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Credit risk measurement: Evidence of concentration risk in Polish banks' credit exposures^{*1}

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Abstract

In recent years, there has been a lot of scientific research stressing the importance of understanding and measuring concentration risk in credit portfolios. The article presents credit risk measurement within the capital requirements regulation of the corporate sector. Main objective is to assess the financial stability of the banking sector from a credit risk perspective. The empirical analysis was based on the individual data from different sources (covering the period 2007 -2018), which are as follows: prudential reporting, business register, financial and behavioural data and balance of payments. This paper analyses the exposure of Polish banks to credit risk arising from different economic sectors. The evaluation includes the firm-level probabilities of default, loss given default, expected losses and unexpected losses. The measures of expected and unexpected losses were estimated by using a structural multi-risk factor approach. While conducting the research, it has been noticed that a credit risk differs across various industries as well as at different phases of economic cycle. Furthermore, the research results indicate that both from the standpoint of individual banks and prudential authorities the correlation risk is being underestimated.

Key words: corporate sector; concentration risk, capital requirements regulation

JEL classification: G21, G32

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1. Introduction

According to the Basel Capital Accord introduced in 1988 by the Basel Committee on Banking Supervision, which was a capital measurement system based on the credit risk measure, banks should have their own funds at a level not lower than 8% of risk-weighted assets and liabilities (with four classes of off-balance sheet assets and liabilities distinguished, assigning them arbitrary weights). However, this simplicity turned out to be the main element of criticism of the Basel Capital Accord – assets from the same group were treated equally, without the possibility of taking into account different levels of risk. In fact, this approach did not measure the actual level of risk. In June 2004, after long analyses and discussions, a New Capital Accord was published, consisting of three pillars – estimating the sum of minimum capital requirements for credit, market and operational risk (Pillar I), determining the basic role of banking supervision (Pillar II) and banks' obligations to maintain appropriate market discipline (Pillar III). Nevertheless, despite the amendment to the concept of setting minimum capital requirements (standardized approach), as well as the possibility of banks using the internal rating (IRB) method, the risk measurement to which the bank is exposed still remains inaccurate. The last method allows for the application of internally calculated risk parameters, which significantly reduces the level of required capital compared to the standard method. These are based on three key parameters for each of the exposures: probability of default (PD), loss given default (LGD), and exposure at default (EAD). Estimations of these parameters may be used to estimate expected loss (EL) or unexpected loss (UL). Concurrently, in addition to calculating regulatory capital, these parameters also have a broad range of applications as they are the input data for banks in the economic capital models.

The concentration risk has not been fully included in the first pillar of the New Capital Accord. This is due to the fact that in relation to credit risk, the IRB approach assumes that the portfolios are perfectly diversified. The ASRF (Asymptotic Single Risk Factor) model, which assumes that the relationship between individual exposures is explained by one systematic risk factor, does not allow for measuring concentration risk. Therefore, concentration risk is assessed under the principles of Pillar II. Any resulting underestimation of credit risk should be corrected by taking into account the concentration risk. Supervision expects financial institutions to hold sufficient capital to cover all types of risk, including concentration risk.

The aim of this research, taking into account the areas that determine the quality of credit risk management by banks, is to assess credit risk measurement for non-financial enterprises. The above assessment will consist of the following parameters probability of default (PD), loss given default (LGD), exposure at default (EAD), expected loss (EL) or unexpected loss (UL). From 1 January 2018, the new International Financial Reporting Standard (IFRS 9) applies. The method

of calculating provisions for **expected credit losses** (calculated on the basis of PD, LGD and EAD parameters) is subject to change. In the previous approach, loans were divided into defaults and non-defaults. Currently, the loan portfolio is divided into three baskets (stage classification). The first includes exposures for which no significant deterioration of credit quality is identified at the reporting date (credit risk is stable and low). The second basket should include exposures for which a significant deterioration of credit quality was identified on the reporting date (increase in credit risk caused by the occurrence of a default condition). The last, third basket recognizes credit exposures that are in the default state. Whereas for the first basket, the risk parameters PD and LGD are calculated for a twelve-month time horizon, for loans included in the second and third basket they are to be calculated in the lifetime horizon of the loan.

The Internal Ratings-Based (IRB) concept of credit risk assessment is based on the assumption that the risk of a credit portfolio is driven by two factors: systematic risk, resulting from unexpected macroeconomic and market changes and idiosyncratic risk, representing the effect of diverse specific threats related to individual borrowers. In this study, Multi-factor Risk Factor Model was used to estimate unexpected losses [Düllmann and Masschelein 2006, Puzanova, Düllmann 2011], which is derived indirectly from the Merton model (1974). The study extends existing analyzes based on literature, which allows us to capture the relationship between credit risk and the current economic situation. The results of the analysis of the Polish banks' exposure to credit risk will be presented for various corporate sectors.

The paper aims to verify the research question and forth hypotheses described below. **The research question** is whether certain economic sectors are particularly exposed to credit risk arising from both the individual financial situation of borrowers and their joint probability of default in adverse scenarios. **The first research hypothesis** states that economic sectors, which are more concentrated in terms of exposures, experience above average expected losses. **The second research hypothesis** states that the sensitivity of credit risk indicators to different ingredients of default risk, cyclicality and concentration of economic sectors. **The third research hypothesis** states that measures of portfolio risk are positively correlated with the concentration structure of economic sectors, and this can be a problem if banks are overly exposed to concentrated sectors. **The forth research hypotheses** states that Internal Ratings-Based approach assumes only systematic risk without taking into account the sector concentration of the banking portfolio. This aspect is directly relevant for both small and sectorally specialized financial institutions and for the stability of the entire banking system if banks' loan portfolios are excessively exposed to sector risk.

The main contribution of this paper to the literature is follows. First, this paper is to propose a comprehensive assessment of the corporate sector to identify sectoral vulnerabilities, channels of transmission to and from the financial sector; to devise

indicators and tools to assess sectoral risks on exposure size and probabilities of default (by sector and at aggregated credit institutions level). Second, this research has an original concept and high added value as it was performed using representative micro data for over 30,000 non-financial companies per year. Third, for the forecasting bank unexpected losses of non-financial corporations the Multi-factor Risk Model was applied.

The remainder of this paper is organized as follows. Section 2 presents the literature review, and the next two sections – the data and the methodology. Credit risk related to some sectors of the economy, in particular those most sensitive to the business cycle, may have a major impact on banks' loan portfolios. If the portfolio is significantly concentrated on such business sectors, it may incur significant losses during the economic slowdown, reducing the bank's creditworthiness and imposing adjustments on capital reserves. Section 4 presents and discusses the empirical results. While Section 5 concludes the paper.

2. Literature review

Due to the fact that the results of credit risk assessment will be presented on a sectoral basis, the literature review focuses on the presentation of research in the above mainstream, ie the analysis of exposures to the economic sector or sectors related to each other (sector concentration). Currently, supervisory authorities recognize the importance of proper management of industry concentration risk in the stable and safe functioning of banks.

The concentration risk has not been fully taken into account in the first pillar of the New Capital Accord. This is due to the fact that with regard to credit risk, the IRB approach assumes that portfolios are perfectly diversified. ASRF model (Asymptotic Single Risk Factor), assuming that the relationship between individual exposures is explained by one systematic risk factor, does not allow to measure concentration risk ($X_i = r_i S + \sqrt{1 - r_i^2} \varepsilon_i$, where X_i – solvency of the enterprise, variable with standard normal distribution, S – total number of enterprises, r_i^2 – the linear correlation coefficient between X_i and X_j (assuming that the X variables are correlated with each other), ε_i – random variable, a specific factor for everyone X_i). In view of the above, the risk of concentration is subject to assessment under the principles of Pillar II. Any resulting under-estimation of credit risk should be adjusted by taking into account the concentration risk. Supervision expects financial institutions to maintain capital of sufficient size to cover all types of risk, including concentration risk.

Research by Düllmann (2006), Düllmann and Masschelein (2006) focusing on risk concentration in banks' loan portfolios presents the potential impact of concentration

in business sectors on economic capital for loan portfolios using a simplified model. For the corporate loans portfolio, the economic capital increased by 20%, which indicates a significant impact of the sectoral concentration on the size of economic capital, this is argued with too much financing from loans of one sector with the largest share in the economy. In an article issued by the Bank of International Settlements (2006), the research was used for banks originating from Belgium, Sweden, Germany, Italy, Japan, Spain, Canada and the United Kingdom in order to obtain information on how banks perceive the risk of concentration of corporate portfolios. Düllmann (2006), based on the analysis of the sectoral concentration, presents the Infection Model on the basis of which it attempts to estimate the correct impact of risk concentration on Value at Risk. Dietsch, Petey (2011) with the help of an extended one-factor model showed that more factors affect credit risk. Lack of heterogeneity between sectors may result in growing credit risk by concentration of exposures without a simultaneous increase in capital offsetting credit losses. Diversity across sectors seems to have a significant impact on the diversity of credit risk. Numerous theoretical and empirical articles in the area of the capital structure theory as well as the literature on the determinants of companies' bankruptcy confirm this conclusion (Doumpou, Lemonakis, Niklis, Zopounidis 2019, Bernard, Denuit, Vanduffel 2018, Pérez-Martín, Pérez-Torregrosa, Vaca 2018). Specifically, concentration or specialization in some industries may even question regulatory, minimum capital requirements. Loss Given Default are lower for the largest sector-specific credit exposures than for significantly smaller credit exposures. The survey also focused on the relationship between the loan portfolio and the unexpected part of credit risk. Banks with concentrated portfolios have a smaller, unexpected part of credit risk than banks with diversified portfolios.

Céspedes et al. (2005) presented a corrective one-factor model, taking into account the portfolio diversification effect. The authors present an example for four sectors. The probability of insolvency of debtors belonging to the first two sectors is 1%, and for the other two 0.5%. Expected LGD was assumed to be 100%. It turns out that for the fourth sector the share of credit exposures at the moment of default in the total EAD is 10% (for other sectors it is 25%, 25% and 40% respectively), while economic capital is 3.4% (for other sectors 31.9%, 17.2% and 47.5% sectors). The above effect can be explained by the low PD for this sector and the low level of intra-sector correlation, amounting to 8.6% (for other sectors 20.1%, 12.4% and 21.9%). Heifitfield et al. (2006) present a study on the impact of systematic and idiosyncratic risk on the distribution of portfolio losses. The systematic risk is the main factor affecting the VaR and is independent of the size of the portfolio. The idiosyncratic risk in large portfolios (banks) is diversified, but in small portfolios (banks) it plays a significant role. These results show that the most important task in managing loan portfolios is appropriate systematic risk management. The concentration of small, poorly diversified portfolios can increase unexpected losses by 10% on average over the year, which requires proper management of the

name concentration or an increase in economic capital. Morinaga, Shiina (2005) showed that the potentially miscalculation calculation of sector concentration risk by incorrectly assigning borrowers to the appropriate sectors results in an underestimation of risk. In order to reduce the underestimated amount, the portfolio manager should independently define the relevant sectors for the portfolio and not use general sector definitions. Tasche (2006) pointed out that asymmetric single risk factor models are not able to capture the name concentration and, consequently, the possibility of underestimating the risk in the portfolio. The results obtained show that the impact of sector diversification by more than one systematic factor on the portfolio is moderate, but still significant for the risk contribution. Minderhoud (2006) obtained and with the probability of systemic risk occurring in the financial sector higher than in others, because the balance sheets of financial institutions are inter alia through mutual exposures on the interbank market. The above relationship between Dutch financial institutions is only visible after mergers. The results obtained suggest that systemic risk is a potentially important threat to the stability of the financial sector in the Netherlands.

Dullmann, Scheicher and Schmieder (2006) analyzed the impact of sector concentration and name concentration. Asset correlations seem to change significantly over time, for the market model the range is from 4% to 16%, and even larger for the sector model. In addition, the market model increases economic capital by 10% to 90% higher than the sectoral model. Dietsch and Petey (2011) assess the suitability of the Asymptotic Single Factor Risk model. They point out that deviations from the model assumptions (excellent granularity and a single source of systemic risk) can cause discrepancies in economic capital. Most retail banks have detailed portfolios, so concentration risk relates to correlated defaults between debtors. One of the disadvantages of the ASRF model is the exclusion of concentration risk. Any violation of ASRF hypotheses, as mentioned earlier, involves the risk of concentration. Additional surcharges are needed to cope with sector concentration. Semper, Beltran (2011) Propose an alternative concentration indicator to measure the sector's concentration risk. Long (2012) conducted research to assess the performance of models with one risk factor. The ASRF assumes that the idiosyncratic risk is fully diversified and the correlation depends solely on the relationship with the systemic risk. However, real portfolios are rarely evenly distributed and perfectly fine-grained. Therefore, the use of ASRFs when these assumptions are not met can have a large and significant impact on the assessment of risk measures. The author obtained that asset correlation errors have a significant impact on economic capital measurements. For medium portfolios (up to 1,000 companies), economic capital can be reduced by an average of 11%, for small portfolios (up to 100 companies) by 16%, and for large portfolios (10,000 companies) by 10%. Therefore, multi-factor risk models are recommended because one risk model is simplified and can significantly affect estimated risk measures.

Jahn, Memmel, Pfingsten (2013) show that banks reduce credit risk by focusing on individual sectors and collecting information about them, thanks to which they obtain smaller, average loan loss ratios. In addition, the study showed that credit risk loss ratios are lower for the largest sector-specific credit exposures than for significantly smaller credit exposures. The study also focused on the relationship between the loan portfolio and the unexpected portion of credit risk. It has been proven that banks with concentrated portfolios have a smaller unexpected portion of credit risk than banks with diversified portfolios. Chen, Wei and Zhang (2013) studied the impact of loan portfolio diversification on bank risk by creating an extension of the HHI index that takes into account the systemic risk of sectors. The high values of this new HHI indicate that the bank's loan portfolio is not only concentrated but also focused on sectors with high systemic risk. Therefore, high values of this indicator suggest that a given bank is exposed to high risk. In the entire banking sector, the HHI index fell in the years under consideration. However, the risk-adjusted HHI increased sharply in 2011. This may be related to the increased exposure to sectors with higher systemic risk, such as construction, real estate and the increased systemic risk of these sectors simultaneously.

The amount necessary to cover the costs related to risky activities is affected not only by the financial situation but also by the socio-economic situation. This aspect was addressed by Holub, Nyklicek, Sedlar (2015) examining Czech banks. As a macroeconomic factor, they assumed systemic risk. They learned that during the economic slowdown the state finances only the industries from which it has the highest revenues, and this results in the effect of concentration of loans in one industry, so also the increase in economic capital.

To sum up, concentration risk is one of the special risks in banking activity and its inappropriate management, lack of appropriate policies and regulations, or incomplete measurement may lead to financial problems of the bank. The measurement of concentration risk is important from the macro-prudential perspective.

3. Methodology

This chapter presents the methodology related to the estimation main "ingredients" of credit risk. These are based on three key parameters for each of the exposures: probability of default (PD), loss given default (LGD), and exposure at default (EAD). Estimations of these parameters may be used to estimate expected loss (EL) or unexpected loss (UL).

3.1. Credit assessment system

If a credit institution should rely on the Internal Ratings Based Approach (IRB) then the key risk factor under the IRB approach is the probability of default (PD). The European central banks outside the EURO zone have developed a ICAS system³ which include PD model, used for assessment of risk in the non-financial corporations sector, both on the system level and on the level of individual credit institutions, in conditions of high risk concentrations and in stress testing. This part of article shows the process in which the Nehrebecka's PD model was developed.

Credit assessment system to estimate non- financial corporations' default risk has two stage internal ratings (Figure 1). **Statistical model** consists of the following parts (see Nehrebecka, 2016):

Quantitative – financial factors (F) based on two different components: one that considers historical data retrieved from the Prudential Reporting, and one that uses financial statement data of the enterprises concerned.

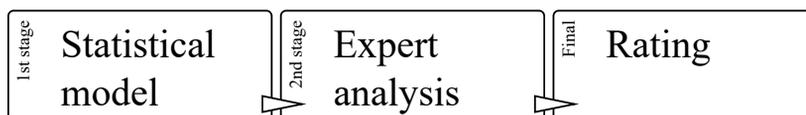
Qualitative – behavioural factors (B) (localization of the entity, industry, size of employment, legal form, year of establishing, description of the owner, payment morality)

Sector riskiness (S) – industry variables.

The model was combined by the following formula:

$$y = F_{\alpha} B_{\beta} S^{\gamma} \quad (1)$$

Figure 1: Credit assessment procedure



Source: Authors' procedure

Probability of Default (PD) was calculated for a 12-month horizon. The statistical PD is evaluated monthly. The analysis was performed with the use of a logistic regression on categorized variables transformed using the Weight Of Evidence (WoE) approach. The WoE calculation is based on the classification of the values

³ The source of ICAS includes the central banks of Germany, Spain, France, Italy, Ireland, Slovenia, Portugal and Austria. According to the official website of the European Central Bank <http://www.ecb.europa.eu>, accessed on November 29, 2019.

of the input variable into categories by maximizing the information value of each category and, in turn, the difference between the categories (the supervised discretization method), with the transformed WoE values and information value calculated for each category i and in aggregate for all variable:

$$WoE = \ln \left(\frac{\% \text{ "good" }}{\% \text{ "bad" }} \right) \quad (2)$$

Weight of evidence facilitates interpretation of results, allows for information shortages modelling and has a greater number of degrees of freedom compared to raw data. WoE has the advantage, that no special treatment of missing and/or outliers is necessary. Outliers are not cut off, and missing values simply form a category of their own. Scoring methods have been used to create an indicator for grading the companies in the case of defaults. While developing the model, the number of potential predictors was reduced on the basis of Information Value statistics. The quality of the model is assessed according to the most popular criteria, such as the GINI statistics, the Kolmogorov-Smirnov test and Area Under Receiver Operating Characteristic. Previous model took only financial factors into consideration (see Nehrebecka 2016).

In order to perform the calibration, the scores were bucketed with (more or less) same number of defaults in each bucket. After that, the Default Rate in each bucket was transformed. Such modified Default Rate was transformed into odds. PD was calculated using the below formula: $PD = \frac{e^x}{1 + e^x}$, where: $X = \beta_2 * SCORE + \beta_1$. The theoretical relationship between the score and logarithm of odds (which from the nature of logistic regression should be linear) was used to obtain estimates of the calibration function. The accuracy of obtained estimated PD's for each calibration function was tested with the Population Stability Index. PSI is used to measure difference between distributions of two categorized variables. The larger the value of the index, the larger the statistical distance between the two distributions. As suggested by literature the rule of rejecting the hypotheses that distributions are close to each other is when PSI exceeds 0.25. After obtaining PD values, scores were mapped to ratings according to the master scale.

While validating model calibration, it is worth testing the calibration power of both individual classes and the entire internal ratings.

- The first group of tests can only be applied to one single rating grade over a single time period (binomial Clopper and Pearson test, binomial Agresti and Coulla test, binomial Wald test, corrected binomial Wald test, binomial Wilson test, corrected binomial Wilson test, one-factor-model (Emmer, Tasche 2005) and an important aspect is to take into account the correlation of the default phenomenon between individuals therefore (De Servigny, Renault 2002), three additional tests were used moment matching approach and granularity adjustment approach (Tasche, 2003).

- The second group of tests provide more advanced methods that can be used to test the adequacy of the default probability prediction over a single time period for several rating grades (Spiegelhalter test, Hosmer-Lemeshow test, Blöchlinger test).

Expert analysis comprises additional qualitative and quantitative criteria (industry and market position, management, the group framework, financial position and performance of the company, financial flexibility and self-financing capability, newspaper entries, other) which may change the rating proposal from the 1st stage. The expert model consists of 10 categories. Assessment result per category: plus / zero / minus („plus” means a notching up by one rating class, „minus” means a notching down of one rating class).

3.2. Loss given default

When creating the assessment of credit risk, as part of the Internal Ratings Approach, loss given default (*LGD*) is also required to assess the size of the credit risk and the capital requirement calculation. Research on the loss given default began to gain momentum only in the 21st century. Most empirical work on LGD for loans began to arise after the introduction of the New Capital Accord in 2004. In the first works on modeling losses due to default [Altman, Gande and Saunders 2010; Arner, Cantor, Emery 2004; Cantor and Varmy 2010] linear regression was used. The Basel Committee on Banking Supervision (2005) points to the importance of adequate estimates for economic downturns and unexpected losses. Board of Governors of the Federal Reserve System (2006) proposes the computation of Downturn LGD measures by a linear transformation of means [$Downturn\ LGD = 0,08 + 0,092 * E(LGD)$]. Most academic and practical credit risk models focus on mean LGD predictions. However if we consider two loans with different distributions (a uniform and a beta) but the same means values then unexpected losses differ. A relatively new method for modeling the loss given default, which was also used in this research, is quantile regression [Somers and Whittaker 2007; Krüger and Rösch 2017]. While other methods only allow estimating the mean or variance of LGD, quantile regression allows for the modeling of all quantiles of the dependent variable. In this way, it is easy to obtain measures in the event of a downturn and unexpected losses.

In order to calculate the LGD parameter, the Recovery Rate (RR) should be initially estimated. RR is defined as one minus any impairment loss that has occurred on assets dedicated to that contract (see IAS 36, Impairment of Assets) / Exposure at Default. Most LGDs are nearly total losses or total recoveries which yields to a strong bimodality. The mean is given by 37% and the median by 24%, i.e., LGDs are highly skewed. Both properties of the distribution may favor the application of quantile regression because most standard methods do not adequately capture bimodality and skewness. Furthermore, many LGDs are lower than 0 and higher

than 1 due to administrative, legal and liquidation expenses or financial penalties and high collateral recoveries.

The regression model can be presented as follows (see Nehrebecka, 2019):

$$\text{Recovery Rate}_{i,t} = f(\text{Intercept}, \text{Debt Characteristics}_i, \text{Bank Characteristics}_i, \text{Firm Characteristics}_{i,t-1}, \text{Macroeconomic Variables}_{t-1})$$

3.3. Expected credit loss

Credit risk arises from two sources, systematic risk and idiosyncratic risk. Systematic risk affects the whole market since it's the effect of unexpected changes in the macroeconomic environment or financial market. No firm is indifferent to the conditions on the market, hence this risk is unavoidable and only partly diversifiable. Idiosyncratic risk, however, can be completely diversified away, since it's the effect of changes in an asset or a company's situation at the microeconomic level.

The new standard outlines a „three-stage” model („general model”) for impairment on credit quality:

Stage 1 includes financial instruments that have not had a significant increase in credit risk since initial recognition or that have low credit risk at the reporting date (credit risk is at a constant, low level).

In accordance with IFRS 9, the expected credit loss is calculated in various ways for individual baskets.

STAGE 1:

$$ECL_{\text{stage 1}} = PD_{12M} * LGD_{\text{non-default}} * EAD_1$$

PD_{12M} – probability of default within twelve months on the reporting date; $LG D_{\text{non-default}}$ – loss due to default on exposures not in the default condition as at the reporting date; EAD_1 – exposure value at the time of default as of the date of reporting.

Stage 2 includes financial instruments that have had a significant increase in credit risk since initial recognition (unless they have low credit risk at the reporting date) but that do not have objective evidence of impairment.

STAGE 2:

$$ECL_{\text{stage 2}} = \sum_{t=1}^T PD_t * LGD_t^{\text{non-default}} * EAD_t$$

PD_t – probability of default within twelve months at time t ; $LG D_t^{\text{non-default}}$ – loss due to default at time t , for exposures not in default state; EAD_t – exposure value at the time of default at time t ; T – maturity of the financial instrument.

Stage 3 includes financial assets that have objective evidence of impairment at the reporting date.

STAGE 3:

$$ECL_{stage\ 3} = EAD_1 * LGD_{default} * KOIM$$

$LGD_{default}$ – loss due to default on the given reporting date, for exposures in the default condition; EAD_1 – exposure value at the time of default at the given reporting date; $KOIM$ – correction of impairment interest

3.4. Unexpected credit loss

Important characteristics of credit risk modeling include the un-expectancy of default events, the rarity of occurrence of these types of events and the inherency of credit risk. The Asymptotic Single Risk Factor model, which is a simplified approach to the IRB formula, assumes that the loan portfolio is well fragmented, which means that the idiosyncratic risk is completely diversified and the size of economic capital depends only on the occurring systematic risk. In reality, however, the loan portfolio is not perfectly diversified and in a situation where there is a concentration of exposures, the IRB formula underestimates the required economic capital.

Therefore, it is advisable to use a multifactor model in which a different systemic risk factor will affect each sector and, therefore, assets of debtors belonging to the same sector will be strongly correlated with each other, while for different sectors, this correlation will be low. Merton's multifactor model assumes that the rate of return on the assets of individual borrowers is affected by the systematic risk factors with a normal distribution and the idiosyncratic risk factor characteristic for each borrower, which also has a normal distribution.

Setup based on Düllmann and Masschelein (2006):

$$L = \sum_{s=1}^S \sum_{i=1}^{M_s} \sum_{j=1}^J D_{\{X_{S,i} \leq \Phi^{-1}(PD_i)\}} \cdot EXP_{S,i,j} \cdot LGD_{S,i,j}$$

Calculation of quantiles, eg Value at Risk, requires simulation of portfolio loss distribution. The Monte Carlo method is usually used for this. However, the disadvantage of models based on simulations is their time-consuming and, more importantly, portfolio dependency. This means that if a new exposure is included in the portfolio, the loss distribution must be simulated again. Therefore, it is not possible to calculate the contribution of the new loan to the value at risk of the portfolio relatively easily using simulations.

4. Empirical data and analysis

4.1. Data sources

The empirical analysis was based on the individual data from different sources (from the years 2007 to 2018), which are:

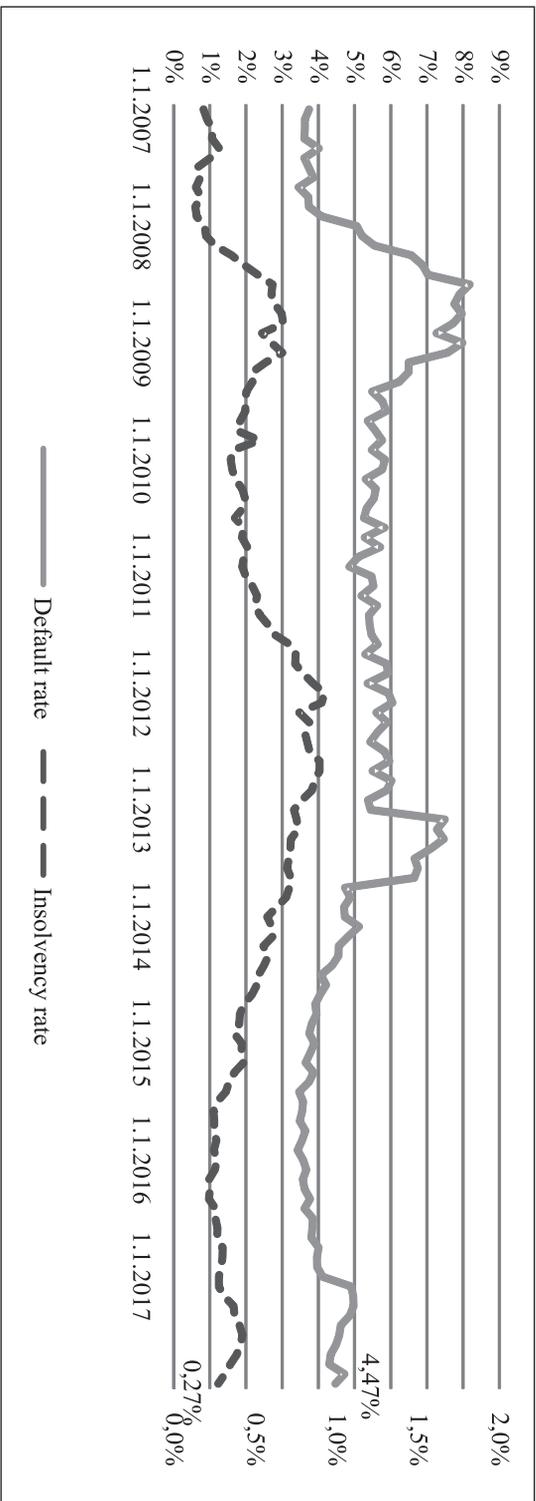
- Data on bank borrowers' defaults are drawn from the Prudential Reporting managed by Narodowy Bank Polski. Act of the Board of the Narodowy Bank Polski no.53/2011 dated 22 September 2011 concerning the procedure and detailed principles of handing over by banks to the Narodowy Bank Polski data indispensable for monetary policy, for periodical evaluation of monetary policy, evaluation of the financial situation of banks and bank sector's risks. Large exposures – for a bank that is a joint-stock company, state-run bank and a non-associated cooperative bank – mean exposures towards one enterprise in excess of 2,000,000 PLN.
- Data on insolvencies come from a database managed by The National Court Register, that is the national network of Business Official Register.
- Financial statement data (source: AMADEUS, NOTORIA, BISNODE).
- Data on external statistics of enterprises (source: Narodowy Bank Polski).

The following sectors were removed from the *Polish Classification of Activities 2007* sample: *section A (Agriculture, forestry and fishing)*, *K (Financial and insurance activities)* due to the specifications of these activities and separate regulations that might apply to them. The following legal forms were analyzed: partnerships (unlimited partnerships, professional partnerships, limited partnerships, joint stock-limited partnerships); capital companies (limited liability companies, joint stock companies); civil law partnership, state owned enterprises, branches of foreign entrepreneurs.

Probability of default (PD) is one of the key parameters which must be estimated in credit risk modelling. In particular, it is especially important when designing classes of risks or comparing different rating scales. It seems, however, that too little attention is paid to the various possible definitions of default in practice, although a clear understanding of the definition of default is key for proper interpretation of the estimated PD. I present two definitions of default in the area of credit risk assessment. The "narrow" definition (*failure*) is based on the assessed entity filing a formal application for bankruptcy proceedings and the "broad" definition (*default*) as per the definition in Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012 (§178 CRR⁴).

⁴ "Article 178
Default of an obligor

Figure 2: Insolvency rate and default rate in period 2007-2018



Source: Authors' calculations

During the global financial crisis in 2007-2009 a decline in the GDP growth rate was recorded from 6.6% to 3.2% in Poland and the number of declared bankruptcies in the economy increased by 54.6%. At the turn of 2008/2009, the default rate was at the level of 8%. In 2012 the courts declared the bankruptcy of 877 business entities, which was the highest result for 8 years. This state of affairs can be partly explained by the economic downturn in 2012. In the case of the default rate, the second local maximum (7.5%) was noticed. The default rate today is still declining and is at around 4.5% (Figure 2).

Table 1: Banks' credit exposure to non-financial firms by instrument in 2018

Instrument Type	Exposure in mld PLN	Share of exposure In %	N firms	N banks	HHI by firms	HHI by banks	HHI by sectors
Total exposure	477.4	100%	17 119	44	0.2%	9.7%	16%
Balance sheet exposure							
Loans	276.0	58%	15 598	44	0.15%	9.2%	7.6%
Bonds	7.7	2%	84	11	12.1%	32.5%	25.9%
Off-balance sheet exposure							
Guarantees	51.1	11%	4 195	32	1.4%	11%	15.4%
Open credit lines	118.9	25%	12 028	35	0.3%	11.1%	7%

Source: Authors' calculations

Table 1 presents the banks' exposure to the non-financial corporation sector in 2018 divided into balance sheet exposure, including: loans and other receivables, debt instruments and off-balance sheet exposure, including: guarantee, open credit lines. The concentration index (HHI) was calculated for each financial instrument, both in terms of lenders and borrowers. Banks' exposure to the corporate sector was highest in loans and other receivables (58% of total exposure). In addition, in the case of loans and other receivables, the concentration index had the lowest level in terms of both lenders and borrowers- in contrast to debt securities which represent concentrated markets, with several banks holding large shares of debt securities. Over half of the off-balance sheet exposure was, however, open credit lines.

1. A default shall be considered to have occurred with regard to a particular obligor when either or both of the following have taken place:

- (a) the institution considers that the obligor is unlikely to pay its credit obligations to the institution, the parent undertaking or any of its subsidiaries in full, without recourse by the institution to actions such as realizing security;
- (b) the obligor is past due more than 90 days on any material credit obligation to the institution, the parent undertaking or any of its subsidiaries. Competent authorities may replace the 90 days with 180 days for exposures secured by residential or SME commercial real estate in the retail exposure class, as well as exposures to public sector entities). The 180 days shall not apply for the purposes of Article 127."

Table 2: Credit exposure by economic sector in period 2007-2018

– in percent

SECTORS	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Mining and quarrying	0.89	0.90	1.12	1.24	1.19	1.65	1.96	3.74	4.01	3.41	2.86	2.66
Energy, water and waste	9.27	6.88	7.20	7.37	8.32	11.25	10.79	11.38	10.48	8.69	7.92	8.02
Industrial processing	33.69	34.25	32.68	31.37	29.88	28.43	28.36	26.61	27.25	27.72	27.50	28.34
Agri-food industries	7.83	7.00	6.82	6.50	5.72	5.63	5.75	5.44	5.46	5.22	5.34	5.25
Textiles, clothing and footwear	0.66	0.48	0.45	0.45	0.46	0.41	0.41	0.38	0.41	0.39	0.45	0.47
Wood, paper products and printing	3.29	3.26	2.98	2.87	2.64	2.42	2.25	1.98	2.02	2.13	2.13	2.16
Chemicals industry	1.89	2.00	1.89	1.65	1.66	1.74	1.80	1.45	1.44	1.62	1.62	2.28
Pharmaceuticals industry	0.63	0.52	0.50	0.59	0.54	0.68	0.67	0.53	0.43	0.48	0.43	0.39
Manufacture of rubber and plastics	3.67	3.95	4.30	4.18	3.79	3.83	3.17	3.49	3.50	3.97	4.25	4.13
Metallurgy and metalworking	4.03	4.37	4.22	4.16	4.15	4.03	3.99	3.76	3.83	4.09	4.19	4.51
Metal manufactures	6.04	6.43	5.63	5.41	5.25	4.87	5.39	5.16	5.62	5.09	4.86	5.01
Construction	13.91	15.79	15.79	16.24	16.19	14.26	11.22	10.56	11.16	11.67	12.55	11.75
Trade	18.06	17.17	17.99	18.31	18.48	18.63	18.06	18.32	18.33	18.43	19.53	19.81
Motor vehicles trade	2.54	2.35	2.42	2.55	2.51	2.71	2.60	2.56	2.79	3.38	3.94	4.25
Wholesale trade	12.94	12.02	11.73	12.61	12.82	12.29	11.20	11.37	10.86	10.55	10.92	10.88
Retail trade	2.58	2.80	3.84	3.16	3.16	3.63	4.26	4.39	4.68	4.50	4.67	4.68
Transportation and storage	2.61	2.52	2.06	2.47	2.51	2.77	3.43	3.92	3.97	3.59	3.48	3.54
Accommodation and food service activities	1.24	1.37	1.64	1.75	1.64	1.61	1.69	1.77	1.70	1.96	1.88	1.87
Information and communication	4.58	4.22	4.20	3.95	3.44	3.28	4.59	4.54	3.96	4.50	4.82	4.72
Real estate activities	10.98	12.37	12.62	12.22	13.70	13.02	14.80	13.96	13.68	13.46	12.17	11.97
Professional, scientific, technical, administration and support service activities	4.22	3.88	3.88	4.12	3.73	4.10	4.00	4.09	4.26	5.27	5.79	5.98

Source: Authors' calculations

Table 3: Concentration by borrowers (HHI) in period 2007-2018

SECTORS	– in percent												
	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	
Mining and quarrying	5.99	5.09	4.54	4.93	5.43	10.98	21.64	42.41	51.45	60.66	50.05	58.08	
Energy, water and waste	7.21	6.17	5.15	7.63	12.24	10.34	10.75	9.81	7.62	8.02	8.86	10.64	
Agri-food industries	0.80	0.86	0.86	0.79	0.77	0.82	0.75	0.69	0.77	0.71	0.75	0.69	
Textiles, clothing and footwear	2.34	2.55	2.50	2.77	2.39	2.33	2.42	2.13	2.09	2.15	2.78	2.84	
Wood, paper products and printing	3.78	2.86	3.11	2.46	2.25	2.16	1.59	1.25	1.25	1.21	1.05	1.08	
Chemicals industry	4.06	3.36	3.36	3.08	3.62	3.80	4.59	3.52	6.71	5.42	4.80	10.02	
Pharmaceuticals industry	14.11	14.85	10.37	24.92	35.47	49.42	33.92	26.28	19.27	18.66	16.10	30.18	
Manufacture of rubber and plastics	1.08	0.71	0.75	0.74	0.60	0.62	0.51	0.61	0.62	0.97	1.34	1.61	
Metallurgy and metalworking	1.57	1.77	1.70	1.30	1.27	1.32	1.23	1.13	1.02	1.21	1.20	2.48	
Metal manufactures	1.41	1.67	1.59	1.57	1.67	1.57	2.06	2.83	2.90	2.04	1.12	1.14	
Construction	0.77	0.56	0.57	0.71	0.75	0.67	0.67	0.72	0.94	0.85	0.90	0.79	
Motor vehicles trade	0.89	1.01	0.93	0.92	0.82	0.81	0.82	0.90	0.93	1.08	1.17	1.06	
Wholesale trade	0.52	0.53	0.47	0.48	0.55	0.46	0.47	0.54	0.49	0.47	0.47	0.48	
Retail trade	1.75	1.83	1.52	2.10	2.26	4.65	4.80	6.05	4.82	4.42	4.05	3.58	
Transportation and storage	3.03	2.09	1.91	2.03	2.17	1.97	2.02	2.85	2.47	1.66	1.32	1.32	
Accommodation and food service activities	2.77	2.01	1.54	1.32	1.76	1.79	1.11	1.70	1.35	2.11	2.65	5.49	
Information and communication	11.35	12.17	14.82	9.62	6.51	6.59	12.40	11.46	10.52	11.40	10.50	9.59	
Real estate activities	0.55	0.48	0.52	0.47	1.47	1.37	0.34	0.31	0.31	0.35	0.31	0.34	
Professional, scientific, technical, administration and support service activities	5.59	4.22	4.66	4.59	3.90	3.33	4.26	3.32	2.99	3.59	4.08	2.85	

Source: Authors' calculations

According to the research question over 70% of banks' total exposure to non-financial enterprises (Table 2) is concentrated in four sections: industrial processing (28%), trade (20%), real estate services (12%) and construction (12%) and this structure has changed since 2007. Due to the high heterogeneity of industrial processing, its subsectors were also specified. It is worth noting that among the sections of industrial processing the lowest discussed shares were recorded in the textile and clothing (0.48%) and pharmaceutical (0.39%) industries, which may be related to high values of financial independence and self-financing of these entities.

Based on the literature review, the highest value of total exposure and number of exposures was observed for commercial services and supplies (34% of exposure) and consumer discretionary (15% of exposure) in the German banking system. A comparison of the relative share of the sector decomposition between the aggregated German, French, Belgian and Spanish banking systems shows that the numbers are similar (Düllmann and Masschelein, 2006). In the case of Czech enterprises the dominant industries from the exposure structure perspective are real estate activities, manufacturing and wholesale and retail trade; maintenance and repair of motor vehicles (Holub, Nyklíček, Sedlář, 2015).

In addition, it was observed that the dominant sector of enterprises from industrial processing in 2007. (33% of total involvement) changed its share in 2018. up to 28% and almost equaled with enterprises from other services together with enterprises servicing the real estate market (compared to 2007: 20%). These changes are important information for supervisory organizations and should be taken into account when determining macro-prudential policy.

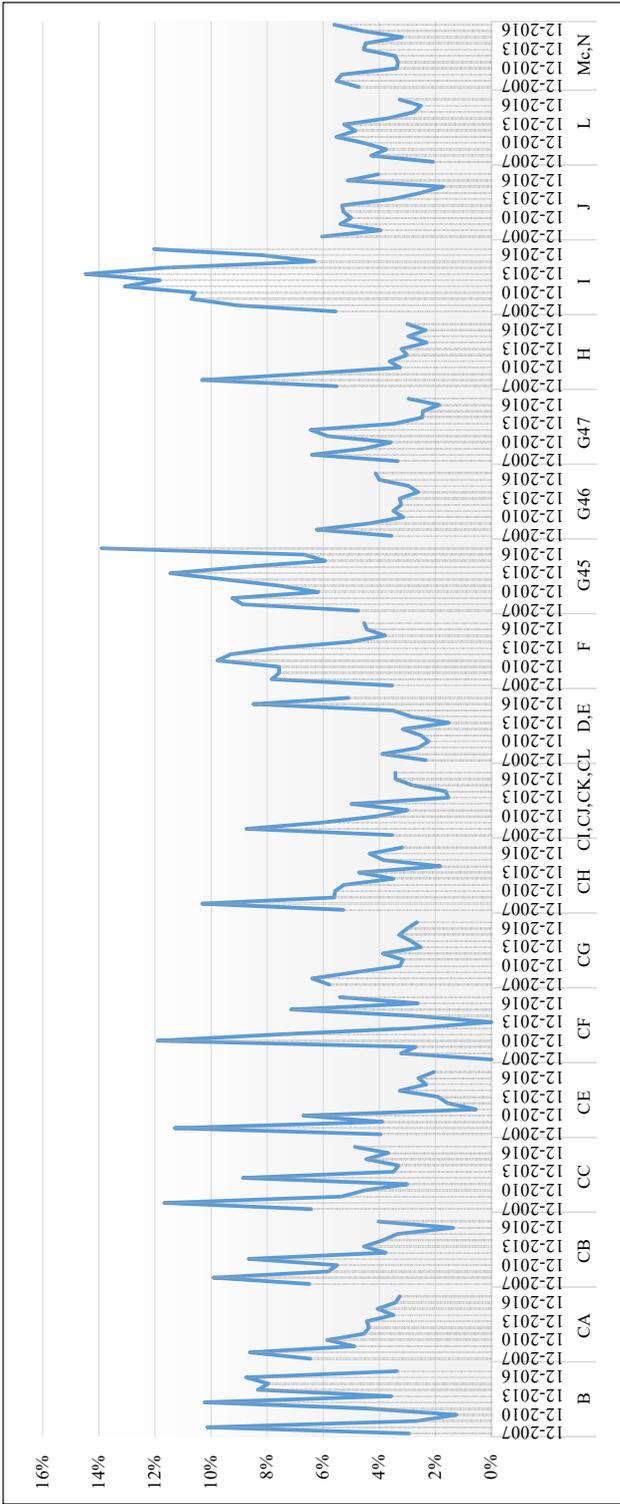
The following sectors are heterogeneous in terms of the number and size of borrowers approximated by the average level of exposures: mining and quarrying, energy, water and waste, information and communication, pharmaceutical industry – they represent the sectors of large borrowers. Consequently, these sectors show a high level of concentration of external financing (Table 3). The reason being that in addition to very significant concentrations of lending in the energy industry, the regional dependence on oil implied a strong correlation between the health of the energy industry and local demand for commercial real estate (Düllmann, 2006).

4.2. Analysis

This chapter presents the evaluation of non-financial corporation sector includes the main "ingredients" of credit risk. These are based on three key parameters for each of the exposures: probability of default (PD), loss given default (LGD), and exposure at default (EAD).

Figure 3 presents the weighted average PD of enterprises in particular years according to the section of their activity. The probability of default was the first

Figure 3: Non-financial companies' weighted average PD, by sector of activity



Source: Authors' calculations

extreme in all sections in 2008 (except the pharmaceuticals industry and information and communication). The decline in orders caused by reduced external demand and already felt the downturn in the industry in the domestic market, has reduced the level of sales, production and limiting disorder cooperate with cooperators. The highest PD during this period was observed in wood, paper products and printing (12%) and chemicals industry (11%). Another large increase in PD was in 2012-2013 in accommodation and food service activities (14%), in motor vehicles trade (11%), construction and mining and quarrying (10%). The recession in construction in 2008-2013 resulted in the bankruptcy of many construction companies due to the decline in investment outlays, despite the improvement of the situation after 2013, construction is still considered a high risk industry. In 2016, the highest default rates for the analyzed enterprises were taken by mining enterprises (9%), municipal services (8%). In situations of crisis or in a high-risk period, there is a high likelihood of companies becoming insolvent. Banks are preparing for this event by accumulating economic capital to cover losses due to unpaid loans. Economic capital is determined as the difference between the Value at Risk at the agreed confidence level and the expected loss in a given loan portfolio. Banks strive to minimize economic capital, even when there is a high risk of insolvency, allocate to the unexpected credit risk loss as the smallest part of the portfolio to be able to devote as much as possible to profitable investments and maintain an active position on the market.

Another required element in credit risk modeling is the knowledge of the correlation of risk factors. In the literature the correlation of risk factors is approximated by using correlations of the return rates on company shares. Based on the obtained parameters PD we calculated sectoral default rate dynamic correlations estimates to approximate risk factors correlations (Table 4). Therefore, we carry out a pairwise rolling cross-correlation analysis on a scale-by-scale basis, with a window length of 60 rolling months.

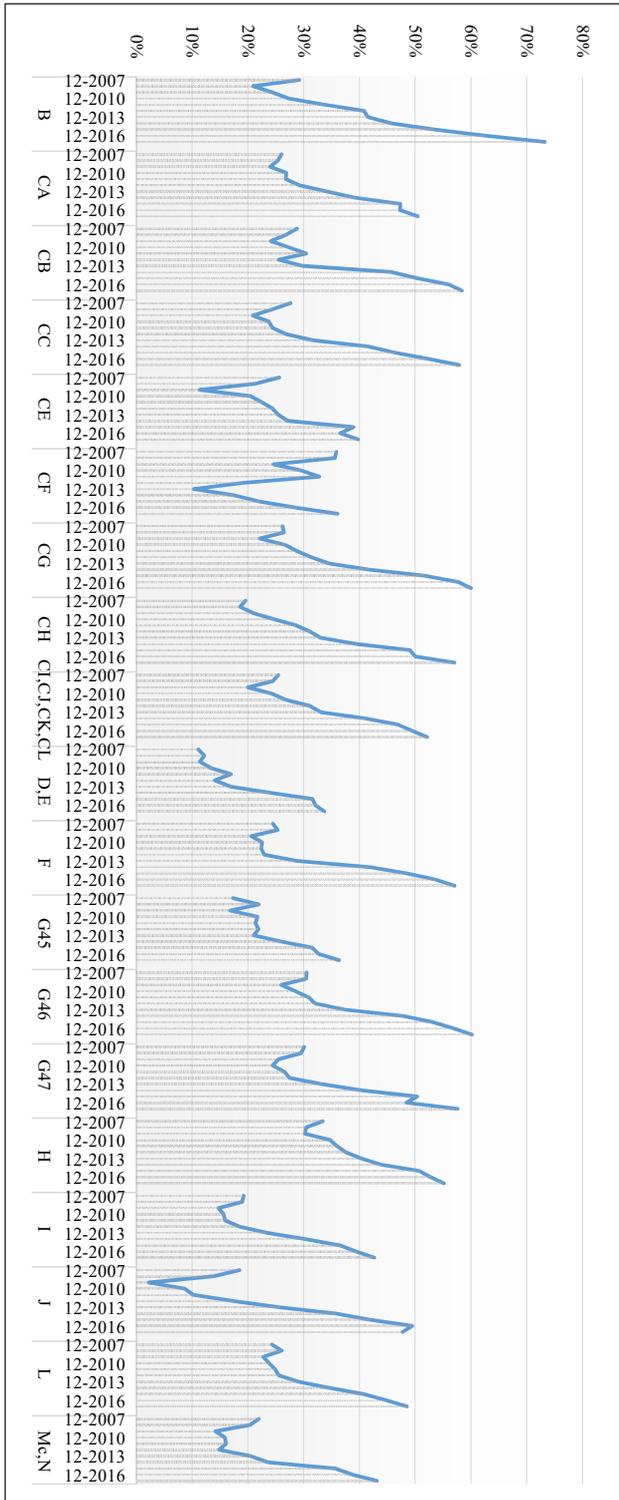
Table 4: Sectoral default rate correlations

Sectors	B	CA	CB	CC	CE	CF	CG	CH	CJ	CK	CL	C other	DE	F	G45	G46	G47	H	I	J	L	Mc,N	OTHERS
B	1																						
CA	0.5208	1																					
CB	0.2344	0.4117	1																				
CC	0.4541	0.4544	0.2822	1																			
CE	0.376	0.4155	0.1194	0.2556	1																		
CF	0.4632	0.0439	0.1871	0.253	0.0267	1																	
CG	0.4774	0.5986	0.2603	0.7573	0.4382	0.2453	1																
CH	0.3939	0.6191	0.2955	0.4378	0.1661	0.0815	0.5005	1															
CJ	0.3974	0.1644	0.0725	0.8432	0.2176	0.4023	0.6306	0.3733	1														
CK	0.0621	0.4939	0.4097	0.2325	0.0262	0.5245	0.28	0.657	0.0204	1													
CL	0.0271	0.497	0.2788	0.1475	0.0497	0.0552	0.0049	0.0154	0.5105	0.2504	1												
C other	0.4713	0.812	0.5762	0.5464	0.3166	0.1581	0.4913	0.7259	0.2678	0.7122	0.374	1											
DE	0.6171	0.8038	0.6465	0.5706	0.4205	0.0776	0.5897	0.6002	0.3579	0.4305	0.3102	0.8426	1										
F	0.1035	0.1064	0.0047	0.4012	0.1496	0.2801	0.2806	0.372	0.5602	0.3192	0.6986	0.1016	0.0697	1									
G45	0.5256	0.8058	0.6792	0.5925	0.2509	0.046	0.5743	0.6565	0.3363	0.559	0.4119	0.9176	0.8682	0.005	1								
G46	0.2629	0.5243	0.613	0.4068	0.077	0.0253	0.2831	0.4145	0.1995	0.3601	0.3711	0.624	0.571	0.0588	0.7121	1							
G47	0.3471	0.6593	0.7131	0.3876	0.4067	0.3711	0.3533	0.5915	0.1523	0.6631	0.2503	0.8852	0.8444	0.2331	0.8012	0.5552	1						
H	0.1959	0.1632	0.2938	0.4036	0.3421	0.4379	0.2217	0.3134	0.4374	0.3707	0.502	0.4081	0.3262	0.6857	0.2942	0.1639	0.5622	1					
I	0.5892	0.8805	0.6163	0.4978	0.4108	0.017	0.5417	0.6186	0.1977	0.5081	0.4659	0.9108	0.9301	0.0614	0.8979	0.6143	0.8428	0.2932	1				
J	0.033	0.3508	0.194	0.4449	0.5101	0.4047	0.5108	0.4055	0.2982	0.5058	0.1455	0.4224	0.4175	0.67	0.3073	0.1454	0.5494	0.385	0.385	1			
L	0.466	0.6038	0.721	0.544	0.4128	0.0184	0.4662	0.3077	0.2697	0.3331	0.3177	0.7553	0.8169	0.0088	0.7971	0.5995	0.786	0.3406	0.8121	0.3466	1		
Mc,N																							
OTHERS																							

Note: "B" – Mining and quarrying; "CA" – Agri food industries; "CB" – Textiles, clothing and footwear; "CC" – Wood, paper products and printing; "CE" – Chemicals industry; "CF" – Pharmaceuticals industry; "CG" – Manufacture of rubber and plastics; "CH" – Metallurgy and metalworking; "CJ" – Metal manufacturing; "CK" – Retail trade; "CL" – Energy, water and waste; "C other" – Construction; "DE" – Motor vehicles trade; "G45" – Wholesale trade; "G46" – Information and communication; "G47" – Real estate activities; "H" – Transportation and storage; "I" – Accommodation and food service activities; "J" – Information and communication; "L" – Real estate activities; "Mc,N" – Professional, scientific, technical, administrative and support service activities.

Source: Authors' calculations

Figure 4: Non-financial companies' median LGD, by sector of activity



Source: Authors' calculations

We observe that sectoral correlations range from 0.93 between real estate activities and motor vehicles trade to 0.005 between textiles, clothing and footwear and wholesale trade while the median correlation is 0.41. Certain sectors present low correlations: chemicals industry, pharmaceutical industry, metal industry. Highly correlated sectors (correlation greater than 65%) are agri-food industry, construction, motor-vehicles trade, retail trade, accommodation and food activities. In the case of German enterprises, the strongly correlated sectors were: the material sector, the capital goods sector, transport and the luxury goods sector (Düllmann and Masschelein, 2007).

The yearly median of LGD is visualized in Figure 4. The number of defaults increased during the Global Financial Crisis. In the last crisis, the loss severity returned to a high level, where it remains since then. Pharmaceuticals industry was characterized by the highest loss given default in 2008, while in 2017 – in mining and quarrying (71%). Enterprises operating in industries where the market is small have higher losses in the event of the company's insolvency due to the lack of active bidders' market. If the market is not liquid, it is more difficult for creditors to recover the amounts due, and the time may be increased until they are collected. It is worth noting that if the assets of an insolvent company are so specific that they cannot be used in another industry, then the difficulties with their sale result in an increase in the LGD.

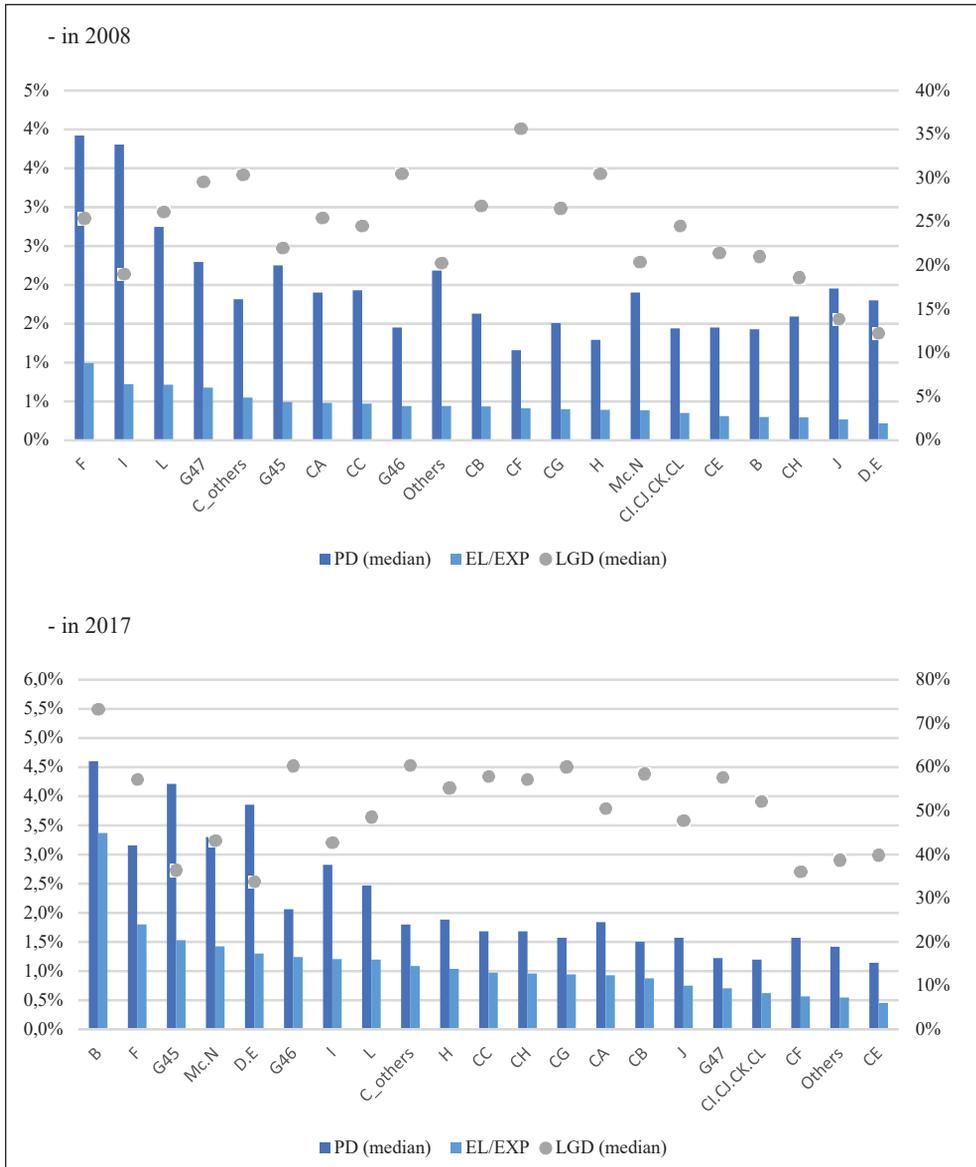
5. Results and discussion

Main objective is to assess the financial stability of the banking sector from a credit risk perspective. For non-financial corporations in Poland, Credit Assessment System can estimate the risk of default during the coming year (parameter PD). Based on the estimation of the Recovery Rate model, Loss Given Default was obtained. Figure 5 presents expected losses (EL) by sectors activity and main "ingredients" of Credit Risk: median of PD and median of LGD in 2008 and 2017.

According to the first research hypothesis, real estate activities, motor vehicles trade, construction, accommodation and food service activities, mining and quarrying report expected losses which are above the average. In 2017, sectors such as professional, scientific, technical, administration and support service activities; energy, water and waste and wholesale trade were also above the average. Among them real states activities, construction, wholesale trade and energy, water and waste, which present a large part of banks' credit exposures. Turning to main "ingredients" of Credit Risk it is interesting to notice that model based LGD estimates average around 45% in 2017 (about 50% for analysis by Duellmann and Masschelein, 2006; Tola 2010), with outliers such as agri food industries in 2008 and mining and quarrying in 2017 and pharmaceuticals industry in 2008 and

energy, water and waste in 2017. In 2008, real estate and motor vehicles trade firms are very risky with PD exceeding 4,9%. In 2017, the highest PD was found for mining and quarry and motor vehicles trade firms (see: Figure 5).

Figure 5: Credit risk measures: expected losses and its components by economic sectors



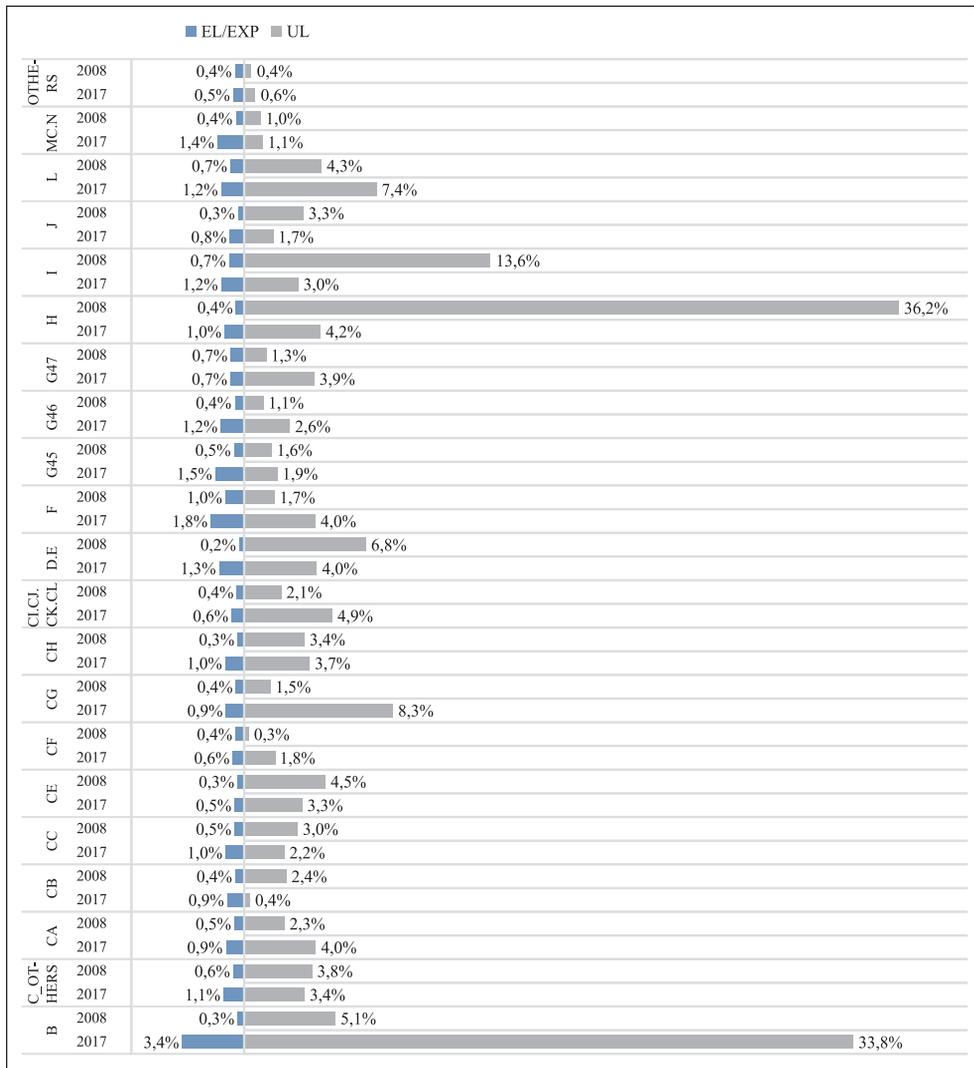
Source: Authors' calculations

Automotive industry is one of the showpieces of the Polish economy, and global concerns are eager to invest in Poland. However, we analyze the success of the above industry through the prism of producers. Poland is one of the leading exporters of car parts and it seems that in the coming years our position in this respect will strengthen. The situation in the trade in cars sector, which generates as much as 62% of the indebtedness of the automotive industry listed in the National Debt Register, is completely different. **So we do not reject the second research hypothesis** which states that the sensitivity of credit risk indicators are different ingredients of default risk, cyclical and concentration of economic sectors.

For German enterprises from the year 1980 till 2001, the lowest PD was found in the mining and energy sector, while the highest one in construction, while asset correlations were generally low ranging from 0.5% in oil, chemicals and pharmaceuticals to 3.5% in metal (Rosch, 2003). It is reasonable and sensible to assume that PD's change through time in relation to the economies cycle.

Figure 6 presents expected losses (EL) and unexpected losses (UL) by economic sectors for comparison in 2008 and 2017. Unexpected losses estimate average on about 5% and range from 0.3% for energy, water and waste in 2008 (0.4% for textiles, clothing and footwear in 2017) and 36% for pharmaceuticals industry in 2008 and about 33% for mining and quarrying in 2017. The degree of correlations between sectors is also reflected in the correlation of insolvency events. In 2017 Mining and quarrying is moderately correlated compared to other sectors, while the risk of mining and quarrying increases 10 times. This fact most probably results from the high concentration in this sector – at the time of a weak economic situation, several large borrowers may go bankrupt. To sum up, we cannot reject **the third research hypothesis** which states that measures of portfolio risk are positively correlated with the concentration structure of economic sectors, and this can be a problem if banks are overly exposed to concentrated sectors.

Figure 6: Credit risk measures: expected losses and unexpected losses by economic sectors



Source: Authors' calculations

It is also worth noting the manufacture of rubber and plastics sector is moderately correlated compared to other sectors and the risk in this sector increased 9 times in 2017. Although the manufacturing of rubber and plastics sector is characterized by absolute risk measures below 1% (the ratio of the expected loss is 0.9%), in the case of a negative scenario, the losses increase significantly more than in other sectors. In 2017, the largest increases in the number of bankruptcies took place in the sector of rubber production and plastic products.

According to the forth hypotheses, the analyses show that the increase in credit losses is sensitive to the size of the sectoral risk factors correlations, PD and concentration in the sector.

6. Conclusions

A comprehensive panel data set was collected, which included information on the amount of credit exposures for listed and unlisted companies, the level of PD at the level of the individual borrower and the value of LGD. The data was collected mainly from four sources: prudential reporting (information about company loans at an individual level), Business Official Register (data on insolvencies/bankruptcies), financial statement data and balance of payment for external statistics of enterprises. Analyzing the pre-database banking credit exposures were divided into different types, in particular: loans, financial guarantees, bonds, lines of credit. Corporate loans constituted the largest share (58% of exposures) and were characterized by the lowest level of concentration, measured by the HHI ratio.

Previously unprecedented element in the study of sectoral risk, and which was used in this study was the variation probability of default for individual borrowers in the business cycle. In earlier analyzes, the PD value was the same for all borrowers (e.g. Duellmann and Masschlein, 2006). The PD data was estimated based on the Internal Credit Assessment System. The second value necessary in the study – LGD coefficient – was obtained as a result of quantile regression. The historical loan losses recorded by the National Bank of Poland were used for estimation. The LGD estimate at the level of individual exposures significantly contributes to the accuracy of the obtained results (in previous studies, LGD values were adopted at a constant level). The database had information about the insolvency of entities, including Recovery Rate for unpaid loans, information on exposures, information about the debtor's area of operations.

Another element of credit risk modeling is knowledge of the correlation of risk factors. In the literature, the correlation of risk factors is approximated by using correlations of the return rates on company shares. In this study, correlations of default rates were estimated. Highly correlated sectors are agri-food industry, construction, motor-vehicles trade, retail trade, accommodation and food activities. Over 70% of banks' total exposure to non-financial enterprises is concentrated in four sections: industrial processing (28%), trade (20%), real estate services (12%) and construction (12%). The average LGD parameter for sectors was approx. 45% (which is a value very close to the hypothetical LGD). In 2017 the mining and quarrying sector is characterized by high riskiness, with PD exceeding 4.7%.

The ratio of the expected and unexpected loss to the exposure for individual sectors over one-year horizon was calculated. The analyzes show that the increase in credit losses is sensitive to the size of the sectoral risk factors correlations, PD and concentration in the sector.

A high concentration of the bank's exposures to the economic sectors, which are more sensitive to fluctuations in the business cycle, can significantly affect the bank's credit risk. This is particularly important during the slowdown or recession phase, because then the excessive concentration of credit in sectors sensitive to changes in the economic situation may lead to the materialization of financial losses threatening the solvency of the institution. From the point of view of financial stability (macroeconomic perspective), the risk is not in a single bank, but in a set of banks that are exposed due to simultaneous involvement in a given sector of the economy. Financial problems of clients from the same industry may thus influence significantly the situation of many banks (unrelated capital and organization) and threaten the entire economy. It is worth emphasizing the significance of industry concentration risk and point out that the conducted analysis may indicate the need for the banking supervision authority to develop new macro-prudential policy instruments.

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Mjerenje kreditnog rizika na primjeru izloženosti riziku koncentracije poljskih banaka¹

Natalia Nehrebecka²

Sažetak

Posljednjih godina velik broj znanstvenih istraživanja ističe važnost razumijevanja i mjerenja rizika koncentracije u kreditnim portfeljima. U članku je prikazano mjerenje kreditnog rizika u okviru regulative o kapitalnim zahtjevima za korporativni sektor. Glavni cilj je procjena financijske stabilnosti bankarskog sektora iz perspektive kreditnog rizika. Empirijska analiza temeljila se na pojedinačnim podacima iz različitih izvora (razdoblje 2007. – 2018.), a to su: bonitetno izvještavanje, poslovni registar, podaci o financijama i ponašanju i platna bilanca. Ovaj rad analizira izloženost poljskih banaka kreditnom riziku koji proizlazi iz različitih gospodarskih sektora. Procjena uključuje vjerojatnost neplaćanja na razini tvrtke, gubitak u zadanom vremenu, očekivane gubitke i neočekivane gubitke. Mjere očekivanih i neočekivanih gubitaka ocijenjene su korištenjem pristupa strukturalnog faktora s višestrukim rizikom. Za vrijeme istraživanja uočeno je da se kreditni rizik razlikuje u različitim industrijama kao i u pojedinim fazama poslovnih ciklusa. Nadalje, rezultati istraživanja pokazuju da se, kako sa stajališta pojedinih banaka tako i sa stajališta bonitetnih vlasti, rizik koncentracije podcjenjuje.

Gljučne riječi: korporativni sektor, rizik koncentracije, Uredba kapitalnih zahtjeva (CRR)

JEL klasifikacija: G21, G32

¹ Zahvale: Željela bih se zahvaliti profesoru Ryszardu Kokoszczyńskom na vrijednim komentarima.

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