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Distribution of credit-risk concentration in particular sectors of the economy, and economic capital before and during the COVID-19 pandemic

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Abstract

The aim of the work underpinning this paper has been to track the evolution of tail risk in banks' NPL portfolios present under normal and worst conditions (before and during the pandemic of COVID-19), and to estimate the impact of sector concentration risk on amounts of economic capital. Results further allowed for analysis of different sectors with a view to determining which is riskiest. The study makes use of a multi-factor structural model, given that each sector is affected by a different systematic risk factor, with the assets of borrowers from the same sector thus correlated markedly, even as correlations between sectors are low. The research has in fact sought the further development of methodology proposed by Düllmann and Masschelein in 2006—in the direction of improved accuracy of economic-capital estimates, thanks to alternate means of mapping out the sectoral factor correlation matrix. The empirical analysis was based on individual data from Prudential Reporting under the National Bank of Poland, as well as market data. Results reveal an increase in tail risk through the 2015–2017 period, as followed by the onset of a decline. Where the paper's second aim is concerned, there is found to be support for the idea that economic capital may be increased where sector concentration in the portfolio of a bank is accounted for. Tail risk is found to be concentrated in the sectors of construction and real estate, with accommodation and food services becoming more volatile during the pandemic. A channel for risk transfer between the financial and corporate sectors is thus found to exist. Thanks to the work done we have a better understanding of the impact of sectoral concentration of individual banks' lending activities on level of risk, with the possibility of this gaining application as stress tests are conducted, and as supervisory recommendations from Poland's Financial Supervision Authority are formulated.

Keywords Sector concertation risk · Economic capital · Multi-factor structural model · Monte Carlo methods

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1 Introduction

Concentration risk is one of the specific types of risk in banking whose inappropriate management, non-subjection to appropriate policies and regulations, or incomplete measurement may all give banks financial problems. Examples here might be the concentration of bank lending in the energy sector in Texas and Oklahoma in the 1980s; as well as over-exposure to the construction and development sector in Sweden in the early 1990s, and in Spain and Ireland in 2000. The materialisation of concentration risk during the global financial crisis of 2008–2009 was in turn a source of huge losses for European and global banks that left them weakened economically, financially, and as regards operational security. Such circumstances ensure the huge importance from a macroprudential point of view of concentration risk being measured.

The effects of the COVID-19 pandemic will hit home just as soon as we see restriction of the emergency measures that governments, central banks and regulators across Europe have introduced. That said, it is reasonable to expect that banks struggling currently with declining interest margins and low profitability, among other things, will prove to be most affected by the crisis, where there is marked concentration in sectors more affected by the pandemic, i.e. hospitality, transport and some manufacturing sub-sectors; as well as in those other sectors already characterised by a high level of non-performing loans on account of COVID. The pandemic may emerge as concentrating bank exposures to the domestic government sector to an excessive degree. This is to say nothing of Poland's energy transformation, with its requirement for a very considerable amount of investment (given costs at the level of 1.6 trillion PLN estimated for 2021–2040.

The risk that banks' credit portfolios will be affected by concentration mainly arises out of over-exposure to a single entity or related entities (name concentration), or out of over-exposure to a given economic sector or related sectors (sector concentration) (see Heitfield et al., 2005). Currently, supervisors interested in banks operating in a stable and safe way recognise the importance of appropriate management of sector concentration risk.

The Committee of European Banking Supervisors (CEBS 2010) has presented its broad and comprehensive definition of concentration risk, which is said to relate mainly to lending activities, and not only to risk associated with loans granted to individual borrowers or groups of related borrowers, but also to other major exposures of related assets or liabilities ensuring that disturbances in certain markets or sectors of the economy are able to threaten institutional stability.

Concentration risk has not been taken full account of in Pillar I of the New Capital Accord, given that, where credit risk is concerned, the IRB approach assumes perfect diversification of portfolios. As the Asymptotic Single Risk Factor (hereafter ASRF) model assumes that the relationship between individual exposures is explained by one systematic risk factor (see Basel Committee on Banking Supervision 2006), it does not provide for concentration risk being measured. Accordingly, concentration risk is assessed under Pillar-2 principles (see Basel Committee on Banking Supervision 2019). Any resulting underestimation of credit risk ought to be corrected for concentration risk. A supervisory authority anyway expects financial institutions to hold sufficient capital to cover all types of risk, including concentration risk.

Recommendation C developed by the Polish Financial Supervision Authority is a collection of good practices regarding concentration-risk management (see Polish Financial Supervision Authority 2016). It takes account of provisions of Polish law, in particular the Banking Law Act of August 29, 1997, and the provisions of the CRR Regulation. Recommendation C enshrines a comprehensive and forward-looking approach to concentration-risk management in banks, with the latter regarded as an element essential if operations are to be stable and safe. It is in fact divided into six parts, including the identification, measurement or estimation of concentration risk, tools supporting the process whereby that is managed; approaches to prevention and reduction; and monitoring plus reporting.

That said, the regulations and guidelines published by both foreign and Polish supervisory authorities offer little guidance on how to measure sector concentration risk accurately, and how to take account of it as capital requirements for credit risk are calculated. This matter has in fact been taken up repeatedly in studies by many economists, who have applied various models and methodologies as they seek to estimate the impact of sector concentration risk on amounts of economic capital.

The literature distinguishes two types of method by which to measure sectoral concentration risk, i.e. the heuristic (otherwise "ad hoc") and the multi-factor (see Gupton et al. 1997; Gordy 2003; Bluhm et al. 2003)

2003). Heuristic methods are most helpful in the determination of limits and concentration ratios, even as they fail to take account of dependence between individual business sectors where credit risk is concerned; or to provide information on the economic capital needed to hedge against concentration risk.

The multi-factor models are the more interesting of the two kinds, given possibilities for solutions more varied than with, for example, the ASRF model. Conceptually, they are underpinned by the existence of dependent relationships (nonzero correlations) between the values of borrowers' assets belonging to different portfolios. Impacts of the market factor on this value may vary in strength, depending on the sector of the economy to which a given entity belongs. Certain sectors may prove more sensitive to changes in the business cycle. Moreover, there may be other factors of importance beyond the differential impacts the same market factor is able to exert on the value of borrowers' assets. Some may have an independent effect on those assets, depending on whether they belong to the sector.

The work underpinning this article has sought to track the evolution of tail risk in banks' NPL portfolios, as present under normal and worst-case conditions (i.e. before and during the pandemic); and to estimate the impact of sector concentration risk on the amount of economic capital. Analysis of the different sectors with a view to identifying the riskiest one was a further possibility arising out of the work.

Sectoral concentration equates to a lack of sectoral diversification of the loan portfolio. The risk of excessive concentration in a given sector materialises where there is a deteriorating situation in a sector of the economy to which a bank has a high level of exposure. The study of that issue forming the basis of this paper has deployed a simulation-based Multi-Factor Model to estimate the loss distribution of non-financial enterprises of commercial banks in Poland, in line with the effect on each sector of a differentiated systematic risk factor, and with the effect that assets of borrowers belonging to the same sector will correlate strongly with each other, even as that correlation will be limited for different sectors.

This work has basically entailed further development of the methodology proposed by Düllmann and Masschelein in 2006—in the direction of improved accuracy of economic-capital estimates, thanks to alternate means of mapping the sectoral factor correlation matrix. Results are expected to contribute to a better understanding of the impact of sectoral concentration of lending activities of individual banks on risk level; and may be used in both the running of stress tests, and the formulation of supervisory recommendations by Poland's Financial Supervision Authority.

This paper contributes to the literature in the following ways. First, scientists engaged in credit-risk modelling have worked on specific elements thereof, such as probability of default, recovery rates, and default correlations. Moreover, research mainly focuses on analytically feasible models, through an assumption of independence or Gaussian processes, and with a view to mathematical expressions in closed form being obtained. This limits flexibility, as well as the applicability of the model to the actual behavior of risk factors. There is a need to consider all realities in credit portfolios, in order to model credit risk, not only by considering appropriate models for each risk factor, but also by ensuring that account is taken of their empirical interactions and individual characteristics, especially in periods of economic recession, e.g. due to COVID-19. Secondly, the existing literature does not contain precise descriptions of the measurement of sectoral concentration, hence this article's contribution to that body of literature. The article describes the methodology pursued. Thirdly, there is verification as to whether a difference can be noted between the designated Economic Capital (hereafter EC) on the basis of the Basel Guidelines, and the analytical model or use of Monte Carlo simulations. This objective seems quite important, especially now that the proper use of risk-management models, on capital markets in particular, is looking to be a matter of crucial importance. Fourth, the research is carried out using a unique database, which includes data on bank exposures to non-financial sector enterprises, corporate Probability of Default (hereafter PD) and model Loss Given Default (hereafter LGD) estimates (based on historical data). Fifth, as the work implements simulation-based Multi-Factor Models, the risk of default is not synchronised across sectors, and the degree of exposure to shocks varies from one to another. As the flexible nature of the simulation-based methods allows for assessment of the evolution of concentration over time, this can prove helpful as micro- and macroprudential authorities seek to detect sectoral risks in individual banks, and in the banking system in general.

The remainder of this paper is organised as follows. The next two sections present the related literature in more detail. Section 4 presents the methodology, and Sect. 5 the data, while Sect. 6 presents and discusses the empirical results, as well as concluding the paper in its final part.

2 Measurement of sector concentration risk

The literature distinguishes between two types of method for measuring sector concentration risk, i.e. heuristic (ad hoc) methods and multi-factor models (see Lutkebohmert 2009; CEBS 2010; Holub et al. 2015).

Measures of the risk of ad hoc concentration are: the Herfindahl–Hirschman index (i.e. Semper and Beltran 2011; Basel Committee on Banking Supervision 2019), Shannon–Wiener Index, Moody Diversification Index, Pielou Evenness Index and Simpson Index. In addition, concentration analysis makes use of concentration curves, correlations in the portfolio, and Analysis of Variance–Covariance (see De Servigny, Renault 2002; Rosch 2003; Fasnacht 2007), as well as the Gini Coefficient. The Shannon–Wiener Index is useful in studying concentration, but in terms of biodiversity, as is the Pielou Index. However, in the literature, the concentration ratio, the concentration curve, the GINI ratio and the Herfindahl–Hirschman ratio are all used often in measuring credit concentration, including as regards sectors.

The main drawback of the Lorenz Curve is the way it precludes comparison of two portfolios in terms of their concentration, if two curves intersect. When they are separate, the lower Lorenz Curve indicates a higher concentration of the loan portfolio. The Lorenz Curve is not an optimal measure of risk as it only shows the deviation from a uniform distribution; not taking account of numbers of loans in portfolios. The concentration of credit is also dependent on the amount of exposure making up a portfolio. Like the Lorenz Curve, GINI has a major disadvantage, in the way that it fails to address the issue of portfolio size, as a factor affecting the degree of concentration.

While heuristic methods are mostly helpful in determining limits and concentration ratios, two important limitations are their failures to take account of the dependent relationships between individual business sectors in the area of credit risk, and to provide information on the economic capital needed to hedge concentration risk. Nevertheless, multi-factor models are methods of greater accuracy when it comes to the assessment of sector concentration risk.

Loan portfolio risk may arise from two sources (i.a. de Servigny and Renault 2002, Heitfield et al. 2006, Lutkebohmert 2009).

As systematic risk reflecting unexpected macroeconomic and market changes. Risk affects all borrowers, but the latter may vary in their sensitivity to its impact. The impact of systemic factors on the credit portfolio risk cannot be eliminated through diversification (i.a. Saldías, 2013);

As idiosyncratic risk, on the basis of diverse threats posed to individual borrowers. This risk is diversified in a situation whereby the loan portfolio is more fragmented, i.e. where the largest loan exposures account for a smaller share of the portfolio (Aas, 2005; Lutkebohmert, 2009).

In the ASRF model derived from the Vasicek (2002) model—a simplified approach to the IRB formula—it is assumed that the credit portfolio is fragmented perfectly, meaning that the idiosyncratic risk is completely diversified and the amount of economic capital depends only on the systematic risk present. In reality, however, the loan portfolio is not perfectly diversified, and in the case of exposure concentration, the IRB formula underestimates the required economic capital. The assumption of the presence of a single risk factor in the ASFR model precludes precise measurement of sector concentration risk. It should be noted that, as credit concentration risk is examined, the two risk components described above cannot be considered independently of each other. For example, a loan portfolio with a very large number of small exposures, and therefore without the first type of name concentration, may nevertheless prove highly concentrated sectorally, with the effect that dependencies between individual loan exposures are generated.

It is therefore advisable that a multi-factor model be deployed, in which each sector will be affected by a different systematic risk factor (in the ASRF model, all borrowers are affected by the same single risk factor), with the consequence that the assets of debtors belonging to the same sector will be strongly related to each other, i.e. correlated; while for different sectors this correlation will be low. The multi-factor Merton Model assumes (see Lutkebohmert 2009) that rates of return on the assets of individual borrowers are influenced by K systematic risk factors with a normal distribution; and the idiosyncratic risk factor characteristic for each borrower, which also has a normal distribution. The calculation of quantiles, such as Value at Risk (hereafter VaR), requires a simulation of the portfolio loss distribution. Monte Carlo methods are usually used for this. Nevertheless, the disadvantage of simulation-based models is their time-consuming nature and, more importantly, portfolio dependence. This means that, when a portfolio includes a new exposure, the loss distribution must be simulated anew. Hence, by using simulation methods it is not possible to achieve relatively simple calculation of the contribution a new loan makes to a portfolio's VaR.

3 Review of research on sectoral risk and business-sector concentration

Overall, the topic has gained broad discussion in academia. The different approaches to measurement reflect the way in which credit risk is an important factor in the management of both risk and banks, and the research presented affords many key insights into issues.

The literature distinguishes between two types of method for measuring sector concentration risk, i.e. heuristic (ad hoc) methods and multi-factor models. One example of research using heuristic methods was the analysis carried out by Kijek and Kijek (2008). Those authors presented the methodology for assessing the structure of the loan portfolio that might support a bank making a loan decision. Additionally, Kijek and Kijek presented a methodology for assessing the economic and financial condition of economic sectors, as well as measuring, modelling and forecasting sectoral risk.

The methodology proposed by the author has gained verification empirically. The subject of the study has been the economic and financial situation of the branches and divisions of the Polish processing business sector, as well as the level of sector risk present in selected industries.

Additionally, Morinaga, Shiina (2005), Gürtler et al. (2008), Long (2012), Dietsch and Petey (2009), Semper and Beltran (2011), Jahn et al. (2013) and Accornero et al. (2018) all showed how the asymptotic single risk factor model may prove disadvantageous. Long (2012) assessed the effectiveness of models with one risk factor, pointing to the key problem of asset correlation errors resulting from simplified single risk factor models leading to default correlation errors. In the case of medium-sized portfolios, economic capital could decrease by 10.64% on average, while corresponding figures in the cases of small and large ones were 15.67 and 9.62%, respectively. It is therefore advisable to use multi-factor risk models, because the individual ones are simplified, and can have a major impact on the estimated risk measures. Dietsch and Petey (2009) sought to assess the usefulness of the asymptotic ASRF model, by reference to French SMEs. They concluded that differences in capital ratios between sectors are large enough to leave a homogeneous assumption in the ASRF as both irrational and redundant.

Several suggested improvements to existing methodology are present in the literature, with the "infection model" from Düllmann (2006), an ASRF extension owing to Tasche (2006), the alternative Herfindahl–Hirschman index (hereafter HHI) index from Semper and Beltran (2011), and the HHI extension achieved by Chen et al. (2013). Tasche (2006) conducted a study to further expand the ASRF structure, focusing on the inability of a single asymptotic risk model to grasp the concentration of the name, and hence the possibility of risk in a portfolio going underestimated. He proposed extending the Basel II Model, thereby allowing several risk factors to be considered instead of one. The presented material related closely to that of Pykhtin (see Pykhtin, 2004). One of the disadvantages of the ASRF model is the exclusion of concentration risk. If sectoral concentration is to be addressed, additional subsidies are needed. For example, the Spanish regulator requires the use of the HHI index, which treats all sectors as equally risky. Cespedes et al. (2006) presented a correcting one-factor model accounting for the effect of portfolio diversification. The capital diversification factor is a function of both sector size and sector correlation. The adjusted amounts of economic capital estimated by means of the ASFR by the diversification factor allow for a more accurate measurement of sector concentration risk. Semper and Beltran (2011) therefore proposed an alternative concentration ratio by which to measure concentration risk in the sector, pointing to the disadvantages of the approach being applied. Estimating variance and covariance for different sectors can be problematic, as these variables are not observable directly, making a proxy necessary. The ones recommended as satisfactory are sectoral indices. Chen et al. (2013) also focused on the concentration index, developing an extension of the HHI index in order to measure sectoral arrangements. Those authors in fact constructed a new index called the risk-adjusted HHI. This takes the formula HHI and multiplies it by the calculated beta value, where beta is defined as the covariance of market return and sector return divided by the variance of market return.

This article is related to a number of studies on credit risk (i.a. Bucur and Dragomirescu, 2014). Proposing a macroeconomic approach, Virolainen (2004) drew attention to the convergence between the levels of default in the corporate sector and macroeconomic variables. When the corporate loan market in Finland was examined, it emerged that the factors strongly influencing the level of insolvency included changes in GDP, interest rates and enterprises' debt ratios. The results of stress tests showed that, as both expected and unexpected losses were relatively small, the credit risk generated by the corporate sector in Finland did not pose a threat to the financial stability of the banking system. Saldías (2013) looked at earlier studies related to heterogeneity in enterprise sectors, analysing systematic and idiosyncratic determinants of insolvency risk in the Euro-area corporate sector. Failure to consider heterogeneity, with analysis confined to macro-financial risk factors, was found to result in underestimation in terms of overall credit-risk management as well as financial stability analysis.

Düllmann and Masschelein (2006) drew on German data to estimate the potential impact of sector concentration on the amount of economic capital. The credit portfolio risk measurement was performed using the Credit Metrics model, by way of Monte Carlo simulation. The study made simplifying assumptions as regards the homogeneity of PD and a fixed LGD in each of the sectors of the economy. Its results showed that, when the impact of sector concentration was considered, unexpected losses amount to 10% of the exposure of the loan portfolio; while compared to a perfectly diversified portfolio, the amount of economic capital is increased by 20–37%. Additionally, studies by Düllmann et al. (2007) assessed the impact of sector and name concentration. The added value of this article lies in its estimate of the asset correlation over time, and in the business sector as a whole; and a detailed analysis of the impact of asset correlation on economic capital. One of the main conclusions is that asset correlations appear to fluctuate considerably over time, with the range in the case of market models being 4 to 16%, while that for sectoral models is even wider. A similar approach has also been used in this article, credit risk being measured with a structural multivariate model using Monte Carlo simulation.

Heitfield et al. (2005) investigated the effects of systematic and specific risk on credit losses faced by large US wholesale banks. From the analysis presented by the authors, it can be concluded that systematic risk is an important factor affecting the value of the portfolio at risk, in the cases of both large and small portfolios. The former appear to be better diversified across sectors than the latter. Even though idiosyncratic risk is not as important as systematic risk, it can still influence credit losses. For small portfolios that are not well diversified, the concentration of names can increase unexpected losses greatly. Growth can average 10% on an annual basis, so banks of this type should strongly manage the name concentration, or increase economic capital to cover these unexpected losses. In the case of large portfolios, idiosyncratic risk appears to be of limited importance. Accornero et al. (2018), Düllmann and Masschelein (2006) and Puzanova and Düllmann (2013) used a multivariate model to estimate expected and unexpected losses at the level of individual banks, sectors, and the entire banking system. According to the authors, a high concentration of bank exposures to sectors of the economy that are more sensitive to business-cycle fluctuations might increase a bank's credit risk markedly, especially in periods of slowdown and recession. The research showed a positive correlation between the credit risk generated by the loan portfolio and the latter's concentration.

A particular problem is seen to arise when the bank involves itself excessively in a given sector of the economy.

In summary, the Basel capital framework provides a simple and transparent model that does not include the risk of portfolio concentration explicitly. However, mention should be made of the Basel Committee on Banking Supervision's literature review (Basel Committee on Banking Supervision 2018), which showed how the Basel III framework related to the Sectoral Countercyclical Capital Buffer (hereafter SCCyB) might be extended in terms of its sectoral application. Scientists make it clear that sectoral macroprudential tools are needed. This article will use a structural multivariate model to detect credit risk across sectors, an issue that is gaining momentum in macroprudential analysis. The evolution of tail risk in the NPL portfolio of banks will be analysed, with identification of the factors contributing to the evaluation of tail risk (e.g. through the ratio of unexpected to expected loss).

4 Methodology: the multi-factor structural model

This article seeks to investigate the extent to which sectoral concentration contributes to the growth of economic capital. The value of the latter is understood as the difference between the specified percentile (95, 99, 99.5, 99.9) of the loss distribution and the expected loss. Economic capital can be determined for VaR under normal and stressed conditions. Stressed VaR is the method used right after VaR, and is based primarily on the identification of stress conditions. However, given the pro-cyclical nature of the minimum capital requirement for market risk determined on the basis of VaR under standard conditions, supervisory institutions introduced a new version for the value at risk under stressed conditions.

The loss distribution is computed through a series of Monte Carlo simulations, set up after Düllman and Masschelein (2006) as:

$$L = \sum_{s=1}^{S} \sum_{i=1}^{I_S} D_{\{X_{s,i} \leq \Phi^{-1}(PD_i)\}} \cdot \mathrm{EXP}_{s,i} \cdot \mathrm{LGD}_{s,i} \tag{1}$$

where:

- L is the potential loss,
- $s \in \{1, \dots, S\}, S$ is the number of sectors,
- $i \in \{1, \dots, M_s\}, I_s$ is the number of borrowers in the sector,
- $EXP_{s,i}$ is the credit exposure,
- $LGD_{s,i}$ is the Loss Given Default,
- D is a binomial variable, equal to 1 if $X_{s,i} \leq \Phi^{-1}(PD_i)$,
- PD_i is Probability of Default,
- $X_{i,s}$ is the company's asset return,
- $X_{s,i} \leq \Phi^{-1}(PD_i)$ means that if the company's asset return is below the default threshold defined by the Probability of Default (PD_i), there is a default of the company,
- $\Phi(\bullet)$ is the cumulative standard normal distribution function.

The multi-factor default-model is an adaptation of the model after Merton (1974). We assume a portfolio of I clients with various exposures EAD_i, asset correlations ρ_i, PD_i and LGD_i. Then, the firm's asset return ($X_{i,s}$) takes the form:

$$X_{i,s} = \sqrt{r_i} Y_s + \sqrt{1 - r_i} \varepsilon_{i,s}, \varepsilon_{i,s} \sim N(0, 1) \tag{2}$$

where:

- $X_{i,s}$ is the company's asset return,
- r_i is a loading factor measuring the sensitivity of asset returns to a risk factor,
- $s \in \{1, \ldots, S\}, S$ is the number of sectors,
- $i \in \left\{1, \ldots, I_s\right\}, I_s$ is the number of borrowers in a sector,
- Y_s is a sector risk factor,
- $\varepsilon_{i,s}$is an idiosyncratic risk factor.

The sector risk factors ($Z_1, \ldots, Z_S$) can be expressed as a linear combination of factors:

$$Y_s = \sum_{k=1}^{S} \alpha_{s,k} Z_k, \text{with} \sum_{k=1}^{S} \alpha_{s,k}^2 = 1, Z_k \sim N(0, 1) \tag{3}$$

where:

- Y_s is a sector risk factor,
- $Z_1, \ldots, Z_S$ are sector risk factors,
- $k \in \{1, \ldots, S\}, S$ is the number of sectors,
- The matrix ($\alpha_{s,k}$) is obtained from a Cholesky decomposition of the factor correlation matrix.

In what follows, there will be a usage of the analytical method for measuring sector concentration risk, which is based on the multi-factor Merton model. This method is the VaR analytical model.

4.1 Dynamic conditional correlation: the GARCH model

The Dynamic Conditional Correlation (hereafter DCC-) GARCH model was used to estimate correlations of equity indices, which are then used as risk-factor correlations. The DCC-GARCH model belongs to the multivariate GARCH model family. It is used widely to model conditional variances and correlations. The advantage of the DCC model is that it allows for a time-varying correlation matrix. A further asset is computational simplicity, as the number of parameters estimated is independent of the number of assets (Engle 2002). A broad number of assets to be correlated can therefore be included.

The DCC-GARCH specifications assume that r_t is a $nx1$ vector of n log asset-returns at time t. The given model is as in the following formula:

$$r_t = \mu_t + \in_t, \in_t \sim N(0, H_t) \tag{4}$$

where:

- μ_t is the expected value of the conditional r_t,
- ϵ_t is an error term,
- H_t is the conditional covariance matrix of error terms.

The conditional covariance matrix of error terms (H_t) can be decomposed as:

$$H_t = D_t R_t D_t \tag{5}$$

where

- $D_t = diag\{\sigma_{it}\}$ is a diagonal matrix of conditional standard deviations of the i-th asset in period t from the standard univariate GARCH model $\sigma_t^2 = \gamma_i + \sum_{p=1}^{P} \alpha_i \in_{i,t-p}^2 + \sum_{q=1}^{Q} \beta_i h_{i,t-q}$, where $\alpha_i, \gamma_i, \beta_i$ are parameters of the model),
- $R_t = \{\rho_{ij,t}\}$ is the time-varying correlation matrix with $\rho_{ii,t} = 1, i = 1, \ldots n$.

The estimation process consists of two steps. In the first, n univariate GARCH models are estimated, one for each return series. The unconditional correlation matrix of standardised returns $\overline{R}$ and the unconditional covariance matrix of negative standardised returns $\overline{Q}$ are then estimated.

The correlation dynamics are given by the equation:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

where:

- $Q_t = (1 - a - b) \cdot \overline{Q_t} + a \cdot \left(\epsilon_{t-1}\epsilon_{t-1}^{'}\right) + b \cdot Q_{t-1}$, a and b are scalars,
- Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t,
- $\underline{Q} = E\left[\epsilon_t \epsilon_t^{'}\right]$ is in turn the unconditional covariance matrix of the standardized errors ϵ_t.

The parameters a and b are scalars, which must satisfy two conditions to ensure positive unconditional variances (Gjika and Horváth, 2013): $a \geq 0 \& b \geq 0$ and $a + b < 1$.

5 Data

The empirical analysis was based on loan portfolios which reflect characteristics of bank portfolios obtained from the Prudential Reporting managed by the National Bank of Poland, *NBP* (reflecting Resolution of the Board of *Narodowy Bank Polski* No. 53/2011 of 22 September 2011, which related to procedure and detailed principles whereby banks would supply the NBP with data indispensable to its pursuit and periodic evaluation of monetary policy, as well as evaluation of the financial situation facing banks, and banking-sector risk). The so-called large exposures for banks exceed 2 M PLN in the case of a single joint-stock company, state-run bank or non-associated cooperative bank. The sample covers branches of foreign banks located in Poland. For the purposes of further work, sectors excluded from the Polish Classification of Economic Activity 2007 sample were those in Sections "Agriculture, forestry and fishing" and "Financial and insurance activities". This was a reflection of the specific nature of these activities and the separate regulations capable of applying to them. The legal forms analysed were in turn partnerships (unlimited, professional, limited or joint-stock limited); capital companies (limited liability or joint stock); civil-law partnerships, state-owned enterprises and Poland-based branches of foreign enterprises.

Reference to Table 1 makes it clear that there are currently no more marked aggregate effects of the COVID-19 pandemic. This reflects the way in which governments, central banks and regulators all reacted quickly to the pandemic in order to curb its worst consequences. Cutbacks on government or central-bank bailouts is likely to exacerbate weaknesses, especially for smaller banks.

The total number of obligors obtained was 17,160 enterprises as of March 2020 before the onset of COVID-19 (16,555 companies during COVID-19 (March 2021)). The structure of the analysed sample by size and business section / subsection for activities of non-financial enterprises in large and small & medium-sized commercial banks is as presented in Fig. 1. Most enterprises with full involvement in large commercial banks are concentrated in the sections of wholesale trade (small enterprises predominate), real-estate activities (microenterprises predominate) and construction, while in the case of small & medium-sized commercial banks it is real-estate activities (microenterprises), construction (predominantly microenterprises), construction (also predominantly microenterprises), trade in motor vehicles and wholesale trade.

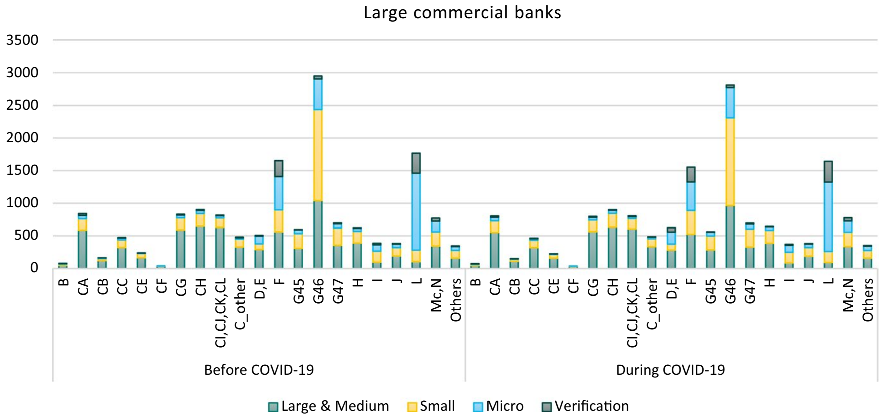
6 Results: portfolio composition

6.1 Description of the benchmark portfolio

For the impact of sector concentration to be studied, it was necessary to establish a benchmark for total credit exposures (Table 2). For the purposes of this study, the NACE classification was transformed in line with expert groups, on the basis of experience contained in the work of the Working Group on Risk Assessment operating within the European Commission. Exposures from the financial sector were not included, due to the specific nature of that sector. In addition, it was noted how the degree of heterogeneity in the "Industry" sector was high, with the decision therefore taken to divide it into smaller sub-sectors. The probability of default for each borrower was defined on the basis of ICAS for Polish enterprises (Nehrebecka 2018, 2021a, b). The LGD level was in turn established for each enterprise on the basis of the model presented in Nehrebecka (2019a), Nehrebecka (2019b).

Table 1 Structure of the analysed sample – before COVID-19 (March of 2020) and during COVID-19 (March of 2021). *Source:* author's own elaboration

	# OF BANKS		# OF OBLIGORS		% OF DEFAULT	
	Before COVID-19	During COVID-19	Before COVID-19	During COVID-19	Before COVID-19	During COVID-19
Large commercial banks	11	10	15 532	15 147	1 158	1 075
Small and medium-sized commercial banks	33	30	2 472	2 083	336	345



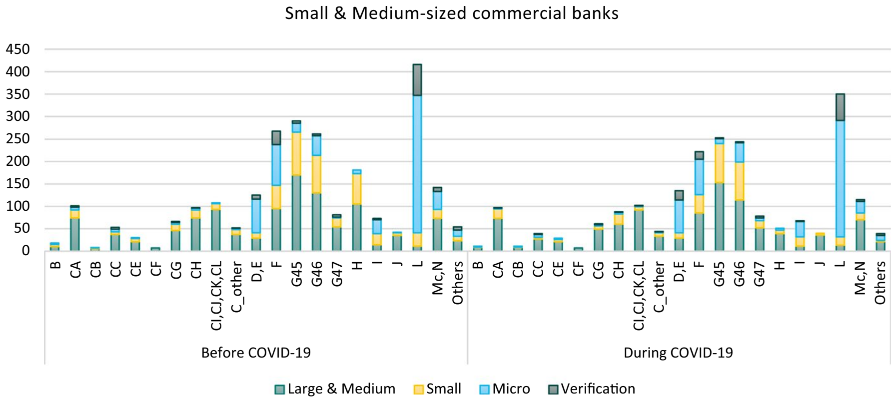


Fig. 1 Structure of the analysed sample by size and section / subsection for non-financial enterprises. Note: "B"—Mining and quarrying; "CA"—Agri food industries; "CB"—Textiles, clothing and footwear; "CC"—Wood, paper products and printing, "CE"—Chemicals industry, "CF"—Pharmaceuticals industry, "CG"—Manufacture of rubber and plastics, "CH"—Metallurgy and metalworking, "CI_CJ_CK_CL"—Metal manufactures, "DE"—Energy, water and waste, "F" – Construction, "G45"—Motor vehicles trade, "G46"—Wholesale trade, "G47"—Retail trade, "H"—Transportation and storage, "I"—Accommodation and food service activities, "J"—Information and communication, "L"—Real estate activities, "Mc,N" -Professional, scientific, technical, administration and support service activities *Source*: author's own elaboration

Before the pandemic of COVID-19 the total value of exposure in the portfolio was PLN 291,116 M, while their amount is 15 k obligors, which means that the portfolio can be considered highly diversified. Average PD is equal to approximately 2.4%. The average LGD is 40%—a value close to 45% on the basis of the unsecured loans, determined by the supervision under the Internal Rating-Based approach contained in Basel II. Moreover, in accordance with the guidelines on Prudential Reporting managed by the National Bank of Poland, data on the size of exposures are included in monthly reports, in respect of borrowers whose liabilities exceed PLN 2 M. With COVID-19 an increase in numbers of insolvencies

Table 2 Composition of the benchmark portfolio – before COVID-19 (March 2020) and during COVID-19 (March 2021). *Source:* author's own elaboration

Sector	Before COVID-19					During COVID-19				
	Total credit exposure (PLN)	Number of exposures	% exposure	PD	LGD	Total credit exposure (PLN)	Number of exposures	% exposure	PD	LGD
B	3 151 M	74	1.1%	1.2%	33%	1 925 M	65	0.8%	6.3%	10%
CA	17 245 M	807	5.9%	3.6%	51%	16 357 M	768	6.5%	2.2%	55%
CB	1 669 M	163	0.6%	4.2%	28%	1 348 M	144	0.5%	4.4%	31%
CC	8 170 M	477	2.8%	1.5%	33%	6 619 M	443	2.6%	3.7%	56%
CE	6 160 M	231	2.1%	1.2%	17%	5 530 M	212	2.2%	1.6%	30%
CF	2 134 M	35	0.7%	2.6%	0%	1 948 M	34	0.8%	2.4%	0%
CG	13 591 M	794	4.7%	1.5%	45%	11 977 M	738	4.7%	1.1%	55%
CH	13 383 M	898	4.6%	1.6%	55%	9 739 M	850	3.9%	2.6%	55%
CI_CJ_CK_CL	13 920 M	775	4.8%	1.8%	46%	12 125 M	740	4.8%	2.2%	38%
C_other	8 327 M	457	2.9%	2.6%	40%	6 114 M	436	2.4%	2.9%	58%
DE	16 260 M	542	5.6%	2.1%	32%	13 907 M	555	5.5%	3.1%	6%
F	23 496 M	1 512	8.1%	2.9%	54%	20 365 M	1 302	8.1%	2.6%	61%
G45	13 127 M	686	4.5%	5.3%	8%	9 999 M	627	4.0%	7.6%	15%
G46	29 413 M	2 785	10.1%	2.2%	56%	23 232 M	2 528	9.2%	1.8%	60%
G47	13 081 M	684	4.5%	1.7%	53%	11 131 M	642	4.4%	2.6%	49%
H	8 298 M	692	2.9%	1.1%	41%	6 280 M	581	2.5%	2.2%	16%
I	7 445 M	439	2.6%	6.4%	41%	7 253 M	426	2.9%	17.4%	34%
J	15 962 M	316	5.5%	1.1%	60%	12 871 M	288	5.1%	2.1%	67%
L	47 298 M	2 050	16.2%	2.1%	36%	44 422 M	1 875	17.6%	3.2%	37%
Mc,N	24 309 M	728	8.4%	2.9%	41%	24 624 M	680	9.8%	1.8%	52%
Others	4 677 M	376	1.6%	2.7%	34%	4 756 M	354	1.9%	3.7%	53%
TOTAL	**291 116 M**	**15 521**	**100%**	**2,4%**	**40%**	**252 523 M**	**14 288**	**100.0%**	**3%**	**40%**

Bold values indicate the results of the statistics of the considered enterprises was recorded in all business sectors. The COVID-19 pandemic started in March 2020, and the severest restrictions were in force in Poland at that time. However, it is only with a delay that the liquidity situation of businesses reflects the difficulties companies have experienced in the last 12 months. Moreover, the increase in numbers of insolvencies also results from the frequent use of simplified procedures to approve arrangements introduced by the Covid Act.

6.2 Intra- and inter-sectoral correlations

Given the way that correlations of corporate assets were not observable, market practices were estimated by calculating correlations using the DCC-GARCH model. The model was calculated on the basis of daily returns on sector indices in the period from December 2015 to March 2020. Sectors are generally found to be correlated with each other to only a limited degree (Table 3). However, it is worth noting that moderate correlations are displayed by: "Energy, water and waste" and "Mining and quarrying", as well as "Information and communication" and "Retail trade".

The next step was to define the intra-sector concentration. The factor weight is r_i =0.5 after Düllmann and Masschelein (2006), matching the relevant internal-ratings capital requirements, based on the economic capital for the underlying portfolio and equal to the internal-ratings capital requirements for corporate exposures and PD of approximately 2%, and LGD of 40% with an annual maturity.

6.3 Economic capital

To estimate the EC matrix based on the simulation of the loss distribution using Monte Carlo methods, the Cholesky matrix was determined and the Y_s matrix (the matrix size [number of scenarios] x [number of sectors]) presented in formula (2). Y_s was generated with random variables of the standard normal distribution and by multiplication with the Cholesky Matrix, providing for appropriate correlation in the case of the generated pseudo-random numbers (sectorally). The specific risk component—matrix ε_i, representing idiosyncratic risk (specific to each company) presented in formula (2), was adopted as random variables with the standard normal distribution (matrix size [number of scenarios] x [number of enterprises]). Determined matrices were then substituted for the calculation of X_i presented in formula (2). A check was then carried out for cases in which a given company in a scenario is below the solvency threshold, which is to say where there is application of the formula:

$$X_i \leq \Phi^{-1}\left(PD_i\right) \tag{7}$$

Losses in each scenario were calculated as equal to the product of exposure, LGD and 0 or 1 depending on whether the firm had defaulted. Economic capital is determined as the difference between the VaR and the expected loss. 95%, 99%, 99.5% and 99.9% VaR for simplicity have been calculated over 50,000 replications.

Table 3 Correlation matrix based on the results of DCC-GARCH. *Source:* author's own elaboration

Sector	B	CA	CB	CC	CE	CF	CG	CH	CI_CJ_CK_CL	C_other	DE	F	G45	G46	G47	H	I	J	L	Mc,N	Others
B	100	13	10	11	37	19	22	20	32	5	47	35	19	28	34	32	9	43	16	37	12
CA		100	2	6	12	6	11	10	23	4	8	14	11	10	16	12	16	12	17	11	10
CB			100	7	9	9	11	6	13	16	14	14	8	13	5	1	1	11	18	14	5
CC				100	14	-1	1	16	9	7	4	9	-1	15	13	19	5	20	18	4	0
CE					100	8	14	16	23	4	28	21	27	23	23	19	5	37	8	24	9
CF						100	-1	12	16	13	5	5	6	9	16	2	15	14	-8	15	5
CG							100	23	17	14	11	22	8	26	17	16	6	15	9	12	10
CH								100	32	23	15	26	14	33	32	24	16	23	25	24	21
CI_CJ_CK_CL									100	11	36	36	18	23	26	21	21	37	19	27	27
C_other										100	2	11	3	13	22	-2	0	7	1	4	4
DE											100	30	21	22	30	23	11	41	22	29	16
F												100	21	25	22	19	10	23	25	17	14
G45													100	30	10	14	13	16	8	34	11
G46														100	28	11	11	28	18	34	12
G47															100	27	22	46	11	31	12
H																100	15	28	16	19	17
I																	100	4	12	16	3
J																		100	12	25	19
L																			100	14	16
Mc,N																				100	10
Others																					100

Also made use of was the Stressed VaR (S-VaR), as developed in relation to market risk. S-VaR is also now used increasingly in Credit Risk. The computation of S-VaR follows the rules of VaR, but only considers the worst losses and scenarios. It is typical for the worst 50% losses (i.e. those of largest size) to be considered, with VaR at level α then computed.

The results are presented in Table 4. It is worth noting that the economic capital value was calculated assuming heterogeneous PD at the level of individual exposures. It is further worth noting that the analytical methods do not take PD heterogeneity into account, unlike the Monte Carlo simulations. They do not require aggressive calculations and are expressed by means of a relatively simple formula.

Basel performance is unreliable in normal economic situations and in times of crisis or downturn in which the probability of occurrence of extremes is greater. This is because the application of a more sophisticated model raises the level of economic capital by approximately twice the amount suggested by Basel. This shows the effect of simplifying the complex interactions and unrealistic assumptions for each of the individual risk factors in portfolio risk. Additionally, it is worth mentioning that, when the IRB approach is applied, the same capital charges are obtained for banks with different levels of sectoral concentration.

The histogram below (as Fig. 2) demonstrates the tail distribution of portfolio losses beyond the 99 percentile. This is skewed positively, showing how the likelihood of extreme events is markedly lower when set against events close to the VaR at that level. The comparison of S-VaR of different percentiles with the corresponding Expected Shortfalls (hereafter ES) at that level demonstrates higher values for the latter. The results obtained on the basis of the presented stress tests underestimate the occurrence of exogenous shocks, such as those related to the COVID-19 pandemic.

Using information from the loss distribution estimated for each year, Fig. 3 shows Expected Loss (hereafter EL) and the three final measures of credit risk—VaR, Unexpected Loss (hereafter UL) and ES—at 99.9% in 2013–2021. Additionally, the repo rate and market VaR have been shown in the above-mentioned chart.

To allow for comparisons between different years, all credit-risk measures are presented as a percentage of total exposure. All measures follow a similar pattern: a steady increase between 2015 and 2017, followed by a decline post-2017. VaR of 99.9% and ES of 99.9% change in parallel as the loss distributions are strictly monotonic, decreasing in the tail. During this period, ES ranged from 3.2 to 5.5%, with EC of 99.9% from 12 to 26%. As of March 2020, EL was roughly 3.2%, while UL was 12.8%. The gap between EL and UL was in fact shrinking post-2017. However, the COVID-19 pandemic has been associated with a re-emerging upward trend for all measures related to credit risk. Central Bank interventions during the ongoing pandemic ensured the smooth operation of the repo market and partly contained the worsening impact of the pandemic (see Fig. 3, repo rate). These effects are also seen in the literature that focuses on the impact on the COVID-19 pandemic. The Fed's efficiency in providing liquidity has helped stabilise conditions on short-term funding markets (Li et al. 2020). Increased financial stability is achieved through the purchase of corporate bonds (Flanagan and Purnanandam, 2020). As a result of the intervention of the European Central Bank, the repo market in the Euro Area has

Table 4 Economic capital—March 2020. *Source:* author's own elaboration

	Normal scenarios				Worst scenarios			
Confidence level	99%	95%	99.5%	99.9%	99%	95%	99.5%	99.9%
Expected losses	PLN 9 432 M							
VaR (PLN)	40 198 M	35 792 M	42 146 M	46 553 M	42 266 M	37 668 M	43 852 M	47 885 M
ES (PLN)	43 028 M	38 769	44 851 M	48 960 M	44 770 M	40 644 M	46 463 M	50 093 M
EC_{sim} (PLN)	30 765 M	26 359 M	32 713 M	37 121 M	32 833 M	28 234 M	34 419 M	38 452 M
EC_{sim} (% OF PORTFOLIO)	10.57%	9.05%	11.24%	12.75%	11.28%	9.70%	11.82%	13.21%
Time for realisation	7 h for each case							

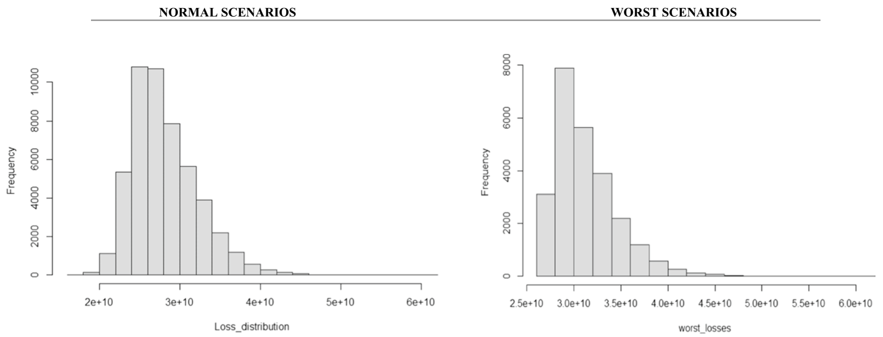


Fig. 2 Histogram of loss distribution—March 2020. *Source*: author's own elaboration

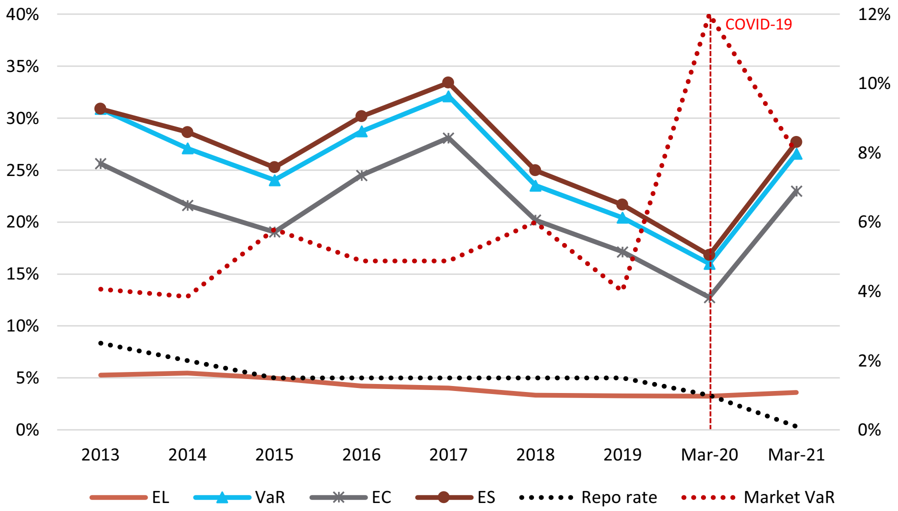


Fig. 3 Credit-risk measures based on loss distribution for the Polish loan portfolio. *Source*: author's own elaboration. *Note*: *Market VaR:* in order to determine the market VaR logarithmic returns on the assets of banks (source: https://stooq.com/q/d/?s=wig_banki&i=d) were calculated and VaR estimates were compared from historical simulation, GARCH models (GARCH(1,1) with normal distribution, GARCH(1,1) with skewed normal distribution, GARCH(1,1) with skewed t distribution) and filtered historical simulation. The selection of the appropriate model was made in line with results obtained using the Kupiec and Christoffersen tests

been able to continue operating in an uninterrupted manner (Billio et al. 2020). In addition, on bank loan spreads have improved (Hasan et al. 2021).

The study also applied the market banking risk measure (market VaR) (Fig. 3). Markets and supervisors often disagree on the risk assessment of a banking portfolio, and this can be explained by reference to uncertainty as regards the financial condition of a bank, and its prospects. In addition, it is an important source of asymmetrical information that influences bank lending policies and profitability (see Vallascas and Hagendorff, 2013). Since risk-weighted assets are ill-calibrated to bank asset market measure of bank portfolio risk, these differences must be taken into account.

6.4 The sequence of portfolios characterised by increasing sector concentration

The impact of sector concentration risk on EC size was investigated through the development of a homogeneous artificial portfolio consisting of a large number of small exposures (where the share of a single loan in the portfolio was less than 0.0002%). A benchmark portfolio was then created, in which the shares of individual sectors correspond with reality—i.e. the sectoral structure obtained from the input data. The probability of insolvency for each borrower was assumed to be 2%, with each loan ascribed to a different debtor. The LGD level has been fixed at 45%.

In the next step, six new portfolios were created through successive modifications to the benchmark portfolio. The creation algorithm was as follows: 1/3 of the exposures from each sector were reallocated to one selected sector (i.e. to G46). The entire procedure is repeated until all loans belong to one sector (concentration in one industry). The increase in sectoral concentration in subsequent portfolios is reflected in the increasing HHI (from 7.43% giving the benchmark portfolio to 100% for the sixth, fully concentrated portfolio, see Table 5). Due to the fact that correlations of companies' assets are not observable, these were estimated by calculating the stock-index correlations on the basis of the DCC-GARCH model. A much more difficult task was to calculate the weighting factor determining the value of the intra-sector correlation. An r_i value at the level of 0.5 was assumed for all sectors, which means that the intra-sector correlation is 25%. In turn, the cross-sector correlation of assets can be calculated as the product of the weighting factors for the two sectors and the cross-sector correlation of the factors. The above input parameters constituted the baseline scenario of the study.

6.5 The impact of sector concentration on economic capital

This article examines the effect of an increase in sectoral concentration on the amount of economic capital, defined as the difference between the 99 percentile of the loss distribution and the expected loss. It can be concluded from the study that economic capital increases with the increase in concentration (see Table 6). For the corporate loan portfolio, economic capital increased by 16.15%, comparing the previously defined benchmark portfolio and the first portfolio (created by performing one iteration in line with the algorithm). In turn, for the fifth portfolio, the increase was as great as 54.50%. The above results indicate a major impact of sector concentration on the amount of economic capital (see Table 6).

To check the sensitivity of the obtained results (changes in economic capital), in relation to the magnitudes of adopted input parameters, three scenarios were considered: (1) lower PD for borrowers—from 2 to 0.5%, (2) a factor correlation matrix with higher values (i.e. assuming the highest mean correlation between individual

Table 5 Composition of the benchmark portfolio—March 2020. *Source:* author's own elaboration

Sector	Bench-mark portfolio	Number of exposures	Exposure value (PLN)	The value of a single exposure	Share of a single com-pany	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
B	1.1%	5 411	3 150 M	582 232	0.0002%	0.72%	0.48%	0.32%	0.21%	0.14%	0.00%
CA	5.9%	29 618	17 245 M	582 232	0.0002%	3.95%	2.63%	1.76%	1.17%	0.78%	0.00%
CB	0.6%	2 866	1 668 M	582 232	0.0002%	0.38%	0.25%	0.17%	0.11%	0.08%	0.00%
CC	2.8%	14 031	8 169 M	582 232	0.0002%	1.87%	1.25%	0.83%	0.55%	0.37%	0.00%
CE	2.1%	10 579	6 159 M	582 232	0.0002%	1.41%	0.94%	0.63%	0.42%	0.28%	0.00%
CF	0.7%	3 664	2 133 M	582 232	0.0002%	0.49%	0.33%	0.22%	0.14%	0.10%	0.00%
CG	4.7%	23 342	13 590 M	582 232	0.0002%	3.11%	2.07%	1.38%	0.92%	0.61%	0.00%
CH	4.6%	22 986	13 383 M	582 232	0.0002%	3.06%	2.04%	1.36%	0.91%	0.61%	0.00%
CI_CJ_CK_CL	4.8%	23 908	13 920 M	582 232	0.0002%	3.19%	2.13%	1.42%	0.94%	0.63%	0.00%
C_other	2.9%	14 302	8 327 M	582 232	0.0002%	1.91%	1.27%	0.85%	0.57%	0.38%	0.00%
DE	5.6%	27 926	16 259 M	582 232	0.0002%	3.72%	2.48%	1.65%	1.10%	0.74%	0.00%
F	8.1%	40 355	23 496 M	582 232	0.0002%	5.38%	3.59%	2.39%	1.59%	1.06%	0.00%
G45	4.5%	22 546	13 127 M	582 232	0.0002%	3.01%	2.00%	1.34%	0.89%	0.59%	0.00%
G46	10.1%	50 517	29 412 M	582 232	0.0002%	40.07%	60.05%	73.36%	82.24%	88.16%	100.00%
G47	4.5%	22 467	13 081 M	582 232	0.0002%	3.00%	2.00%	1.33%	0.89%	0.59%	0.00%
H	2.9%	14 251	8 297 M	582 232	0.0002%	1.90%	1.27%	0.84%	0.56%	0.38%	0.00%
I	2.6%	12 787	7 445 M	582 232	0.0002%	1.70%	1.14%	0.76%	0.51%	0.34%	0.00%
J	5.5%	27 415	15 961 M	582 232	0.0002%	3.66%	2.44%	1.62%	1.08%	0.72%	0.00%
L	16.2%	81 236	47 298 M	582 232	0.0002%	10.83%	7.22%	4.81%	3.21%	2.14%	0.00%
Mc,N	8.4%	41 752	24 309 M	582 232	0.0002%	5.57%	3.71%	2.47%	1.65%	1.10%	0.00%
Others	1.6%	8 033	4 677 M	582 232	0.0002%	1.07%	0.71%	0.48%	0.32%	0.21%	0.00%
HHI	**7.43**					**18.91**	**37.32**	**54.39**	**67.89**	**77.84**	**100.00**
TOTAL	**100%**	**499 992**	**291 116 M**	**582 232**							

Bold values indicate the results of the statistics of the considered enterprises

Table 6 Economic capital—March 2020. *Source:* author's own elaboration

Parametr	Benchmark portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Expected losses	**PLN 2 620 M**						
PD = 2%, LGD = 45%, number of exposures = 499 992							
VaR (PLN)	13 183 M	14 889 M	16 026 M	17 200 M	18 244 M	18 940 M	20 332 M
EC_{sim} (PLN)	10 563 M	12 269 M	13 406 M	14 580 M	15 624 M	16 320 M	17 712 M
EC (% OF PORTFOLIO)	3.63%	4.21%	4.61%	5.01%	5.37%	5.61%	6.08%
EC growth		**16.15%**	**26.92%**	**38.03%**	**47.91%**	**54.50%**	**67.68%**
verification of Robust results							
ASS (1): PD = 0.5%, LGD = 45%, number of exposures = 499 992							
VaR (PLN)	5 896 M	6 271 M	8 338 M	9 164 M	9 714 M	10 081 M	10 815 M
EC_{sim} (PLN)	3 276 M	3 651 M	5 718 M	6 544 M	7 094 M	7 461 M	8 195 M
EC_{sim} (% OF PORTFOLIO)	1.13%	1.25%	1.96%	2.25%	2.44%	2.56%	2.82%
EC_{sim} growth		**11.42%**	**74.52%**	**99.71%**	**116.51%**	**127.71%**	**150.10%**
ASS (2): PD = 2%, LGD = 45%, number of exposures = 499 992, correlation = max value							
VaR (PLN)	23 301 M	26 205 M	30 108 M	31 587 M	33 623 M	34 979 M	37 693 M
EC_{sim} (PLN)	20 681 M	23 585 M	27 488 M	28 967 M	31 003 M	32 359 M	35 073 M
EC_{sim} (% OF PORTFOLIO)	7.10%	8.10%	9.44%	9.95%	10.65%	11.12%	12.05%
EC_{sim} growth		**14.04%**	**32.92%**	**40.07%**	**49.91%**	**56.47%**	**69.59%**
ASS (3): PD = 2%, LGD = 45%, number of exposures = 499 992, correlation = min value							
VaR (PLN)	12 013 M	13 497 M	17 677 M	20 518 M	22 436 M	23 715 M	26 272 M
EC_{sim} (PLN)	9 393 M	10 877 M	15 057 M	17 898 M	19 816 M	21 095 M	23 652 M
EC_{sim} (% OF PORTFOLIO)	3.23%	3.74%	5.17%	6.15%	6.81%	7.25%	8.12%
EC_{sim} growth		**15.79%**	**60.29%**	**90.53%**	**110.95%**	**124.56%**	**151.79%**
ASS (4): PD = 2%, LGD = 45%, number of exposures = 499 992, correlation = 0,9							
VaR (PLN)	42 961 M	47 498 M	50 522 M	52 067 M	52 587 M	52 934 M	53 628 M
EC_{sim} (PLN)	42 961 M	47 498 M	50 522 M	52 067 M	52 587 M	52 934 M	53 628 M
EC_{sim} (% OF PORTFOLIO)	14.76%	16.32%	17.35%	17.89%	18.06%	18.18%	18.42%

Table 6 (continued)

Parametr	Benchmark portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
EC_{sim} growth		**10.56%**	**17.60%**	**21.19%**	**22.41%**	**23.21%**	**24.83%**

Bold values indicate the summary results of the study sector factors), (3) a correlation matrix whose correlation between all sectors is constant and is the minimum from the value of the original correlation matrix, and (4) a correlation matrix whose correlation between all sectors is constant and equals 0.9.

The results of the four robustness checks are as summarised in Table 6.

It emerged that, for the seven portfolios analysed (the benchmark and the six created using the algorithm described previously), the greatest increase in economic capital can be observed under the first and third scenarios. This phenomenon can be explained by the greater difference between the intra- and inter-sectoral correlations.

The conclusion would be that the observed substantial relative increase in EC due to the introduction of sector concentration is robust in the face of realistic variation of the input parameters. Furthermore, this increase in EC may be even greater, depending on the underlying dependence structure. The above analysis is particularly important in the context of the current situation. Analysis of the concentration of exposures shows how the COVID-19 pandemic may result in banks being overexposed, to the domestic government sector for example.

6.6 Expected shortfall contribution in particular sectors of the economy

From a practical perspective in banks, the main application of VaR- (ES-) based models specifically in the context of credit risk is the determination of the linked amount of economic capital. From a high-level point of view, the allocation itself is therefore a slightly secondary issue, because VaR (ES) itself is most important, answering a question as to how much capital an institution should hold if it is to protect itself against unexpected losses over a given time horizon and at a given confidence level. The method of VaR (ES) allocation depends greatly on the use of conclusions from this allocation in further business processes. In the main, allocation methods can classed as:

1. Resulting from the model (see Gundlach and Lehrbass 2004):

(a) The customer's (credit VaR) share—defined as the conditional EL of the customer assuming that the total loss for the entire portfolio equals the credit Value at Risk for the agreed confidence level—is a measure of portfolio sensitivity to the risk associated with such individual elements as clients and groups thereof, portfolio segments, etc., which allows for the identification of clients whose contributions to risk are considerable, and is mainly used to measure and check the concentration risk of individual portfolio clients;

(b) The client's share of risk is defined as its share of the standard deviation of the portfolio loss scaled linearly to the quantile level at a given confidence level, and thus interpreted as a measure of uncertainty and used typically to measure customer profitability in the context of an entire portfolio;

2. Resulting from the proportion of Earnings at Risk (hereafter EaR)—in a quite specific approach whose rectitude in some respects is nevertheless difficult to deny;

3. Reflecting various proportional/marginal/allocation combinations based on the risk correlation (often the measured PD) of individual portfolios.

In summary, it is possible to simplify the allocation described in point 1 b), making it easier to understand the business, but the results of the

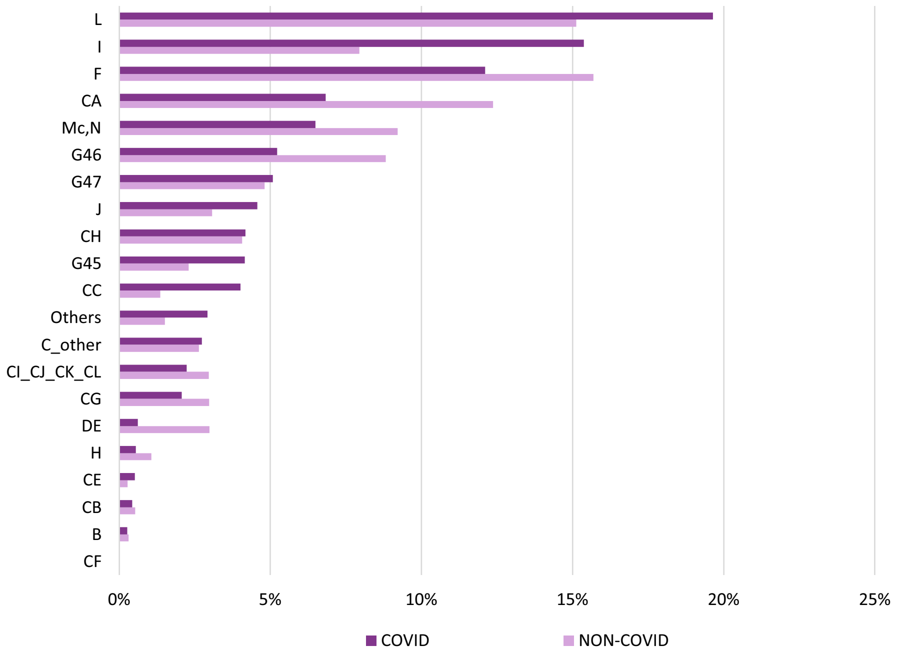


Fig. 4 Contributions to ES (99:9%) for the Polish loan portfolio. Contributions for each year must sum up to 100%. *Source*: author's own elaboration

allocation do not change much. It emerged that the CreditRisk + model generates a very similar result where allocation is based on $EAD \cdot PD \cdot LGD \cdot \textit{the power of interdependence between clients}$. This power of interdependence was understood as a measure based on the strength of the default-rate correlation in individual sectors in which clients operated. The general conclusion is that, if account is taken of all components that affect the structure of the distribution of the modelled loss (from which the quantile is VaR), such an allocation is practical and rational.

Figure 4 shows the contribution of each sector to the ES prior to the pandemic of COVID-19 and in the course of it. There is a distinct concentration of tail risk in two sectors, *i.e.* real estate and construction, which together account for more than half of the ES. The contribution of the real-estate sector has been increasing compared with the two periods before COVID-19 and during COVID-19, while the role of the construction sector is in decline. The sector related to accommodation and food services should also be mentioned in the COVID-19 context.

7 Conclusion and policy implications

This article examines the extent to which sector concentration contributes to growth in economic capital, as well as assessing the effectiveness of analytical methods in measuring sector concentration risk. Unexpected losses were estimated using the multivariate model described in the articles by Düllmann and Masschelein (2006), (2007), and Düllmann and Puzanova (2011), as derived indirectly from the model after Merton (1974). Additionally, this article has focused on the development of the methodology proposed by Düllmann and Masschelein, in the direction of improved accuracy of economic-capital estimation, thanks to alternate ways of mapping the sector factor correlation matrix. Moreover, the article contains a detailed description of the methodology applied.

It is worth noting that the study used a unique database, *inter alia* with data concerning bank exposures to non-financial sector enterprises, corporate PDs and model LGD estimates (based on historical data). Portfolios were characterised by reference to their degree of diversification, with aggregate, relative exposures of domestic banking represented sector by sector. Exposures from the financial sector were not included, in recognition of that sector's specific nature. In addition, it was possible to note the high degree of heterogeneity characterising sectors of industry, hence the study's more-precise division into industrial groups.

However, the first goal of the work detailed involved the tracking of the evolution of tail risk in banks' NPL portfolios. In line with the model proposed in this article, this risk is seen to have increased markedly in the 2015–2017 period, before starting to decline. The decline in end-risk measures such as value for risk and ES was much more marked than the reduction in expected loss. It would be useful to analyse further the ratio of unexpected to expected losses, this being particularly influenced by the correlation in the event of borrower default.

The second purpose of this study has been to estimate the impact of sector concentration risk on the amount of economic capital. The New Capital Accord includes a mathematical formula that combines the value of credit risk resulting from the statistical model with the minimum capital requirements limiting a bank's potential losses. The IRB concept is based on the assumption that the portfolio credit risk is the resultant of: specific risk (Idiosyncratic Risk) representing the effect of diverse, random and mutually unrelated threats to individual borrowers (a credit portfolio with infinite fragmentation), and systematic risk resulting from simultaneous market and macroeconomic impacts on all borrowers. Gordy (2003) defined the ASRF model, which, in order to adapt to IRB, has assumptions regarding the loan portfolio that are not very strong (similar clients and dependence between exposures is explained by a single systematic risk factor). The risk weights estimated using the IRB method are unchanged from portfolio to portfolio, which is to say that capital requirements for each individual credit exposure do not depend on the portfolio to which they belong. However, the above assumption may lead to potential discrepancies between the estimates obtained from IRB modelling and effective economic capital. As this study shows, a bank's accounting for sector concentration in its portfolio can produce a twofold increase in its capital. This aspect is important for both small financial institutions specialising in certain sectors, and the overall stability of the banking system, where banks' credit portfolios are exposed excessively to sectoral risk.

The conclusions of the study reflect the results of portfolio models for credit risk, which show that the concentration of exposures in sectors may result in an increase in VaR. When the impact of sector concentration is taken into account, unexpected losses amount to 10.57% of the exposure of the loan portfolio under normal conditions, and 11.28% in the worst-case scenario, while compared with a perfectly diversified portfolio, the amount of economic capital is increased by 16–68%. From the point of view of financial stability (the macroeconomic perspective), the risk does not lie with a single bank, but with a set of banks that are exposed due to simultaneous involvement in a given sector of the economy. In this way, the financial problems of clients from the same business sector may destabilise the situation of many banks (not related to each other by capital and organisation), and threaten the entire economy. It is worth emphasizing the importance of sector concentration risk, and noting how this analysis may indicate a need for the banking supervision authority to develop new instruments of macroprudential policy, e.g. by introducing additional capital charges in the case of exposures to a given sector, and introducing restrictions on the granting of large loans to companies belonging to a given industry.

The paper also considers, not only the concentration but also the characteristics of the different sectors, in an effort to rank the most risky sectors. Both before the pandemic and in the course of it, tail risk proves to be markedly concentrated in the two sectors of construction and real estate, together accounting for more than half of the ES. Additionally, in the pandemic context, the sector relating to accommodation and food services needs mentioning, even as this of course comes as no real surprise.

This study has successfully analysed the potential effects of systemic sector concentration risk. Such concentrations of exposures may represent a channel for risk transfer from the corporate sector to the financial sector and vice versa. The research has looked at systemic differences between business sectors in terms of credit risk under normal and stressful conditions, while the article also examines the credit risk arising from the sectoral concentration of banking portfolios, *i.e.* from potential under-diversification by business sectors.

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