristics like management, financial position, sources of funds and financial reporting, their ability to pay the loan and specific factors of the industry sector (Castro, 2013).

Casey & O‘Toole (2014) include a number of unsystematic control variables in their empirical model to control the firm creditworthiness and risk. Specifically, they split firm risk and quality into two separate categories:

- Trading quality, demand and production risk.
- Financial risk.

To control for the former, they include controls of firm‘s profitability, historical and predicted sales growth, business outlook, labour and non-labour costs. To control for financial risk, the researchers include indicators for changes in firms‘ capital positions, debt to asset ratios, interest expenses and credit histories (Casey, O‘Toole, 2014).

The factors influencing the systematic credit risk are:

- Macroeconomic factors like the employment rate, growth in gross domestic product, stock index, inflation rate, and exchange rate movements, etc.
- Changes in economic policies like changes in monetary and tax policies, economic legislation changes, as well as import restrictions and export stimulation.
- Political changes or changes in the goals of leading political parties.

All these variables can have an important influence on the likelihood of borrowers paying their debts, but as changes in economic policies and political changes are difficult to examine, the literature has mainly focussed on the macroeconomic factors (Castro, 2013). According to Teker, Pala & Kent (2013) the main systematic credit risk variables are nine economic (GDP per capita, inflation rate, trade balance, international reserves, fiscal balance, export growth rate, debt to GDP, financial depth and efficiency, and exchange rate) and three political variables: political stability, government effectiveness and corruption levels. Macroeconomic shocks can feed into banks' balance sheets through the credit risk transmission channel following deterioration in the credit quality of loan portfolios that can cause significant losses for banks and may even mark the onset of a banking crisis. A large number of researches found that bank loan portfolio quality can be explained by both macroeconomic conditions and other idiosyncratic features. Recent studies show that factors like borrower type, loan category, quality of institutions, and form of banking organization are major determinants of credit risk (Love, Ariss, 2014).

There is a close link between business cycles, bank credit, and banking crises. The financial crises were often accompanied by deep and lasting recessions. According to the financial instability hypothesis a period of prolonged prosperity may induce speculative euphoria and excess borrowing which push the economy on the brink. This view became popular during the recent world financial crisis and challenged the consensus macroeconomic models based on rational behavior of agents (Bucher, Dietrich, Hauck, 2013). The expansion phase of the economy is usually characterized by a relatively low rate of non-performing loans, as both consumers and firms face a sufficient stream of income and revenues to service their debts. However, as the booming period continues, credit is extended to lower-quality debtors and subsequently, when the recession phase sets in, the non-performing loans tend to increase. The unemployment rate may provide additional information regarding the impact of economic conditions. An increase in the unemployment rate should influence negatively the cash flow streams of households and increase the debt burden. With regards to firms, increases in unemployment may signal a decrease in production as a consequence of a drop in effective demand. This may lead to a decrease in revenues and a fragile debt condition (Castro, 2013). The empirical literature provides evidence on the linkages between business cycles and performance in banking. In a booming economy, revenues of households and businesses improve and increase the ability to service debt payments. In their quest to increase market share during a boom, banks extend their lending activities often reaching out for lower credit quality borrowers. Especially the low interest rates are a driving force of the housing bubbles (Steiner, 2014). However, the extension of credit to subprime borrowers inevitably increases non-performing loans (NPLs) when a recession subsides and asset prices fall. Still, it is well known that poor asset quality is one of the major causes of bank failures. Thus, macroeconomic shocks are inevitably transmitted to banks' balance sheets through a worsening of their credit portfolio. To examine the macroeconomic determinants of credit risk, studies generally use different proxiesof loan quality, including loan loss provisions, NPLs, and loan write-offs (Love, Ariss, 2014). The financial crisis in 2008 made people pay more attention to the issues of mortgages. After all, they paid a great price for the default problems. Intuitively, lending institutions increased risk premiums as the default risk increased. This result shows that the real estate investors may default if lending institutions (banks) require excessive risk premiums. Interest rates and house prices are the primary factors affecting the mortgage default or payment options (Chih-Hsing, Ming-Chi, Wen-Yuan, 2014).

Business cycles can have great impact on the credit portfolio of banks because the firms‘ profitability and solvency changes with the business cycle. Apart from the management problems and other firm specific issues that would cause a loss in its profitability, changes in market and economic conditions (such as changes in interest rates, stock market, exchanges rate, unemployment rates, and industry specific shocks) may affect the overall profitability of the firm. In general, in an expansion, demand is high and business is strong: firms have higher probability to profit and therefore fewer defaults will happen. Whereas during a recession, keeping a business profitable is more challenging and it is more likely for a firm to default. Therefore the firm's performance, which is associated with its risk profile, is directly tied to the business cycle and the whole state of macroeconomy (Qu, 2008). The banks and other market participants in credit boom period were simply unaware of the level of risks they were taking. In particular the bank managers may simply have grossly underestimated the shortcomings of their own risk models and their processes of internal control (Milne, 2014).

Hence, it appears that banks' asset quality reinforces the business cycle in a procyclical manner and the high NPLs that many countries currently face adversely affect the pace of economic recovery. When the asset bubble began to burst, financial institutions woridwide had to concede that the value of loan portfolios was being strongly eroded. This again led to a fatal negative spiral, with a loss of confidence in the individual financial institutions and the entire market. Liquidity in the markets dried up completely, and on a global scale the first real woridwide crisis in the financial system became a reality. Restoring of financial confidence in some countries led to a permanent transfer of losses to the public sector, as the private sector‘s risk takers were bought out. In more polemical terms: profits from the excesses of the preceding period were privatised, while the losses were socialised. Having said that, there was little inclination among political decision-makers to try out the alternative – allow the financial system to fail. The real economy is far too dependent on a well-functioning financial system for that to be allowed to happen (Rohde, 2011).

The initial level of liquidity and banking development are positively linked to long-term economic growth, productivity growth and capital accumulation (Asal, 2012). Banks are vulnerable to external shocks because they finance illiquid assets with liquid liabilities and such fundamental shocks are the main driver of financial crises. In the business cycle view of bank instability the economic agents observe a leading economic indicators that correlate with future asset returns. With the unfolding of economic recessions, the value of bank assets is reduced and the value of the collateral that is pledged by borrowers may also be impaired, thereby increasing the likelihood of a banking crisis (Love, Ariss, 2014).

The financial sector development promotes economic growth by enhancing physical capital accumulation. Following this evidence, the studies of Ngare, Nyamongo & Misati (2014) affirmed that financial sector development is key to economic growth subject to dismantling financial repression. The literature has recognized the important role played by credit markets in shaping real outcomes. A credit expansion by reducing interest rates would increase investment relative to savings. The rising consumer prices as a result of increased consumption, indicates that consumer goods are more profitable than producer goods, thus forcing producers to reassess investment plans. That situation would eventually cause recession. An alternative theory which stresses the importance of financial institutions in understanding business cycles suggests that the financial innovations and periods of economic tranquility will encourage greater risk taking. This will result in excessive leverage and a lower quality of investment during the rising cycle. The overheating economy will bring about a tightening in monetary policy which will eventually cause recession (Karfakis, 2013). In the economy the disposable income, corporate profits, and total spending are highly related. The disposable income and revolving credit cause the aggregate spending. Spending in turn causes corporate profits. There is, however, some feedback effect, as spending causes disposable income. Revolving credit as well as corporate profits also causes disposable income. The over-expansion of credit when profits and house prices are declining and the informational asymmetries on the quality of credit slows the economy and leads to the recession (Dore, Singh, 2012).

The researchers found a substantial increase in credit risk during the recent financial crisis period and documented the impact of GDP growth, share price indices, unemployment rate, interest rates, credit growth and the real exchange rate. The results support the hypothesis that the growth of finance harms banking performance and deteriorates NPLs dynamics due to the overheating of the economies. When the economy of a country deteriorates, the downgrades in the credit quality of an entire loan portfolio is typical signalling deterioration in the credit quality of firms affected by adverse economic conditions. These credit quality dynamics highlight the importance of credit migration modelling as an integral part of modern credit risk solutions (Gavalas, Syriopoulos, 2014). The researches also revealed that a positive shock to capital inflows and to GDP growth results in favorable changes in all bank-level variables, whereas higher lending rates may lead to adverse selection problems and hence to a drop in loan portfolio quality (Love, Ariss, 2014).

The nature of the recent financial crisis in Europe has brought to the fore concerns regarding firms‘ capacity to access traditional bank lending. While the constraints may be higher in crisis countries, such bank rejections may reflect the accurate re-pricing of firm-specific risk by financial institutions as opposed to banking reductions in credit supply at the country level. The large firms in higher income economies show a greater prevalence of traditional financing compared to those in low income economies. Firm age is also significant, because younger firms typically rely more on other financing alternatives than on bank finance for both short-term (working capital) and long-term (investments) financing. In part, these findings are likely to reflect that smaller firms may represent greater risk, with growth more uncertain and loans more difficult to monitor. The findings indicate that older, larger and more profitable firms tend to make fewer late payments. By contrast, highly indebted debt firms are found to be more likely to make late payments (Casey, O‘Toole, 2014). In the Baltic States small and medium enterprises form the largest part of companies, providing the majority of jobs. Small firms find it difficult to obtain commercial bank financing, especially long-term loans, for a number of reasons, including lack of collateral, difficulties in proving creditworthiness, small cash flows, inadequate credit history, high risk premiums, underdeveloped bank-borrower relationships and high transaction costs. Access to finance plays a significant role in the development of the company, while the company‘s development level is dependent on the availability of financial services (Rupeika-Apoga, 2014).

Many studies document the influence of the macroeconomic risk on banks‘ financial condition. In addition, the macroeconomic downturn influences the loan portfolio diversification level. The homogeneity of bank portfolios would increase in response to an increase in macroeconomic risk and uncertainty. The macroeconomic shocks affect bank signals about expected returns and the greater economic uncertainty hinders banks' ability to foresee investment opportunities. The deteriorating information quality should lead to a narrowing of the cross-sectional composition of bank portfolios, as banks reducing the risk tend to allocate assets in their portfolio more homogeneously when macroeconomic uncertainty increases (Calmes, Theoret, 2014). Notwithstanding the above arguments, Chan, Karim, Burton & Aktan (2013) also highlight the possibility that diversification in the activities of financial institutions can result in value reduction via poor investment decisions. In this context, moral hazard can lead managers of banks to take on risks that are entirely borne by shareholders, resulting in higher cost inefficiencies as well as a larger proportion of non-performing loans. When the loan portfolio quality decreases banks can look for more non-interest income activities, but this diversification can also adversely affect banks' efficiency levels by disturbing revenue stability. Moreover, the involvement of banking institutions in non-interest income activities might increase fixed costs, resulting in higher operational leverage (Chan, Karim, Burton, Aktan, 2013).

The indicators of bank stress are closely correlated with the indicators of stress in government securities markets, illustrating the perceived financial interdependency between governments and their countries' banks (Allen, Moessner, 2013). Banking system stability and public finances sustainability are mutually reinforcing each other in the long-term. Promoting a conservative macroprudential policy, which favors a relatively constant credit supply dynamic and close to growth potential, contributes to maintaining the cyclical component of budget revenues at around zero. At the same time, implementing a disciplined budget policy creates the prerequisites of a favorable development in the trading book value of credit institutions, where government bonds play a leading role (Moinescu, 2013). The rising external indebtedness may create the macroeconomic backdrop for a financial crisis (Steiner, 2014). The banking, macroeconomic and sovereign debt crises are interlinked in several ways. First, the sovereign debt holdings of euro-area banks are so large that if some of the debt-stressed sovereigns (Greece, Ireland, Italy, Portugal, and Spain) cannot pay their debts, the banking system as a whole is insolvent. Second, and at the same time, attempts at fiscal austerity to relieve the problems due to sovereign stress are slowing growth. Yet without growth, especially in the stressed sovereigns, the sovereign debt crisis will persist. To complete the circle, continued troubles for the banks could bankrupt certain sovereigns, already struggling under the weight of supporting the banks within their jurisdictions, and failure of these banks could lead to a broken credit channel, which in turn could become a further constraint on growth (Shambaugh, 2012).

Generally, financial crises are rather a mechanism that amplifies rather than triggers the recession. They are actually a change in direction for the production growth, leading to a series of insolvencies in the debts to the banks, to a restraint of other crediting activities, and reaching new production decreases, with new reimbursement problems. Moreover, banking crises are accompanied, more often than not, by other types of crises, such as exchange rate crises, internal and external debt crises, inflation crises. Almost invariably, banking crises lead to abrupt decreases of the revenues coming from taxation, while other factors leading to deeper deficits may include the application of automatic mechanisms of fiscal stabilization, contra-cyclical fiscal policies and higher interest rates, through the increase of the risk-related additional benefits and the downgrading to lower rating classes (Adam, Iacob, 2012). The traditional approach in addressing the interaction between the budget deficit and credit to private sector has at its centre-point the crowding-out effect during recessions. The more government borrows from the local market, the lower credit supply to non-financial corporations and households is. Fewer private sector financing puts additional pressure on GDP contraction, which degenerates later on in lower reimbursing capacity of debtors. Hence, second round effects of crowding-out the private sector lead to both lower fiscal revenues and higher non-performing loans in the banking sector (Moinescu, 2013).

The financial safeguarding of the banking sector, the revenue decrease and the fiscal stimulation packages that accompany a great deal of the banking crises involve the fact that there are growing budget deficits, adding up on top of the existing governmental debt stock. Consequently, it is no wonder that the true heritage of banking crises is a higher level of the public debt. And the main reason of the governmental debt explosion is the inevitable fall of the revenues from taxes triggered by the deep long-term contractions of the economic production (Adam, Iacob, 2012).

For the crucial importance of banks in the countries‘ financial systems and whole economies, the activity of banks is highly regulated. The deregulation of the banking industry by easing entry and lowering economic rents to bank charters has the potential to elicit bank financial policies that will increase the incidence of bank failures. At all times and particularly, to avoid banking crises, regulators devise mechanisms to monitor banks‘ risk taking behavior. It is commonly argued that disruption in the financial system can lead to a reduction in investment and other economic activity.

Further, bank depositors face profound loss because of bank failures and governments tend to incur large costs in remedying a banking crisis. To avoid this type of systemic form of bank insolvency, all jurisdictions have emphasized greater reliance on market discipline in the regulatory framework along with implicit government support and explicit deposit insurance for banks‘ creditors, central bank‘s lending of last resort, and bank insolvency resolution procedures (Haq, Faff, Seth, Mohanty, 2014). First Capital Adequacy Accord (Basel I) was directed towards restriction of credit risks. Basel II was issued, adding operational risk, as well as a supervisory review process and disclosure requirements. Basel II also updated and expanded upon the credit risk weighting scheme introduced in Basel I, not only to capture the risk in instruments and activities that had developed since 1988, but also to allow banks to use their internal risk rating systems and approaches to measure credit and operational risk for capital purposes. The new Capital Adequacy Accord (Basel III) adopted in late 2010 is aimed at consolidation of banking system and toughening of requirements towards capital structure at commercial banks (Kudinska, Konovalova, 2012).

In response to the 2007 – 2009 global financial crisis BCBS issued the series of documents to address specifically counterparty risk in derivative transactions, strengthening of liquidity standards, and market risk framework. Consolidating all these, the BCBS released the Basel III framework entitled “Basel III: A Global Regulatory Framework for more Resilient Banks and Banking systems” in December 2010 (revised in June 2011).

According to the BCBS, the Basel III proposals have two main objectives:

- To strengthen global capital and liquidity regulations with the goal of promoting a more resilient banking sector.
- To improve the banking sector’s ability to absorb shocks arising from financial and economic stress.

Basel III contains various measures aimed at improving the quantity and quality of capital, with the ultimate aim of improving the loss-absorption capacity in both going concerns and liquidation scenarios. Remaining the minimum capital adequacy ratio at 9%, the Tier I capital ratio increased to 7% with the equity component stipulated at 5,5% (Table 1.5.1). The new concepts introduced by Basel III are of capital conversion buffer and countercyclical capital buffer. The capital conversion buffer ensures that banks are able to absorb losses without breaching the minimum capital requirement, and are able to carry on business even in a downturn without deleveraging. This is not part of the regulatory minimum. So while the 9% minimum capital requirement remains under Basel III, there is an added 2,5% as capital cushion buffer (Jayadev, 2013).

Table 1.5.1

Minimum regulatory capital prescriptions as % of risk weighted assets (Jayadev, 2013)

		Basel II (current)	Basel III (as on March 31, 2018)
A = B + D	Minimum total capital	9	9
B	Minimum Tier-1 capital	6	7
C	Minimum common equity Tier-1 capital	3,64	5,5
D	Maximum Tier-2 capital (within total capital)	3	2
E	Capital conservation buffer (CCB)	-	2,5
F = C + E	Minimum common equity Tier-1 capital + CCB	3,6	8
G = A + E	Minimum total capital + CCB	-	11,5
H	Leverage ratio (to total assets)	-	4,55

In the aftermath of the crisis the BCBS emphasized the importance of additional reserves as a means of crisis prevention and proposed new measures to evaluate their adequacy. The accumulation of reserves, however, contains costs that have been neglected so far: while reserves might effectively protect the banks and domestic economy from external shocks, their global and continuous accumulation might create systemic risks (Steiner, 2014). At the same time, the higher capital levels prescribed by Basel III will penalize commercial banks. The need for traditional banks to increase their own funds will have two consequences. First, since capital is costly and there is a race for deposits, banks will have to increase the price of their loans, making credit more expensive with negative consequences on growth and no additional positive effects on stability. Second, there will be a tendency to reduce lending in order to shrink the denominator of capital ratios (Caprio Jr., D'Apice, Ferri, Puopolo, 2014).

Bank regulators can achieve their desired safety goals by the risk-weights used in calculation of bank capital. However, risk-based capital standards can contribute towards a credit crunch where banks are encouraged to invest in government securities or mortgaged backed securities which require low levels of capital rather than making business loans which have higher risk weighting and thus higher capital requirements. A number of additional country-level factors could also be important to bank risk taking such as bank concentration ratio, explicit deposit insurance, economic freedom index, stock market turnover, real gross domestic product (GDP) growth rate and gross national income (GNI) per capita. Bank concentration ratio can show a positive or a negative relationship with bank risk depending on the intensity of bank competition (Haq, Faff, Seth, Mohanty, 2014).

To solve the banking crises the governments of countries can take the particular actions. In a first instance, in reaction to a banking crisis, governments set up safety plans leading to an increase in public deficits (Candelon, Palm, 2010). Duchin & Sosyura (2014) studied two types of regulatory interventions: disciplinary actions and mandatory capital support. The authors found that both types of interventions are generally associated with lower risk taking and liquidity creation at disciplined banks. Their evidence also yields two important conclusions: the consequences of government interventions vary depending on the business cycle and have an effect mainly in non-crisis years, and disciplinary actions against banks generate spillover effects on other banks, providing the latter with a competitive advantage (Duchin, Sosyura, 2014).

Financial institutions can also be supported by off-balance sheet operations such as government guarantees to commercial banks. The fiscal cost of the latter measure is difficult to evaluate as there is no direct liquidity support, but the risk associated with the potential exercise of the guarantee leads investors to ask a higher risk premium from the country or institution providing the insurance. Finally, the real consequences associated with the banking crisis affect government tax revenues, which will shrink, and government spending, which will rise, through social security and through measures designed to stimulate global demand. This automatic stabilizer mechanism deepens the budget deficit and increases the debt, calling for even more procyclical discretionary fiscal policies. This mechanism is particularly important for members of the European Monetary Union that committed themselves to limiting their fiscal deficits and debt. As a consequence, this restrictive fiscal policy could increase the probability of default for households, increasing the amount on non-performing loans, again putting tensions on the banks' balance sheet (Candelon, Palm, 2010).

After the collapse of Lehman Brothers in 2008, many governments in the euro area and elsewhere committed large resources to guarantee and rescue financial institutions. This led to increasing public debt and thereby higher risk of sovereign default. The governments' exposures to financial sector weakness became more prominent as the crisis progressed. Investors perceived this as a credit risk transfer from the banking sector to governments, and thereby sovereign debt spreads widened while risk spreads of financial institutions narrowed. For example, sovereign spreads for Ireland started to increase after the government extended a guarantee to the banking system (Alsakka, Gwilym, 2013).

The analysis of scientific publications has shown that debtors‘ credit risk in banks has the significant dependence on the macroeconomic factors of a country. The development of internal credit risk assessment models must include not only specific characteristics of loan applicants, but the macroeconomic indicators must be also taken into consideration. There is no one set of macroeconomic variables defined in the scientific researches that are important for the credit risk of debtors, however the GDP and its growth, consumption, investment, wages, inflation, unemployment rate are often mentioned. The research proved that the performance of banks is highly influenced by the economic environment and, conversely, the economic development of a country is dependent on the condition of commercial banks and whole financial system. In the economic recession the restricted credit supply usually slows the recovery of economy, so the ability to keep the banking system stable is crucial for every country. As the business cycles are typical for the economies of countries, the understanding of their consistent patterns is very important not only for banks and their supervisors, but for the every enterprise and household this knowledge allows to manage the finances more efficiently. The growth of non-performing loans is often related to the misunderstanding of economic processes and the irresponsible borrowing. This problem for households is especially difficult to solve in the economic downturns.

The recommendations of BCBS in Basel III guidelines suggest the analysis of macroeconomic conditions in credit risk assessment process, so the further empirical research aims to reveal the main effects of business cycle on credit risk in banks and their financial indicators. The statistical data of Lithuania and other EU countries will be analyzed to assess how the indicators of banks were influenced by recent economic downturn. The empirical results may ease the understanding for bankers and other researchers the relations of main economic factors and credit risk. This understanding may improve the credit risk management in banks and reduce the loss caused by macroeconomic fluctuations. The statistical analysis will allow to evaluate quantitativey the recent problems in banks and to acquire the ability to manage the credit risk in more complex way for the future from the lessons of recent economic downturn.

2. THE EMPIRICAL STATISTICAL RESEARCH STRUCTURE AND METHODS

The empirical research aims to assess the changes of credit risk related banks' performance indicators, the macroeconomic changes in Lithuania and other European Union (EU) countries, and to find the interrelations between these factors. The research consists of 8 parts that are based on the statistical analysis of Lithuanian and EU indicators. The research structure and expected results are shown in Figure 2.1.

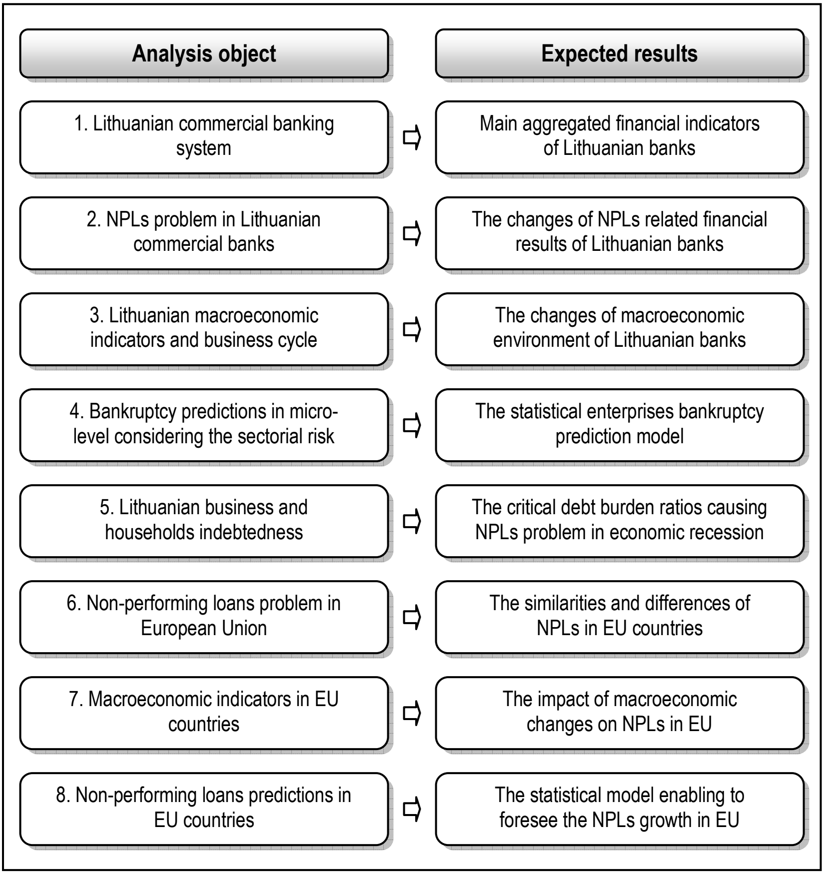


Figure 2.1. The empirical research structure and expected results

Further the research structure, statistical data and analysis methods are explained.

1. Lithuanian commercial banking system. This chapter aims to present the Lithuanian commercial banking system, to estimate the changes of main balance-sheet entries: the assets, loan portfolio and deposits.

2. The problem of non-performing loans and the changes of financial condition in Lithuanian banks. The statistics of non-performing loans (NPLs), the credit risk related financial indicators of interest income, net interest income, net profit, impairment of loans, return on assets, return on equity will be analyzed. The analysis results will show the deterioration of main financial rates of Lithuanian banks when the proportion of non-performing loans increased. The stock market data analysis also will measure the decrease of listed bank's shares prices after the deterioration of banks' loan portfolio quality and financial results.

3. The changes of commercial banks macroeconomic environment in Lithuania. The business cycle in Lithuanian economy will be substantiated by the macroeconomic indicators of GDP, exports, imports and gross capital formation (investments). As the solvency and credit risk of business enterprises depend on their financial condition, the main financial indicators of revenue, net income and net profitability will be analyzed. The number of profitable and loss-making companies, the bankruptcy statistics will reveal the changes of Lithuanian credit risk in different stages of business cycle. The analysis of creditors' claims statistics will measure the risk for banks to loose the lent money in case of a company's bankruptcy. The households' credit risk related economic indicators of compensation of employees, consumption expenditures of households, the average wages, unemployment and inflation rates will indicate how the problems of NPLs in Lithuanian banks increased after the deterioration of these rates. The changes of realty price index will be interrelated with the economic recession and impairment of loans. The research suggests that in the credit risk management of banks the public finance indicators of general government revenue and expenses, budget deficit, public debt are also good predictors of NPLs growth. The correlation analysis of mentioned variables will prove their interdependence and strong impact on NPLs in banks.

4. Enterprises credit risk assessment model considering the industry sectors sensitivity to the macroeconomic changes. Analyzing the set of bankrupted and profitable Lithuanian enterprises the statistical bankruptcy prediction model will be developed. The multivariate adaptive regression splines and logistic regression methods will be employed for the analysis of enterprises' financial ratios. Extending the credit risk determinants from the enterprise's micro-level, the industry sectors statistical data will be analyzed to measure the sensitivity of these sectors to the fluctuations of business cycle. In general these interrelations will be estimated by the canonical analysis and polynomial regression methods. The variables of the number of bankrupted companies, revenue, income before taxes, profitability of main activity, the proportion of loss-making enterprises in every sector will allow to attribute the sectorial bankruptcy risk ranks that can help banks to assess the credit risk of such loan applicants expecting the macroeconomic changes in the country. The comparative analysis of Lithuanian districts will be implemented aiming to highlight the relative differences of industry sectors' credit risk. The average net profitability, return on assets, current ratio, quick ratio and debt ratio values in the last year before the companies bankruptcy will be analyzed what can help banks to foresee the risk of a particular company to bankrupt if these financial ratios differ in the industry sectors. The cluster analysis will classify the sectors into 3 groups and the critical average financial ratios warning about the enterprises' bankruptcy will be calculated.

5. Business and households indebtedness indicators as factors of NPLs problem in banks. In this chapter the Lithuanian enterprises and households indebtedness as the important factor of the ability to repay debts will be analyzed. The statistics of loan portfolio dynamics in Lithuanian banks will be presented and the relative indebtedness indicators of companies and households will be calculated. The overall loan portfolio, business, households loans, GDP, Lithuanian enterprises' revenue and compensation of employees indicators will be used to calculate the relative indebtedness ratios. The estimation of ratios changes will allow to highlight the critical over-indebtedness levels in the peak point of Lithuanian business cycle that later turned into the oppressive debt burden for business and households causing the extensive growth of NPLs in Lithuanian banks. The reasons of this situation also will be suggested accenting the problem of irresponsible borrowing that was evident in Lithuania until the economic recession.

6. Non-performing loans problem in European Union. The non-performing loans statistics of European Union in this chapter will be presented, what allows to understand the situation in the EU countries. The Lithuanian NPLs will be analyzed in the context of EU average values. The interrelations of GDP to one inhabitant and NPLs in banks will be estimated to measure the strength of EU countries economy and the NPLs problems in banks. The dynamics of the aggregated European Union banks' assets, loan portfolio, deposits, interest income, net interest income and net profit will be presented. The capital adequacy ratios of EU and Lithuanian banks will be analyzed comparing them to estimate the strength of commercial banking systems in the EU and to evaluate the ability of banks to absorb the unexpected losses.

7. The dependence of non-performing loans problem on macroeconomic conditions in European Union. In this chapter the EU countries will be classified into four groups of low, lower medium, higher medium and high NPLs in banks. The average macroeconomic indicators to 1 inhabitant (GDP, exports, investments, compensation of employees, consumption expenditures of households and general government) will be compared between these groups aiming to prove that the economic strength of a country is the very important determinant of NPLs in commercial banks. The EU countries will be selected that suffered from the highest NPLs and the dynamics of macroeconomic indicators in these years will be estimated. This will allow to conclude how the deterioration of macroeconomic conditions in a country increases the non-performing loans amount in its banks.

8. The NPLs in European Union countries prediction model. The statistical model for the prediction of NPLs changes will be developed in this chapter. The set of macroeconomic indicators will be formed and their basic indices reflecting the changes of macroeconomic rates will be used as the independent variables. Because the changes of NPLs in EU countries can be different, the countries in the first stage of analysis will be separated into three groups. The logistic regression, factor analysis and *probit* regression methods will be employed for this purpose. The countries classification accuracy will be measured. The discriminant analysis models will be developed to classify the EU countries according to the expected low or high growth of the non-performing loans. The model's prediction ability will be tested analyzing the out-of-sample data.

The statistical data of Statistics Lithuania, Bank of Lithuania, EUROSTAT, European Central Bank and World Bank will be used in the empirical research.

3. THE EMPIRICAL STATISTICAL RESEARCH

3.1. Lithuanian commercial banking system

The number of domestic banking groups and stand alone banks, foreign (EU and non-EU) controlled subsidiaries and foreign (EU and non-EU) controlled branches in Lithuania is shown in Figure 3.1.1.

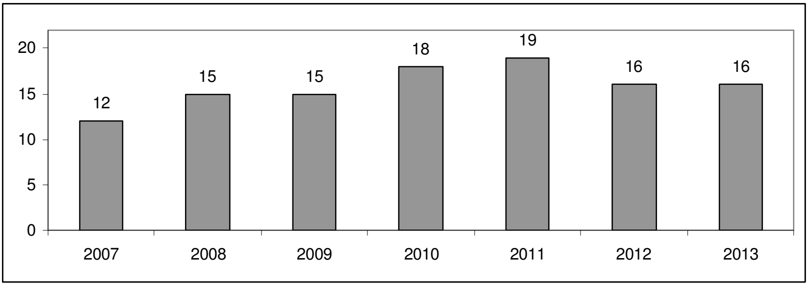


Figure 3.1.1. The number of banks in Lithuania (European Central Bank, 2014)

In 2014 the number of banks in Lithuania and their types are given in Table 3.1.1.

Table 3.1.1

The number of banks in Lithuania in 2014 (Bank of Lithuania, 2014)

Bank type	Number
Deposit money banks	7
Foreign bank representative offices	2
Foreign bank branches	8
Total	**17**

Financially the size of a country‘s banking system can be measured by the consolidated assets of commercial banks. Bank assets are the physical and financial property of a bank, what a bank owns, in particular it is the physical and financial property an financial. The most notable asset categories are loans which generate the interest revenue, investment securities and money. In 2013 the assets of Lithuanian banks was 22,4 billion EUR. The highest assets of 26 billion EUR was in 2008 while in period of 2009 – 2012 it decreased to 21,5 billion EUR (Figure 3.1.2).

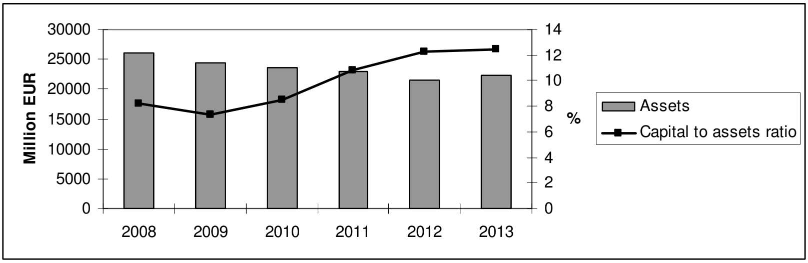


Figure 3.1.2. The Lithuanian banks assets and the capital to assets ratio (Bank of Lithuania, 2014; World Bank, 2014)

One of the banking system strength measures is the capital to assets ratio which is calculated as the ratio of bank capital and reserves to total assets. Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. Capital includes tier 1 capital (paid-up shares and common stock), which is a common feature in all countries‘ banking systems, and total regulatory capital, which includes several specified types of subordinated debt instruments that need not be repaid if the funds are required to maintain minimum capital levels (these comprise tier 2 and tier 3 capital). Total assets include all nonfinancial and financial assets. The least capital to assets ratio (7,3%) in Lithuanian banks was in 2009 while in further years it constantly increased to 12,5% in 2013 (Figure 3.1.2).

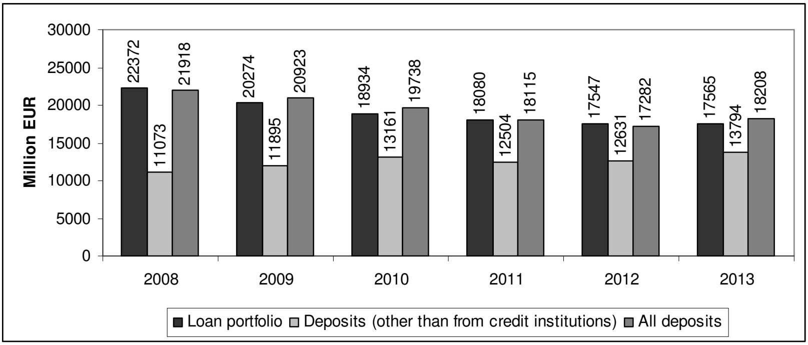


Figure 3.1.3. The loan portfolio and deposits in Lithuanian commercial banks (Bank of Lithuania, 2014)

The loan portfolio of Lithuanian banks in 2013 was 17,6 billion EUR, the deposits – 18,2 billion EUR (Figure 3.1.3).

3.2. The problem of non-performing loans and the changes of financial condition in Lithuanian banks

The Lithuanian commercial banks, according to the statistics published by World Bank, since 2009 met the problem of very high proportion of non-performing loans in their loan portfolios. Bank non-performing loans to total gross loans are the value of non-performing loans divided by the total value of the loan portfolio (including non-performing loans before the deduction of specific loan-loss provisions). Particularly the most negative situation was in 2009 when the proportion of non-performing loans increased by 17,9% and reached 24%. This high rate with slight fluctuations remained until 2010, while since 2011 the constant decrease of NPLs in Lithuanian commercial banks was observed (Figure 3.2.1).

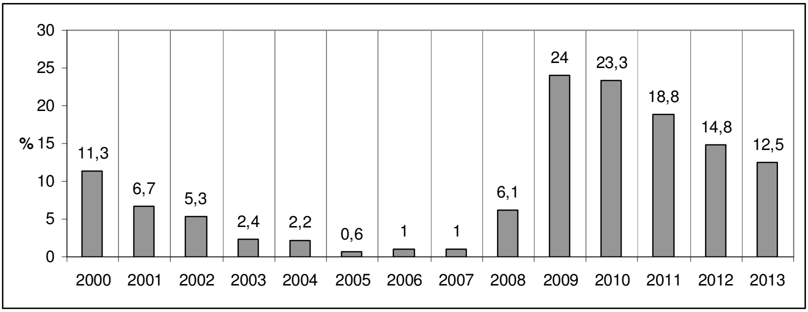


Figure 3.2.1. The non-performing loans to total gross loans in Lithuanian commercial banks (World Bank, 2014)

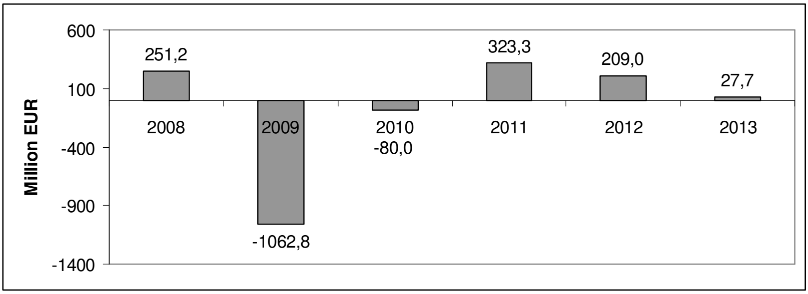


Figure 3.2.2. Total profit or loss of Lithuanian banks from continuing and discontinued operations after tax (Bank of Lithuania, 2014)

The total profit of Lithuanian banks from continuing and discontinued operations after tax as the main final financial result was affected very negatively by this deterioration of loan portfolio quality. The sudden loss of Lithuanian banks in 2009 was 1 062,8 million EUR (Figure 3.2.2). In 2010 this loss decreased by 92,5% to 80 million EUR and in further years the profitable activity of banks was recovered.

The other main financial indicators in profit (loss) statement affected by the high NPLs are the banks‘ interest income and the impairment of loans and other receivables. The highest interest income of Lithuanian banks was 1 459,1 million EUR in 2008 and in further years it decreased in average by 17,2% yearly. In 2013 the interest income was only 568,8 million EUR (Figure 3.2.3).

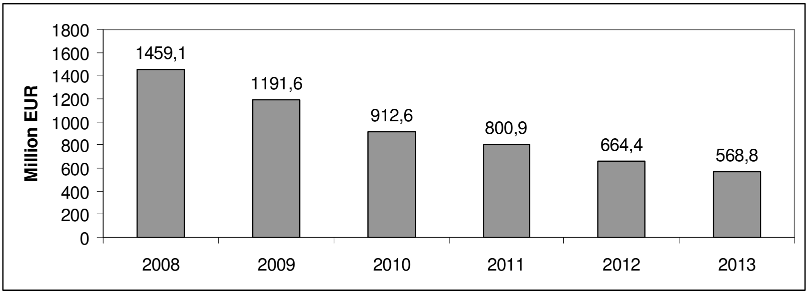


Figure 3.2.3. The interest income of Lithuanian banks (Bank of Lithuania, 2014)

When the debtors fulfil all their financial obligations for banks they have the valuable loans as the profit making assets in the balance sheets. In case of the debtor’s default the loans are classified into two types: the overdue but not impaired loans and the impaired loans. The overdue loans have the delayed loan repayments or interest payments but the value of loan has not decreased. A loan is impaired when it is not likely the lender will collect the full value of the loan because the creditworthiness of a borrower has fallen. When enough time has passed since the payment had to be made for the lender and it is suspected that the payments intermit, the default occurs. It means the borrower has failed to meet the terms a lender provided to restore a loan payments. In this case, the loan would be considered impaired if the lender feels there is not evidence the debt will be collected based on the borrower's financial status, credit status and other factors. The lender will pursue either restructuring or foreclosure as a result of the impaired status of the debt. The banks calculate this amount by subtracting the amount expected to be recovered on the loan from the initial book amount of the loan. If a lender issues a mortgage for m_A EUR but expects to recover only m_B EUR, when $m_A > m_B$, the impairment amount would be $m_A - m_B$ EUR. The banking accounting rules require lenders to report impaired loans. This gives customers, investors and credit raters a full picture of the lender's financial condition. A bank with too many impaired loans and not enough loans in good standing could be at risk of insolvency and bankruptcy. The statistical data of Lithuanian banks shows that in 2009 the impairment of loans and other receivables including leasing increased by 794,8% from 127,8 to 1 143,5 million EUR (Figure 3.2.4). In 2010 it decreased to 201,2 million EUR and in 2011 this rate became negative. While in two further years the impairment was 14,9 and 10,1 million EUR.

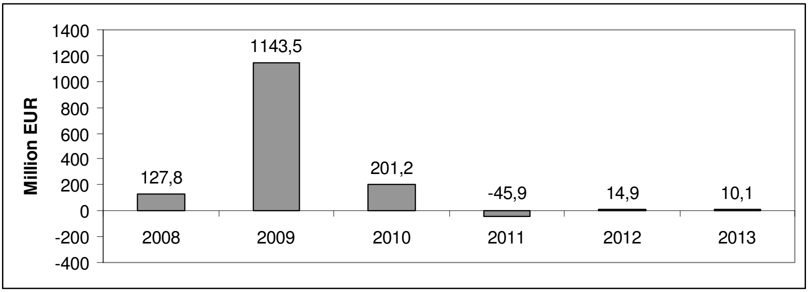


Figure 3.2.4. The impairment of loans and other receivables (including leasing) of Lithuanian banks (Bank of Lithuania, 2014)

The relative financial indicators ROE and ROA also reflect the deterioration of banks‘ financial condition in 2009 (Figure 3.2.5).

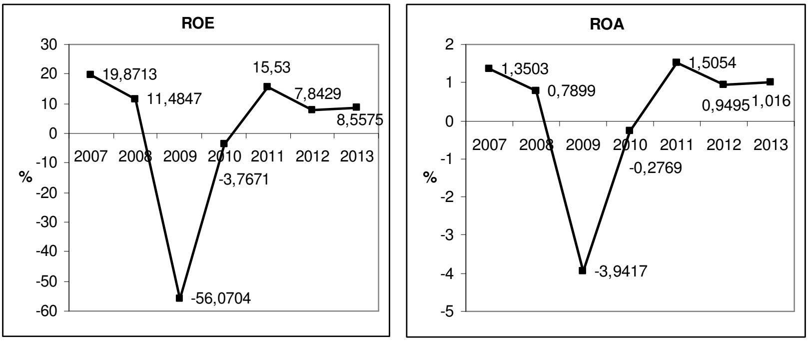


Figure 3.2.5. The ROE and ROA rates of Lithuanian banks (European Central Bank, 2014)

The highest return on equity (ROE) of Lithuanian domestic banking groups and stand alone banks, foreign controlled subsidiaries and foreign controlled branches was in 2007 – 19,9%. When the proportion of NPLs increased in 2009 this rate decreased to -56,1% and in 2010 it still remained negative. These negative rates indicate that banks were not able to earn financial returns on their employed capital. Low returns often turn into lower net profit, which leads to a bank's inability to pays expenses and other financial obligations. Without a substantial return on this capital, a bank may suffer low income and be unable to pay for its administrative expenses or other standard costs. Banks' negative return on equity also does not allow to pay the financial returns to investors for the use of their capital. The only way to stop this loss is to find profitable investing options to increase the return on equity. But banks operate in highly regulated markets, so they must consider the requirements of central bank managing risks and finances. While the return on equity for banks should be strong enough to keep the proper financial condition, to get the high returns it can be problematic, because the main drivers of banks' profitability remain earnings, efficiency, risk-taking and leverage that should be managed. ROE is a short-term indicator and must be interpreted as a snapshot of the current health of banks. It does not take into account either institution's long-term strategy or the long-term damages caused by the crisis.

It the ROE is a measure of equity holders returns and the potential growth on their investments, the return on assets (ROA) is an indication of the operational efficiency of the bank. One of the biggest economic considerations in the banking system is the maintenance of a profitable commercial banks. The main sources of bank profits originate from transaction fees on financial services and the interest spread on resources that are held in trust for clients who, in turn, pay interest on the asset. The ROA of Lithuanian domestic banking groups and stand alone banks, foreign controlled subsidiaries and foreign controlled branches from 1,4% in 2007 decreased to -3,9% in 2009 and in 2010 it remained negative (Figure 3.2.5). This unfavourable situation caused a serious concern in banks' risks management because the profitability is bank's first line of defence against unexpected losses, as it strengthens its capital position and improves future profitability through the investment of retained earnings. An institution that persistently makes a loss will ultimately deplete its capital base, which in turn puts equity and debt holders at risk.

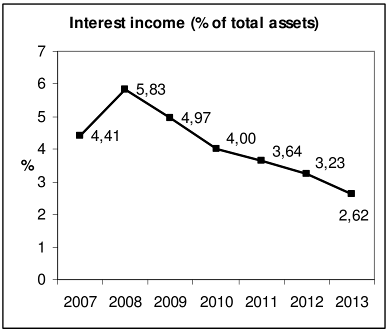
The structure of total banking assets according to ROE rates is given in Table 3.2.1. In 2007 the highest proportion of banks assets (60,1%) had the ROE indicator higher than 20%. The rest assets had ROE positive up to 15%. In 2008 the 97,3% of assets ensured the ROE rate in range 5 – 20%, while 2,7% was loss making. This was the beginning of banks loss problem and in 2009 the ROE < 0 had the proportion of 99%, in 2010 – 73,5%. In further years mostly the profitable activity of Lithuanian banks was observed which in 2011 and 2013 ensured the ROE > 20% in 68,7% – 69,3% of total banks‘ assets.

Table 3.2.1

The percentage of total banking assets of institutions according to ROE rates

Year	ROE (%)					
	< 0	0 – 5	5 – 10	10 – 15	15 – 20	> 20
2007	0,0	2,0	7,6	30,3	0,0	60,1
2008	2,7	0,0	33,7	34,1	29,5	0,0
2009	99,0	1,0	0,0	0,0	0,0	0,0
2010	73,5	26,5	0,0	0,0	0,0	0,0
2011	1,6	12,1	16,9	0,0	0,0	69,3
2012	0,6	44,0	22,8	32,7	0,0	0,0
2013	0,0	3,8	8,4	0,0	19,1	68,7

The banks‘ ability to use the assets effectively an to earn income from credits can be measured by the relative indicators of the interest income and the net interest income to total assets (Figure 3.2.6).



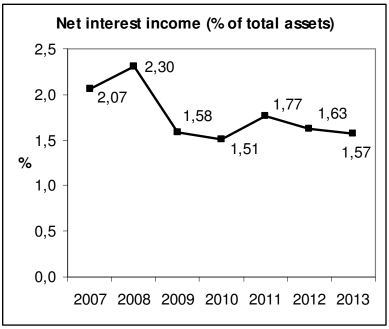


Figure 3.2.6. The interest income and net interest income percentage of total assets in Lithuanian banks (European Central Bank, 2014)

The highest interest income to total assets ratio of Lithuanian banks was in 2008 – 5,83% and since 2009 it decreased to 2,62% (Figure 3.2.6). The net interest income to total assets ratio has not the constant decrease tendency in this period. From 2,3% in 2008 it decreased to 1,58% and 1,51% in 2009 – 2010 while in further years it has not reached the previous values higher than 2%.

The another measurement of banks performance can be the stock market data. If the stock market is effective, usually when the financial condition of companies deteriorates, the investors react to these negative changes in the demand of shares. So the fall in financial rates is related to its share prices. In Lithuania only one bank („Šiaulių bankas“) is listed in the Main List of NASDAQ OMX Baltic stock market. In 2008 the highest share price of this bank was 1,01 EUR white the least price in 2009 was 0,18 EUR. The amount of this sudden decrease in one year was 82,2% (Figure 3.2.7).

Figure 3.2.7. The share prices of one Lithuanian listed bank (NASDAQ OMX Baltic, 2014)

The analysis of Lithuanian commercial banks financial data has shown that the deterioration of their financial condition is coincident with the sudden growth of non-performing loans in 2009. Due to this reason the activity of banks became loss making, their interest income started to decrease and many of loans have impaired. This typical situation was observed in all banks according to the return on equity rate distribution. So, it can be concluded that this negative situation was driven by the systemic factors that are related to the all banks performance results. The next chapter aims to analyze the macroeconomic changes in Lithuania that affected the sudden growth of non-performing loans in commercial banks loan portfolios and disimproved their financial results. The understanding of main affects of macroeconomic changes on credit risk can help to manage this risk in banks more effectively.

3.3. The changes of commercial banks macroeconomic environment in Lithuania

The analysis of other credit risk and macroeconomy researhers' results published in scientific publications has shown that the economic recession usually negatively influences the ability of debtors in banks to repay their credits. The loan portfolio quality depends on the banks' macroeconomic environment, so the analysis of their relations are important for every bank. The recent macroeconomic indicators reflect the significant business cycle fluctuations in Lithuanian economy therefore the effect of these fluctuations on the non-performing loans in banks in this chapter will be analyzed.

The general Lithuanian macroeconomic indicators of gross domestic product (GDP), exports (EXP), imports (IMP) and gross capital formation (investments, INV) are shown in Figure 3.3.1.

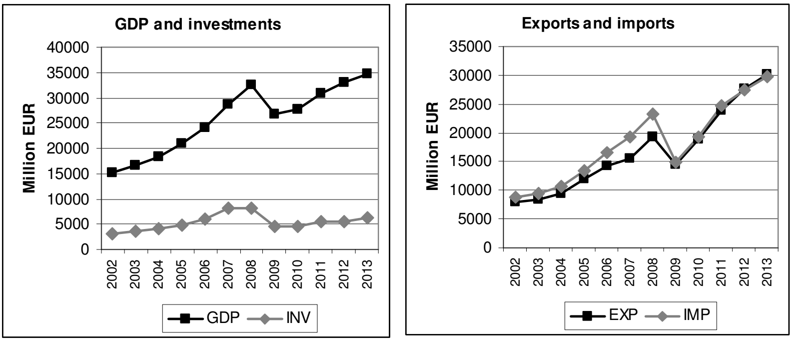


Figure 3.3.1. The GDP, investments, exports and imports of Lithuania (EUROSTAT, 2014)

The graphs of apparently show the fluctuations of business cycle and the 2009 year's downturn in Lithuanian economy. The Lithuanian macroeconomic indicators in year 2008 were the highest as it was the peak point of business cycle. In the most downturn of year 2009 the GDP decreased by 17,8% from 32 414 million EUR to 26 654 million EUR. GDP is a measure of the economic activity, defined as the value of all goods and services produced less the value of any goods or services used in their creation. The business activity slowdown also reflects the decrease of investments by 44,3% from 8,2 to 4,6 billion EUR. The international trade indicators were significantly negatively affected by economic downturn. In 2009 the fall of exports was 25,2% when it decreased from 19,3 to 14,5 billion EUR. The changes of imports are more significant: it decreased by 35,6% from 23,2 to 15 billion EUR. After this considerable economic downturn, in 2010 the stabilization of macroeconomic indicators was observed and the economic growth has started. In period of 2010 – 2013 the average annual GDP growth rate is 6,8%, exports – 20,4%, imports – 19,2%. The restrained growth is visible in investments that in 2013 since 2009 increased only by 38,6% and in 2013 it was only 77,2% of the year's 2008 value.

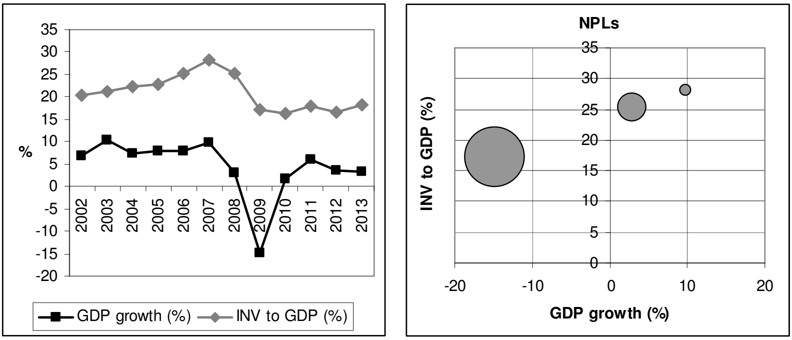


Figure 3.3.2. The GDP growth, investments to GDP and NPLs in Lithuanian banks (EUROSTAT, 2014; World Bank, 2014)

According to the statistics of EUROSTAT in 2009 the Lithuanian real GDP growth rate was -14,8%. In this case the GDP at current prices is valued in the prices of the previous year and thus the computed volume changes are imposed on the level of a reference year, so the production and services price movements do not inflate the growth rate (Figure 3.3.2). The highest relative investments to GDP rate (28,1%) was in 2007 which constantly decreased until 2010 to 16,3%. The Figure 3.3.2 also indicates the relation between the GDP growth, investments to GDP and non-performing loans in Lithuanian banks. The least point of this graph denotes the 1% of NPLs in banks when the real GDP grew 9,8% and the investments were 28,15 of GDP in 2007. The middle-sized point is the 6,1% of NPLs in banks (year 2008) when the real GDP grew only 2,9% and the investments decreased to 25,3% of GDP. The largest point in the right chart of Figure 3.3.2 denotes the highest proportion of NPLs in 2009 together with the worsened real GDP growth and the investments to GDP rates.

The another group of banks' environment indicators related to the credit risk of debtors are the aggregated business indicators of Lithuanian enterprises. The business cycle fluctuations are visible in the aggregated revenue and net income of Lithuanian companies (Figure 3.3.3). The business revenue constantly grew until 2008 with the average annual increase rate of 19,3%. In 2008 the revenue of Lithuanian companies reached 63 650 million EUR and it was the peak point of economics growth. Next year the business revenue decreased by 29,4% to 44 966 million EUR. This was the only year of enterprises revenue slump, thus after the year 2009 the revenue constantly grew again and in 2012 it was 64 845 million EUR or 144,2% of the 2009 year‘s revenue.

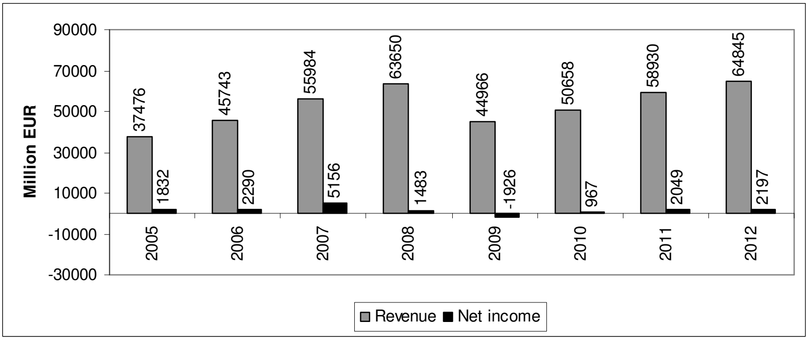
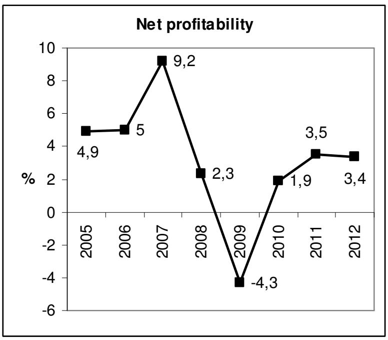


Figure 3.3.3. The aggregated revenue and net income in Lithuanian companies (Statistics Lithuania, 2014)

The highest net income as the final financial result of Lithuanian companies was in 2007 when it reached 5 156 million EUR (Figure 3.3.3). Despite the increasing revenue in 2008, the net income in this year decreased by 71,2% to 1 483 million EUR.



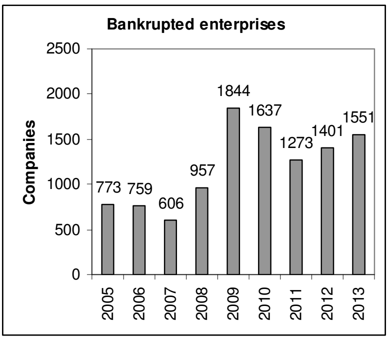
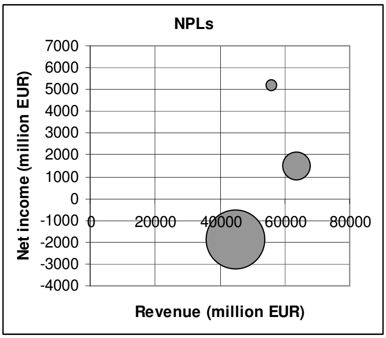


Figure 3.3.4. The aggregated net profitability of Lithuanian companies and bankruptcies (Statistics Lithuania, 2014)

So, it can be concluded that in the peak point of business cycle the net income starts to decrease one year before the fall of revenue. The growth of enterprises‘ expenses in 2008 affected the decrease of net income by 71,2% to 1 483 million EUR but this indicator still remained positive. The worst situation was in 2009 when the aggregated net income of Lithuanian companies was negative (-1 926 million EUR), also the net profitability ratio of this year was negative (Figure 3.3.4). This was the only year of aggregated loss-making activity of Lithuanian companies and in further years the net profit margin was positive in range of 1,9% – 3,5%.

The loss making activity of Lithuanian companies in 2009 caused the growth of their bankruptcies. In 2009 the number of enterprises where the bankruptcy process was started increased by 92,7% to 1 844 companies (Figure 3.3.4). The higher number of bankrupted companies means the increasing unability to fulfil the financial obligations for banks and other creditors. That undoubtedly causes the increase of credit risk and growth of non-performing loans.

The statistical relation between Lithuanian enterprises revenue, net income, net profitability, number of bankruptcies and non-performing loans in the peak point of business cycle and economic recession (years 2007 – 2009) in diagram form is visualized in Figure 3.3.5. In the right graph the points are situated almost in line what confirms that NPLs in banks have the tendency to grow when the net profitability of enterprises is decreasing and the number of bankrupted companies grows. However the points in the left side of grapf are not exactly in line where the relations between Lithuanian enterprises revenue, net income and NPLs is shown.



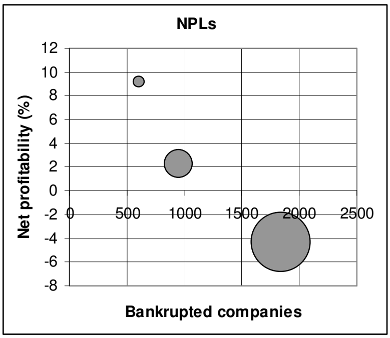


Figure 3.3.5. The relation of aggregated Lithuanian companies indicators and NPLs in banks (Statistics Lithuania, 2014; World Bank, 2014)

As was proved previously the net income of Lithuanian enterprises started to decrease in the last year of the revenue growth in 2008. So the least number of NPLs was in 2007 when the net income of companies was the highest, but the revenue had not reached the maximal value. The highest proportion of NPLs in banks was observed when the revenue of companies decreased and their activity was loss making in 2009.

The year 2009 is extraordinary in Lithuanian business statistics because the number of loss-making companies (27 074) was 1,4 times higher than profitable (19 282). The similar number of these companies was in 2008 and 2010, while in other years the profitable companies in Lithuanian business structure dominate (Figure 3.3.6). Compared to the year 2009, in further period of economic growth, the number of profitable companies increased by 72% in 2012 to 33 170 enterprises. Also the number of loss-making companies decreased by 17,5% to 22 345 enterprises. In the group of profitable enterprises the highest profit of 6 547 million EUR was in 2007, which in 2009 decreased by 70% to only 1 964 million EUR (Figure 3.3.6). The highest loss of loss-making companies was also in 2009 when it reached 3 704 million EUR. These indicators in years 2010 – 2012 have shown the significant improvement that reflect the better business situation in companies and recovery in whole Lithuanian economy.

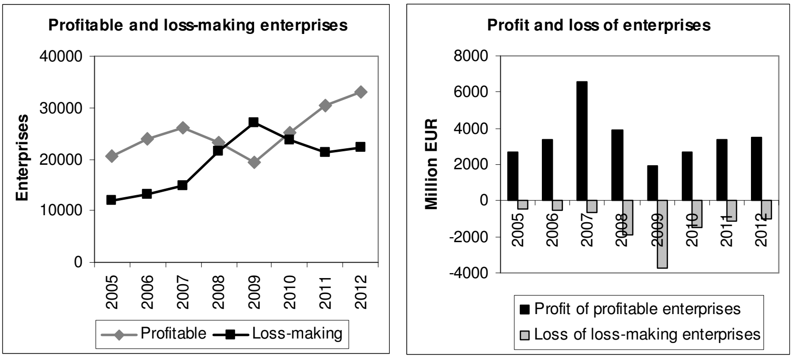


Figure 3.3.6. The indicators of profitable and loss-making Lithuanian companies (Statistics Lithuania, 2014)

The statistics of fulfiled claims of creditors affirms the high credit risk of enterpises financial condition deterioration. In the period of 1993 – 2012 only 29,2% of claims with mortgage in bankrupted companies were fulfiled (Table 3.3.1). The banks credits without mortgage have the proportion of only 2,7% because banks together with other creditors belong to the III row creditors according to Lithuanian Enterprises Bankruptcy

Law. The I row creditors are the employees and the agriculture subjects that supplied the production for the bankrupted enterprises. The fulfiled claims in this group are 56,4%. The II row creditors are the government (tax payments), the State social insurance fund and the creditors of bankrupted companies that have the guarantees from government to repay the loans. In this group statistically 8,6% of claims are fulfiled in case of enterprises‘ bankruptcy.

Table 3.3.1

The claims of creditors in Lithuanian bankrupted enterprises in 1993 – 2012 (Enterprises Bankruptcy Management Department, 2013)

Claims of creditors	Valid claims		Fulfiled claims		Fulfiled claims (%)
	Million EUR	%	Million EUR	%	
Mortgage credits	856,7	22,5	250,5	49,8	29,2
I row creditors	210,8	5,5	118,9	23,6	56,4
II row creditors	1 017,4	26,8	87,9	17,4	8,6
III row creditors	1 719,3	45,2	46,1	9,2	2,7
Total	**3 804,2**	**100**	**503,4**	**100**	**13,2**

The banks‘ economic environment indicators related to the households credit risk are also very important. The compensation of employees (COE), consumption expenditures of households (CEH) and the unemployment rate (UNE) were analyzed. Like the other analyzed Lithuanian indicators, the significant decrease of COE and CEH was observed in 2009 (Figure 3.3.7).

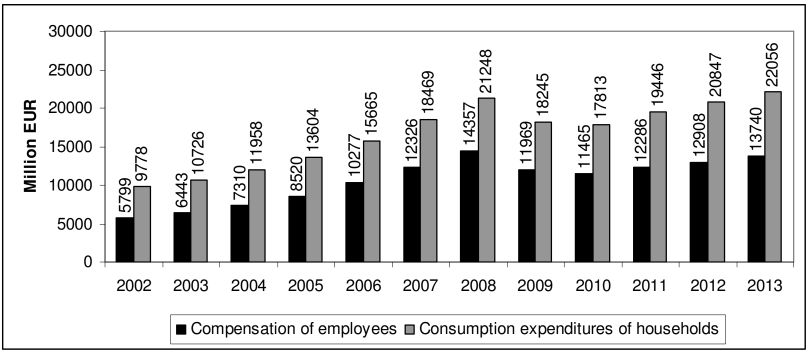


Figure 3.3.7. The compensation of employees and consumption expenditures of households in Lithuania (EUROSTAT, 2014)

The compensation of employees is the important factor influencing the ability of households to repay the consumer and realty loans for banks. In period of 2002 – 2008 this rate in average increased by 16,3% every year and in 2008 reached 14 357 million EUR. But next year the COE suddenly decreased by 16,6% to 11 969 million EUR. This slump of employees‘ compensation in 2009 reduced the final consumption expenditure of households and non-profit institutions serving households (CEH) by 14,1%. This fall is undoubtedly related not only to the credit risk increase of households but also on the riskiness of business enterprises. The decrease in consumption expenditure negatively affected the ability of Lithuanian enterprises to repay the business loans, because the decreased demand of goods and services in home market reduced the revenue and profit of companies.

The average wages before and after taxes of one employee in Lithuania is shown in Figure 3.3.8.

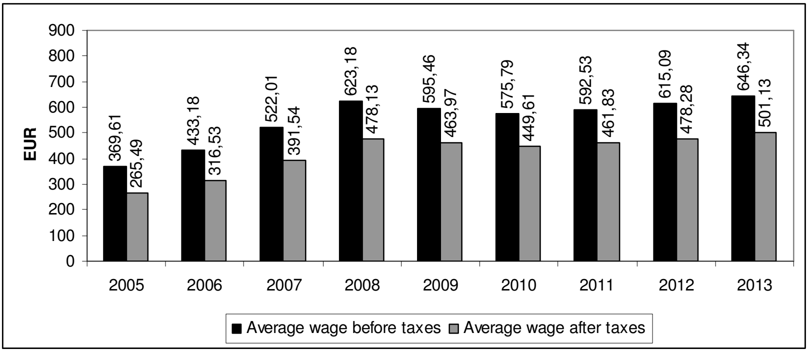


Figure 3.3.8. The average wages before and after taxes in Lithuania (Statistics Lithuania, 2014)

The growing wages until 2008 stimulated to increase consumption together with borrowing when the part of the households‘ expenses in this period were financed by banks‘ credits. So in the economic peak point of 2008 the average wage after taxes of Lithuanian employees was 478,13 EUR and the highest consumption expenditures of households reached 21,2 billions EUR (Figure 3.3.7). Also the loan portfolio in Lithuanian banks was the highest in this year and reached 22 372 million EUR (Figure 3.1.3). In 2009 the decrease of wage after taxes was only 3%, so it can be supposed that the significant decrease of aggregated compensation of employees was affected by the growth of unemployment.

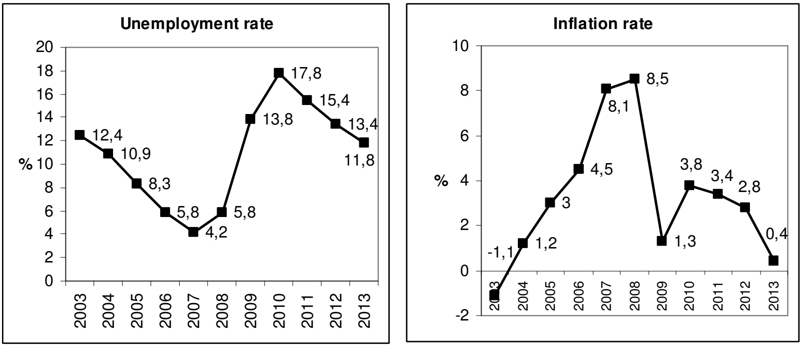


Figure 3.3.9. The unemployment and inflation rates in Lithuania (Statistics Lithuania, 2014)

The unemployment in 2009 increased by 8% to 13,8%, but the peak was reached in 2010 when this rate was 17,8% (Figure 3.3.9). The higher unemployment rate as the factor of households‘ income slump increases risk of loss for banks in retail credits. The analysis results allow to maintain that there is a lag in 1 year between social and business statistics related with the economic downturn. The GDP, exports and investments were the least in 2009 but the highest unemployment rate and the least compensation of employees, consumption expenditures of households and the average wages were in 2010. So, after the economics growth period the significant deterioration of households‘ financial condition in 2009 – 2010 is evident. This business cycle fall effect had negative impact to the households credit risk in Lithuania that suddenly met the lack of financial resources after short period of economic growth and reasonless expectations.

The consumption intensity and economic atcivity in a country also reflects the inflation rate which calculation is based on the consumer price index measuring the changes in the prices of goods and services. In Lithuania the highest inflation rate was in 2007 – 2008, when the economy was in the peak point of business cycle (Figure 3.3.9). The prices increase when demand for goods and services grows. The companies create inflation when they raise their prices to cover higher supply prices and maintain profit margins. When inflation is high, overall prices are rising within the economy. In such environment, businesses generally have little trouble raising prices to their customers. When the consumers see the high inflation they usually expect prices to rise. That makes it easier for business to justify price hikes. However, when inflation is fairly low, it makes it extremely difficult for most companies to raise prices for goods and services. So, the inflation rate is the important indicator reflecting the state of an economy. That is visible in Lithuanian economy statistics when in the downturn of 2009 the inflation rate decreased from 8,5% to 1,3%. The inflation‘s relationship with supply and demand of goods or services means that it affects the financial decisions of consumers and lending amounts. Because the inflation is a sign of a growing economy and the deflation is a sign of recession, this indicator can allow to foresee the credit risk changes of loan portfolios in banks.

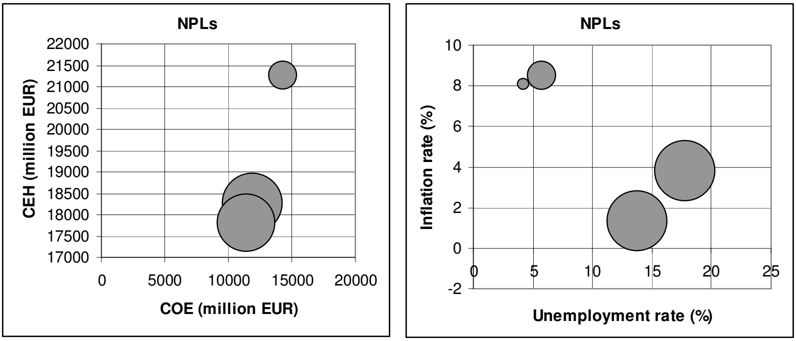


Figure 3.3.10. The relation of compensation of employees, consumption expenditures of households, unemployment, inflation rate and NPLs in banks (Statistics Lithuania, 2014; World Bank, 2014)

The dependence between compensation of employees, consumption expenditures of households and non-performing loans in changing stages of Lithuanian business cycle (years 2007 – 2010) is shown in Figure 3.3.10. The decrease of COE and CEH in economic downturn significantly increased the number of NPLs in banks. The related to this situation growth of unemployment and the typical decrease of inflation after economic boom period cause the increase of NPLs.

The credit risk of households loans is closely related to realty price index. Buying a residential property the inhabitants make the high amount transactions that offten are financed by credits. Further the residential property as their most valuable assets credits expenses are the most significant component of households’ total expenses. The risk of a household‘s default increases when the realty prices start to decrease. So the realty price index measures how the prices of residential properties are changing over time. The realty price index describes the price developments of all residential properties purchased by households (flats, detached houses, terraced houses, etc.), both newly built and existing, independently of their final use and independently of their previous owners. This index is the important indicator not only for households, but also for banks evaluating the expected loss if the debtor will not repay the credit. The realty price index serves as a timely, accurate indicator of house price trends at various geographic levels. It also provides housing economists with an improved analytical tool that is useful for estimating changes in the rates of mortgage defaults, prepayments and housing affordability in specific geographic areas.

According to the statistics of Lithuanian banks the value of loans in 2009 decreased by 1 143,5 million EUR and next year (in 2010) it decreased by 201,2 million EUR. These negative changes in loan portfolio quality are interrelated with the realty price index calculated by the Statistics Department of Lithuania. The basic period in Figure 3.3.11 is year 2010 when the realty price index was equal to 100%. The very significant decrease of -45,3% in realty prices was observed in economic recession of 2009 and that increased the loss given default (LGD) values in banks. If the debtors had not repaid the credits, banks had to realize the realty assets in the market with significantly lower prices.

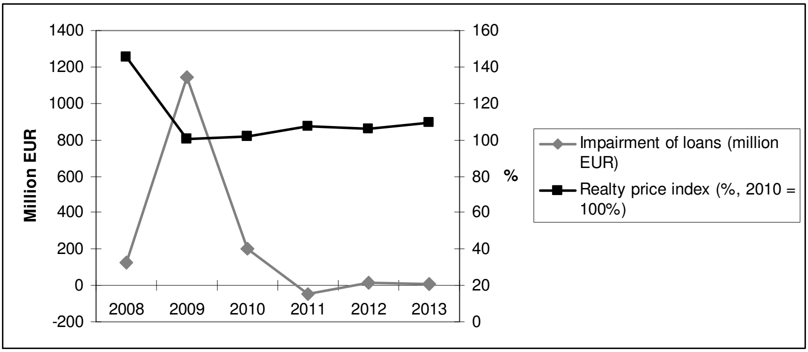


Figure 3.3.11. The realty price index and the impairment of loans in Lithuanian banks (Statistics Lithuania, 2014; Bank of Lithuania, 2014)

The 2009 year’s growth of non-performing loans in commercial banks is also related to the worsened economic indicators of Lithuanian public sector. In 2004 – 2008 the Lithuanian general government revenue increased in average 17,3% yearly and in 2008 reached 11 219 million EUR. In this period the general government expenditures were also similar, so Lithuania had the balanced budget. But in 2009 the revenue decreased by 15,8% to 9 449 million EUR. This fall in revenue caused the necessary stopping of expenditures growth. The general government expenditures in

2009 – 2013 were stable at 11 708 – 11 974 million EUR and this positive tendency allowed to reduce the national budget deficit (Figure 3.3.12).

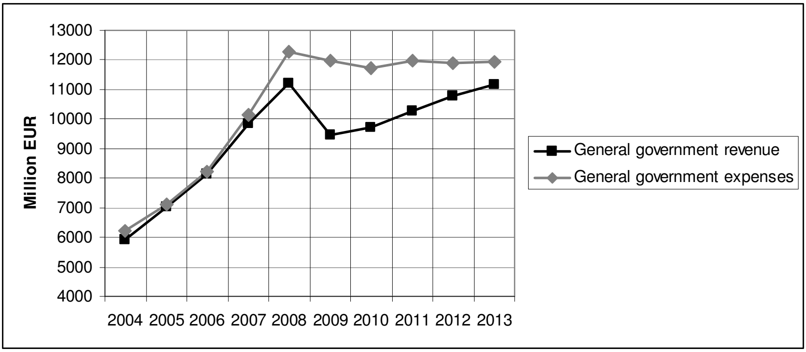


Figure 3.3.12. Lithuanian general government revenue and expenses (Statistics Lithuania, 2014)

The highest national budget deficit of 2 514 million EUR was in 2009, but due to the regenerative revenue in 2013 the deficit decreased to 745 million EUR (Figure 3.3.13). In economic growth period of 2004 – 2007 the general government budget deficit to GDP was in range of [-1,5%; -0,4%]. The pre-crisis 2008 year‘s indicators can be considered as warning about 2009 year‘s oncoming downturn, because the general government budged deficit suddenly increased by 269,2% and it became -3,3% of GDP. In 2009 when the problem of high non-performing loans in commercial banks emerged, the Lithuanian general government budget deficit was higher by 769,9% compared to year 2007 and it became -9,4% of GDP.

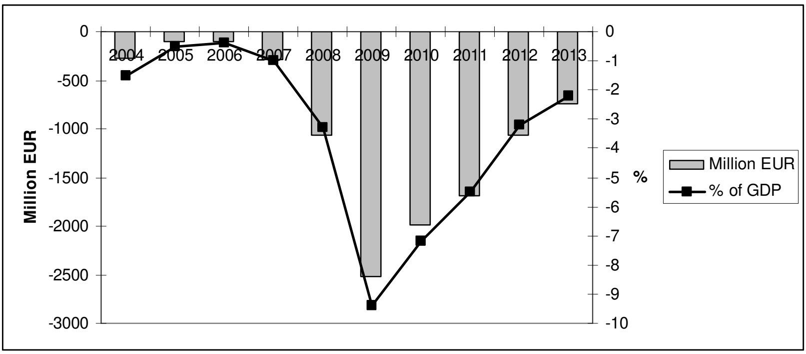


Figure 3.3.13. Lithuanian general government deficit (EUROSTAT, 2014)

Since 2009 the worsened Lithuanian economic environment is also visible in the statistics of general government debt. In 2004 – 2008 the average annual debt growth was 9,3%, but in 2009 – 2013 the debt increased in average 22,1% yearly (Figure 3.3.14). So, the large part of government expenses are financed by loans not earning the sufficient revenue inside the country. The stopped growth of general government expenditures reduced the income of business enterprises and households partly disimproving their financial condition and reducing solvency in the credits repayments for banks.

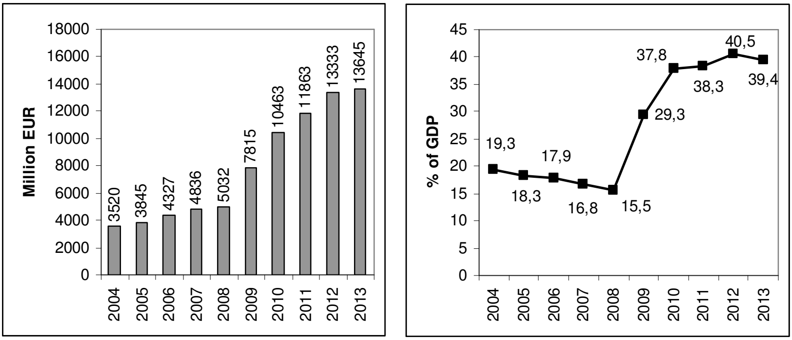


Figure 3.3.14. Lithuanian general government gross debt (EUROSTAT, 2014)

The analysis of banks‘ economic environment changes has proved that the growth of non-performing loans in Lithuanian commercial banks is closely related to the deterioration of economics in 2009. The correlation analysis was implemented to measure quantitatively these relations (Table 3.3.2). The analyzed variables can be classified into 4 groups:

- Banks finance: non-performing loans (NPLs), return on equity (ROE) and return on assets (ROA).
- Business economics: gross domestic product (GDP), investments (INV), exports (EXP), imports (IMP) and number of bankrupted companies (BNK).
- Social indicators: compensation of employees (COE), consumption expenditures of households (CEH) and unemployment rate (UNE).
- Public finance: general government deficit to GDP ratio (GDF) and general government debt to GDP ratio (GGD).

Table 3.3.2

The correlation matrix of banks finance, business economics, social and public finance indicators

	NPLs	ROE	ROA	GDP	INV	EXP	IMP	BNK	COE	CEH	UNE	GDF	GGD
NPLs		-0,65	-0,61	-0,39	-0,97	0,01	-0,25	0,91	-0,58	-0,38	0,94	-0,89	0,69
ROE	-0,65		0,99	0,59	0,61	0,45	0,64	-0,71	0,38	0,41	-0,37	0,83	-0,08
ROA	-0,61	0,99		0,65	0,55	0,54	0,71	-0,65	0,40	0,47	-0,31	0,82	0,01
GDP	-0,39	0,59	0,65		0,37	0,87	0,96	-0,16	0,81	0,96	-0,19	0,66	0,23
INV	-0,97	0,61	0,55	0,37		-0,08	0,20	-0,89	0,66	0,40	-0,95	0,79	-0,77
EXP	0,01	0,45	0,54	0,87	-0,08		0,96	0,19	0,45	0,77	0,26	0,41	0,67
IMP	-0,25	0,64	0,71	0,96	0,20	0,96		-0,07	0,61	0,86	0,01	0,61	0,45
BNK	0,91	-0,71	-0,65	-0,16	-0,89	0,19	-0,07		-0,32	-0,09	0,83	-0,75	0,70
COE	-0,58	0,38	0,40	0,81	0,66	0,45	0,61	-0,32		0,91	-0,56	0,59	-0,30
CEH	-0,38	0,41	0,47	0,96	0,40	0,77	0,86	-0,09	0,91		-0,27	0,57	0,11
UNE	0,94	-0,37	-0,31	-0,19	-0,95	0,26	0,01	0,83	-0,56	-0,27		-0,69	0,86
GDF	-0,89	0,83	0,82	0,66	0,79	0,41	0,61	-0,75	0,59	0,57	-0,69		-0,28
GGD	0,69	-0,08	0,01	0,23	-0,77	0,67	0,45	0,70	-0,30	0,11	0,86	-0,28	

The proportion of NPLs in banks is highly related to the amount of investments, bankruptcies and unemployment rate ($|r| \in [0{,}91; 0{,}97]$). The public finance indicators of general government deficit to GDP ratio and general government debt to GDP ratio also can be the NPLs predictors, because their $|r| \in [0{,}69; 089]$. The profitability of banks (ROE and ROA) is significantly dependent on almost all indicators except GGD. Analyzing the general economic indicators the GDP rate has the strong linear relations with exports, imports, compensation of employees and consumption expenditures of households where the correlation coefficients are in range of [0,81; 0,96]. The other values of significant correlations affirm the importance of systemic factors in banks‘ environment analysis and the ability of risk managers to extract the necessary information can improve the banks‘ financial results.

The analyzed in this chapter macroeconomic and other indicators have certainly affirmed the fluctuations of business cycle in Lithuanian economy and it is evident that these fluctuations highly affected the credit risk of debtors in commercial banks and their financial results. The changes of non-performing loans and banks‘ consolidated financial data in different phases of business cycle allow to maintain about the evident dependence between them. The impact of macroeconomic factors on the debtors‘ ability to repay debts in Lithuania is very strong. The loan portfolio quality of banks is highly dependent on the changes of economic environment. The understanding of this dependence and the analysis of macroeconomic indicators can help to manage credit risk more effectively in comercial banks.

3.4. Enterprises credit risk assessment model considering the industry sectors sensitivity to the macroeconomic changes

In credit risk management in banks the main problem is to assess the creditworthiness of loan applicants. The wide range of statistical techniques can be applied in the classification models development. In this research the classification of Lithuanian enterprises into default and non-default groups was implemented by multivariate adaptive regression splines (MARS) and logistic regression (LR) methods.

The data sample for the model‘s development consists of 195 Lithuanian companies (145 not bankrupted and 50 bankrupted). The 11 financial ratios of 3 years were included into analysis (Table 3.4.1) that were calculated according to balance-sheets and income statements.

Table 3.4.1

The Lithuanian enterprises financial ratios

No.	Ratio and calculation
1.	Gross profit margin (GPM): *Gross profit / Net sales*
2.	Main activity profit margin (APM): *(Sales – (Cost of goods sold + Operating expenses)) / Sales*
3.	Net profit margin (NPM): *Net income / Sales*
4.	Return on assets (ROA): *Net income / Total assets*
5.	Return on equity (ROE): *Net income / Shareholders’ equity*
6.	Current ratio (CR): *Current assets / Current liabilities*
7.	Working capital to total assets (WCA): *(Current assets – Current liabilities) / Total assets*
8.	Debt ratio (DR): *Total liabilities / Total assets*
9.	Long-term debt ratio (LDR): *Long-term debt / (Long-term debt + Shareholders’ equity)*
10.	Asset turnover (AT): *Sales / Total assets*
11.	Retained earnings to total assets (REA): *Retained earnings / Total assets*

The analyzed financial ratios involve 3 years so the indexes at the abbreviations of financial ratios x_t denote the year of the data: {t = 1, the last year; t = 2, one year before; t = 3, two years before (e.g. 2013, 2012 and 2011). The developed models classify enterprises into 2 groups: low (0) and high (1) risk of bankruptcy in the next 1 financial year:

$$Y_{t+1} = f(x_i),\ i = t,\ t-1,\ t-2 \quad (3.4.1)$$

The multivariate adaptive regression splines (MARS) is a nonparametric procedure that makes no assumption about the underlying functional relationship between the dependent and independent variables. MARS constructs this relation from a set of coefficients and basis functions from the data. The independent variables, basis functions and the model parameters are combined to determine the credit risk class of a company.

The mathematical model of MARS is:

$$Y = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X) \quad (3.4.2)$$

Where M is the number of non-constant terms in the model; $h_m(X)$ – the basis functions; β_m – the weights; β_0 – the intercept.

The weights of MARS equations are calculated in Table 3.4.2.

Table 3.4.2

The weights (β_m) of MARS equations

Basis function	**Low bankruptcy risk (0)**	**High bankruptcy risk (1)**
BF_1	0,2370247070	-0,237024707094566
BF_2	0,0268583197534090	-0,0268583197534090
BF_3	-0,214058110308261	0,214058110308261
BF_4	-2,31211924651472	2,31211924651472
BF_5	1,27914838327317	-1,27914838327317
BF_6	-0,101888271406899	0,101888271406899
BF_7	-0,599616496296886	0,599616496296887
BF_8	1,00291145843225	-1,00291145843225
BF_9	0,0664933123712619	-0,0664933123712619
BF_{10}	0,435027694980797	-0,435027694980797
BF_{11}	-0,2872030472	0,287203047288994
BF_{12}	-0,0291739471055231	0,0291739471055231
Intercept (β_0)	-0,2266233855	1,22662338555876

The basis functions of low (0) and high (1) bankruptcy risk models are given in Table 3.4.3.

Table 3.4.3

The basis functions of MARS models

BF_i	Basis functions
BF_1	$max\ (0;\ REA_1 + 1,34350088326142)$
BF_2	$max\ (0;\ -1,34350088326142 - REA_1)$
BF_3	$max\ (0;\ 0,181725208479310 - ROE_2)$
BF_4	$max\ (0;\ ROE_1 - 0,157559662373134)$
BF_5	$max\ (0;\ ROE_1 + 0,331967032482701)$
BF_6	$max\ (0;\ LDR_2 - 0,154025608509773)$
BF_7	$max\ (0;\ 0,154025608509773 - LDR_2)$
BF_8	$max\ (0;\ ROE_1 - 0,409103563474388)$
BF_9	$max\ (0;\ AT_2 - 0,894278549689584)$
BF_{10}	$max\ (0;\ APM_1 + 0,585223984830065)$
BF_{11}	$max\ (0;\ 0,0822812198773560 - WCA_2)$
BF_{12}	$max\ (0;\ AT_1 - 1,89461961678967)$

In the MARS model the basis functions $max\ (0;\ x - t)$ and $max\ (0;\ t - x)$ are used as decision points to determine which value will be used in the model at a given knot. In the model the basis function BF_1 is $max\ (0;\ REA_1 + 1,34350088326142)$. The analysis process is:

- If $REA_1 + 1,34350088326142 > 0$, then the basis function $BF_1 = REA_1 + 1,34350088326142$.
- If $REA_1 + 1,34350088326142 < 0$, then $BF_1 = 0$.

In the model the basis function BF_2 is $max\ (0;\ -1,34350088326142 - REA_1)$. The analysis process is:

- If $-1,34350088326142 - REA_1 > 0$, then the basis function $BF_2 = -1,34350088326142 - REA_1$.
- If $-1,34350088326142 - UBA_1 < 0$, then $BF_2 = 0$.

The similar analysis must be implemented in all other knots of developed MARS model. In the credit risk assessment the company must be classified into low or high bankruptcy risk group according to the higher value of dependent variable (*Y*).

To improve the credit risk assessment of enterprises the other statistical classification model was developed employing the logistic regression method which allows to predict the dependent variable *P(Y)* in range [0; 1]. When solving the objects classification into two groups problem, the classification threshold must be set in this interval.

The mathematical model of logistic regression (LR) is:

$$P(Y)=\frac{e^{\alpha+\sum\beta_i x_i}}{1+e^{\alpha+\sum\beta_i x_i}} \tag{3.4.3}$$

Where x_i – the independent variables (financial ratios of enterprises); β_i – the regression coefficients; α – the intercept.

The regression coefficients are calculated in Table 3.4.4.

Table 3.4.4

The coefficients (β_i) of logistic regression model

Ratio (x_i)	Coefficient (β_i)		Ratio (x_i)	Coefficient (β_i)
GPM_1	-5,1912		NPM_2	10,8645
APM_1	28,0961		ROA_2	21,1961
NPM_1	24,8496		WCA_2	1,4305
ROA_1	-3,3699		DR_2	-19,1355
ROE_1	1,0890		LDR_2	4,1088
CR_1	-0,2079		AT_2	2,8039
WCA_1	-2,6060		REA_2	-9,2097
DR_1	6,0516		GPM_3	6,7497
REA_1	5,8731		APM_3	-13,7134
GPM_2	-6,9159		NPM_3	44,7345
APM_2	-20,6438		Intercept (α)	4,5082

The classification threshold of the logistic regression model was set to 0,5. It means if *P(Y)* $\in$ [0; 0,5) a company is classified into the low bankruptcy risk group. If *P(Y)* $\in$ [0,5; 1] a company is classified into the high bankruptcy risk group.

Table 3.4.5

The classification matrix

Predicted	**Observed**	
	Work (0)	**Bankruptcy (1)**
Work (0)	TN_{MARS} = 144 TN_{LR} = 144	FN_{MARS} = 11 FN_{LR} = 5
Bankruptcy (1)	FP_{MARS} = 1 FP_{LR} = 1	TP_{MARS} = 39 TP_{LR} = 45

The classification accuracy of MARS and LR models is shown in the classification matrix (Table 3.4.5). The true positive (TP), true negative (TN), false positive (FP) and false negative (FN) rates were calculated. The false rates indicate the classification errors. According to these rates the overall accuracy (OA), sensitivity (Se) and specificity (Sp) of developed models were calculated to compare the classification results and evaluate the suitability of models in credit risk assessment (Table 3.4.6).

Table 3.4.6

The classification accuracy indicators (%)

Rate	Calculation	MARS	LR
Overall accuracy	TP + TN / (TP + TN + FP + FN)	93,85	96,92
Sensitivity	TP / (TP + FN)	78,00	90,00
Specificity	TN / (TN + FP)	99,31	99,31

The higher overall classification accuracy was reached by logistic regression model (96,92%). The correct classification of working companies (Sp) in both models is the same (99,31%). The logistic regression model is able to classify the bankrupted companies more precisely, because the sensitivity of this model is 90% compared to the MARS model which correctly classified 78% of bankrupted companies. The misclassification of bankrupted companies was different so the developed MARS and logistic regression models were combined to the aggregated classification algorithm to improve the classification results (Table 3.4.7).

Table 3.4.7

The classification rules of aggregated model

Classification rules		**Logistic regression**	
		Work ↓	**Bankruptcy ↓**
MARS	**Work →**	Work	Bankruptcy
	Bankruptcy →	Bankruptcy	Bankruptcy
Overall accuracy = 96,92%; Se = 92,00%; Sp = 98,62%			

When the logistic regression and MARS models were joined, the overall accuracy remained the same as in the LR model (96,92%) but the sensitivity increased by 2% and the specificity decreased by 0,69%. Usually it is more important for banks to classify correctly the risky clients because they can cause a higher loss due to not repaid credits. Otherwise, if a bank does not finance the solvent company the implied loss consists of only not earned interest income. So banks should combine the MARS and LR models for the better classification performance. In the practice of banks it is necessary to classify the loan applicants into 8 or more risk groups attributing them credit ratings {AAA, AA, A, BBB, BB, B, C, D}. The development of such credit risk assessment models needs more complex research analyzing the financial data of enterprises in micro level. This study is directed to the macro factors of credit risk, so the economic environment of banks and enterprises in more detailed way are being analyzed.

The developed MARS and logistic regression model predicts the possibility of enterprise's bankruptcy in next financial year with 96,92% probability. It analyzes only the financial data of companies and prediction is based only on this information. In addition, it is important for banks to take into account the systematic risk of particular industry sectors, because almost all of them in Lithuania were significantly influenced by the economic downturn in 2009 and 2010.

Table 3.4.8

The statistics of bankrupted companies in different industry sectors (years 2003 – 2013)

Sector	**A**	**B**	**C**	**D**	**E**	**F**
Total	339	11	2009	21	60	2074
Average	30,8	1,6	182,6	1,9	5,5	188,5
St. dev.	4,8	1,1	52,0	1,6	3,3	137,3
V (%)	15,7	72,2	28,5	82,7	61,0	72,8
Sector	**G**	**H**	**I**	**J**	**K**	**L**
Total	3869	1151	589	209	61	424
Average	351,7	104,6	53,5	19,0	5,5	38,5
St. dev.	77,3	79,4	33,6	9,2	2,8	36,6
V (%)	22,0	75,9	62,8	48,5	51,2	95,0
Sector	**M**	**N**	**P**	**Q**	**R**	**S**
Total	597	340	41	50	149	136
Average	54,3	30,9	3,7	4,5	13,5	12,4
St. dev.	33,7	24,7	2,3	2,8	6,8	7,4
V (%)	62,1	79,9	61,3	60,9	50,1	60,2

The abbreviations of sectors in Table 3.4.8 were set according to industry classification of Statistics Lithuania. The sectors were analyzed: agriculture, forestry and fishery (A), mining (B), manufacturing (C), electricity, gas, steam supply and air conditioning (D), water supply and waste works (E), construction (F), wholesale and retail, motor vehicle repair

(G), transportation and storage (H), settlement and feed services (I), information and communications (J), financial and insurance services (K), immovable property operations (L), profession, science and technical activity (M), administration services (N), education (P), health services (Q), recreation (R), other services (S). The total number of bankrupted companies in 2003 – 2013, average number of 1 year, standard deviation and coefficient of variation (V) were calculated in these sectors. The highest numbers of bankruptcies are in wholesale and retail, motor vehicle repair, construction, manufacturing and transportation and storage. These four sectors together compound 75% of total bankruptcies in the analyzed period. In Table 3.4.9 the sectors are sorted according to the annual average number of bankruptcies. The ranks for the sectors were attributed. The higher rank [1, 2, ...] means higher number of bankruptcies in the particular sector.

Table 3.4.9

The sorted sectors according to the average number of bankruptcies in one year

Rank	1	2	3	4	5	6	7	8	9
Sector	G	F	C	H	M	I	L	N	A
Rank	10	11	12	13	14	15	16	17	18
Sector	J	R	S	K	E	Q	P	D	B

The number of enterprises and the relative rates of bankruptcies to total enterprises are shown in Figure 3.4.1.

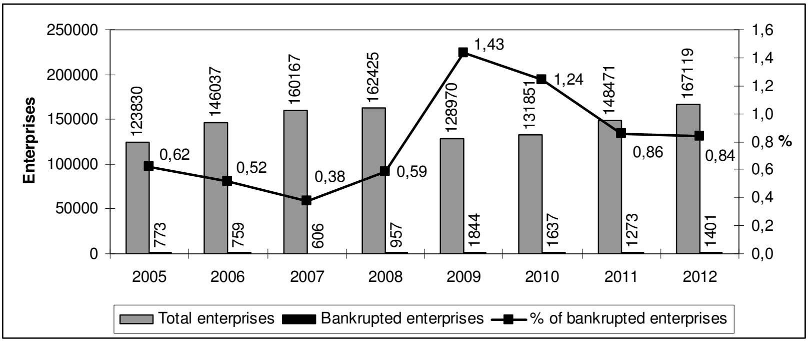


Figure 3.4.1. The number of enterprises and bankruptcy statistics (Statistics Lithuania, 2014)

In the economics growth period of 2005 – 2007 the proportion of bankruptcies in total number of Lithuanian enterprises was decreasing from 0,62% to 0,38%. The 2008 year‘s increase of this rate to 0,59% can be considered as early crisis warning indicator, because in the economic recession of 2009 the rate of bankrupted companies increased to 1,43%. Further the recovering economy reduced this relative rate of bankruptcies to 0,84% in 2012. While the overall number of bankruptcies significantly increased in 2009, the calculated standard deviations and coefficients of variation in Table 3.4.8 point that the fluctuations of bankrupted companies in sectors is different. So, it is worth to ascertain the sectors that are sensitive to the fluctuations of business cycle in whole economy.

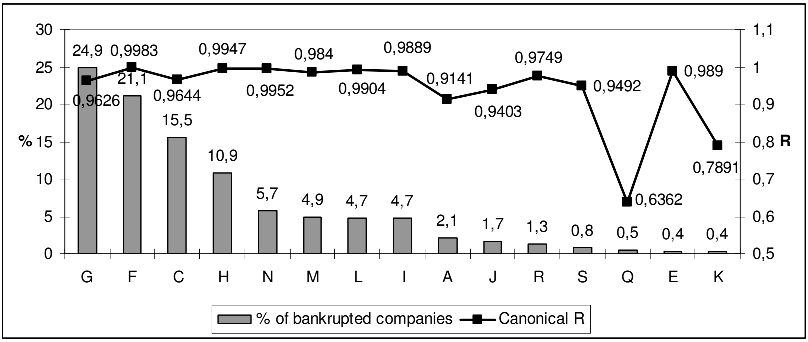


Figure 3.4.2. The average proportion of bankrupted companies by industry sector and canonical R values

The line chart in Figure 3.4.2 indicates the canonical correlation coefficients between 5 Lithuanian macroeconomic rates of years 2003 – 2011 and the number of bankrupted companies in every industry sector. These macroeconomic indicators were included into canonical analysis: GDP to 1 inhabitant, compensation of employees, exports, gross fixed capital formation (investments), the final consumption expenditure of households and non-profit institutions serving households. The correlation is very strong in all sectors except the health services (Q) together with financial and insurance sector (K). The number of bankruptcies in these two sectors are not very sensitive to the changes in macroeconomic environment, because their canonical correlation coefficients are 0,6362 and 0,7891. The number of bankruptcies in other sectors highly correlate with the changes in macroeconomic environment.

The polynomial regression models were developed to model the changes of bankrupted companies number in industry sectors. The charts of two sectors (L and D) with the highest coefficients of variation (according to Table 3.4.8) are shown in Figure 3.4.3. The independent variable (*x*) in the polynomial regression models is a year number, the dependent variable (*y*) is the number of bankrupted companies. The polynomial regression curves visualize the degree of bankrupted companies number fluctuations in the different stages of business cycle.

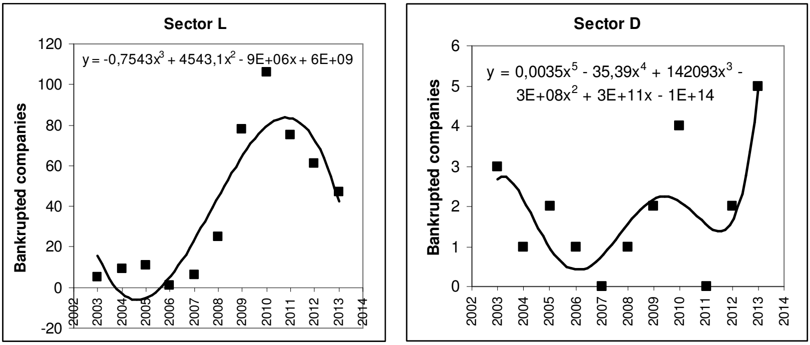


Figure 3.4.3. The polynomial regression models of bankrupted companies in sectors with the highest coefficients of variation

The immovable property operations, electricity, gas, steam supply and air conditioning sectors are very sensitive to the macroeconomic changes because the coefficients of variation are 82,7% – 95%. The fluctuations of polynomial regression curves in Figure 3.4.3 reflect this volatility.

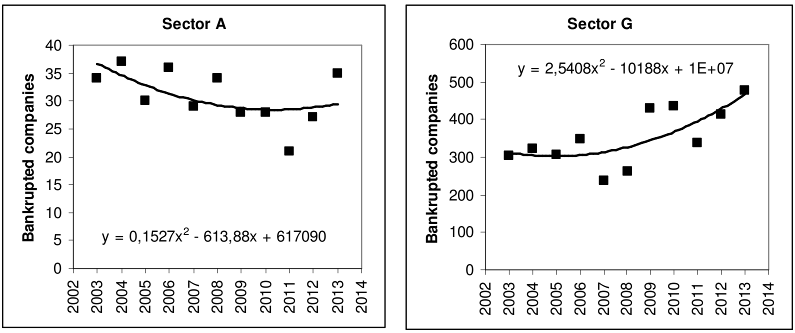


Figure 3.4.4. The polynomial regression models of bankrupted companies in sectors with the least coefficients of variation

The coefficients of variation in agriculture, forestry and fishery, wholesale and retail, motor vehicle repair sectors are lesser, therefore the polynomial regression curves are not so much fluctuating (Figure 3.4.4). These differences of variation rates reflect the different credit risk for banks in particular industry sector. The sensitivity of enterprises loss to the economic environment is not the same. So it is worth to implement the analysis that can help banks to identify the most risky sectors when the macroeconomic conditions of a country deteriorate. These results can be useful when in the credit risk assessment the estimated default probability of company is acceptable for bank. But for the evaluation of long term debt perspectives the impact of macroeconomic fluctuations on enterprises' credit risk changes is very important.

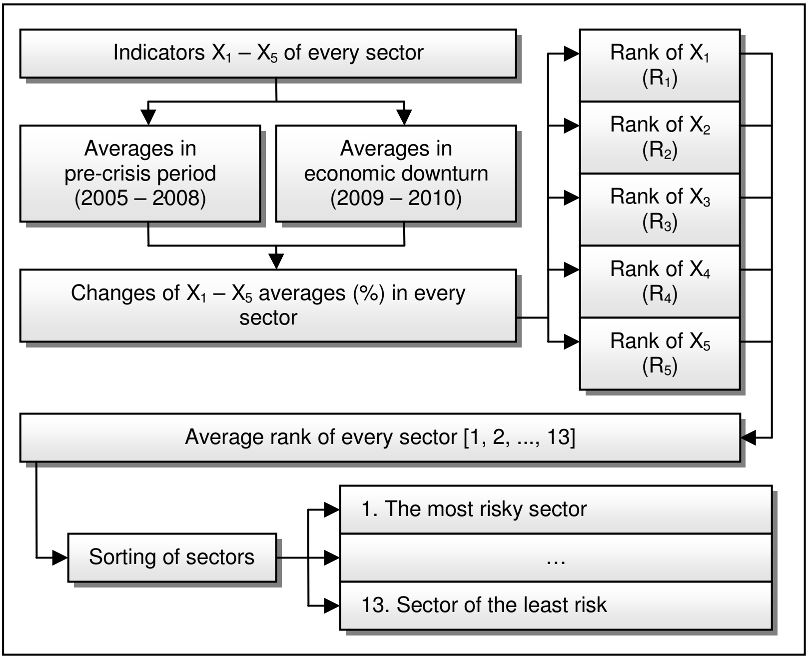


Figure 3.4.5. The rank attribution process in sectorial analysis

The sensitivity of industry sectors to macroeconomic changes was estimated analyzing 5 indicators:

- Sector's number of bankrupted companies in a year (X_1).
- Sector's revenue (X_2).
- Sector's income before taxes (X_3).

- Sector‘s profitability of main activity (X_4).
- Proportion of loss-making companies in a sector (X_5).

The years 2005 – 2008 were considered as the pre-crisis period, while the downturn’s rates included years 2009 and 2010. The average values of pre-crisis period, in downturn and the changes of averages in every sector were calculated. According to changes of averages the ranks R_i in range of [1; 13] were attributed for the analyzed sectors. The ranks attribution process is shown in Figure 3.4.5. The sectors A, K, M, P and S were not included into further analysis because of the unavailable statistical data. Ranks attributed to other sectors according to 5 indicators and the calculated average ranks are given in Table 3.4.10.

Table 3.4.10

Ranks attributed to industry sectors

Bankruptcy risk	**Industry sector**	**R_1**	**R_2**	**R_3**	**R_4**	**R_5**	**Average rank**
High	F	4	1	5	4	1	3
	I	6	4	1	3	5	3,8
	L	1	9	2	1	6	3,8
	R	7	2	4	6	2	4,2
Medium	N	2	7	6	5	9	5,8
	J	5	5	10	9	4	6,6
	G	11	6	8	8	3	7,2
	H	3	8	7	10	8	7,2
	B	12	3	9	7	7	7,6
Low	D	8	12	3	2	13	7,6
	C	10	11	11	11	10	10,6
	E	9	10	12	12	11	10,8
	Q	13	13	13	13	12	12,8

The sectorial analysis results allowed to classify the Lithuanian industry sectors into three groups according to their bankruptcy risk in economic recession:

- The most risky sectors are: construction (F), settlement and feed services (I), immovable property operations (L), and recreation (R).
- The medium bankruptcy risk sectors are: administration and services (N), information and communications (J), wholesale and retail (G), transportation and storage (H), and mining (B).

- The sectors of low bankruptcy risk are: electricity, gas supply, air conditioning (D), manufacturing (C), water supply and waste works (E), and health services (Q).

In Figure 3.4.6 the changes of bankrupted companies before economic downturn and during the downturn were compared in the highest and least risk sectors (3 enterprises from every sector). In the construction sector (F) the deterioration of macroeconomic conditions increased the average number of bankrupted companies by 305,6%, settlement and feed services (I) – 139,3%, immovable property operations (L) – 755,8%. Three sectors from the end of Table 3.4.10 were influenced by the economic downturn not so significantly. The average number of bankrupted companies in manufacturing (C) sector increased by 53,7%, water supply and waste works (E) – 87,5%. The least risky is health services sector which was not negatively influenced by macroeconomic changes in 2009 and 2010. This period increased the average number of bankruptcies only by 6,7%.

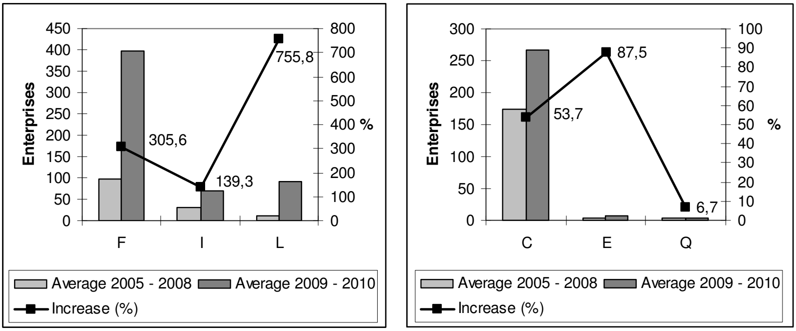


Figure 3.4.6. The changes of average bankrupted enterprises in high and low bankruptcy risk groups

The analysis of industry sectors riskiness in economic recession was extended into the regional view. The distribution of bankrupted enterprises in every sector was analyzed in 10 districts of Lithuania. The correlation coefficients were calculated to ascertain is the riskiness of sectors equal in all districts or are there any significant differences (Table 3.4.11). All calculated correlation coefficients are very high in range [0,76; 0,99] what means that the estimated consistent patterns of industry sectors risk is typical in all districts. The least similarities are in Vilnius and Tauragė, Vilnius and Marijampolė, Klaipėda and Tauragė, Klaipėda and Marijampolė districts where the correlation coefficients are less than 0,8.

Table 3.4.11

The bankrupted companies distributions correlation coefficients of industry sectors in 10 districts of Lithuania

	Alytus	Kaunas	Klaipėda	Marijampolė	Panevėžys	Šiauliai	Tauragė	Telšiai	Utena	Vilnius
Alytus	1,00	0,94	0,92	0,96	0,94	0,97	0,93	0,93	0,97	0,90
Kaunas	0,94	1,00	0,97	0,82	0,95	0,93	0,84	0,97	0,92	0,98
Klaipėda	0,92	0,97	1,00	0,78	0,87	0,87	0,77	0,91	0,85	0,98
Marijampolė	0,96	0,82	0,78	1,00	0,88	0,94	0,95	0,84	0,95	0,77
Panevėžys	0,94	0,95	0,87	0,88	1,00	0,97	0,95	0,98	0,98	0,88
Šiauliai	0,97	0,93	0,87	0,94	0,97	1,00	0,95	0,95	0,99	0,87
Tauragė	0,93	0,84	0,77	0,95	0,95	0,95	1,00	0,90	0,98	0,76
Telšiai	0,93	0,97	0,91	0,84	0,98	0,95	0,90	1,00	0,94	0,92
Utena	0,97	0,92	0,85	0,95	0,98	0,99	0,98	0,94	1,00	0,85
Vilnius	0,90	0,98	0,98	0,77	0,88	0,87	0,76	0,92	0,85	1,00

Despite the fact that the sectorial riskiness differences are not signficant in Lithuanian districts, it is possible relatively to compare the proportions of bankruptcies to determine in what districts the enterprises of a particular sector are more risky. The distribution of 5 sectors that have the highest number of bankrupted companies every year according to Table 3.4.9 are given in Table 3.4.12

Table 3.4.12

The distribution of bankrupted companies in 10 districts of Lithuania

District	**Industry sector**				
	G	**F**	**C**	**H**	**M**
Alytus	26,1	21,7	18,8	24,6	1,4
Kaunas	25,5	26,0	17,6	13,4	5,8
Klaipėda	19,9	29,6	14,2	15,0	5,6
Marijampolė	25,9	13,0	20,4	31,5	0,0
Panevėžys	29,0	17,4	23,2	13,8	4,3
Šiauliai	27,9	16,2	17,6	18,4	2,2
Tauragė	29,6	11,1	25,9	22,2	0,0
Telšiai	30,7	24,0	25,3	12,0	1,3
Utena	27,3	14,5	21,8	20,0	3,6
Vilnius	19,5	25,6	14,2	12,6	6,9

The companies of wholesale and retail sector (G) have the higher bankruptcy risk in Panevėžys, Šiauliai, Tauragė, Telšiai and Utena districts. The construction (F) companies are more risky in Alytus, Kaunas, Klaipėda, Telšiai and Vilnius. The districts that have the higher bankruptcy risk in other sectors are highlighted in grey (Table 3.4.12).

The average net profitability, return on assets, current ratio, quick ratio and debt ratio of sectors one year before the enterprises‘ bankruptcy are calculated in Table 3.4.13. These ratios in the credit risk management can help banks to foresee the bankruptcy of companies in the next financial year if their financial indicators reach the estimated values.

Table 3.4.13

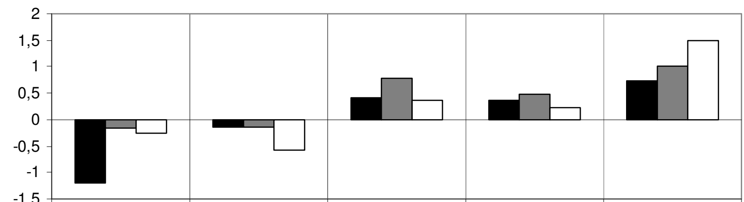
The average financial ratios one year before the bankruptcy in industry sectors (Statistics Lithuania, 2014)

Sector	Net profitab.	ROA	Current ratio	Quick ratio	Debt ratio
A	-0,0365	-0,0332	0,74	0,54	0,97
C	-0,157	-0,1976	0,7	0,38	0,98
E	-0,1451	-0,4583	0,53	0,34	1,1
F	-0,0938	-0,0845	1,14	0,4	0,92
G	-0,0549	-0,0962	1	0,45	0,92
H	-0,179	-0,2599	0,65	0,46	1,15
I	-0,4318	-0,4623	0,34	0,17	1,41
J	-0,2033	-0,1388	0,45	0,36	1,05
L	-0,1841	-0,0306	1,68	0,35	0,86
M	-0,3892	-0,2454	0,66	0,51	0,84
N	-0,1349	-0,1067	0,4	0,31	1,05
P	-0,2139	-0,8354	0,23	0,16	1,96
R	-1,205	-0,145	0,42	0,37	0,74
S	-0,0547	-0,224	0,59	0,5	1,3
All	**-0,1201**	**-0,1383**	**0,93**	**0,42**	**0,96**

The average financial ratios vary in different sectors, so the cluster analysis by the method of *k*-means was implemented to classify the sectors into three groups according to the profitability, solvency and indebtedness ratios of Table 3.4.13. The members of clusters are:

- Cluster 1: R.
- Cluster 2: A, C, F, H, J, L, N, S.
- Cluster 3: E, I, P.

Mostly the average bankruptcy warning ratios of enterprises can be considered as cluster‘s 2, because this cluster has 71,4% of analyzed sectors. So the analysts can use these values as the most common in pre-bankruptcy state of business enterprises. The sectors in clusters 1 and 3 have some pecularities in the companies‘ financial condition. In cluster 1 there are companies of recreation services where in the one year before bankruptcy the higher negative net profitability and lower debt ratio are typical compared to other clusters. The cluster 3 consists of water supply, waste works, settlement, feed services and education sectors where the lower return on assets and higher debt ratio are typical compared to other clusters.



	NPM	ROA	CR	QR	DR
■ Cluster 1	-1,205	-0,145	0,42	0,37	0,74
▦ Cluster 2	-0,159167	-0,146744	0,7789	0,49	1,0133
□ Cluster 3	-0,2636	-0,585333	0,3667	0,2233	1,49

Figure 3.4.7. The average values of financial ratios in clusters of industry sectors

The analysis results of this chapter allowed to develop the statistical model applying the multivariate adaptive regression splines and logistic regression methods to predict the enterprises bankruptcy in next financial year with the probability of 96,92%. If the company in credit risk assessment process is acceptable according to its financial data, the sectorial riskiness analysis results can help banks to rank the enterprises according to this feature. The district of enterprise’s location is also one of factors that has the impact on the bankruptcy possibility in case of macroeconomic downturn. The comparative analysis allowed to highlight the distribution values in industry sectors that point the higher enterprises’ bankruptcy risk in the particular district of Lithuania. The average financial ratios of profitability, solvency and capital structure help to understand the typical financial condition in the last year of the enterprise’s performance. If the rates impend to these values, the loan application must be rejected.

3.5. Business and households indebtedness indicators as factors of NPLs problem in banks

The ability to repay credits also depends on the debtor's indebtedness level. Not all loan applicants, especially households, understand the risk of default and the essence of credits repayment burden at the moment of credit agreement signing. That causes the problem of irresponsible borrowing which increases the credit risk of loan applicants and non-performing loans.

Analyzing the statistical data it is evident that in 2009 together with the macroeconomic downturn and the NPLs growth in banks it was the problem of high indebtedness of banks' clients. Since 2001 the business loans portfolio increased by 612,7% to 10 370 million EUR in 2008. The households loans portfolio in this period increased by 3 875,5% to 8 746 million EUR (Figure 3.5.1). The average annual business loans growth rate in 2001 – 2008 was 32,4%, the households loans – 69,2% yearly. Since 2008 the loan portfolio in Lithuanian banks is decreasing.

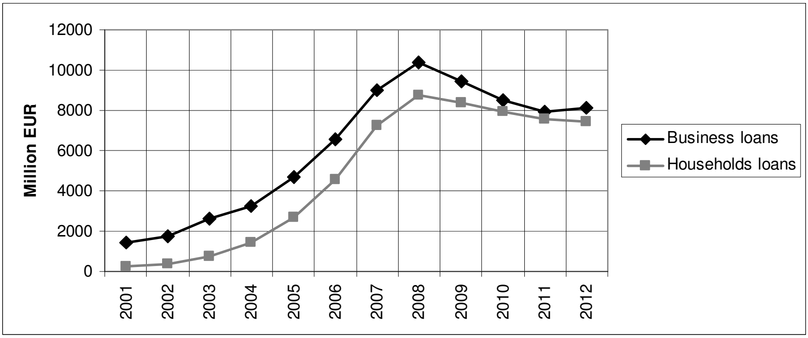


Figure 3.5.1. The Lithuanian banks consolidated loan portfolio (Bank of Lithuania, 2013)

The borrowing activity in Lithuanian banks is seen in the statistics of new loans of a year (Figure 3.5.2). The peak point of credits in LTL was in 2007 (5 721,6 million EUR) while the new credits in EUR were highest in 2008 (8 930,1 million EUR). The overall amount of new credits in 2008 was 13 331,5 million EUR. So it is evident that the growing Lithuanian economy stimulated to borrow and the credits were easily obtainable. In 2009 the recession in Lithuanian economy started to reduce the annual borrowing amounts.

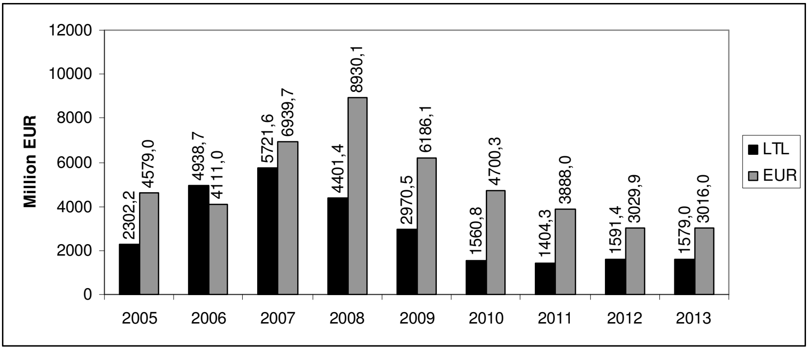


Figure 3.5.2. The new loans of Lithuanian banks in LTL and EUR (Bank of Lithuania, 2014)

In Table 3.5.1 the indebtedness rates were calculated that reflect the changes of debt burden for Lithuanian business enterprises and households. The estimated critical indebtedness indicators before the economic downturn (year 2008) statistically can help to foresee the similar problems for banks in future.

Table 3.5.1

The indebtedness rates of business enterprises and households in Lithuania (%)

Rate	2005	2006	2007	2008	2009	2010	2011	2012
BL/R	44,9	55,9	60,4	70,7	85,5	64,1	54,3	48,5
BL/GDP	22,2	27,3	31,2	32,0	35,4	30,7	25,6	24,7
HL/COE	31,8	44,6	58,8	60,9	69,9	69,1	61,6	57,5
HL/GDP	12,9	19,0	25,2	27,0	31,4	28,6	24,4	22,5
LP/GDP	35,2	46,3	56,5	59,0	66,8	59,3	50,1	47,2
LP/COE	86,5	108,6	131,6	133,2	148,7	143,4	126,2	120,4

The business loans (BL) in 2008 reached the peak point when the average financial debt for Lithuanian banks of 1 company was 242,4 thousands EUR. Also the households loans (HL) in 2008 were the highest when 1 Lithuanian inhabitant had in average 2,599 thousands EUR debt for banks. The important factor of debtors credit risk increase and insolvency in 2009 can be considered the high indebtedness of year 2008, that became too high debt burden for enterprises and households in deteriorated macroeconomic environment. The relative rates of business loans to revenue (BL/R), business loans to GDP (BL/GDP), households loans to compensation of employees (HL/COE), households loans to GDP (HL/GDP), banks‘ loan portfolio to GDP (LP/GDP) and loan portfolio to compensation of employees (LP/COE) were calculated in Table 3.5.1 to measure the business and households indebtedness in Lithuania. When the revenue of Lithuanian companies in 2009 decreased by 29,4% (Figure 3.3.3), statistically the Lithuanian companies had to accrue for banks in average 85,5% of revenue if a company wanted to repay all financial debts. Similarly the economic downturn in 2009 increased the credit risk of households credits, because not only the value of assets significantly decreased as indicated the realty price index analysis, but also the coefficient of households debt to compensation of employees highly increased. In 2009 the Lithuanian employees for 1 EUR of their salary had 0,699 EUR of debts for banks. The total loan portfolio of Lithuanian banks to GDP reached 66,8%, the loan portfolio to compensation of employees rate – 148,7%.

The year 2009 was the macroeconomic downturn in Lithuania, so predicting the banking problems the most important indebtedness indicators for banks are the year’s 2008 rates. It can be concluded that the deterioration of banks’ loan portfolio in next year is very probable when these relative indicators reach the estimated values:

- Business loans to revenue rate – 70,7%.
- Business loans to GDP – 32%.
- Households loans to compensation of employees – 60,9%.
- Households loans to GDP – 27%.
- Lithuanian banks‘ total loan portfolio to GDP – 59%.
- Lithuanian banks‘ total loan portfolio to compensation of employees – 133,2%.

These high indebtedness indicators, especially related to the Lithuanian households, implicate the problem of irresponsible borrowing in the country. There are several factors related to the creditors and debtors that facilitate the irresponsible financing behaviour in credit markets. For lenders, the aim of high returns from loans as the investment instrument and the insufficient financial regulation are among the most important motivations. For borrowers, these factors include easy access to credit and lack of financial knowledge. The reasons of the adverse households debt position often includes the excessive spending by the consumers, using the credit for general living expenses and debt repayments, interest and charges on the credit taken and the raising of the credit limits by the lender. Usually the low-income borrowers are experiencing repayment difficulties due to unforeseen circumstances, poverty-level incomes, the lack of welfare provision and the misunderstanding that the debt can spiral out of control.

The criticism is directed for giving the responsibility entirely to people that borrow more than they can afford. Even the ordinary borrowing and expenses can get people into unmanageable debt in some circumstances outside of their control.

The irresponsible borrowing by credit institutions customers plays a role in creating the current financial crises. Often the publicly debased idea of saving importance may be one reason of stimulating the need to borrow for the less financially educated persons and causing their over-indebtedness. For many people this view is still dominant in their understanding of financial decision making. Ultimately, the uneducated persons resort to the secondary, unregulated markets which charge excessive interest rates. Especially the payday loans are often considered as an absolute last resort solving the financial problems of households, but using them will likely crucify the personal finances and spiral the debt out of control. The exorbitant rates charged on desperate borrowers exacerbates indebtedness and loans are never paid off, raising social concerns.

Undoubtedly, defaulting is costly to both the lender and the borrower. It is therefore in the interest of both parties to avoid the default stage which may ultimately lead to bad individual or corporate reputation, litigations and court judgements. The continued advancement of credit to people who clearly are not able to pay back is not just irresponsible lending but also the operational risk issue within the lending institution. For the lenders to be considered as responsible, they must serve their credit markets in a sustainable way through the value-enhancing loans. The over-lending, especially to already over-indebted loan applicants further commits them into a spiralling cycle of indebtedness, further exacerbating the deep financial problems. The consumers, financial providers and intermediaries need to take the responsibility for their role within the financial system of a country. This adds weight to the need for a more financially responsible and inclusive financial services sector. In this way, the notion of responsibility needs to be shared between the government, financial services and individuals but this responsibility needs to be proportionate and fair.

The economists highlight the fact that they tend to see individuals as rational actors responding to changing economic conditions. Leading from this understanding of the rational finance manager, the education is the key solution of personal over-indebtedness problem. Indeed the recent policy conjecture must focus on the strategic priorities to address the issue of over-indebtedness problem and the education must appear to be the key approach. There is a desire to increase levels of financial capability and awareness improving people's ability to take control of their own finances.

3.6. Non-performing loans problem in European Union

The statistical data of World Bank shows that since 2009 the growth of average bank non-performing loans (NPLs) to total gross loans in EU countries was observed. In 2006 – 2008 this rate was stable in range 2,15 – 2,75%, but after this period the continued average increase rate of NPLs was 0,91% yearly and in 2013 this rate reached 7,3%. The Lithuanian NPLs statistics in the context of European Union average in this period is outstanding (Figure 3.6.1). But in 2009 the sudden NPLs growth was not a systemic banking problem of EU, because the values of NPLs significantly differ. The proportions of non-performing loans in 28 EU countries are given in Table 3.6.1.

Table 3.6.1

The non-performing loans in banks of EU countries, %
(World Bank, 2014)

Country		2006	2007	2008	2009	2010	2011	2012	2013
Austria	AT	2,7	2,2	1,9	2,3	2,8	2,7	2,8	2,9
Belgium	BE	1,3	1,2	1,7	3,1	2,8	3,3	3,8	3,8
Bulgaria	BG	2,2	2,1	2,4	6,4	11,9	15	16,6	...
Cyprus	CY	...	...	3,6	4,5	5,6	9,6	18,6	30,3
Czech Republic	CZ	...	2,4	2,8	4,6	5,4	5,2	5,2	5,2
Germany	DE	3,4	2,6	2,9	3,3	3,2	3	2,9	...
Denmark	DK	...	0,6	1,2	3,3	4,1	3,7	6	4,8
Spain	ES	0,7	0,9	2,8	4,1	4,7	6	7,5	8,2
Estonia	EE	0,2	0,5	1,9	5,2	5,4	4	2,6	1,5
Finland	FI	...	...	0,4	0,6	0,6	0,5	0,5	...
France	FR	...	...	2,8	4	3,8	4,3	4,3	4,3
United Kingdom	UK	0,9	0,9	1,6	3,5	4	4	3,7	...
Greece	EL	61,8	53,7	4,7	7	9,1	14,4	23,3	31,3
Hungary	HU	2,6	2,3	3	6,7	9,8	13,4	15,8	17,6
Ireland	IE	0,5	0,6	1,9	9,8	12,5	16,1	24,6	24,6
Italy	IT	6,6	5,8	6,3	9,4	10	11,7	13,7	15,1
Lithuania	LT	1	1	6,1	24	23,3	18,8	14,8	12,5
Latvia	LV	0,5	0,8	2,1	14,3	15,9	14,1	8,7	6,4
Malta	MT	7,1	5,9	5,5	6,2	7,4	7,3	8,2	9,2
Netherlands	NL	...	...	1,7	3,2	2,8	2,7	3,1	3,2
Poland	PL	7,4	5,2	2,8	4,3	4,9	4,7	5,2	5,2
Portugal	PT	...	2,8	3,6	4,8	5,2	7,5	9,8	11
Romania	RO	...	2,6	2,7	7,9	11,9	14,3	18,2	21,6
Slovak Republic	SK	3,2	2,5	2,5	5,3	5,8	5,6	5,2	5,1
Slovenia	SI	2,5	1,8	4,2	5,8	8,2	11,8	15,2	18
Sweden	SE	0,1	0,1	0,5	0,8	0,8	0,7	0,7	0,6
Croatia	HR	5,2	4,8	4,9	7,7	11,1	12,3	13,8	15,4
Luxembourg	LU	0,1	0,4	0,6	0,7	0,2	0,4	0,1	0,2

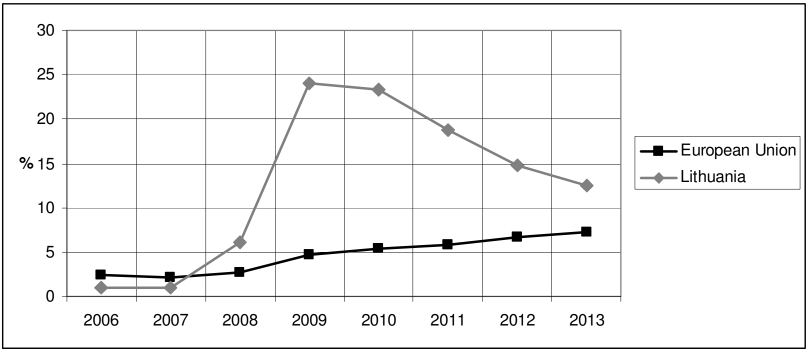


Figure 3.6.1. The NPLs in European Union (World Bank, 2014)

The average GDP to 1 inhabitant and NPLs rates were calculated for every EU country in the period of 2006 – 2013. These values in diagram form are shown in Figure 3.6.2 which is divided into four parts. Two countries were not included into this chart as the outliers: Luxembourg has the very high average GDP to 1 inhabitant rate (78 479 EUR) and the average of NPLs is low (0,34%), Greece has the very high average NPLs (25,66%) and the GDP to 1 inhabitant is 19 099 EUR. In the group of high GDP and low NPLs there are 35,7% of EU countries, low GDP and high NPLs – 35,7%, low GDP and low NPLs – 21,5%, high GDP and high NPLs – 7,1%.

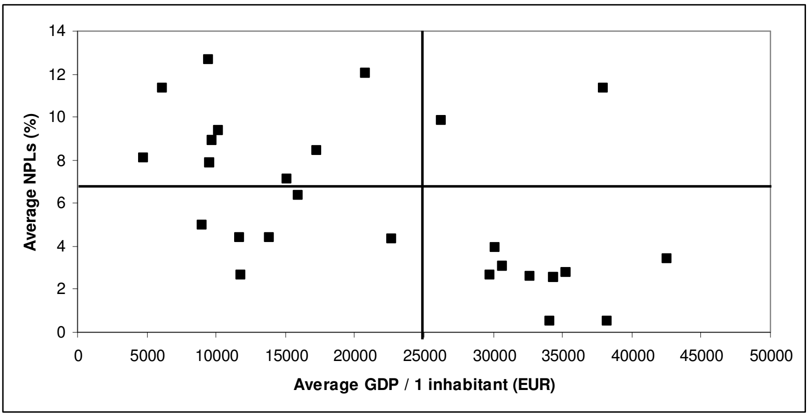


Figure 3.6.2. The average GDP to 1 inhabitant and average NPLs in EU (EUROSTAT, 2014; World Bank, 2014)

The average values of GDP and NPLs allow to maintain that the problem of high NPLs is typical in EU countries with lower GDP indicator while the countries with more developed economy have less problem of NPLs in commercial banks. Estimating the impact of economic conditions on NPLs in a country's banks it is more important the dynamics of analyzed rates rather than static averages, so in further chapters of this research these relations will be analyzed.

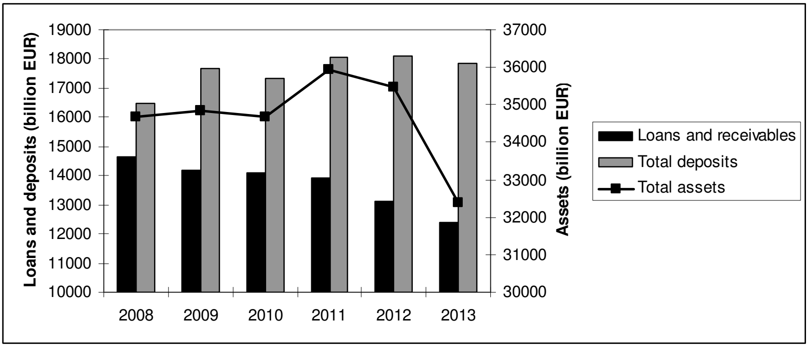


Figure 3.6.3. The loan portfolio, deposits and total assets in EU banks (European Central Bank, 2014)

In overall EU like in Lithuania since 2008 the decreasing loan portfolio and growing deposits tendencies were observed (Figure 3.6.3).

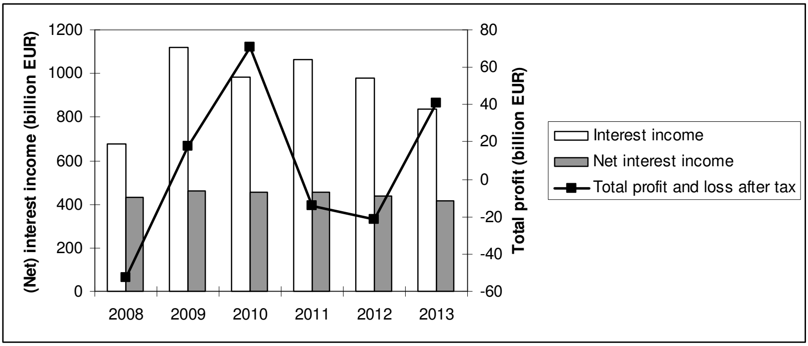


Figure 3.6.4. The interest income, net interest income and total (net) profit in EU banks (European Central Bank, 2014)

The loan portfolio in EU banks since 2008 decreased by 15,6% from 14 665 to 12 379 billion EUR in 2013. The deposits from credit ans non-credit institutions with slight fluctuations increased by 8,3% from 16 481 billion EUR in 2008 to 17 853 billion EUR in 2013. The total assets of the EU banks in 2012 and 2013 had tendency to decrease. The highest aggregated assets of 35 926 billion EUR was in 2011 while in 2013 it decreased to 32 381 billion EUR.

The loss-making activity in EU banks was in 2008, 2011 and 2012, so these indicators are not coincident with Lithuanian where the loss-making banks were in 2009 and 2010. It can be concluded that the loss-making activity of Lithuanian banks in 2009 year‘s downturn became by one year later than in all European Union. The fluctuating EU banks‘ interest income from 679 to 1 122 billion EUR in 2008 – 2013 not influenced their net interest income significantly that were in range from 417 to 459 billion EUR (Figure 3.6.4).

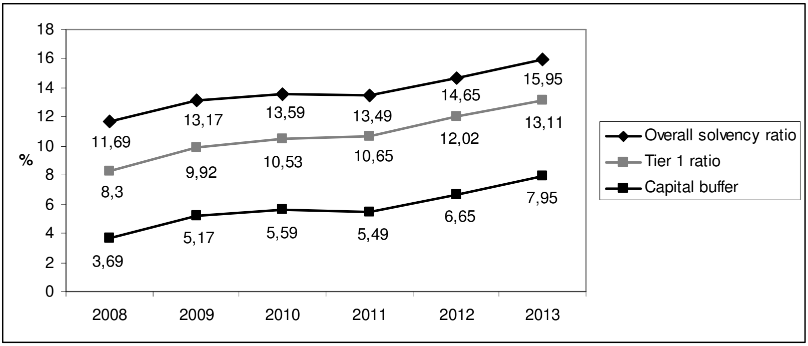


Figure 3.6.5. The capital adequacy indicators in EU banks (European Central Bank, 2014)

The capital adequacy indicators of European Union banks since 2008 are growing (Figure 3.6.5) what points that banks can absorb sufficient losses through their shareholders’ equity rather than through customer deposits or other funding sources. Only the slight deterioration is visible in 2011 when the overall solvency ratio and the capital buffer decreased by 0,1%. The overall solvency ratio ir calculated the regulatory capital of banks dividing by the risk-weighted assets. The overall solvency ratio from 11,69% in 2008 increased to 15,95% in 2013.

The Basel III from 2010 requires banks to hold 4,5% of common equity and 6% of Tier 1 capital of risk-weighted assets. Tier 1 capital is the core measure of a bank‘s financial strength from a regulator‘s point of view.

It is composed of core capital, which consists primarily of common stock and retained earnings, but may also include non-redeemable non-cumulative preferred stock. Also the Basel III agreement introduced the additional capital buffers: a mandatory capital conservation buffer of 2,5% and a discretionary counter-cyclical buffer, which would allow national central banks to require up to another 2,5% of capital during periods of high credit growth. The capital buffer in the EU banks from 3,69% in 2008 increased to 7,95% in 2013.

The Tier 1 capital ratio in the European Union banks since 2008 increased from 8,3% to 13,11%. It is the ratio of a bank‘s core equity capital to its total risk-weighted assets. Risk-weighted assets are the total of all assets held by the bank weighted by credit risk according to a formula determined by the country‘s central bank. The European Union central banks follow the Basel Committee on Banking Supervision (BCBS) guidelines setting the formulas for asset risk weights calculation. Non-risky assets like cash and currency usually have zero risk weight, while certain loans have a particular risk weight of their value.

The Lithuanian banks‘ capital adequacy ratios in period of 2008 – 2013 also were growing with the small slump in 2011 as in all EU. Despite the problem of NPLs compared to the EU average in Lithuania was more complicated, the capital adequacy rates since 2010 are higher than all EU averages (Figure 3.6.6).

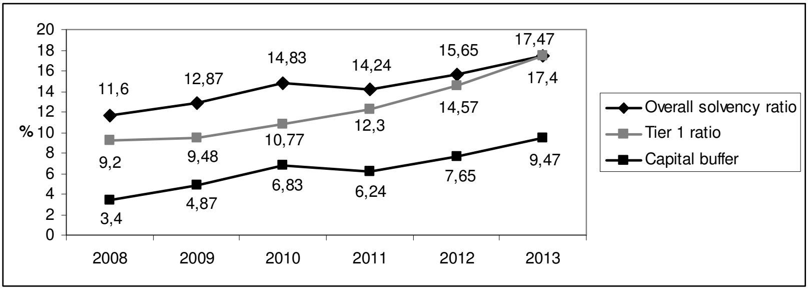


Figure 3.6.6. The capital adequacy indicators in Lithuanian banks (European Central Bank, 2014)

The analysis results of this chapter allow to conclude that the NPLs problem in EU is not coincident compared the indicators of different countries in the same years. The macroeconomic and other specific factors of every country can have the impact on the NPLs in banks, so the further chapters aim to answer the question about these dependencies.

3.7. The dependence of non-performing loans problem on macroeconomic conditions in European Union

This analysis aims to classify the EU countries into four groups according to the NPLs in banks of years 2008 – 2012. Also the interrelations between the macroeconomic indicators and NPLs will be analyzed.

The countries were sorted according to the precentage of NPLs in banks and the ranks {1, 2, ..., 28} were attributed for every country in all years (Table 3.7.1). Lithuania is in the end of the list in all years except 2012 when it was in the 21st place.

Table 3.7.1

The ranked EU countries according to the NPLs in banks

NPLs	Rank	2008	2009	2010	2011	2012
Least	1	FI	FI	LU	LU	LU
↓	2	SE	LU	FI	FI	FI
↓	3	LU	SE	SE	SE	SE
↓	4	DK	AT	AT	AT	EE
↓	5	UK	BE	BE	NL	AT
↓	6	BE	NL	NL	DE	DE
↓	7	NL	DK	DE	BE	NL
↓	8	AT	DE	FR	DK	UK
↓	9	EE	UK	UK	UK	BE
↓	10	IE	FR	DK	EE	FR
↓	11	LV	ES	ES	FR	PL
↓	12	BG	PL	PL	PL	CZ
↓	13	SK	CY	PT	CZ	SK
↓	14	RO	CZ	CZ	SK	DK
↓	15	CZ	PT	EE	ES	ES
↓	16	ES	EE	CY	MT	MT
↓	17	FR	SK	SK	PT	LV
↓	18	PL	SI	MT	CY	PT
↓	19	DE	MT	SI	IT	IT
↓	20	HU	BG	EL	SI	HR
↓	21	CY	HU	HU	HR	LT
↓	22	PT	EL	IT	HU	SI
↓	23	SI	HR	HR	LV	HU
↓	24	EL	RO	BG	RO	BG
↓	25	HR	IT	RO	EL	RO
↓	26	MT	IE	IE	BG	CY
↓	27	LT	LV	LV	IE	EL
Highest	28	IT	LT	LT	LT	IE

Further the minimal, maximal values, median, 1st and 3rd quartiles of NPLs were found (Table 3.7.2). The EU countries were classified according to these criterions of every year:

- Low NPLs group: min – 1st quartile.
- Lower medium NPLs group: 1st quartile – median.
- Higher medium NPLs group: median – 3rd quartile.
- High NPLs group: 3rd quartile – max.

Table 3.7.2

The statistical indicators of NPLs in EU countries

Statistics	2008	2009	2010	2011	2012
Min	0,4	0,6	0,2	0,4	0,1
1st quartile	1,85	3,3	3,65	3,6	3,55
Median	2,75	4,7	5,4	5,8	6,75
3rd quartile	3,6	6,775	9,85	12,575	14,9
Max	6,3	24	23,3	18,8	24,6

To form the four groups of European Union countries the analysis results of 2008 – 2012 years were conjoined and the sums of ranks according the data of Table 3.7.1 were calculated. The countries that belong to each group and their ranks are given in Table 3.7.3.

Table 3.7.3

The classified EU countries and their NPLs ranks

Low NPLs	**Country**	LU	FI	SE	AT	NL	BE	UK
	Rank	8	8	14	26	30	33	40
Lower medium NPLs	**Country**	DK	DE	EE	FR	PL	CZ	ES
	Rank	43	46	53	54	63	70	70
Higher medium NPLs	**Country**	SK	PT	MT	CY	SI	LV	BG
	Rank	74	84	95	95	102	105	106
High NPLs	**Country**	HU	HR	RO	IT	IE	EL	LT
	Rank	107	112	112	113	117	118	132

The ranking results allow to conclude that countries with the least percentage of non-performing loans in commercial banks are: Luxembourg, Finland, Sweden, Austria, Netherlands, Belgium and United Kingdom. The countries with very high percentage of NPLs are: Lithuania, Greece, Ireland, Italy, Romania, Croatia and Hungary. So, Lithuania is one of the countries in the EU that has the most serious problems of NPLs in banking sector. Further analysis aims to estimate the main macroeconomic factors that causes the negatively enlarged NPLs indicator in EU countries.

Table 3.7.4

Average macroeconomic rates to 1 inhabitant (EUR)

	GDP	EXP	INV	COE	CEH	CEG
Low NPLs	41 977,7	37 448,9	7 669,5	20 955,0	19 545,2	9 225,2
Lower medium NPLs	23 733,8	11 294,7	4 553,1	11 809,7	12 790,8	5 413,3
Higher medium NPLs	14 169,8	9 000,5	2 600,5	6 358,8	8 723,6	2 728,9
High NPLs*	11 043,3	5 580,0	2 000,1	4 414,1	7 117,6	2 057,8
High NPLs	16 769,7	10 290,7	2 702,0	6 922,3	9 829,9	3 177,6

*Italy and Ireland were excluded as outliers

The average values of macroeconomic indicators (years 2010 – 2012) in groups of countries are calculated in Table 3.7.4.

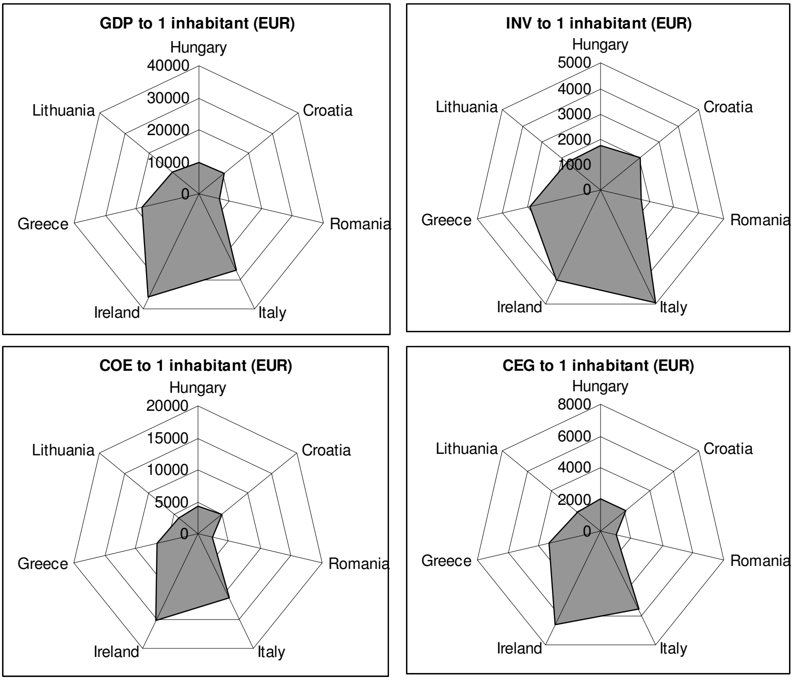


Figure 3.7.1. The outstanding macroeconomic indicators of Italy and Ireland in group of high NPLs countries

There are significant differences of 6 relative average macroeconomic indicators in these groups of years 2010 – 2012 that the latest statistical data was available. Two countries (Italy and Ireland) were excluded from the macroeconomic analysis because their indicators are outstanding in the group of high NPLs (Figure 3.7.1), so these countries were considered as the outliers. The first three rates are related to business activity in the countries – GDP, exports (EXP) and investments (INV). The average GDP to 1 inhabitant in group of low NPLs is higher 3,8 times, exports – 6,7 times, investments – 3,8 times than in group of high NPLs. The second two rates are related to the income of inhabitants – compensation of employees (COE) and consumption expenditures of households (CEH). The average compensation of employees in group of low NPLs is higher 4,7 times, consumption expenditures of households – 2,7 times. The public finance related indicator of general government consumption expenditures (CEG) in these groups differs 4,5 times.

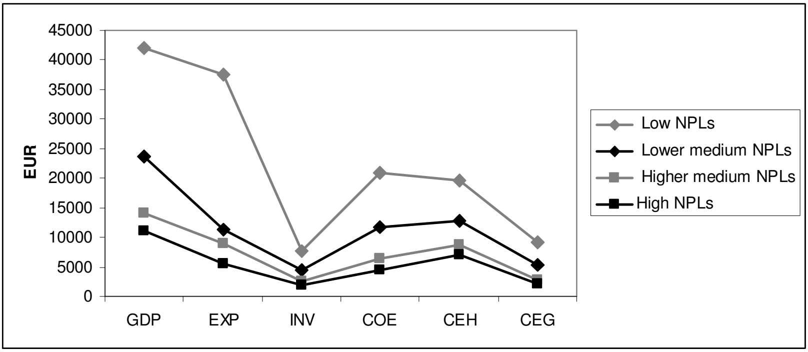


Figure 3.7.2. The average macroeconomic indicators in groups of EU countries

The analyzed average macroeconomic indicators in order of low NPLs → lower medium NPLs → higher medium NPLs → high NPLs groups constantly decrease (Figure 3.7.2). The lines of this graph do not intersect. These results affirm that macroeconomic strength of a country is very important factor of NPLs problem in commercial banks. The banking systems of EU countries with imperfect macroeconomic conditions suffer far more from debtors that are not able to meet their financial obligations.

In addition to the static NPLs and macroeconimic rates analysis, the dynamics of 2006 – 2013 years rates was analyzed. The most significant changes of NPLs interrelated to the changes of 6 macroeconomic indicators in the EU countries are shown in Table 3.7.5.

Table 3.7.5

The changes of NPLs and macroeconomic rates of EU countries (%)

Country	Year	ΔNPLs	ΔGDP	ΔEXP	ΔINV	ΔCOE	ΔCEH	ΔCEG
LT	2009	+17,9	-17,0	-24,6	-44,3	-15,9	-13,4	-5,5
LV	2009	+12,2	-18,0	-16,4	-41,1	-24,6	-19,4	-20,0
CY*	2013	+11,7	-6,9	-3,6	-22,4	-11,1	-6,0	-9,7
CY*	2012	+9,0	-0,9	-0,9	-17,0	-4,1	+0,6	-4,9
EL	2012	+8,9	-7,3	+0,9	-19,4	-12,2	-8,5	-6,7
IE*	2012	+8,5	+0,8	+5,9	+1,4	+0,1	+0,1	-1,5
EL*	2013	+8,0	-5,8	+0,5	-13,2	-10,8	-7,4	-7,3
IE	2009	+7,9	-11,2	-3,9	-34,2	-10,3	-13,2	-4,7
BG*	2010	+5,5	+3,8	+25,5	-18,5	+5,6	+3,2	+3,4
RO	2009	+5,2	-14,6	-14,1	-35,3	-17,6	-18,2	-6,5
RO*	2010	+4,0	+5,9	+22,6	+6,4	-5,3	+8,9	-6,8
EL	2011	+5,3	-4,6	+7,5	-19,4	-7,5	-3,0	-10,0
CY	2011	+4,0	+0,2	+4,0	-10,7	+0,5	+2,2	+0,4
BG	2009	+4,0	-0,7	-19,0	-15,3	+6,5	-5,5	-2,5
HU	2009	+3,7	-13,3	-17,6	-17,4	-13,4	-12,8	-10,0
HU*	2011	+3,6	+3,1	+11,0	-0,8	+2,5	+3,5	-1,3
SI	2011	+3,6	+1,7	+11,2	-3,9	-0,7	+2,4	+2,1
EE	2009	+3,3	-13,8	-22,6	-39,8	-13,0	-15,1	-2,8
Average 1	-	+7,0	-5,5	-1,9	-19,2	-7,3	-5,6	-5,2
Average 2	-	+6,9	-9,0	-8,6	-25,5	-9,8	-9,5	-6,0

In analyzed 18 cases with the most significant NPLs growth the average changes of macroeconomic indicators were calculated (Average 1). Statistically the most significant NPLs increase in EU countries was caused by the average decrease of GDP by 5,5%, exports – 1,9%, investments – 19,2%, compensation of employees – 7,3%, consumption expenditures of households – 5,6%, consumption expenditures of general government – 5,2%. Mostly when the percentage of NPLs grows (in 38,9% of cases analyzed) all 6 macroeconomic indicators in a country deteriorate. In 44,4% of cases deteriorated 5 macroeconomic indicators. Conversely, in 8,35% of analyzed cases only 1 indicator disimproved and in 8,35% cases 2 indicators disimproved. This situation mostly was in countries that met the NPLs growth repeatedly: Romania and Bulgaria in 2010, Hungary in 2011, Ireland in 2012, Cyprus in 2012 and 2013. These cases in Table 3.7.5 are marked with asterisks (*). This can be explained by the business cycle effect when the economy recovers after 1 or 2 years, but the NPLs continue growing as the consequence of the previous sharp downturn of a country‘s economy. To identify the main effects of economic downturn on the NPLs growth these cases were eliminated from the calculation of second averages for the macroeconomic rates changes (Average 2 in Table 3.7.5). Now it can be concluded that the most significant NPLs growth in EU countries is related to the average decrease of GDP by 9%, exports – 8,6%, investments – 25,5%, compensation of employees – 9,8%, consumption expenditures of households – 9,5%, consumption expenditures of general government – 6%.

The analysis results of this chapter allow to maintain that the worsening macroeconomic indicators of EU countries are typical together with the increasing non-performing loans percentage in commercial banks. So, this affirms that the deteriorative macroeconomic conditions in a country significantly causes the increase of NPLs. In general the economic downturn's effect in analyzed countries is also evident, because mostly the analyzed macroeconomic rates had negative changes when the NPLs in countries' banks grew. So, the banks of EU countries with the least economic rates in the downturn of business cycle have considerably higher risk to meet the problem of sudden non-performing loans growth.

3.8. The NPLs in European Union countries prediction model

The statistical model was developed to predict the proportion of non-performing loans in commercial banks of a country. The NPLs in the EU banks in 2008 – 2012 were analyzed. The data for analysis was selected according to the changes of non-performing loans in 3 years period. The cluster analysis was implemented to form 3 clusters of 28 European Union countries in these years (Figure 3.8.1). To predict the growth of non-performing loans the datum-level is necessary with the low NPLs and their significant increase afterwards. So the indicators of years 2008 – 2010 were selected for further analysis.

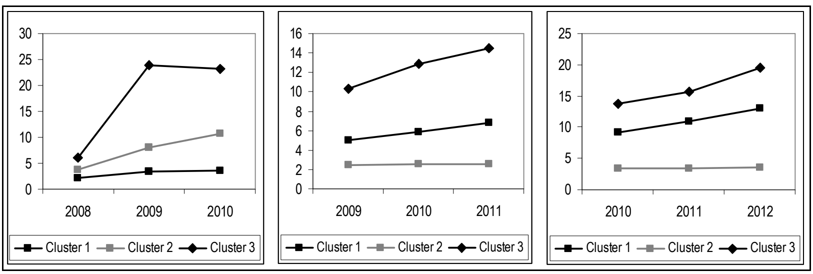


Figure 3.8.1. The average NPLs in clusters of EU countries

The countries that belong to each cluster are shown in Table 3.8.1. The main part of countries (60,7%) are in Cluster 1, where the basic individual index of increase in non-performing loans is the least (1,63 and 1,76). The higher basic index (2,15 and 2,86) have 35,7% of the EU countries. In one country (Lithuania) the percentage of non-performing loans in banks increased 3,93 times (years 2008 – 2009) afterwards in 2008 – 2010 this index was lower (3,82). So, Lithuania in this sample represents the excessive growth of NPLs in banks.

Table 3.8.1

The clusters of EU countries

Cluster	Countries	%	i_{2009}	i_{2010}
C_1	AT, BE, CY, CZ, DE, DK, ES, EE, FI, FR, UK, NL, PL, PT, SK, SE, LU	60,7	1,63	1,76
C_2	BG, EL, HU, IE, IT, LV, MT, RO, SI, HR	35,7	2,15	2,86
C_3	LT	3,6	3,93	3,82

The scheme of NPLs prediction in a country and the independent variables are shown in Figure 3.8.2.

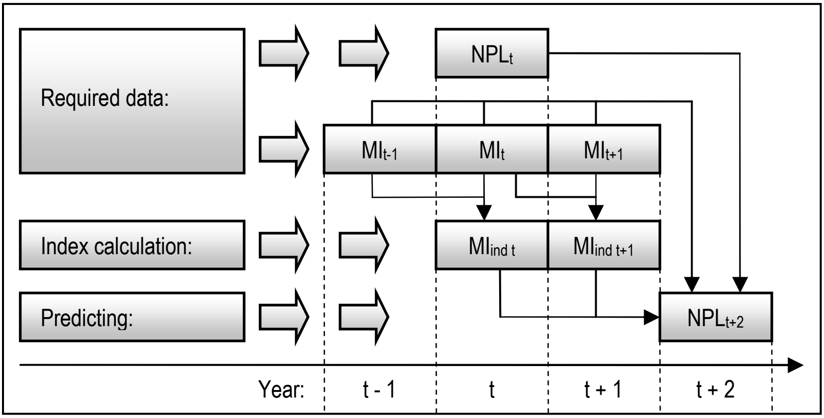


Figure 3.8.2. The data used for NPLs prediction

The NPLs prediction model was developed that is applicable when the NPLs in a country of current year *t* are about 2,1% – 6,1% as the averages of all clusters in 2008. The banks in year *t* knowing the non-performing loans (NPL_t) in the country's banks and the macroeconomic data (*MI*) of years $t-1$, t and $t+1$ can predict the NPLs of year $t+2$.

The set of macroeconomic indicators (28 EU countries) was used developing the NPLs prediction model:

- Basic index of exports of goods and services (EUR/1 inhabitant) – EXP_i.
- Basic index of imports of goods and services (EUR/1 inhabitant) – IMP_i.
- Basic index of investments (EUR/1 inhabitant) – INV_i.
- Basic index of compensation of employees (EUR/1 inhabitant) – COE_i.
- Basic index of final consumption expenditure of households (EUR/1 inhabitant) – CEH_i.
- Basic index of final consumption expenditure of general government (EUR/1 inhabitant) – CEG_i.
- Real GDP growth rate (%) – $GDPG_i$.
- Investments to GDP rate (%) – $GDPI_i$.

The changes of macroeconomic indicators (*MI*) were estimated by calculating the basic individual indices:

$$MI_{ind\ t} = \frac{MI_t}{MI_{t-1}} \text{ and } MI_{ind\ t+1} = \frac{MI_{t+1}}{MI_{t-1}} \qquad (3.8.1)$$

Because in clusters the NPLs differ significantly, the first stage of NPLs prediction is to classify a country into the particular cluster. The countries classification scheme is depicted in Figure 3.8.3.

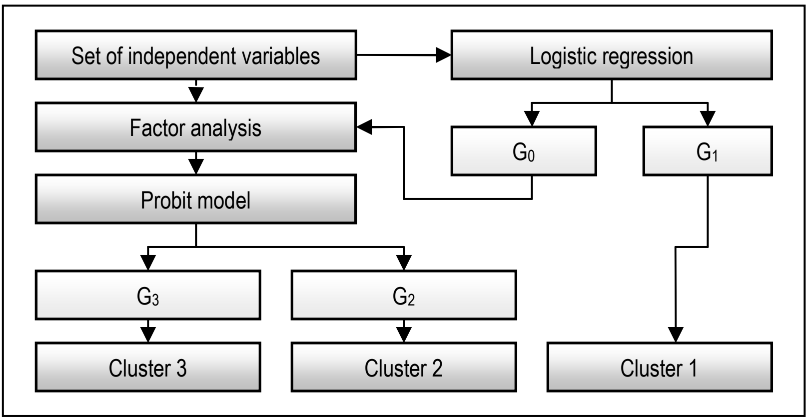


Figure 3.8.3. The countries classification scheme

The logistic regression model was developed to classify the countries into groups G_0 and G_1.

$$P(Y)=\frac{e^{\alpha+\sum\beta_i x_i}}{1+e^{\alpha+\sum\beta_i x_i}} \tag{3.8.2}$$

Where x_i – the independent variables (indices of macroeconomic rates); β_i – the regression coefficients; α – the intercept.

The regression coefficients are calculated in Table 3.8.2 (Column *Variable*).

Table 3.8.2

The regression coefficients of logistic regression model

Distribution: BINOMIAL. Link function: LOGIT.				
Variable	**Estimate**	**Standard**	**Wald**	**p**
Intercept	102,908	79,5748	1,672426	0,195934
EXP_t	-192,181	133,6995	2,066151	0,150601
EXP_{t+1}	200,448	141,1479	2,016757	0,155571
IMP_t	151,820	120,1385	1,596954	0,206335
IMP_{t+1}	-161,140	134,2814	1,440033	0,230134
INV_t	-266,762	167,6640	2,531450	0,111598
INV_{t+1}	167,122	109,4824	2,330113	0,126893
COE_t	130,931	97,5326	1,802129	0,179455
CEH_t	61,149	64,9260	0,887032	0,346283
CEH_{t+1}	-19,844	32,6861	0,368595	0,543771
CEG_t	-178,469	116,2509	2,356853	0,124734
$GDPG_t$	5,028	3,2263	2,428501	0,119147
$GDPG_{t+1}$	-4,918	3,1984	2,364322	0,124138
$GDPI_t$	0,228	0,8492	0,072247	0,788093

The countries classification threshold was set to 0,5. If $P(Y) \in [0; 0,5)$ a country is classified into group G_1 and into Cluster 1. If $P(Y) \in [0,5; 1]$ a country is classified into group G_0 and further analysis is needed to separate the countries into Cluster 2 and Cluster 3. The classification results are in Table 3.8.3 ("Response" – actual value, "Predicted" – predicted value).

The groups of countries were denoted:

- Cluster 1 – "0" (group G_1).
- Cluster 2 and cluster 3 – "1" (group G_0).

The classification accuracy of logistic regression model – 96,4%. In all sample only Spain was classified incorrectly.

Table 3.8.2

The countries classification results of logistic regression model

Country	Response	Pred.	LINEAR	Standard	Lower CL	Upper CL
BE	0,000000	0,002378	-6,0390	4,92721	0,000000	0,973868
BG	1,000000	0,999715	8,1637	7,28874	0,002189	1,000000
CZ	0,000000	0,044708	-3,0619	4,35649	0,000009	0,995834
DK	0,000000	0,000006	-11,9704	8,06188	0,000000	0,978763
DE	0,000000	0,334536	-0,6877	1,62069	0,020548	0,923349
EE	0,000000	0,194507	-1,4210	2,48758	0,001839	0,969368
IE	1,000000	0,964251	3,2948	4,92667	0,001724	0,999998
EL	1,000000	0,535427	0,1419	1,88501	0,027852	0,978886
ES*	0,000000	0,572714	0,2929	1,80943	0,037202	0,978945
FR	0,000000	0,000001	-14,0590	8,59992	0,000000	0,942487
HR	1,000000	0,999972	10,4790	7,98583	0,005636	1,000000
IT	1,000000	0,091283	-2,2981	1,78909	0,003005	0,770030
CY	0,000000	0,182156	-1,5018	2,47488	0,001739	0,966068
LV	1,000000	1,000000	25,4801	18,77387	0,000012	1,000000
LT	1,000000	0,999895	9,1634	10,04435	0,000027	1,000000
LU	0,000000	0,192285	-1,4352	2,22244	0,003045	0,948859
HU	1,000000	0,905263	2,2571	3,18106	0,018385	0,999795
MT	1,000000	0,688274	0,7921	2,04537	0,038539	0,991845
NL	0,000000	0,000387	-7,8562	5,66406	0,000000	0,962498
AT	0,000000	0,180594	-1,5123	1,78713	0,006594	0,879784
PL	0,000000	0,000000	-26,9100	18,05393	0,000000	0,999791
PT	0,000000	0,036343	-3,2777	3,34565	0,000054	0,963723
RO	1,000000	0,772621	1,2232	2,35734	0,032385	0,997110
SI	1,000000	0,287677	-0,9067	1,90566	0,009549	0,944188
SK	0,000000	0,540781	0,1635	1,81088	0,032743	0,976171
FI	0,000000	0,348687	-0,6248	2,01825	0,010146	0,965473
SE	0,000000	0,000000	-22,8286	13,83002	0,000000	0,986316
UK	0,000000	0,125537	-1,9410	2,98840	0,000410	0,980471

*Misclassification of Spain.

To reduce the amount of statistical data, for the initial macroeconomic variables indices of countries classified into group G_0 the factor analysis was accomplished and 4 factors (F_1 – F_4) were extracted. The factor score coefficients were calculated for the each initial variable (Table 3.8.3) that allow to calculate new independent variables (factor scores) for further *probit* analysis. The common factor is expressed by the linear combination of initial variables:

$$F_j = \beta_{j1}x_1 + \beta_{j2}x_2 + \ldots + \beta_{jn}x_n \quad (3.8.3)$$

Where β_{ji} – the factor score coefficients; x_i – the initial variables.

The factor scores of factors F_1 – F_4 were involved as independent variables and the *probit* model was developed. The factor scores are in Table 3.8.4.

The *probit* model is:

$$Z = 8{,}46679 + 4{,}92774 \cdot F_1 + 0{,}76422 \cdot F_2 + \\ +3{,}93935 \cdot F_3 + 2{,}29868 \cdot F_4 \quad (3.8.4)$$

The classification of countries according to Z value:

- If $Z \geq 0$, a country is attributed to group G_2 (Cluster 2).
- If $Z < 0$, a country is attributed to group G_3 (Cluster 3).

Table 3.8.3

Factor score coefficients

Rotation: Unrotated. Extraction: Principal components.				
Variable	**Factor 1 (F_1)**	**Factor 2 (F_2)**	**Factor 3 (F_3)**	**Factor 4 (F_4)**
EXP_t	-0,109707	-0,025589	-0,143992	0,072134
EXP_{t+1}	-0,078122	-0,055440	-0,129208	0,428482
IMP_t	-0,097599	0,065035	-0,143689	0,107427
IMP_{t+1}	0,038803	0,146043	-0,198468	0,262533
INV_t	-0,093528	0,088011	0,191197	0,127314
INV_{t+1}	-0,027929	0,168368	0,199040	0,011646
COE_t	-0,120458	-0,033160	0,040011	0,084335
COE_{t+1}	-0,054314	0,160612	0,057181	-0,179771
CEH_t	-0,113259	-0,002136	-0,127232	-0,131172
CEH_{t+1}	-0,020158	0,149572	-0,140657	-0,395950
CEG_t	-0,101566	-0,069727	-0,137733	0,025365
CEG_{t+1}	-0,055929	0,109377	-0,231714	-0,280652
$GDPG_{t-1}$	-0,087002	-0,103726	-0,077587	-0,211359
$GDPG_t$	-0,087378	0,116862	-0,069029	0,243664
$GDPG_{t+1}$	0,050630	0,166905	-0,002514	0,140799
$GDPI_{t-1}$	-0,086382	-0,110352	0,109225	-0,148907
$GDPI_t$	-0,104243	-0,016713	0,226107	-0,008970
$GDPI_{t+1}$	-0,078630	0,070262	0,314008	-0,004195

Table 3.8.4

Factor scores of clusters C_2 and C_3 countries

Country	Factor 1	Factor 2	Factor 3	Factor 4
Bulgaria	-1,34121	1,23901	1,27865	-0,07776
Ireland	1,49167	-0,96204	0,03090	0,87661
Greece	0,56816	0,53977	-0,46776	-1,35773
Croatia	-0,14287	0,54148	0,61470	-0,06985
Italy	1,24119	0,34554	0,61726	-0,55984
Latvia	-0,47945	-2,26367	0,80177	-0,79498
Lithuania	-1,09366	-0,79447	-1,86313	-0,34451
Hungary	0,81649	0,05177	0,53436	1,36695
Malta	0,48954	0,95135	-1,71453	0,34451
Romania	-1,30360	-0,05951	-0,04484	1,74631
Slovenia	-0,24625	0,41077	0,21262	-1,12971

According to Z values (column *Linear* in Table 3.8.5) all countries were classified correctly into clusters C_2 and C_3 (*Response* = *Predicted*). So the classification accuracy of the developed *probit* model is 100%.

Table 3.8.5

The classification of countries into clusters C_2 and C_3

Distribution: BINOMIAL. Link function: PROBIT.						
Country	**Response**	**Pred.**	**LINEAR**	**Standard**	**Lower CL**	**Upper CL**
Bulgaria	1,000000	1,000000	7,66282	3409,159	0,00	1,000000
Ireland	1,000000	1,000000	17,21891	3311,324	0,00	1,000000
Greece	1,000000	1,000000	6,71537	1669,134	0,00	1,000000
Croatia	1,000000	1,000000	10,43757	1610,640	0,00	1,000000
Italy	1,000000	1,000000	15,99182	2005,176	0,00	1,000000
Latvia	1,000000	1,000000	5,70525	1385,739	0,00	1,000000
Lithuania	0,000000	0,000000	-5,66107	1227,135	0,00	1,000000
Hungary	1,000000	1,000000	17,77706	2433,529	0,00	1,000000
Malta	1,000000	1,000000	5,64395	1170,774	0,00	1,000000
Romania	1,000000	1,000000	5,83506	1990,351	0,00	1,000000
Slovenia	1,000000	1,000000	5,80796	1843,671	0,00	1,000000

After the classification of countries the second stage of analysis is the prediction of non-performing loans. Because the increase of NPLs in clusters is different, so the different prediction models were developed for the each cluster.

The NPLs prediction model for countries of cluster 1

The discriminant analysis model was developed to classify the countries of cluster 1 into two groups:

- The countries where low NPLs growth in year $t + 2$ is expected.
- The countries where high NPLs growth in year $t + 2$ is expected.

The independent variables in these models are the previously analyzed indices of macroeconomic indicators. The NPLs growth in 2008 – 2010 of these countries was estimated and the class of a country was determined (Table 3.8.6). The median of NPLs growth (ΔNPLs) was set as the classification threshold for countries of cluster 1. The median is equal to 1,6%. The class of a country is:

- If $\Delta NPLs < 1{,}6\%$, the class is low NPLs growth (L_1).
- If $\Delta NPLs \geq 1{,}6\%$, the class is high NPLs growth (H_1).

Table 3.8.6

The classification of cluster's 1 countries according to NPLs growth

Country	ΔNPLs (%)	Class
Belgium	1,1	L
Czech Republic	2,6	H
Denmark	2,9	H
Germany	0,3	L
Estonia	3,5	H
Spain	1,9	H
France	1	L
Cyprus	2	H
Luxembourg	-0,4	L
Netherlands	1,1	L
Austria	0,9	L
Poland	2,1	H
Portugal	1,6	H
Slovakia	3,3	H
Finland	0,2	L
Sweden	0,3	L
United Kingdom	2,4	H

The different discriminant analysis models (M_1 – M_8) were developed to select the independent variables (Table 3.8.7).

Table 3.8.7

The variables of discriminant analysis models

Variable	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
EXP_t	+	+	+	+				+
EXP_{t+1}	+	+	+	+	+	+	+	
IMP_t	+	+	+	+	+			+
IMP_{t+1}						+	+	
INV_t	+	+	+	+	+		+	
INV_{t+1}								
COE_t								+
COE_{t+1}	+	+	+	+	+	+	+	
CEH_t				+	+			
CEH_{t+1}	+	+	+	+	+	+	+	
CEG_t								+
CEG_{t+1}					+	+	+	+
$GDPG_{t-1}$								+
$GDPG_t$					+	+		
$GDPG_{t+1}$						+	+	
$GDPI_{t-1}$				+	+			+
$GDPI_t$			+	+	+	+	+	
$GDPI_{t+1}$		+	+	+	+			+
Accuracy, %	82,35	88,23	8,23	94,12	100	88,23	82,35	82,35

The highest overall classification accuracy (100%) was reached with the model M_5, so this set of independent variables will be used for the classification of cluster's 1 countries.

The discriminant analysis functions are:

$$\begin{aligned} L_1 = -3038{,}26 + 2613{,}65 \cdot EXP_{t+1} - 2523{,}78 \cdot IMP_t + \\ + 10133{,}28 \cdot INV_t + 2931{,}79 \cdot COE_{t+1} - 9133{,}34 \cdot CEH_t + \\ + 5424{,}8 \cdot CEH_{t+1} - 4909{,}37 \cdot CEG_{t+1} - 57{,}57 \cdot GDPG_t - \\ - 90{,}6 \cdot GDPI_{t-1} + 143{,}06 \cdot GDPI_t + 17{,}23 \cdot GDPI_{t+1} \end{aligned} \quad (3.8.5)$$

$$\begin{aligned} H_1 = -2915{,}16 + 2607{,}77 \cdot EXP_{t+1} - 2644{,}25 \cdot IMP_t + \\ + 10236{,}45 \cdot INV_t + 2753{,}53 \cdot COE_{t+1} - 9184{,}97 \cdot CEH_t + \\ + 5392{,}36 \cdot CEH_{t+1} - 4776{,}09 \cdot CEG_{t+1} - 56{,}16 \cdot GDPG_t - \\ - 92{,}81 \cdot GDPI_{t-1} + 140{,}51 \cdot GDPI_t + 22{,}9 \cdot GDPI_{t+1} \end{aligned} \quad (3.8.6)$$

The EU countries of cluster 1 classification results (predicted class and the posterior probabilities) are given in Table 3.8.8.

Table 3.8.8

The discriminant analysis results

Country	Classification		Posterior probabilities	
	Observed	Predicted	Class L	Class H
Belgium	L	L	0,991269	0,008731
Czech Republic	H	H	0,001420	0,998580
Denmark	H	H	0,183238	0,816762
Germany	L	L	0,997412	0,002588
Estonia	H	H	0,001507	0,998493
Spain	H	H	0,000018	0,999982
France	L	L	0,646884	0,353116
Cyprus	H	H	0,000197	0,999803
Luxembourg	L	L	0,991279	0,008721
Netherlands	L	L	0,977088	0,022912
Austria	L	L	0,999984	0,000016
Poland	H	H	0,013280	0,986720
Portugal	H	H	0,450068	0,549932
Slovakia	H	H	0,028913	0,971087
Finland	L	L	0,998934	0,001066
Sweden	L	L	0,950204	0,049796
United Kingdom	H	H	0,003121	0,996879

The countries classification matrix is in Table 3.8.9.

Table 3.8.9

The classification matrix of cluster's 1 countries

Rows: Observed classifications. Columns: Predicted classifications			
	Percent	**L**	**H**
L	100,00	8	0
H	100,00	0	9

The NPLs prediction model for countries of cluster 2

The discriminant analysis model was developed to classify the countries of cluster 2 into two groups:

- The countries where low NPLs growth in year $t + 2$ is expected.
- The countries where high NPLs growth in year $t + 2$ is expected.

The independent variables in these models are the factor scores of macroeconomic indicators (Table 3.8.4). The NPLs growth in 2008 – 2010 of these countries was estimated and the class of a country was determined (Table 3.8.10). The median (Me = 6,5%) of NPLs growth (ΔNPLs) was set as the classification threshold for countries of cluster 2. The class of a country is:

- If ΔNPLs < 6,5%, the class is low NPLs growth (L_2).
- If ΔNPLs ≥ 6,5%, the class is high NPLs growth (H_2).

Table 3.8.10

The classification of cluster's 2 countries according to NPLs growth

Country	ΔNPLs (%)	Class
Bulgaria	9,5	H
Ireland	10,6	H
Greece	4,4	L
Croatia	6,2	L
Italy	3,7	L
Latvia	13,8	H
Hungary	6,8	H
Malta	1,9	L
Romania	9,2	H
Slovenia	4	L

The highest overall classification accuracy (100%) was reached with the below given discriminant analysis model. Two discriminant functions were developed for the classification of cluster's 2 countries.

The discriminant analysis functions are:

$$L_2 = -1{,}94328 + 0{,}97491 \cdot F_1 + 1{,}637 \cdot F_2 - 0{,}98399 \cdot F_3 - 1{,}9289 \cdot F_4 \quad (3.8.7)$$

$$H_2 = -2{,}19305 - 0{,}59906 \cdot F_1 - 1{,}43399 \cdot F_2 + 1{,}82365 \cdot F_3 + 2{,}21585 \cdot F_4 \quad (3.8.8)$$

The EU countries of cluster 2 classification results (predicted class and the posterior probabilities) are given in Table 3.8.11.

Table 3.8.11

The discriminant analysis results

Country	Classification		Posterior probabilities	
	Observed	Predicted	Class L	Class H
Bulgaria	H	H	0,210161	0,789839
Ireland	H	H	0,016677	0,983323
Greece	L	L	0,999941	0,000059
Croatia	L	L	0,562529	0,437471
Italy	L	L	0,979202	0,020798
Latvia	H	H	0,001638	0,998362
Hungary	H	H	0,004185	0,995815
Malta	L	L	0,999343	0,000657
Romania	H	H	0,000112	0,999888
Slovenia	L	L	0,994563	0,005437

The cluster's 2 countries classification matrix is in Table 3.8.12.

Table 3.8.12

The classification matrix of cluster's 2 countries

Rows: Observed classifications. Columns: Predicted classifications			
	Percent	**H**	**L**
H	100,00	5	0
L	100,00	0	5

The NPLs prediction for countries of cluster 3

Because the cluster 3 consists of only one country (Lithuania), it is impossible to develop the discriminant analysis model. So it is considered that the NPLs growth in this cluster is 17,2% as the Lithuanian NPLs change in 2008 – 2010.

The NPLs prediction results

Having the NPLs values of year *t* (NPL_t) and the predicted cluster and class of a country it is possible to predict the expected percentage of non-performing loans of the year $t + 2$ in the country's banks.

In cluster 1 and cluster 2 the decision about the country's class is made by this rule:

- If $L_i > H_i$, a country is classified into class L.
- If $H_i > L_i$, a country is classified into class H.

The expected changes of NPLs in year $t + 2$ of the EU countries are given in Table 3.8.13.

Table 3.8.13

The expected changes of NPLs

Cluster	Class	ΔNPLs	Average ΔNPLs
1	L	Up to 1,6%	0,5625
	H	More than 1,6%	2,4778
2	L	Up to 6,5%	4,04
	H	More than 6,5%	9,98
3	–	About 17,2%	17,2

Test of the developed model

The developed NPLs prediction model was tested considering the year 2009 as the basic and predicting the NPLs in the EU countries for year 2011. This period was selected because according to Figure 3.8.1 in 2009 the least percentages of NPLs were observed and applying the developed model it is possible to predict the NPLs growth after two years. For the clearness the test was divided into different stages.

Stage 1: *Classification of EU countries by the logistic regression model*

The EU countries classification results are given in Table 3.8.14.

Table 3.8.14

Logistic regression analysis results

Country	P(Y)	Group	Cluster
Belgium	1,59736E-05	G_1	1
Bulgaria	1	G_0	Not determined
Czech Republic	0,005103889	G_1	1
Denmark	3,59048E-12	G_1	1
Germany	2,52036E-13	G_1	1
Estonia	8,54674E-18	G_1	1
Ireland	0,998278336	G_0	Not determined
Greece	0,999999955	G_0	Not determined
Spain	0,611735251	G_0	Not determined
France	1,77278E-05	G_1	1
Croatia	0,965070902	G_0	Not determined
Italy	5,57043E-10	G_1	1
Cyprus	2,80243E-08	G_1	1
Latvia	5,55461E-10	G_1	1
Lithuania	7,76221E-17	G_1	1
Luxembourg	4,15237E-11	G_1	1
Hungary	0,997608133	G_0	Not determined
Malta	1,61679E-15	G_1	1
Netherlands	0,456829952	G_1	1
Austria	1,08285E-05	G_1	1
Poland	1	G_0	Not determined
Portugal	4,16344E-05	G_1	1
Romania	0,049035115	G_1	1
Slovenia	2,48729E-07	G_1	1
Slovakia	5,93928E-15	G_1	1
Finland	3,33624E-21	G_1	1
Sweden	1,05144E-09	G_1	1
United Kingdom	0,000530889	G_1	1

Stage 2:	*Factor analysis of G_0 group's countries*

Using the factor score coefficients of Table 3.8.3 the factor scores of G_0 group‘s countries were calculated (Table 3.8.15).

Table 3.8.15

Factor scores of countries in group G_0

Country	Factor 1	Factor 2	Factor 3	Factor 4
Bulgaria	-8,57346	-3,11231	16,6617	-7,91526
Ireland	-4,59466	-2,03745	9,889087	-4,6338
Greece	-6,18016	-2,10764	12,08149	-4,99929
Spain	-7,2331	-1,94639	14,95269	-5,68803
Croatia	-7,0381	-2,74432	14,73392	-6,82967
Hungary	-5,6568	-1,53366	12,62578	-5,0966
Poland	-6,82421	-0,45129	12,26579	-3,65094

Stage 3:	*Classification of group's G_0 countries by the probit model*

The *probit* regression analyzes the factor scores of countries from Table 3.8.15. These factor scores were multiplied by the regression coefficients in Formula 3.8.4. The *probit* regression analysis results allowed to classify all the group's G_0 countries into cluster 2, because $Z > 0$.

Table 3.8.16

Probit regression analysis results

Country	Z	Cluster
Bulgaria	11,28214	2
Ireland	12,57339	2
Greece	12,50332	2
Spain	17,1654	2
Croatia	14,03044	2
Hungary	17,44141	2
Poland	14,42087	2

Stage 4:	*Prediction of NPLs in the EU countries*

When the clusers of every country is known, further the discriminant analysis models can be applied for the prediction of NPLs changes in the EU countries. The discriminant functions (Formulas 3.8.5 and 3.8.6) were applied for the prediction of NPLs changes in cluster 1 (Table 3.8.17).

Table 3.8.17

The prediction of NPLs changes in cluster 1

Country	L_1	H_1	Class	ΔNPLs	Prediction
Belgium	3059,514	3054,677	L_1	0,2	Correct
Czech Republic	2877,675	2884,104	H_1	0,6	Incorrect
Denmark	2843,907	2842,517	L_1	0,4	Correct
Germany	3060,213	3054,159	L_1	-0,3	Correct
Estonia	2906,805	2900,463	L_1	-1,2	Correct
France	2870,781	2870,072	L_1	0,3	Correct
Italy	2969,259	2965,159	L_1	2,3	Incorrect
Cyprus	2835,887	2844,32	H_1	5,1	Correct
Latvia	2902,836	2893,506	L_1	-0,2	Correct
Lithuania	2546,725	2560,161	H_1	-5,2	Incorrect
Luxembourg	3063,318	3058,482	L_1	-0,3	Correct
Malta	3200,952	3197,573	L_1	1,1	Correct
Netherlands	3057,499	3053,65	L_1	-0,5	Correct
Austria	3083,647	3072,513	L_1	0,4	Correct
Portugal	3098,809	3098,905	H_1	2,7	Correct
Romania	3193,118	3220,321	H_1	6,4	Correct
Slovenia	2979,882	2983,273	H_1	6	Correct
Slovakia	2960,74	2949,721	L_1	0,3	Correct
Finland	3015,474	3008,518	L_1	-0,1	Correct
Sweden	3083,84	3080,788	L_1	-0,1	Correct
United Kingdom	2859,452	2853,776	L_1	0,5	Correct

The discriminant analysis results are in columns L_1 and H_1. The countries were classified into the class which has the higher value in these columns. The real changes of NPLs in 2009 – 2011 are given in column ΔNPLs of Table 3.8.17. The classification threshold according to Table 3.8.13 is 1,6%. The predictions were considered as correct:

- If ΔNPLs < 1,6% and class is L_1.
- If ΔNPLs ≥ 1,6% and class is H_1.

Three countries in cluster 1 were misclassified (Chech Republic, Italy and Lithuania). The overall classification accuracy is 85,7%.

The discriminant analysis results of cluster 2 are in Table 3.8.18. All countries were classified into class H_2 predicting the high growth of NPLs in year $t + 2$. Compared to the real changes of NPLs in 2009 – 2011 the prediction accuracy of model is 71,4%. Mostly the predictions warn about the high increase of NPLs because the model's development sample was used with the low NPLs datum-level in 2008. So two of the counties did not reach the classification threshold, only cluster was set correctly (*correct C* in Table 3.8.18). Because there is no test sample of other years in EU with the low NPLs in all EU countries (Figure 3.8.1), the higher classification accuracy in further low NPLs in EU banks period is expected.

Table 3.8.18

The prediction of NPLs changes in cluster 2

Country	L_2	H_2	Class	ΔNPLs	Prediction
Bulgaria	-16,5237	20,25207	H_2	8,6	Correct
Ireland	-10,5506	11,24754	H_2	6,3	Correct (C)
Greece	-13,6635	15,4863	H_2	7,4	Correct
Spain	-15,9228	19,59577	H_2	1,9	Incorrect
Croatia	-14,6215	17,69451	H_2	4,6	Correct (C)
Hungary	-12,5616	15,12667	H_2	6,7	Correct
Poland	-14,3621	16,82078	H_2	0,4	Incorrect

The research results of this chapter affirmed the dependence between NPLs and macroeconomic indicators changes in EU countries and it has proved that the percentage of non-performing loans in banks can be predicted applying the statistical analysis methods. The prediction errors of NPLs growth in analyzed data samples are not high what confirms the sufficient ability of developed models to predict the changes of non-performing loans in banks of a country. Following the macroeconomic changes in a country banks can foresee the possible changes of NPLs in their loan portfolios.

The overall empirical research of this study has shown that Lithuanian commercial banks in 2009 met the very serious problem of non-performing loans. The loan portfolio quality deteriorated together with the economic conditions in the country what decreased the loan portfolio, interest income, net income and other financial results of commercial banks. The research has proved that GDP, exports, imports, investments, compensation of employees, consumption expenditures of households and other macroeconomic ratios are the important factors of debtors‘ credit risk in banks. The decrease of Lithuanian enterprises revenue, profit, the growth of bankruptcies and unemployment had the very significant impact on banks performance in Lithuania. The changes of public finance indicators also allow to foresee the oncoming debtors‘ insolvency problems in banks.

Analyzing the financial ratios of Lithuanian enterprises the statistical model for the bankruptcy prediction was developed. The multivariate adaptive regression splines and logistic regression methods allowed to achieve the overall classification accuracy of 96,92%. The supplementary sectorial analysis estimated the bankruptcy risk level of different industry sectors in the economic recession. The statistical analysis of Lithuanian districts highlighted the differences of bankruptcy risk for the enterprises working in different regions. The calculated average profitability, solvency and capital structure indicators of industry sectors before the bankruptcy allow to foresee the oncoming unability to meet the financial obligations for banks when the rates of enterprises impend to the estimated values.

The business and especially households over-indebtedness rates affirmed the possible problem of irresponsible borrowing in pre-crisis period. The growth of loan portfolio in Lithuanian banks until 2008 shows the former optimistic expectations about the future debt repayments that was stimulated by the growing macroeconomic indicators. But the 2009 year‘s slump in Lithuanian economy caused the very heavy abilities to follow the signed credit agreements of debtors for banks. This research has suggested the relative indicators of households and business indebtedness that allow to foresee the possible problems in the future. The loan portfolio of banks to GDP ratio and other rates reaching the specified critical values can warn banks in advance about the possible debtors‘ insolvency.

The non-performing loans growth since 2009 was observed in all European Union but the Lithuanian problem was outstanding. The loan portfolio of banks since 2008 in EU is decreasing but the capital adequacy indicators of banks are growing. This affirms the proper risk management after crisis in banks and their acquired experience in economic recession. The dependece of macroeconomic conditions in a country and the NPLs problem in EU banks was also proved in this study. The banks of countries with high macroeconomic indicators meet the less problems of NPLs. The economic downturn causes the growth of NPLs in almost all EU countries, so it can be concluded that the macroeconomic strength of a country is very important factor of NPLs problem in commercial banks. The developed statistical NPLs change prediction model allows to foresee the NPLs growth in a country. The research has proved that the statistical analysis techniques are able to find the dependences between the macroeconomics and NPLs. Having the macroeconomic rates of a country it is possible to foresee the NPLs change direction and approximate extent in future.

The research results of this study can help banks to manage the credit risk more effectively considering their macroeconomic environment and the business cycle effects. The requirements of Basel Committee on Banks Supervision in banks can be met more easily understanding the main macroeconomic factors causing the credit risk of debtors. The households also analyzing the results of this study can understand the risk of over-indebtedness and insolvency when the economics of the country worsens. This knowledge managing the personal finance enables to avoid the critical debts burden and to keep the financial wealth in the households.

CONCLUSIONS

1. The commercial banks as the main financial intermediaries play the very important role in the economics by accumulating and intermediating the financial resources, providing the credit operations and financial services, activating the financial flows what influences the economic development of a country. The efficient financial intermediation increases the ability of business enterprises to transfer the industry inputs into outputs that increases the growth of the whole economy. Conversely, the inefficient, loss-making and uncompetitive banks can increase the costs of capital in the economy what leads to the more expensive financing of projects in such an economy. The recent empirical researches with one accord agree that the growth rates of a country's economy are higher when the banks are able to perform their tasks in the financial systems effectively. The countries with more healthy financial systems achieve higher rates of economic growth and the statistical data clearly demonstrates that the origins of financial crises in the countries could be noticed by incompetent or inefficient operations of banks. As the credits are one of the main income sources for banks, the unrestrained credit policy causes the credit booms that are some of the best indicators of financial crises. The scientific studies proved that the credit booms reduce the financial stability in a country when in a recession banks start to scrutinize the borrowers severely and lend passively. At the same time, the limited loan supply affects economic development and further causes economic slowdown. Because of this, the global harmonization of prudential supervision enhancing financial stability and ensuring the performance of banks in different countries is very important.
2. The researchers mainain that during the financial crisis, the more efficient banks demonstrated resilience to external shocks of macroeconomy, what leads to the fact that the economically efficient banks can withstand financial crises better than its inefficient counterpart and can contribute more to the efficient allocation of capital and the stability of the financial system. Because the commercial banks are clearly important to national and even global economic stability, the various indicators are necessary to identify a bank's financial status and operating performance. The analysis has shown that the most important bank-specific characteristics include bank's assets, equity over total assets, return on assets and return on equity, loans-to-total assets, non-performing loans, costs over income and costs over total assets. The impacts of these factors on bank efficiency depends on the specific

circumstances of the banking industry analysed. Although banks‘ performance measurement became quite complex, the key drivers of banks‘ performance remain earnings, efficiency, risk-taking and leverage. The Euopean Central Bank has developed the methodology for the measurement of commercial banks‘ performance where the measures are classified into three groups: traditional, economic and market-based measures of performance. Supplementing the internal performance indicators calculated by banks, the external independent banks‘ performance evaluation is also very important. The ratings attributed by the international rating agencies in one measure reflect the banks‘ activity results and the attractiveness of banks as investments.

3. Banks are the the businesses of persistent taking risk and managing the risks they need to avoid, absorb risk or it can be transferred to other participants. In the scientific literature and banking practice there are many classifications of banks‘ risks and the main risks found in literature are: liquidity, credit, operational, market, exposure, investment, country, legal, reputational, strategic, counterparty, concentration and systemic risk. Considering the systemic factor, banks are considered not as isolated business entities, but as interacting institutions whose failure may produce externalities and put the system’s stability at risk. Compared to other sectors the systematic component of default is particularly significant in the banking industry. In strong macroeconomic shocks banks tend to experience a systemic failure, when a breakdown of the financial system is triggered by a strong systemic event, which severely and negatively impacts the economy in general. Due to the systemic nature of banking the adverse economic shock may cause significant losses in banks and the insolvent bank may default on its interbank payment obligations to other banks what causes more banks to fail. So the recent financial crisis prompted the banking supervisors to designate the credit risk management guidelines from the microprudential to a macroprudential approach aiming to ensure the stability of a whole financial system.
4. The ability to assess the credit risk has the critical importance for banks because the default of even a small number of borrowers can cause the large loss which further leads to the insolvency of bank, so the managers of banks must to ensure that the credit risk management system is appropriately designed and implemented. Mainly banks assess the probability of default of debtors in one year. This probability of default arises from the potential that an obligor is either unwilling to perform on an obligation or its ability to perform such obligation is impaired. Within the banking sector the corrrectly estimated default

probability helps to reduce occurrences of non-performing loans and ensures the appropriate capital allocation. In credit risk management the regulatory capital can be calculated by the standardized approach or banks can develop their own internal ratings models. If a bank develops the own credit risk assessment model, the approval from the national supervisor s necessary to be allowed to use this approach in estimating capital for the risk exposures. The classification of loan applicants into the creditworthy and high default risk groups can be implemented also using the expert systems and credit scoring models, but only the rating systems are relevant for the regulatory capital calculation. With a ratings-based credit risk assessment, the rating allows to determine the interest rate of the loan and the regulatory capital hold by bank for the particular loan depending on its riskiness. In the internal ratings models the default probability of debtors is usually obtained as a function from a set of financial and other variables that provide information about corporate clients: profitability, solvency, capital structure, etc. These financial ratios are widely used by banks, but the current financial crisis and the regulatory requirements prompt banks to consider the economic indicators. For the accurate credit risk assessment the data quality is very important which is measured by accuracy, completeness, timeliness, relevance, objectivity, believability, representational consistency, easily-understandable, accessibility and security. In addition, the research has shown that there are some particular peculiarities in the projects‘ credit risk assessment, where the financial and other data can be unavailable. In this case banks should evaluate the degree of innovation of the project, the professional skills of people who will manage the project, the capabilities, competences, and knowledge of firms involved in the project, the reaction of the target market to the introduction of new services and products. The important credit risk factor for banks is the over-indebtedness mostly of the households which refers to a situation where a household does not have enough money to pay debt and interests after other necessary expenditures have been paid. The information sharing between credit institutions can reduce the possible loss caused by such debtors‘ insolvency. Also in lending practice the higher credit risk is associated with collateral required by banks.

5. The specific characteristics of debtors have the important influence on their likelihood to repay the debts, but the changes in economic environment must be also estimated in banks. The macroeconomic shocks can disimprove the banks’ balance sheets through the deterioration in quality of loan portfolios that can cause significant

losses for banks and may even cause the banking crisis. The researches of different countries affirmed that banks‘ loan portfolio quality can be explained by both specific borrowers‘ features ant the systemic macroeconomic conditions. The expansion phase of the economy is usually coincide with the relatively low proportion of non-performing loans in banks, as both the consumers and enterprises have the sufficient abilities to service their debts by their income and revenues. The sudden negative changes in markets and the whole economy affect the overall profitability of the firms. The growth of unemployment, the decrease of compensation of employees and the consumption expenditures throw households into the deep financial problems and insolvency, because in the economy the disposable income, corporate profits, and total spending are highly related. The banks also deepen the financial crises by themselves, because as the booming period continues, credit is extended to lower-quality debtors and subsequently, when the recession occurs, the growth of non-performing loans becomes inevitable. The unrestricted credit expansion harms banking performance and deteriorates NPLs dynamics due to the overheating of the economies. The recessions usually cause the asset prices fall and still, it is well known that poor asset quality is one of the major causes of bank failures. Thus, the macroeconomic shocks are inevitably transmitted to banks' balance sheets through a worsening of their credit portfolio. Banks are vulnerable to external macroeconomic shocks because they mostly finance illiquid assets with liquid liabilities and such shocks are the main driver of financial crises. These dynamics of credit quality highlight the importance of credit risk modelling and monitoring considering the macroeconomic changes as an integral part of modern credit risk management solutions in banks.

6. The Lithuanian commercial banks in 2009 met the problem of very high proportion of non-performing loans in their loan portfolios when this indicator reached 24% and it remained at almost this level until 2010. However, since 2011 the constant decrease of NPLs in Lithuanian commercial banks was observed. The chain of other negative changes in Lithuanian banks‘ finance was concomitant. The profitable activity of Lithuanian banks suddenly feell into deep loss: the net loss in 2009 was 1 062,8 million EUR, in 2010 this loss decreased by 92,5% to 80 million EUR, in further years the profitable activity of banks was recovered. Before the economic downturn in 2008 the highest interest income of Lithuanian banks was 1 459,1 million EUR which in further years it decreased in average by 17,2% yearly until it reached only 568,8 million EUR in 2013. In 2009 the impairment of

loans and other receivables increased by 794,8% from 127,8 to 1 143,5 million EUR and in 2010 it decreased to 201,2 million EUR. The ROA of Lithuanian banks from 1,4% in 2007 decreased to -3,9% in 2009 and in 2010 it remained negative. These empirical findings affirm the propositions of scientific publications that in the economic recession the NPLs and impairment of loans grow, the financial results of banks deteriorate and the Lithuanian banks have not assessed the credit risk of borrowers properly in the credits expansion period. This unfavourable situation caused a serious concern in banks‘ risks management because the disappearance of bank’s profitability caused the loss of defence against unexpected losses and it weakened the capital position of banks. That shows the importance of the safe capital base of banks in the economic downturn which reduces the possibility of losses for the depositors and shareholders.

7. This study highlighted the main macroeconomic rates of three groups (business, households and public finance) that should be included into the credit risk assessment models in banks. The analyzed macroeconomic indicators apparently have shown the fluctuations of business cycle and the 2009 year‘s downturn in Lithuanian economy. These indicators were the highest in year 2008 as it was the peak point of recent business cycle. In the most downturn of year 2009 the GDP, exports, imports and investments fell significantly. The aggregated business indicators of Lithuanian companies of revenue, net income, the number of profitable and loss-making companies, bankruptcies highly fluctuated. The credit risk of enterprises is directly related to their bankruptcy possibility, so the higher number of bankrupted companies means the increasing unability to fulfil the financial obligations for banks and other creditors. That undoubtedly causes the increase of credit risk and growth of non-performing loans. The statistics of Lithuanian enterprises bankruptcies is very unfavourable for banks because in case of bankruptcy a bank should expect to retrieve of only 2,7% loans without mortgage. The banks‘ economic environment indicators related to the households credit risk also should be analyzed in banks. The significant deterioration of the compensation of employees, consumption expenditures of households and the unemployment rate was observed in 2009. The growing compensation of employees stimulated to increase the consumption together with borrowing until 2008, when the significant proportion of the households‘ expenses in this period were financed by banks‘ credits. Therefore after the economics growth period the sudden deterioration of households‘ financial condition in 2009 – 2010 was evident. This

economic recession effect had negative impact to the households credit risk in Lithuania that suddenly met the lack of financial resources after short period of economic growth and reasonless expectations. The growth of non-performing loans in Lithuanian commercial banks is also related to the worsened economic indicators of Lithuanian public sector. This study suggests that the general government revenue, expenditures, budget deficit and general government debt can be the advantageous predictors of non-performing loans problem in banks.

8. In credit risk management of banks the main problem is to assess the creditworthiness of loan applicants so the model for the classification of Lithuanian enterprises into default and non-default groups was implemented applying the multivariate adaptive regression splines and logistic regression methods. Aggregating these two methods it is possible to predict the enterprise‘s bankruptcy in next financial year with 96,92% probability. The additional advantage of the developed model is the consideration of industry sector’s risk in the economic downturn of the country. The canonical correlation analysis between the Lithuanian macroeconomic rates and the number of bankrupted companies in every industry sector has shown their high sensitivity to the changes in macroeconomic environment. The polynomial regression charts visualized the degree of bankrupted companies number fluctuations in the different stages of business cycle. The different values of calculated variation coefficients reflect the different credit risk for banks in particular industry sector when the economy deteriorates. That indicated the different sensitivity of enterprises losses to the economic environment, so the sectorial analysis was implemented that can help banks to identify the most risky sectors when the macroeconomic conditions of a country deteriorate. The industry sectors were classified into the most risky, the medium risk and the low bankruptcy risk groups. These findings can be useful for banks when the estimated default probability of company is acceptable for bank, but for the assessment of long term debt perspectives the impact of macroeconomic fluctuations on enterprises‘ credit risk changes is very important. The assessment of industry sectors riskiness in economic recession was also extended to the regional factor analysis which affirmed that the estimated consistent patterns of industry sectors risk is typical in all districts. But despite the not signficant sectorial riskiness differences in Lithuanian districts, the relative to comparison allowed to determine in what districts the enterprises of a particular sector are more risky. After that, the average financial ratios analysis results of this study can help banks to foresee the bankruptcy of

companies in the next financial year if their financial indicators reach the estimated values.

9. The study affirmed that the ability to repay credits also depends on the debtor‘s indebtedness level. In Lithuania the average annual business loans growth rate in 2001 – 2008 was 32,4%, the households loans – 69,2% every year. The growing Lithuanian economy stimulated to borrow because the credits were easily obtainable in banks. The recession of 2009 in Lithuanian economy started to reduce the annual borrowing amounts. The indebtedness rates were calculated to measure the changes of debt burden for Lithuanian business enterprises and households. These growth of indebtedness rates, especially related to the Lithuanian households, implicate the problem of irresponsible borrowing in the country when the economy is booming. The banks expected the high returns from loans irrrespective of the debtors‘ insolvency risk, while the borrowers had the easy access to credit and lack of financial knowledge. Because the irresponsible borrowing by credit institutions customers plays a role in creating the financial crises, the relative indebtedness rates were proposed in this study that were calculated using the indicators of of business and households loans, the overall banks‘ loan portfolio, the revenue of enterprises, GDP and compensation of employees. It can be concluded that the deterioration of banks' loan portfolio is very probable when these relative indicators reach the estimated values. So the estimated critical indebtedness indicators before the economic downturn statistically can help for banks to foresee the similar non-performing loans problems in future.
10. The study has shown that since 2009 the growth of non-performing loans not only in Lithuania, but also in other EU countries was observed. The average NPLs percentage of the EU banks in 2006 – 2008 was stable in range 2,15 – 2,75%, but later this rate started to increase in average by 0,91% every year until in 2013 the NPLs reached 7,3%. But the statistics of NPLs in Lithuanian banks considering the context of European Union average in this period is outstanding. The research allows to maintain that the problem of high NPLs is typical in EU countries with lower GDP indicator while the countries with more developed economy have less problem of NPLs in commercial banks. When the NPLs in overall EU like in Lithuania since 2009 increased, as a consequence the decreasing loan portfolio and growing deposits tendencies in the EU banks were observed. Despite the NPLs problem in the EU countries, the capital adequacy indicators of European Union banks since 2008 are growing what affirms that banks are able to absorb sufficient losses and the risk of

loss for depositors and shareholders is low. The Lithuanian banks‘ capital adequacy ratios in period of 2008 – 2013 were also growing with the small fluctuation in 2011 as in all EU. Despite the very high problem of NPLs compared to the EU average, in Lithuanian banks the capital adequacy rates since 2010 are higher than the average values in EU what point to the strong capital base and the ability of Lithuanian banks to withstand the economic recession.

11. The ranking results of the EU countries in this study allowed to classify them into four groups according to the magnitude of NPLs problem in banks. The classification results affirm that Lithuania is one of the countries in the EU that has the most serious problems of NPLs in banking sector. The further analysis estimated the main macroeconomic factors that causes the negatively enlarged NPLs indicator in EU countries. The significant differences of relative average macroeconomic indicators in the groups of EU countries was observed. The macroeconomic indicators of GDP, exports, investments, compensation of employees, consumption expenditures of households and government in these groups constantly decrease compared to the estimated average NPLs growth. The dynamics of macroeconomic rates also affirmed that the deterioration of economic conditions in a country cause the growth of NPLs problem in banks. The commercial banking systems of EU countries with imperfect macroeconomic conditions suffer far more from debtors that are not able to meet their financial obligations.
12. Finally, in this study the statistical model was developed to predict the proportion of non-performing loans in commercial banks of a country. The logistic and probit regression, cluster, factor and discriminant analysis methods were applied to solve the NPLs prediction problem. The model is applicable when the NPLs in a country of current year are at the basis level about 2,1% – 6,1%. The banks in year knowing the current non-performing loans in the country’s banking system and the changes of macroeconomic indicators can predict the possible NPLs growth.

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DEPARTMENT OF ECONOMICS AND BUSINESS

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THE IMPACT OF MACROECONOMIC ENVIRONMENT ON CREDIT RISK IN COMMERCIAL BANKS

Scientific Study

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