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Assessing the impact of economic and financial shocks on SME credit quality: a scenario analysis

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Abstract

We estimate the impact of the Covid-19 pandemic on credit risk changes on a large sample of SME firms. The Altman Z"-Score model, which has proven to be a powerful and robust bankruptcy prediction model across many industries and countries, is used to assess over 1,000 SMEs from seven Polish industrial sectors. Specifically, we assess the vulnerability of the sampled firms to credit downgrades, including the likelihood of becoming insolvent and filing for bankruptcy, over the expected downturn in the real economy. Based on scenario analysis on individual firm financial data, we analyse rating transitions under multiple potential scenarios, focusing on the deterioration of the SME firms' profits, and working capital including an increase in current liabilities. We find that the impact on companies from the various rating equivalent groupings are quite diverse and cannot be explained only by the firms' industrial sector. Of particular importance is the proportion of firms whose credit quality deterioration could result in insolvency. What is perhaps surprising is that the most resilient companies with respect to credit downturns are, apart from the AAA/AA+ and AA/AA-rated, those which initially were assigned to the most risky (CCC) credit rating equivalent class. And, those that were assigned to lower investment grade classes were amongst the least resilient.

Keywords: Covid-19, Altman Z"-Scores, bankruptcy prediction, credit risk, bond rating equivalents

JEL: G01, G12, G15, G23, G24, G32

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1. Introduction

In the spring of 2020, the Covid-19 pandemic started to spread globally (WHO 2020). To limit the spread of the virus, governments imposed several restrictions and limited economic activity in most sectors of national economies. This was also the case of emerging economies – including Poland – where companies from many sectors of the country's economy struggled for months to survive. In the autumn of that year, the pandemic situation was even worse and the key question that arose was whether companies that survived the first lockdown would manage to stay alive during any subsequent ones. With global health concerns about the coronavirus still dominating the news, in this paper we address a question about the financial health of companies both before and after the onset of the Covid-19 pandemic. As an experimental case, we concentrate on the Polish economy because of its advanced status and high level of diversification. Importantly, we postulate that our analytical approach can be utilized to assess economic changes due to other catalysts in addition to pandemic.

We start our analysis with an examination of what the financial health of the sample companies was at the end of the pre-pandemic period, namely at the end of 2019. Up to this time, the economic situation in Poland was very favourable as the GDP growth between 2014 and 2019 averaged over 3% per year. In the last three years of that period, it surpassed 4% annually. There were some uncertainties, such as the trade relations between the USA, China and the European Union, Brexit issues, and the recession situation in the German economy, which is a major trading partner for Polish companies. On balance, however, the good financial situation and the positive future outlook made Polish companies sustain their investment activity at a high level in 2017–2019. Part of those investments were financed with external funds, e.g. bank loans and also bond issues (for details see: Tymoczko, Markowski 2021, p. 45 and p. 99). Although the situation of the Polish companies was very favourable, domestic banks tightened lending policy to the corporate sector long before the news on the coronavirus ravaging the Wuhan area in China and other countries, and despite the fact that the outlook for 2020 was rosy. In this respect, the situation in Poland was entirely different from the US where the amount of corporate debt of both investment and non-investment grade firms was at record high levels, having doubled from 2009 to 2019 at levels of over USD 9 trillion (Altman 2020, p. 67–99).

Here we ask the crucial question, what would happen to the financial and economic condition of the SME companies if distressed conditions negatively affected their performance. Due to the low popularity of financing via corporate bonds and therefore the lack of credit ratings in Poland, that are common in most of the advanced countries, instead we apply a Bond Ratings Equivalent (BRE) methodology, as proposed by Altman (1989). In our analysis, we use the ubiquitous Altman Z"-Score model which is one of the most powerful tools used in bankruptcy prediction (for examples of articles on the accuracy and importance of Altman Z-Score models see: Altman et al. 2017; Das, Hanouna, Sarin 2009; and Levy et al. 2020). We focus our analysis on seven sectors that we believe are the pillars of the national economy, and due to their spill-over effects, their financial condition is crucial for companies operating in other sectors, as well. Using the BRE methodology, we perform scenario analysis to assess the potential credit risk migration caused by the pandemic and suggest that it can be used to simulate potential credit impact in any financial crisis. There is a gap in the literature with respect to the magnitude of the reaction of SME companies to shocks, and the type of financial variables that have a significant effect on the companies' resilience. The goal of this work is to verify the hypothesis that the resilience of companies to shocks depends on their initial credit standing and depends on companies' individual characteristics. We claim that sectoral factors are of secondary importance.

2. Literature review

The impact that the Covid-19 pandemic has had on economic performance and development has led to an increased interest in this issue from different groups of analysts, including scientists, practitioners, regulators and lawmakers. In a short period since March 2020, a reasonable volume of articles, special issues, analytical reports and practical recommendations has been accumulated. Many publications are devoted to assessing the consequences of the impact of the Covid-19 pandemic on the national economies, as well as studying the issues of industry and firm sustainability and the importance of the state support mechanisms. Publications focused on those problems can be divided into four topic groups:

1. general issues of assessing the impact of the Covid-19 pandemic on the economy, evaluating its consequences and analysing possible scenarios,
2. the outbreak of the pandemic and its implications for specific industrial sectors and companies,
3. crisis management and policy recommendations for overcoming the crisis,
4. issues associated with bankruptcy risk of companies in the crisis.

The World Bank (Maliszewska, Mattoo, Van Der Mensbrugghe 2020) stated that the virus that triggered a localized shock in China had afterwards delivered a significant global shock. This study simulated the potential impact of Covid-19 on gross domestic product and trade using a standard global general equilibrium model. They modelled the shock based on an underutilization of labour and capital, an increase in international trade costs, a drop in travel services, and a redirection of demand away from activities that require proximity between people. A baseline global pandemic scenario resulted in gross domestic product falling by 2% below the benchmark for the world; 2.5% for developing countries, and 1.8% for industrial countries. The declines were nearly 4% below the benchmark for the world, in an amplified pandemic scenario in which containment is assumed to take longer than just a few quarters. The biggest negative shock is recorded in the output of domestic services affected by the pandemic, as well as in tourist services. The authors claimed that since the model does not capture fully the social isolation-induced independent contraction in demand and the decline in investor confidence, the eventual economic impact might be much worse.

Fernandes (2020) discussed the economic impact of the Covid-19 crisis across industries and countries. He also provides estimates of the potential global economic costs of Covid-19 and the GDP decline of different countries. The report showed that the economic effects of the outbreak in the first two months of 2020 were being underestimated due to over-reliance on historical comparisons with SARS or the 2008–2009 financial crisis. Service-oriented economies would be particularly negatively affected and have more jobs at risk. Countries like Greece, Portugal, and Spain, which are more reliant on tourism (more than 15% of GDP), will be more affected by this crisis. What’s more, the current crisis was generating spill-over effects throughout supply chains. Therefore, countries highly dependent on foreign trade are more negatively affected.

Sharif, Aloui and Yarovaya (2020) analysed the connections between the recent spread of Covid-19, the oil price volatility shock, the stock market, geopolitical risk, and economic policy uncertainty in the US within a time-frequency framework. They claim that the effect of Covid-19 on the geopolitical risk and economic uncertainty in the world is substantially higher than in the US. Moreover, the Covid-19 risk is perceived differently over the short and the long-run.

Ding et al. (2021) evaluated the link between corporate characteristics and the reaction of stock prices to Covid-19 cases using data on more than 6,000 firms across 56 economies in the first quarter of 2020. They showed that the pandemic-induced drop in stock returns was milder among firms with stronger pre-2020 finances, i.e. those with a higher level of cash holdings, less debt and larger profits. Moreover, another factor was lower exposure to Covid-19 through global supply chains and customer locations, higher corporate social responsibility and less entrenched executives.

Similar conclusions were drawn by Fahlenbrach, Rageth and Stulz (2021), who investigated the reaction of the stock prices of American companies to the Covid-19-induced supply and demand shock. They showed that entities with greater financial flexibility should be better able to fund a revenue shortfall resulting from the Covid-19 shock and benefit less from macroeconomic policy responses. They found that firms more exposed to the Covid-19 shock benefit more from cash holdings and these results cannot be explained by a leverage effect.

Ramelli and Wagner (2020) also examined the stock-price reactions of US firms to the Covid-19 crisis since January 2020. They discovered strong causal evidence for the role of international trade and global value chains in corporate value. They show a negative relationship between stock returns and leverage and a positive one between cash and stock returns.

Gössling, Scott and Hall (2020) analysed the impact of the Covid-19 pandemic on the tourism industry, which was one of the most heavily affected economic sectors worldwide, because it is especially susceptible to measures to counteract pandemics due to restricted mobility and social distancing. Unprecedented global travel restrictions and stay-at-home orders caused the most severe disruption of the global economy since World War II. With international travel bans affecting over 90% of the world population and wide-spread restrictions on public gatherings and community mobility, tourism largely ceased in March 2020. The evidence on the impact on air travel, cruises, and accommodation have been devastating.

Al-Dabbagh (2020) studied the role of the decision maker in crisis management, and analysed the crisis decision-making process, its skills and strategies. Ratten (2021) examined the opportunity to utilize entrepreneurship in times of crisis. He points out that from a practical perspective, the challenges derived from the Covid-19 pandemic require an entrepreneurial way of thinking.

Altman (2020) analysed the impact of the Covid-19 on the credit cycle. The pandemic induced a health crisis that has dramatically affected just about every aspect of the economy, including the transition from a record long benign cycle to a stressed one. He analysed the performance of several key indicators on the nature of credit cycles: default and recovery rates on high-yield bonds, and the number of large firm bankruptcies that were expected over the subsequent twelve months and beyond, yield spreads, distress ratios, and liquidity. The paper is focused on the nonfinancial corporate debt market in the United States which reached a record percentage of the country's GDP at the end of 2019 and continued to increase even during the pandemic. The levered loans and the collateralized loan obligation market was also examined and the vulnerability of the BBB tranche of the corporate bond market, which is increasingly large and important, was also analysed from a perspective of its vulnerability to downgrades over the expected downturn in the real economy. He also analysed the potential impact of the vulnerability of those companies to be downgraded on expected default rates by "crowding out" low-quality debt of other firms – so called "zombies". The Z- and Z"-Scores (Altman 1995; Altman et al. 2021) for a sample of the BBB companies has been used to provide some evidence in this analysis.

Ciampi et al. (2021) reviewed literature on small and medium-sized companies default prediction over 34 years from 1986 to 2019. They indicated that the Covid-19 global crisis was strongly impacting the financial health of the vast majority of SMEs and forcing them to base their chances of survival on turnaround plans. Their analysis allowed them to identify and analyse five streams of future research directions in a changing economic environment. They proposed some new innovative approaches to enhance predictive results of the models by using modern analytical techniques, like artificial intelligence, machine learning, and macro-data inputs which rely on broad data sets. The most significant contribution from those authors in regard to our study is the identification of many opportunities to improve the knowledge on SME default prediction, paving the way to direct the changes of rating inputs imposed by the Covid-19 crisis towards more extensive use of qualitative variables.

In response to the recent elevated corporate credit risk environment in China's credit market, Altman, Hu and Yu (2021) develop a probability of default (PD) measure for Chinese companies using actual corporate bond defaults by applying the Least Absolute Shrinkage and Selection Operator (LASSO) machine learning model. This PD measure is applicable to both publicly listed and unlisted companies and its accuracy outperforms models generated by alternative machine learning techniques and other prominent credit risk measures. Further analysis documents a large pricing effect of corporate default risk using this PD measure in primary and secondary bond markets. The pricing effect of default risk became more pronounced following crucial market events in 2014 that raised market awareness of credit risk. In the cross-section of bond and stock returns, they observe a positive distress risk premium after controlling for common risk factors. Finally, stocks of low PD firms outperformed those of high PD firms during the Covid-19 pandemic.

Some recent research used Altman's Z"-Score model to assess the financial soundness of companies from one economic sector and in one country and across countries, although not always linked directly to the Covid-19 pandemic. Abdullah and Achsani (2020) use Altman's Z and Z"-Score models to analyse potential bankruptcies of national airline companies in Asia after the onset of the Covid-19 pandemic. Swalih et al. (2021) perform a study of the financial soundness of Indian automobile industries. Buzgurescu and Elena (2020) use this model to estimate the bankruptcy risk of Romanian industrial companies. Our proposal takes a much more comprehensive approach to the issue, across the entire spectrum of credit quality. In order to conduct the analysis, data was obtained from a large, randomly selected sample of over 1,000 private SME companies, which were analysed assuming several possible scenarios of corporate sensitivity to the crisis. The data has also been analysed from a sectoral perspective, involving seven important industrial categories, as well as the aggregation of the entire sample. The size and method of selecting a sample allow for the assertion that it is representative.

Levy et al. (2020) analysed the resilience of companies in a possible downturn using the Altman Z-Score model. They calculated the Z-Scores for approximately 1,500 European and North American companies for both the last downcycle (2008–2009) and the current one. They find that this model turns out to be a better directional indicator of post-downturn market performance than the market price itself. According to their opinion, an important feature of the Z-Score model is that it helps highlight three outstanding attributes of resilience: margin improvement, revenue growth, and optionality. The latter is defined as retained additional optional investment opportunities.

3. Methodology

In our analysis we use Altman's Z"-Score model (Altman, Hartzell, Peck 1995), according to the formula:[1]

$$Z" = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \qquad (1)$$

where:

X_1 – (Current Assets – Current Liabilities)/Total Assets,
X_2 – Retained Earnings/Total Assets,
X_3 – Earnings Before Interest and Taxes/Total Assets,
X_4 – Book Value of Equity/ Total Liabilities.

The values obtained from the model were used to calculate Bond Rating Equivalents (BREs) (Altman 1989). BREs allow us to compare Z"-Score values with commonly used ratings published by major rating agencies and are used as a benchmark of creditworthiness. To calculate BREs for the sample companies, we use the updated median values for US Bond Rating Equivalents for 2018–2020 (Table 1), from Altman, Hotchkiss and Wang (2019). This approach is used since there is a lack of formal ratings of the sample companies. To allow for reliable analysis of ratings, there should be an adequate set of companies in each rating category. This data is not available for most emerging markets. Therefore, the only way to compute BREs is to relate the model values to BREs calculated for rated companies from developed markets, like in the US or UK. To define intervals for each rating class, we interpolated by calculating the difference between medians of the adjacent classes and subtract half of it from the upper class. This way we compute the lower bound for the upper rating class, which at the same time is the upper bound for the lower rating class (as an example, the lower bound for the AAA/AA+ rating class is 7.76 (7.92–0.32/2) and 7.55 for the AA/AA- (7.60–0.11/2). Companies with Z"-Scores higher than 7.76 are assigned the AAA/AA+ and those with Z"-Scores higher than 7.55 and lower than 7.76 are assigned AA+/AA BREs. All intervals are right-closed.

In the scenario analysis, we check how companies' Bond Rating Equivalents will perform under different assumptions on financial variables, which may change due to varied economic conditions in the country, and in a broader sense worldwide. In our analysis, we make a plausible assumption that a general downturn in the country's economy will have an impact on individual companies and will negatively affect their financial condition.

Based on the individual firm data, we perform a sensitivity analysis under four different scenarios, focusing on the deterioration of profits and working capital (change in profits affects the level of Retained Earnings (RE) as well as EBIT, and then the change of RE impacts the book value of equity and total assets). Using formula 1, we calculate BREs to check how the analysed companies react in different scenarios. The scenarios were chosen to reflect different possible depths of a downturn in the economy. The following four scenarios are considered:

[1] In the Altman's Z"-Score model X_1 represents the company's liquidity, X_2 represents a financial buffer created over the life of the company, X_3 is profitability, and X_4 is a measure of the financing structure. In other words, this model takes into consideration different dimensions of companies' financial strength, and has proven to be a robust indicator of credit risk. For the robustness of the Z-Score family models please see: Das, Hanouna, Sarin (2009), Iwanicz-Drozdowska et al. (2016), Altman (2019), and Levy et al. (2020). At the same time, one should remember that using a different model may lead to different conclusions.

Scenario 1: a decrease in EBIT margin by 5 percentage points (pp),
Scenario 2: a decrease in EBIT margin by 10pp,
Scenario 3: a decrease in EBIT margin by 15pp,
Scenario 4: a decrease in EBIT margin by 20pp.

We calculate Altman's Z"-Score for each company (formula 1) in all scenarios considered and we assign a BRE. In the next step, we compare the resulting BRE in a scenario considered with the original BRE and calculate the change in the number of the credit rating notches, which is considered as a possible downgrade. Finally, we calculate weighted averages of the differences in two dimensions: by initial rating category (form AAA to CCC-) and for specific sectors.

It turns out that in all scenarios that we analyse, our four scenarios are, on average, more severe than what actually has happened in the county's economy through the second, third and fourth quarters of 2020. The Statistics Poland data shows that companies' net profits fell by 11.4% on average in 2020 in comparison with the previous year (Statistics Poland 2020b). One should keep in mind that government stimulus packages were launched, which mitigated profit declines, and the impact of the pandemic and lockdowns was not the same for all sectors. Our analysis focuses on "what if" questions and we analyse what the financial condition of companies would be if the real economy shocks were more pronounced. Indeed, it was more severe for certain enterprises than the average declines.

3.1. Sample description

The analysed sample includes 1,050 Polish companies, randomly selected from the Polish Court Register database, which belonged to seven sectors: construction, leisure and entertainment, manufacturing, retail, services, transportation and storage, and wholesale.[2] These seven sectors account for 88% of the nation's output (Table 2). The sample comprises data as of 31 December 2019, the last full quarter and annual period before the outbreak of the Covid-19 pandemic. All companies in the sample were small and medium-sized enterprises (SMEs) according to the EU methodology. The largest sector was, by far, manufacturing, which accounted for over 37% of the total output, followed by the services sector with over 20% share of the total output. The smallest sector was Leisure and Entertainment.

The median value of the Total Assets for the analysed companies equalled EUR 12.5 million and the median Total Revenues was EUR 13.9 million (Table 3). The vast majority of sample companies reported positive Retained Earnings and none of them had negative book value of equity. What is more, in the light of the Polish law, none of them could have been considered insolvent.

The largest companies in the sample by median assets belonged to the wholesale sector followed by retail, manufacturing and construction. Amongst the smallest sized firm sectors were service, transportation and leisure and entertainment companies (Table 4). What is worth noting is that the median wholesale company is seven times larger than median company operating in the services sector.

[2] The population for this study was a group of small and medium-sized enterprises in Poland (over 9 employees) determined on the basis of the Statistics Poland (2021). Using sample size determination formula, the minimum sample size for the study was calculated such that: Necessary Sample Size = (Z-Score) – StdDev*(1 – StdDev)/(margin of error). Adopting a 95% confidence level (95% – Z-Score = 1.96), 0.5 standard deviation, and a margin of error +/- 8%, made it possible to establish the minimum required sample size in each sector. As a result, the minimum required sample size has been calculated, namely: Manufacturing – 149; Construction – 146; Wholesale – 148; Retail – 146; Transportation – 143; Leisure and Entertainment – 135; Services – 148. Subsequently, the number of companies for each sector was rounded up. In this way, 150 companies in each sector were accepted for the drawing.

Similar conclusions can be drawn when we look at the median values for Total Revenues (Table 5) (for more statistics please see the Appendix – Tables 14–18).

3.2. Bond Rating Equivalents

Based on the BRE methodology of the Altman Z”-Score model (Table 6 and Figure 1) as of 31 December 2019, 31.5% of the sample companies were assigned Investment Grade (IG) ratings categories and over half of these IG companies were A-rated or higher. Interestingly, the largest Investment Grade class was the AAA/AA+ companies. One of the reasons is that this rating class has no upper limit but companies have to reach the lower limit to be included in this IG. The vast majority of the sample (68.5%) received Non-Investment Grade ratings. The largest number of companies were B and BB rated. In terms of a more granular breakdown using “notches”, the largest rating class was BB- leading the B+ rated by a tight margin. Interestingly, the aggregation of the CCC BREs (181 firms – about one sixth of the sample) showed the vulnerability of those SMEs to potential insolvency in a downturn.

3.3. Scenario analysis

As was previously mentioned, the values obtained from the Z”-Score model are used to calculate BREs for each company as of the end of 2019. Based on this data, we perform a sensitivity analysis under four different scenarios, focusing on the deterioration of EBIT margin by 5, 10, 15, and 20 percentage points. We compare the resulting BRE in a scenario with the original BRE and calculate the difference in the number of the credit rating notches. The ratio of the fixed costs to the total costs is known in literature as operating leverage. Operating leverage is defined here as the percentage change of profits to the percentage change of revenues, which is essentially the elasticity of profits. Finally, we calculate weighted averages of the differences in two dimensions: by initial rating category and by specific sectors. EBIT margin is calculated according to the following formula:

$$EBIT\ margin = \frac{EBIT}{Total\ Revenues} * 100\% \tag{2}$$

where:

EBIT – the Earnings Before Interest and Taxes,

Total Revenues – revenues from sales and any extraordinary activities.[3]

In stress conditions, the EBIT margin can be affected in three ways: 1) lowering of profits at the EBIT level while Total Revenues remain unchanged; 2) an increase of Total Revenues while the EBIT remains the same; 3) a mix of the previous two conditions. When economic conditions deteriorate it is rather a common phenomenon that companies’ sales decline. At the same time, firms cannot slash costs proportionally because some costs are fixed, at least in the short-run. The higher the operating leverage

[3] We had access only to data on Total Revenues. As in most of the cases, the Total Revenues are not significantly different from Revenues from Sales, therefore we consider it as a good proxy for EBIT margins.

the more vulnerable companies are to sales decreases. Therefore, we assert that the EBIT margin is a good indicator of a company's financial condition. Analysing the percentage point decrease of EBIT margins, we can now test companies' BRE sensitivity at different levels, including scenarios in which they operate at losses. These cases are of our prime interest as we postulate that many companies will migrate down the rating scale, especially either from the Investment Grade BRE to Non-Investment Grade (High Yield) or from the High Yield to default. In the worst case scenario, direct migrations from the Investment Grade to default are also possible, although highly unlikely.

As noted, we test companies vulnerability using Altman's Z"-Score model to assign companies Bond Rating Equivalents in every scenario considered. There are three primary ways how the deterioration of the EBIT margin will affect companies' Z"-Scores; depending on their current financial situation and the decisions of their managers on how to respond to the shock. The most important transmission channels are the following:

1. EBIT margin → Retained Earnings → Book Value of Equity → Current Assets → Total Assets → Z"-Score → BREs
2. EBIT margin → Current Liabilities and Total Liabilities → Z"-Score → BREs
3. EBIT margin → Sale of Fixed Assets → Z"-Score → BREs

For sake of simplicity, we assume that if the EBIT margin deteriorates, it is due to lower company profits and the Total Revenues being unchanged (point 1 on the previous page). Moreover, profit changes directly affect the Z"-Score, because they are included in X_2 (Retained Earnings) and X_3 (EBIT), which is not the case of the Total Revenues (Sales are included in the original Z and Z'-Score models but not in the Z"-Score (Altman, Hotchkiss, Wang 2019). Of course, in a real-life situation, any mix of the channels is possible but as our analysis showed, the choice of the transmission channel does not change significantly the results at the aggregated level. If we had increased Current Liabilities by 50% of the losses for firms in distress and reduced the impact on profits by the same amount, the results would be similar to the results in channel 1. Thus, in this work, we assumed that the transmission channel is as it is described in point 1. Above, assuming that a profit or loss that is generated in a scenario affects Retained Earnings, Book Value of Equity, Current Assets and Total Assets. Although we believe that the third mechanism is feasible, it is only applicable to individual companies and not the whole sample in a short period. Selling Fixed Assets, like real estate and machinery and even inventories, is not an easy task and it requires a significant amount of time, especially in an economic downturn. It is much harder than sales of financial assets, which are far more liquid.

In our sample, the actual average EBIT margin in 2019 equalled 6.2% and the median was 3.9%. Twelve companies (1.1% of the sample) reported losses at the EBIT level and at that same time 60 companies (5.7% of the sample) were highly profitable with margins of 20% or more. The EBIT margins ranged from -2.5% to 57.6% (Figure 2). Note that extremely high EBIT margins can be attributed to one-off events like sales of fixed assets or realization of profits on investments in financial assets.

Analysis of the four aforementioned scenarios shows that as simulated profits deteriorate, more and more companies are downgraded especially from the Investment Grade (IG) rating category, which is something that we could have expected (Figure 3). What is also interesting is that if profits fall by 20pp, 62 companies (5.9% of the sample) still maintain their IG category. The largest marginal impact on the BREs is when EBIT margins deteriorate from 5pp to 10pp. When EBIT margins deteriorate by 5pp, 59% of the sample companies report losses and when the margins decrease further by 10pp, as much as 82% of the sample companies have losses. It is worth mentioning that losses negatively affect Retained Earnings, Book Value of Equity, Current Liabilities, Total Liabilities, Current Assets, and Total Assets and hence their impact on Z"-Score is pronounced. This is not the case with profits. Profits, even small, have a positive impact on Z"-Scores and that's why in a situation when EBIT margins deteriorate but companies still maintain positive profitability, their rating class does not change and in some cases it can even improve.

From Figure 4, we can observe that as profits deteriorate, in most cases more and more companies move to the lower rating categories, creating positive skews on the BRE graphs. What is more, in the most severe scenario (-20pp), the most numerous resulting categories are D and all CCCs, together accounting for 86.3% of the total number of the analysed companies. In that scenario, only 62 companies (6% of the sample) maintain Investment Grade rating. The relatively high number of the highest-rated firms is due to their high initial Z"-Scores, significant Retained Earnings that can absorb losses, and low Current and Total Liabilities. Moreover, as was mentioned before, this rating class has no upper limit and it can gather relatively more companies than any lower category. In other words, if their Z"-Score rises, these companies cannot migrate upwards and stay in the AAA rating class. On an aggregated basis, we can state that deterioration of the EBIT margin by more than 10pp has a disastrous effect on the sample companies, resulting in an exceptionally high number of CC/D or CCC-rated entities. An average deterioration of the EBIT margins by 12pp or more is when the most numerous BRE category in the whole sample is CC/D.

Simulation results indicate that potential extensions of lockdowns due to the pandemic will have a devastating effect on the financial condition of companies and are an important insight for a country's government. If the lockdown is extended, resulting in an increased deterioration of companies' profits, the number of bankruptcies may be exceptionally high. State aid may be a relief, but one should remember that if it is financed from debt issuance, it will likely negatively affect the country's economy in the future.

4. Results of the simulation

4.1. Resilience of the sample companies to shocks

One of the key goals of this research was to show the resulting financial condition of the companies from different rating categories under several shock scenarios. To check this, we have calculated the number of notches that each company lost based on various scenarios considered. We have computed an arithmetic average and median deterioration for all companies that initially belonged to a certain rating category. The average "downgrade" varies between 1.7 and 6.2 notches and the median is between 1.0 and 6.0 notches. In all scenarios, there are companies that still maintain their initial BREs, but as the EBIT margins deteriorate more and more the number of the latter falls significantly. The largest marginal drops are observed when margins deteriorate from 5pp to 10pp. Within this range, companies on average turn from being profitable to reporting losses, which significantly affects their Z"-Score. When analysing maximum and minimum downgrades, simulation results again show a clear pattern. As margins deteriorate, the maximum downgrades are more and more pronounced and in the most extreme scenario they reach as many as 15 notches, going from AAA/AA+ to CCC-. The number of companies that maintain their rating class steadily declines and the migrations up decreases (Table 7).

Our analysis of the downgrades in the scenarios considered shows that the observed patterns are not represented by smooth, horizontal lines. The most resilient to shocks are those entities that initially were assigned the CCC-, CCC and CCC+, followed by the AAA and AA+, AA and AA-rated. On the other extreme, there were those companies that initially received A+ to BBB- BREs and then deteriorated the most. It might be striking that there is a clear relationship that can be observed here. The companies that initially received Non-Investment Grade ratings are relatively more resilient than the Investment Grade entities and the lower the initial rating, the more resilient companies are to the shocks. This seems surprising, although this observation partly stems from the structure of ratings. It is obvious that companies that initially had CCC- rating can at most fall by one notch, while the possible downgrades for AAA, AA or A companies can be much greater. One should keep in mind that a downgrade from CCC- is essentially a default classification. This may explain the relatively good performance of the companies from BB+ to CCC- rated corporations. The other factor that plays a crucial role in the case of the AAA/AA+ rated companies is the width of this rating class that has no upper limit. It is clear that for some companies it is much harder to deteriorate from the AAA/AA+ category to AA than from any other rating class (the highest Z"-Score in the sample was 11.61 and it must deteriorate by almost 4 points to make this company fall to the AA rating class). In other words, to analyse the resilience of the sample companies, we have to consider both factors: initial rating category and the width of the rating categories, i.e. some rating categories are harder to be retained when shocks come. In the most severe scenario, an average downgrade of around 10 notches was observed only for the A+ to BBB- rated entities.

In our previous analysis, where we calculate the numbers of notches that companies lost in every scenario, we concluded that entities that belonged to the lower investment grade rating classes were more vulnerable to downgrades than those that belonged to the high-yield, more risky categories. Although this approach sheds light on the possible scale of the downgrades, at the same time it may be perceived as biased. Obviously, B or CCC-rated companies cannot go down more than five or two notches respectively, while for the AAA-rated entities, downgrades can equal as many as 17 notches. We can change this awkward feature by normalizing data, relating the number of notches a company from a respective BRE class falls in a scenario considered to the number of notches between its rating category and CC/D-rating, which is a maximum possible downgrade, i.e. to default. It can be calculated using formula 3:

$$Default\,risk_{BRE} = \frac{N_d}{N_{max}} \tag{3}$$

where:

N_d – the number of notches a company from a respective BRE class goes down in the scenario considered,

N_{max} – the number of notches between the company's rating and CC/D (Default) rating.

As can be seen from formula 3, the values that we obtain fall within the range <0.1>. This approach makes the analysis intuitive and allows for comparisons between the base rating class. From Figure 6, we observe that the shapes of the lines differ significantly from the previous analysis (Figure 5). In general, the lower the initial rating, the more severe the relative drops, which reflects a higher probability of default. Although it should be noted that the negative monotonicity of the lines in all four scenarios is broken by the spikes at the BB+ rated companies, the highest Non-Investment Grade class, and also the A- rated entities. The differences between A and A- rating classes are in the range of 0.01 and 0.03 and are not statistically significant. The BB+ rated entities are relatively more resilient to default than BBB-, BBB and even BBB+ rated companies, which is quite surprising. One of the possible explanations is rating inflation and persistent over-valuation of the non-financial corporate debt market since the last financial crisis (Altman 2020). From the point of view of financing cost, there is a huge difference for companies between being BB+ and BBB- rated, as the latter allows accessing a broader group of investors like pension and mutual funds that can only allocate funds into Investment Grade securities. Therefore, assuming that the Z”-Score model and BRE methodology are objective, we may conclude that some companies that were granted BBB- ratings should be, at least, one notch lower. This would positively affect the median Z-Scores calculated for the BREs of the remaining BBB- rating entities (Table 6). Note that if company was BBB- rated by an agency and its financial condition was in fact worse, which was reflected in the financial variables used in the Z”-Score model, in a shock its Z”-Score will go down significantly, e.g. to the levels observed for companies which were granted BB+ ratings or lower. This means that the BBB- rated company will fall by one notch more than its BB+ counterparts and therefore it will be less resilient to the shock. What is worth noting in the three most severe scenarios, all or nearly all CCC- rated entities fall into the D BRE class. In the most severe scenario, over 90% of the BB-rated or lower entities fall into the default category, which can be considered an extreme and unlikely migration.

4.2. Default scenarios

An important question is how many companies would be considered as defaulted based on every scenario that we analyse. Not unexpectedly, as the EBIT margins deteriorate, there are more and more companies that migrate to the D rating class (Figure 7). In the mildest scenario, only 30 entities (2.9%) of the sample fall into default, while in the most severe one, as many as 652 companies (62.1%) are classified as defaulted. We can comment with hindsight that this scenario was an extreme one and such a shock could materialize only if the lockdown was prolonged and no systemic stimulus from the government in the form of the subsidies, direct lending, and tax relief were introduced.

4.3. Sectoral analysis

We find that the scenarios’ reactions of companies from different sectors are quite diverse. The most vulnerable to shocks are companies from the services sector, the average downgrade in all four scenarios equals 5.11 notches. The most resilient are companies operating in the construction and leisure and entertainment sectors – average downgrade equals 3.01 and 3.14 notches, respectively (Table 8, Figure 8). Based on the available data, it is hard to point out what the key factors behind the different migrations of the BREs are for the companies from different sectors. The average sectoral initial rating does not explain the rating migrations. The average BRE for companies operating in the services and construction sectors is the same (BB-), and therefore we conclude that the individual financial situation of a company plays a major role in explaining the downgrades and not the sectoral factors. In other words, any analysis based only on aggregated sectoral data may lead to wrong conclusions.

The difference in BRE changes between the lightest and the most severe scenarios equals as much as 4.84 notches for the average company. From this point of view, the lowest sensitivity can be observed in the case of the services companies (3.51) and the highest can be observed for the manufacturers (6.45). The services companies react relatively heavily (2.83) when the EBIT margins deteriorate by 5pp and as the profit margin deteriorates further, the average marginal change in notches is also pronounced. On the other hand, the average downgrades for the manufacturing companies are relatively mild in the lightest scenario but they react more intensively to further deterioration of the EBIT margins. In the most severe scenario, they are downgraded by 7.77 notches on average, the highest in the sample.

4.4. Credit risk migrations in the pandemic

As expected, the pandemic in 2020 had a negative impact on the credit risk of the sample companies. The average Z"-Score deteriorated from 5.37 in 2019 to 4.34, equivalent to a decline by two notches from essentially BB- to a B rating equivalent threshold.[4] The resulting, most numerous rating classes in 2020 were the CCC and CCC-. The entire CCC component deteriorated from 17.2% of all firms in 2019, to 40.1% in 2020. Moreover, 34 companies migrated downward to CC/D and would be considered in the bankrupt zone from the point of view of the Z"-Score model (Figure 9). The number of Investment Grade companies declined by almost 65% (from 331 to 117) and they accounted for only 11.1% of the sample compared to 31.5% in 2019. The number of AAA and AA rated companies fell dramatically, with the main inflection rating class being B+, all classes below B+ increased in number after the pandemic year. All rating classes from AAA/AA+ to BB- were less numerous than in the pre-pandemic year.

An important question is what the mechanism was that lead to the deterioration of the credit risk of the SME sample companies. As can be seen from Table 9, the X_2, which represents Retained Earning to Total Assets, decreased most in the pandemic period.

We argue that if the Z"-Score model continues to be relevant and accurate under shock conditions, the high values of the explanatory variables of the model in the pre-pandemic period should explain a large portion of the Z"-Score deterioration in the crisis period. To check this, we ran a regression and its results show that over 87% of the change in the Z"-Score in 2020 can be explained by the change in the variables from 2019 (Table 10). Moreover, three of the four variables (except X_2) are statistically significant at the 0.001 level, and their coefficients do not substantially vary from the original model values. In general, we can state that the model is stable in the shock environment, but what calls for an explanation is the behaviour of the X_2. This leads us to the conclusion that during the crisis companies used their accumulated past Retained Earnings to cover the working capital and interest payments. It was a decision of the companies' management on how they wanted to respond to the shock (see transmission mechanism above) and it explains the low correlation of the X_2 in 2019 and Z"-Score in 2020, which was the lowest among all four variables. We can generalize this conclusion by stating

[4] The Z"-Score threshold for the B class is 4.33 and for the BB is 5.41, which means that in 2019 the sample companies were on the edge between the BB- and BB rating class, while in 2020 they were on the edge between B and B-.

that, in the short-run in a crisis, companies experience liquidity problems and they cover losses with Retained Earnings. If the crisis is persistent, they may be forced to increase their liabilities, sell fixed assets, use revolving loans or commercial credit if possible or if all else fails, file for bankruptcy.[5]

We also check the correlation of the four variables calculated for 2019 with Z”-Scores in 2020. The scatter plots on Figure 10 indicate that X_1 is practically linearly correlated with the Z”-Scores while the rest of the variables are not. To check it formally we run four regressions, one for each individual variable. Regression results show that the X_1 alone explains over 62% of the Z”-Score in 2020 while the other three variables were much less correlated[6] (Table 11). This leads us to the conclusion that the crucial factor of the companies’ resiliency to the crisis was liquidity in the pre-pandemic period. In other words, the higher the companies’ liquidity before the shock the more resilient it is to absorb it.[7]

One of the important questions related to our companies’ resilience in the Covid-19 pandemic was the role played by state aid programmes targeted to support companies in the crisis. As data on the value of state aid for individual firms is not available, we use a proxy. In the Z”-Score model we replace EBIT (in X_3) with Profit on Sales. Since, Profits on Sales does not include “other operational items” and EBIT does, we conclude that the difference between both profit levels in the pandemic period should be mostly ascribed to the state aid received by the companies. In general, assuming the positive value of the state aid, EBIT should be higher than Profit on Sales, and it is true for over 95% of the companies in the sample. Following this argument, the Z”-Score calculated using the original formula with EBIT, should be higher than Z”-Score using the Profit on Sales instead of EBIT. The results confirm this logic, and the average Z”-Score calculated with the Profit from Sales was 4.09 corresponding to one notch deterioration with respect to the original Z”-Score of 4.34 (deterioration from B to B-; see Figure 11). This leads us to the conclusion that the deterioration of the credit risk of the sample companies during the pandemic would have been larger without state aid programmes which helped to maintain companies’ liquidity.

4.5. Sectoral approach

The sectoral analysis shows that the most vulnerable sectors in the pandemic were companies operating in the leisure and entertainment sector. The average Z”-Score dropped by 1.43 points, which was equivalent to a downgrade of four notches from BB to B-. They were followed by the transportation companies that on average experienced a drop by 1.15 or three notches from BB- to B-. This is not surprising as both sectors were heavily hit in the pandemic. The leisure and entertainment companies experienced unapparelled lockdowns and the transportation sector was affected by the general slowdown in the economy. The most resilient to the shock were entities that operated in the services, retail and construction sectors. In their case the Z”-Scores declined on average by 0.85, 0.91 and 0.93. Services companies were flexible in slashing costs and this way they could minimize the impact of the

[5] This pecking order may not be optimal for companies if the shock is long-lasting because banks and suppliers may be reluctant to provide loans or commercial credit in a crisis. In fact, it would be better for companies to do the opposite, i.e. first use bank loans and commercial credit and afterwards go for Retained Earnings.

[6] The R^2 for X_2, X_3 and X_4 were 0.09, 0.12 and 0.11 respectively. All variables were significant at the 0.001 level.

[7] Our analysis shows that in the short term, only liquidity defines resilience to the shock. Companies having high levels of the financial cushion use it to respond to the shock, and these funds will be used in the first step. In our sample, the correlation ratio between the X_2 in 2019 and the difference between X_2 in 2019 and 2020 is 0.94 and R^2 of the regression of X_2 in 2019 on the difference is 0.8947, the coefficient is positive and the results are statistically significant at 0.001 level.

Covid-19 pandemic on their credit standing. Many companies from the retail sector, like supermarket chains, operated relatively normally and many of them moved their operations to the e-commerce channels. Construction companies performed normally as the lockdown did not affect them and the high demand for construction services kept this sector booming. Also the wholesale and manufacturing sectors performed relatively well, experiencing drops of 0.97 and 1.00 (Table 12).

Our analysis shows that state aid played an important role to reduce the magnitude of the downgrades but its impact differs among sectors. What is not surprising is that the largest beneficiary of the state aid were companies operating in the leisure and entertainment sector. Our calculations show that without the aid, the drop of the Z”-Score would have been much more severe, on average equalling 1.93. As a consequence, the average level of the Z”-Scores for these companies would have been the lowest of all sectors (3.69) (Table 13). This corresponds to the CCC rating class and is a six-notch downgrade from the original rating. The average positive impact of the state aid programmes can be estimated at three notches for the leisure and entertainment sector. The impact of the state aid is also visible for the services and transportation companies (0.29 and 0.27 difference of the Z”-Scores), which is slightly less than one notch. The lowest impact of the state aid was in the case of the construction companies. The average drop of the Z”-Score without the state aid would be only 0.07 larger or one--fifth of a notch.[8]

5. Concluding remarks

Our simulations for the SME corporate sector indicate that as the economic situation worsens, the new reality is reflected in a deterioration of profit margins at the EBIT level. In the scenarios considered, the Bond Rating Equivalents (BREs) calculated using Altman’s Z”-Score model indicate that in the most severe scenario, of a decrease of 20pp in EBIT margins, only 6% of the sample companies would preserve Investment Grade rating categories. This is 26pp less than in the base situation when we estimate that 32% of the population of the sample SMEs possess an Investment Grade BRE. In the lightest scenario in which EBIT margins deteriorate by 5pp, only 30 companies fall into the D rating category, but the situation is much worse in the most severe scenario when 62.5% of the analysed companies fall into the D rating. Although in reality it does not mean bankruptcy of these companies, one may expect that for those entities access to financing will be hindered or even impossible. And those companies that would still have access to funding may experience higher costs of such funds and, in some cases, it may lead to further deterioration of their financial standing; in some cases, leading to bankruptcy. This leads us to the conclusion that excessive lockdowns may have serious consequences for the SME companies, especially if they are not accompanied by a systemic stimulus from the government in the form of the subsidies, direct government lending, or tax relief. Even with a bailout, many companies may start to have serious liquidity problems, which in the end may lead to insolvency.

Our analysis shows that the subsequent downgrades from the base case (in 2019) are non-linear with respect to the initial rating category or the economic sector, and by that we positively verify our hypothesis. The severity of the downgrades in different scenarios rather depends on the characteristics of individual companies and cannot be determined at the general or sectoral level. We claim that

[8] The state aid impact was not only different between sectors but also varied within sectors. The distributions of the differences between the original Z”-Scores and Z”-Scores calculated with Profit from Sales can be seen on Figure 12.

such an aggregation would lead to wrong conclusions and bad policy responses to the shocks. By model design, the vulnerability of the companies to downgrades partially depends on their initial rating but the most vulnerable to downgrades at the absolute level are companies that belong to the lower Investment Grade rating categories. This creates a characteristic U- or W-shaped pattern on the graphs when the downgrades calculated in notches are plotted against the initial BRE category. When we normalize data, the shapes of the lines are monotonic and the U- or W-shaped lines are not observed. Two spikes are present, however, in all four scenarios for the BB+ and A- rated base case entities. Finally, the lower the initial rating, the more severe the relative drops, which reflects a higher probability of default. In the most severe scenario (-20pp drop), over 90% of BB and lower rated companies fall into the CC/D BRE class.

Moreover, our analysis shows that the most important variable for companies' resilience during the Covid-19 pandemic was their financial liquidity before the shock, which is represented by X_1 in the Z"-Score model. We also estimated the impact of the state aid programmes on the credit risk of the sample companies. On average, this effect was equivalent to one rating notch, but in the leisure and entertainment sector, which was the most heavily hit in the pandemic, it was equivalent to over three notches.

Further work in this field may be focused on the extension of the sample to companies from other advanced economies and also to emerging economies. International comparison should shed some additional light on the resilience of the companies in the pandemic situation. Moreover, our rating migration model can be developed further to serve as a tool for prediction of credit risk migration based on other economic shocks, in addition to the Covid-19 pandemic.

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Appendix

Table 1
Bond rating equivalents of US companies based on the Z"-Score model

Rating	Median 1996 Z"-Score	Median 2006 Z"-Score	Median 2013 Z"-Score	Median 2019–2020 Z"-Score	Difference between median Z"-Scores
AAA/AA+	8.15 (8)	7.51 (14)	8.80 (15)	7.92 (4)	
AA/AA-	7.16 (33)	7.78 (20)	8.40 (17)	7.60 (10)	0.32
A+	6.85 (24)	7.76 (26)	8.22 (23)	7.49 (19)	0.11
A	6.65 (42)	7.53 (61)	6.94 (48)	7.20 (17)	0.29
A-	6.40 (38)	7.10 (65)	6.12 (52)	6.90 (31)	0.30
BBB+	6.25 (38)	6.47 (74)	5.80 (70)	6.52 (56)	0.38
BBB	5.85 (59)	6.41 (99)	5.75 (127)	6.23 (104)	0.29
BBB-	5.65 (52)	6.36 (76)	5.70 (96)	6.02 (62)	0.21
BB+	5.25 (34)	6.25 (68)	5.65 (71)	5.81 (94)	0.21
BB	4.95 (25)	6.17 (114)	5.52 (100)	5.60 (96)	0.21
BB-	4.75 (65)	5.65 (173)	5.07 (121)	5.22 (80)	0.38
B+	4.50 (78)	5.05 (164)	4.81 (93)	4.80 (81)	0.42
B	4.15 (115)	4.29 (139)	4.03 (100)	4.45 (73)	0.35
B-	3.75 (95)	3.68 (62)	3.74 (37)	4.20 (49)	0.25
CCC+	3.20 (23)	2.98 (16)	2.84 (13)	3.95 (19)	0.25
CCC	2.50 (10)	2.20 (8)	2.57(3)	3.57 (2)	0.38
CCC-	1.75 (6)	1.62 (-)	1.72 (-)	2.90 (2)	0.67
CC/D	0 (14)	0.84 (120)	0.05 (94)	0.30 (85)	2.60

Source: own calculations based on Altman et al. (2019), p. 207, updated to include 2020 data.

Table 2

Polish economic output in 2019, by sectors

Sector (section)	in EUR millions	in %
Manufacturing (Sections B, C, D and E)	394 772	37.3
Services (Section L, M, N, O, P, Q)	213 093	20.2
Wholesale, Retail, and Trade (Section G)	133 274	12.6
Construction (Section F)	97 609	9.2
Transportation and Storage (Section H)	82 309	7.8
Leisure and Entertainment (Section I)	13 637	1.3
Total output	**1 057 358**	**88.4**

Notes:
Statistics Poland reports output data jointly for the Wholesale, Retail, and Trade companies.
For a detailed description of the sections, please see Statistics Poland, Polish Classification of Activities (PKD 2007).
Values were calculated using average prices of the previous year and were converted to euros using the average EUR/PLN rate = 4.2585.

Source: Statistics Poland (2000a).

Table 3

Summary statistics of selected financial accounts of the analysed companies, as of 31 December 2019 (in EUR thousand)

	Average	Median	Minimum	Maximum
Current Assets	11 016.75	7 692.85	233.30	38 222.39
Current Liabilities	8 645.94	6 145.97	118.72	34 885.44
Total Assets	16 655.80	12 505.33	693.67	42 970.37
Retained Earnings	647.32	348.42	-216.04	6 033.02
EBIT	918.87	472.04	-143.35	8 264.41
Book Value of Equity	1 172.01	621.72	3.64	11 118.13
Total Liabilities	12 033.38	8 730.63	416.20	40 686.28
Total Revenues	19 282.71	13 867.84	563.43	49 952.64

Note: all variables are used in Altman's Z"-Score model: $Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$
Exchange rate EUR/PLN = 4.2585 as of 31.12.2019.

Source: own calculation based on data reported by the Polish Court Register (last access: 20.02.2021).

Table 4
Summary data for the analysed companies – total assets, by economic sector, as of 31 December 2019 (in EUR thousand)

Sector	Number of companies	Median Assets	Minimum Assets	Maximum Assets
Construction	150	19 954.29	2 196.06	42 970.37
Leisure and Entertainment	150	10 301.19	1 189.04	31 549.99
Manufacturing	150	22 859.97	1 640.82	42 264.64
Retail	150	24 998.84	1 948.81	42 552.44
Services	150	4 354.44	693.67	22 627.23
Transportation	150	7 028.75	1 695.46	25 108.25
Wholesale	150	31 430.48	2 342.47	42 711.83

Source: own calculation based data reported to the Polish Court Register (last access: 20.02.2021).

Table 5
Summary data for the analysed companies – total revenues, by economic sector, as of 31December 2019 (in EUR thousand)

Sector	Number of companies	Total Revenues		
		Median	Minimum	Maximum
Construction	150	20 677.04	1 802.65	49 348.93
Leisure and Entertainment	150	11 190.90	563.43	47 099.64
Manufacturing	150	26 637.31	1 843.61	49 783.97
Retail	150	29 434.88	2 090.10	49 876.97
Services	150	6 813.68	1 109.87	28 857.25
Transportation	150	7 540.58	1 064.67	44 572.33
Wholesale	150	37 888.08	1 528.46	49 952.64

Table 6
Bond Rating Equivalents for the sample SMEs as of 31 December 2019

BRE	Number of companies	Rating category	Total	In %
AAA/AA+	67	Investment grade	331	31.5
AA/AA-	19			
A+	13			
A	27			
A-	43			
BBB+	47			
BBB	53			
BBB-	62			
BB+	55	High yield	719	68.5
BB	83			
BB-	126			
B+	116			
B	88			
B-	70			
CCC+	60			
CCC	77			
CCC-	44			
CC/D	0			

Note: based on the Altman Z"-Score model. See Altman et al. (2019).

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Table 7

Rating changes calculated as the number of notches and number of companies that migrate down or maintain their initial ratings, by scenarios

	Base -5pp	Base -10pp	Base -15pp	Base -20pp
Median	-1.0	-3.0	-5.0	-6.0
Average	-1.7	-3.7	-5.2	-6.2
Std. Dev.	-1.2	2.0	2.6	3.1
Minimum	-7	-10	-13	-15
Number of companies that migrate down	928	1 027	1 037	1 041
Number of companies that maintain their initial rating	122	23	13	9

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Table 8

Average BRE change under different scenarios, by sector

	Base -5pp	Base -10pp	Base -15pp	Base -20pp	Average	Max-Min
Construction	**-0.51**	-2.51	**-4.03**	-5.23	**-3.07**	4.71
Leisure and Entertainment	-0.34	-2.47	-4.19	-5.56	**-3.14**	5.22
Manufacturing	-1.32	-3.78	-6.01	-7.77	**-4.72**	6.45
Retail	-1.59	-3.72	-5.30	-6.20	**-4.20**	4.61
Services	-2.83	-5.17	-6.09	-6.34	**-5.11**	3.51
Transportation and Storage	-0.97	-2.89	-4.32	-5.26	**-3.36**	4.29
Wholesale	-1.63	-4.03	-5.76	-6.71	**-4.53**	5.09
Average	**-1.31**	**-3.51**	**-5.10**	**-6.15**	**-4.02**	4.84
Max-Min	2.49	2.71	2.06	2.54	2.04	

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Table 9
Descriptive statistics for Z"- Score model 2019 vs 2020

Variable	Mean	Std. Dev.	Minimum	Maximum
X_1 2019	0.1548957	0.1596283	-0.3220558	0.674503
X_1 2020	0.0754803	0.1765734	-0.4631385	0.664212
X_2 2019	**0.1570185**	0.1765504	-0.0736548	1.525967
X_2 2020	**0.0193858**	0.0593932	-0.2802361	0.350383
X_3 2019	0.0664617	0.0726302	-0.0206068	0.535206
X_3 2020	0.0638358	0.0703372	-0.0217689	0.555190
X_4 2019	0.1410086	0.1680845	0.0007060	1.290224
X_4 2020	0.0938519	0.1620443	-0.3593974	1.169305

Source: own calculations.

Table 10
Regression results, X_1–X_4 for 2019 over Z"-Score in 2020

Source	ss	df	MS		Number of observations	1 050
					F(4.1045)	1829.95
Model	1 432.61143	4	358.152859		Prob > F	0
Residual	204.525051	1 045	0.195717752		R-squared	0.8751
Total	1 637.136481	1 049	1.56066395		Adj R-squared	0.8746
					Root MSE	0.4424
zscore2020	**Coef.**	**Std. Err.**	**t**	**P > | t |**	**95% Conf. interval**	
X_1 2019	6.665269	0.0871133	76.51	0.000	6.499433	6.836206
X_2 2019	0.215801	0.1574873	1.37	0.171	-0.093227	0.524828
X_3 2019	6.919425	0.3928306	17.61	0.000	6.148598	7.690252
X_4 2019	1.120937	0.0874080	12.82	0.000	0.949422	1.292452
_cons	2.651625	0.0249663	106.21	0.000	2.602635	2.700615

Source: own calculations.

Table 11

Regression of the X_1 in 2019 over Z"-Score in 2020

Source	ss	df	MS		Number of observations	1 050
					F(1.1048)	1 756.12
Model	1 025.27948	1	1 025.27948		Prob > F	0
Residual	611.857007	1 048	0.58383302		R-squared	0.6263
Total	1 637.13649	1 049	1.56066395		Adj R-squared	0.6259
					Root MSE	0.76409
zscore2020	**Coef.**	**Std. Err.**	**t**	**P > | t |**	**95% Conf. Interval**	
X_1 2019	6.19332	0.1477906	41.92	0	5.303321	6.483319
_cons	3.376551	0.0328646	102.74	0	3.312063	3.441039

Source: own calculations.

Table 12

Estimated state aid impact on credit risk, by sectors

Sector	With state aid	Without state aid
Construction	0.934144	1.006577
Leisure and Entertainment	1.428519	1.925696
Manufacturing	0.978011	1.156281
Retail	0.910943	1.149915
Services	0.854471	1.147642
Transportation	1.151199	1.422638
Wholesale	1.000369	1.143303
Total	1.036808	1.278865

Source: own calculations.

Table 13
Descriptive statistics for Z”-Score in 2019–2020 and Z”-Score based on Profit from Sales, by sectors

Sector/Variable	Number of obs.	Mean	Std. Dev.	Minimum	Maximum
Construction					
zscore2019	150	5.11246	1.310569	2.909149	10.53428
zscore2020	150	4.178316	1.153551	2.021418	7.589622
zscoreps2020	150	4.105883	1.158527	1.273626	7.274672
Leisure and Entertainment					
zscore2019	150	5.614479	1.363511	2.455021	10.31434
zscore2020	150	4.185961	1.100415	0.6168988	6.571716
zscoreps2020	150	3.688783	1.07124	0.5199593	6.361806
Manufacturing					
zscore2019	150	6.159057	1.419096	3.127241	9.833713
zscore2020	150	5.181047	1.131247	1.943185	7.685881
zscoreps2020	150	5.002776	1.075735	1.869876	2.324384
Retail					
zscore2019	150	5.119807	1.373073	2.778061	8.289711
zscore2020	150	4.208865	1.315978	1.784633	7.438766
zscoreps2020	150	3.969892	1.282342	0.7869227	7.343816
Services					
zscore2019	150	5.01508	1.141644	2.490736	10.68762
zscore2020	150	4.160609	1.197439	0.8616146	8.10913
zscoreps2020	150	3.867438	1.461431	-0.5396211	7.352182
Transportation					
zscore2019	150	5.337942	1.63249	2.259553	11.60656
zscore2020	150	4.186742	1.159778	1.75443	7.364852
zscoreps2020	150	3.915304	1.123772	1.385928	7.666174
Wholesale					
zscore2019	150	5.249917	1.274823	2.893795	8.154501
zscore2020	150	4.249548	1.345977	1.638756	7.360939
zscoreps2020	150	4.106614	1.305402	1.609834	7.369065

Source: own calculations.

Table 14
Summary data for the analysed companies – total assets, by economic sector, as of 31 December 2019 (in EUR thousand)

Sector	Number of companies	Median Assets	Minimum Assets	Maximum Assets
Construction	150	19 954.29	2 196.06	42 970.37
Leisure and Entertainment	150	10 301.19	1 189.04	31 549.99
Manufacturing	150	22 859.97	1 640.82	42 264.64
Retail	150	24 998.84	1 948.81	42 552.44
Services	150	4 354.44	693.67	22 627.23
Transportation	150	7 028.75	1 695.46	25 108.25
Wholesale	150	31 430.48	2 342.47	42 711.83

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Table 15
Summary data for the analysed companies – total revenues, by economic sector, as of 31 December 2019 (in EUR thousand)

Sector	Number of companies	Total Revenues		
		Median	Minimum	Maximum
Construction	150	20 677.04	1 802.65	49 348.93
Leisure and Entertainment	150	11 190.90	563.43	47 099.64
Manufacturing	150	26 637.31	1 843.61	49 783.97
Retail	150	29 434.88	2 090.10	49 876.97
Services	150	6 813.68	1 109.87	28 857.25
Transportation	150	7 540.58	1 064.67	44 572.33
Wholesale	150	37 888.08	1 528.46	49 952.64

Table 16
Summary data for the analysed companies – number of employees, by economic sector, as of 31 December 2019

Sector	Number of companies	Median number of employees	Minimum number of employees	Maximum number of employees
Construction	150	132	22	247
Leisure and Entertainment	150	87	17	212
Manufacturing	150	139	21	249
Retail	150	94	9	189
Services	150	73	5	167
Transportation	150	92	15	184
Wholesale	150	147	19	244

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Table 17
The asset turnover ratio, by economic sector, as of 31 December 2019

Sector	Average	Median
Construction	1.05	1.04
Leisure and Entertainment	1.20	1.09
Manufacturing	1.14	1.17
Retail	1.16	1.18
Services	1.35	1.56
Transportation	1.21	1.07
Wholesale	1.18	1.21

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

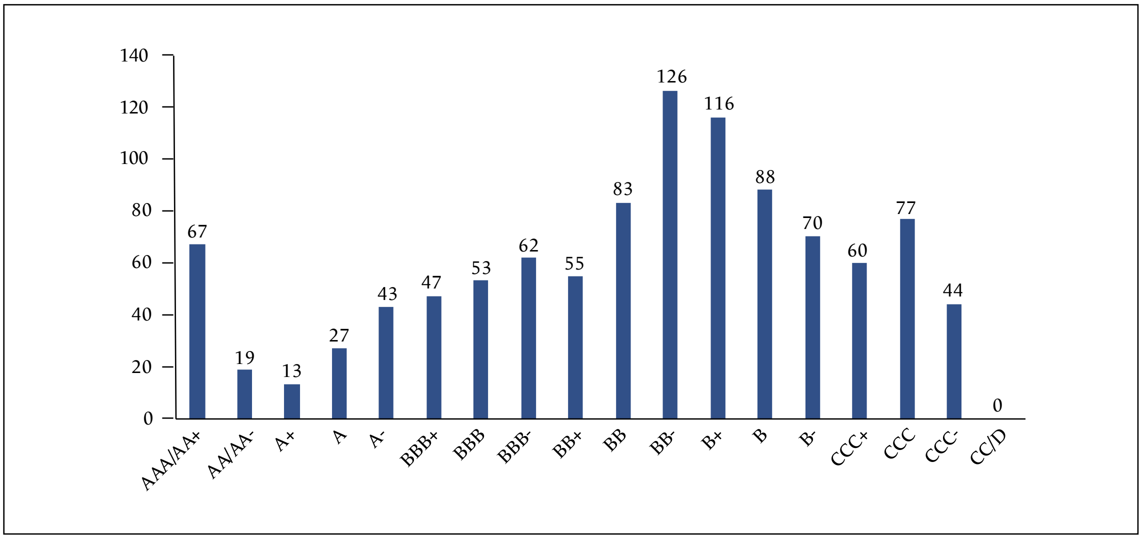
Table 18

Standard Deviation for sample, by economic sector, as of 31 December 2019 (in EUR thousand)

	Construction	Leisure and Entertainment	Manufacturing	Retail	Services	Transportation	Wholesale
Current Assets	9 567.167	5 175.569	8 352.389	10 666.176	3 026.925	4 319.866	11 100.993
Current Liabilities	7 256.123	4 534.923	4 929.924	10 220.528	3 067.653	3 467.836	10 280.035
Total Assets	13 514.949	8 215.832	12 228.966	15 041.235	4 825.002	6 113.340	14 974.641
Retained Earnings	952.681	926.081	798.174	693.269	86.310	568.438	777.346
EBIT	1 409.534	1 224.854	1 177.923	873.566	126.573	719.884	1 057.704
Book Value of Equity	1 837.404	1 077.296	1 901.691	421.872	231.527	1 668.050	1 147.285
Total Liabilities	10 591.077	5 935.909	7 059.460	12 906.357	3 965.396	4 373.533	13 432.619
Total Revenues	14 990.682	11 502.670	13 502.956	17 573.693	5 252.706	8 628.531	18 250.764

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

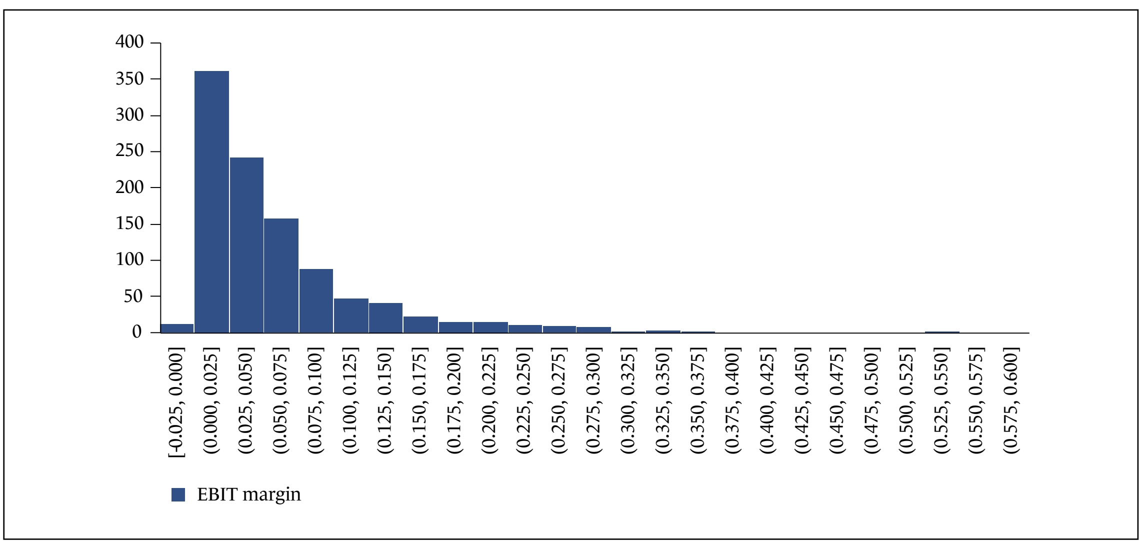
Figure 1
Bond Rating Equivalents for the sample SMEs as of 31 December 2019



Note: the vertical axis represents the number of companies.

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

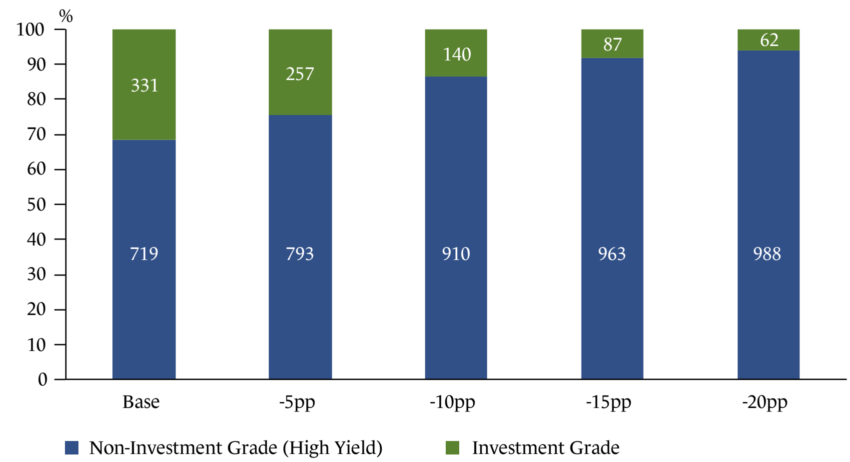
Figure 2
EBIT margins of the sample companies, as of 31 December 2019



Note: EBIT margins are shown as decimals. The vertical axis shows a number of the sample companies that reported certain levels of the EBIT margins. The bin size is 0.01 or 1%.

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 3
Investment Grade and Non-Investment Grade (High Yield) BREs, by various scenarios

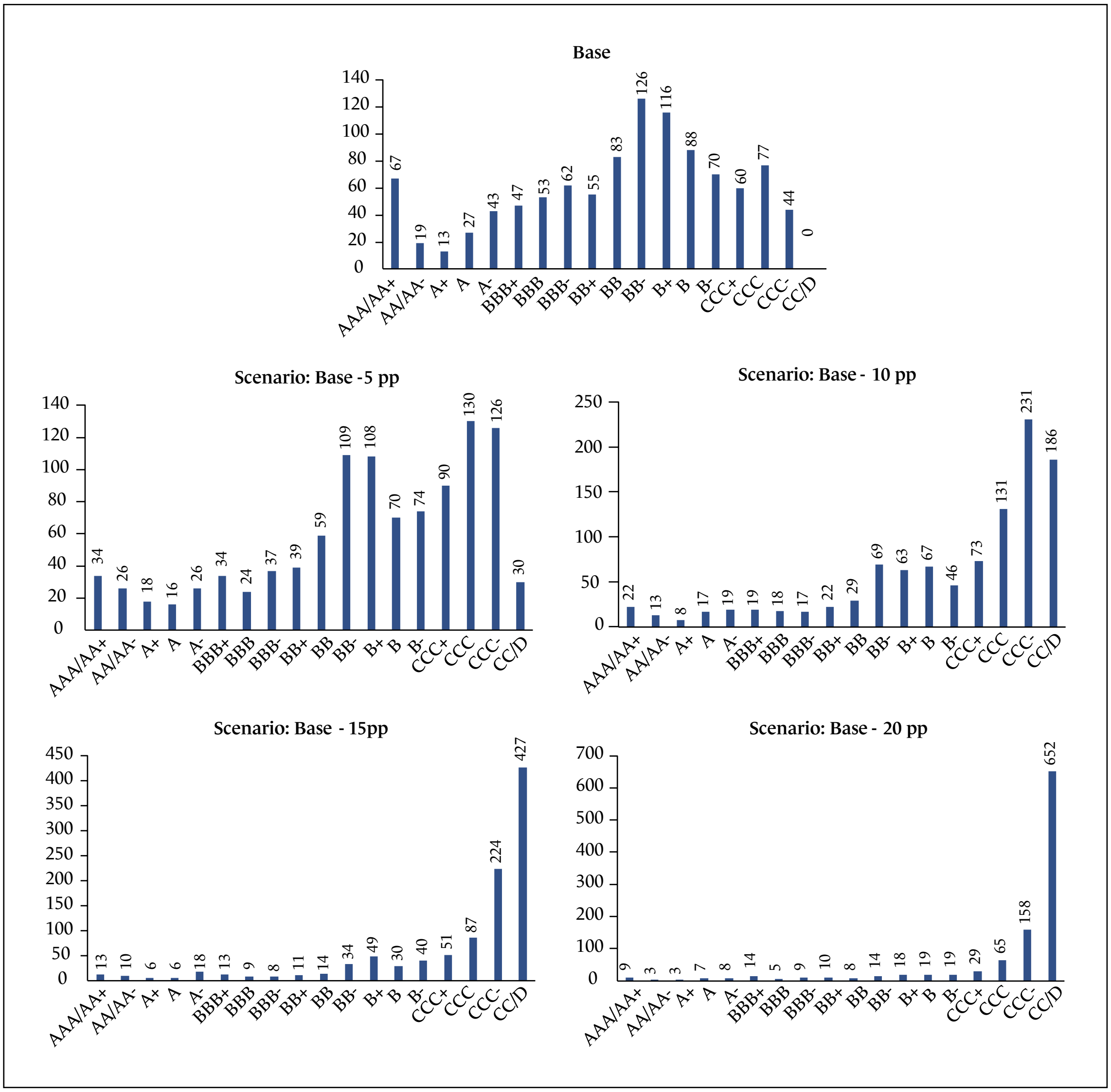


Note: -5pp, -10pp, -15pp and -20pp is EBIT margin deterioration with respect to the base situation. The number of companies that report losses is: 12 (1.1% of the sample), 619 (59.0%), 863 (82.2%), 952 (90.7%) and 990 (94.3%) respectively.

Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 4

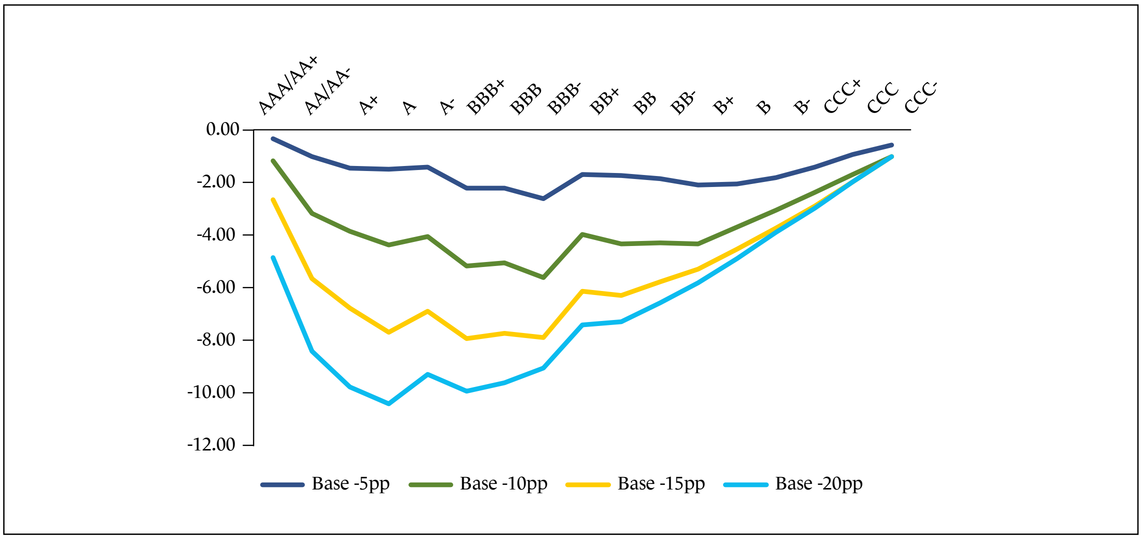
Bond Rating Equivalents, base and by scenarios



Note: the vertical axis represents the number of companies.

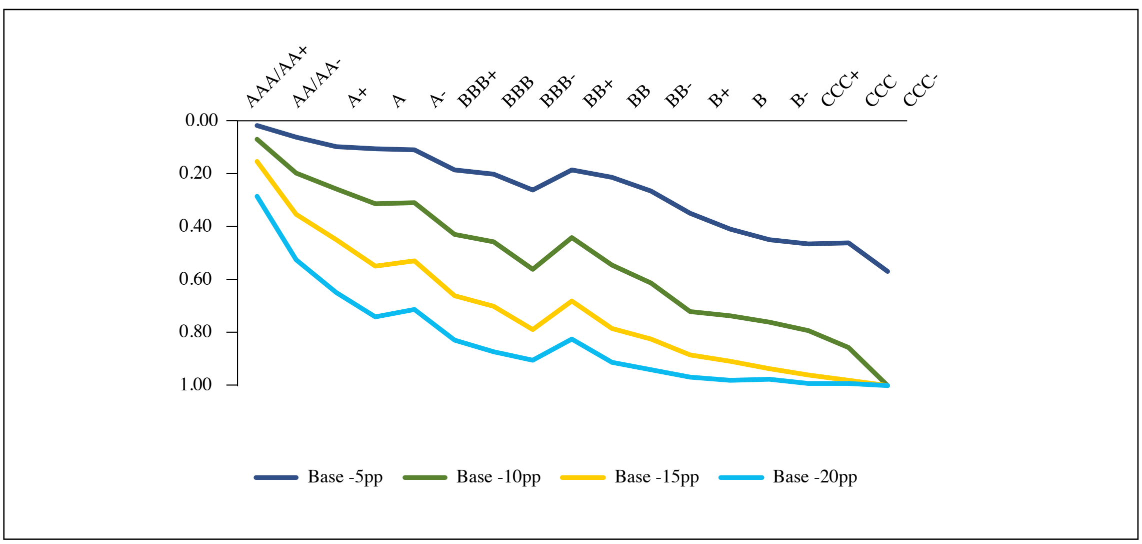
Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 5
Average changes in rating notches, by BRE categories and by scenarios



Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

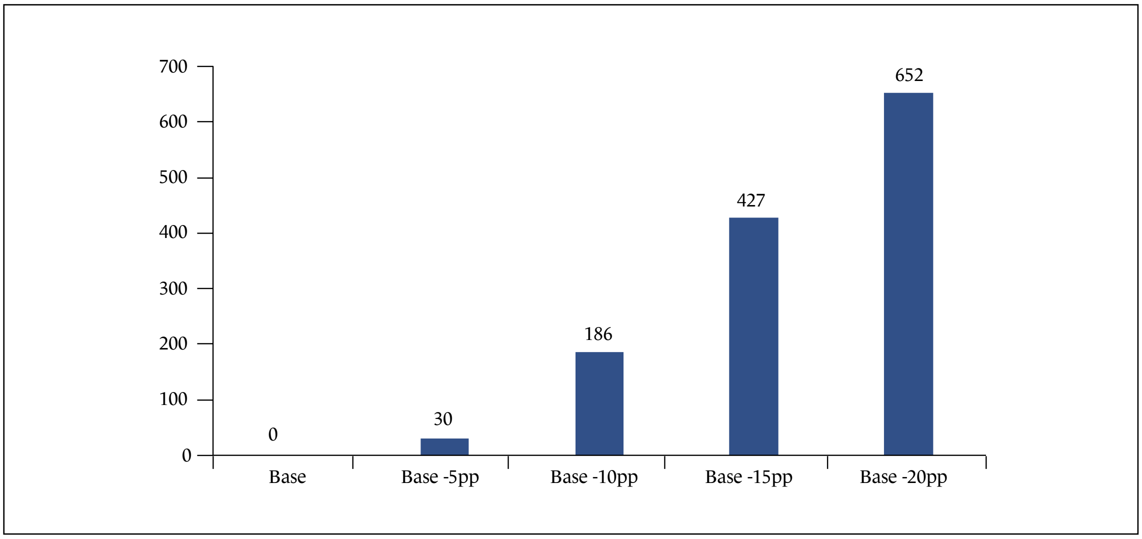
Figure 6
Risk of default, by BRE categories and by scenarios



Note: the closer the value to -1, the higher the probability that companies from an individual BRE will fall to CC/D rating class.

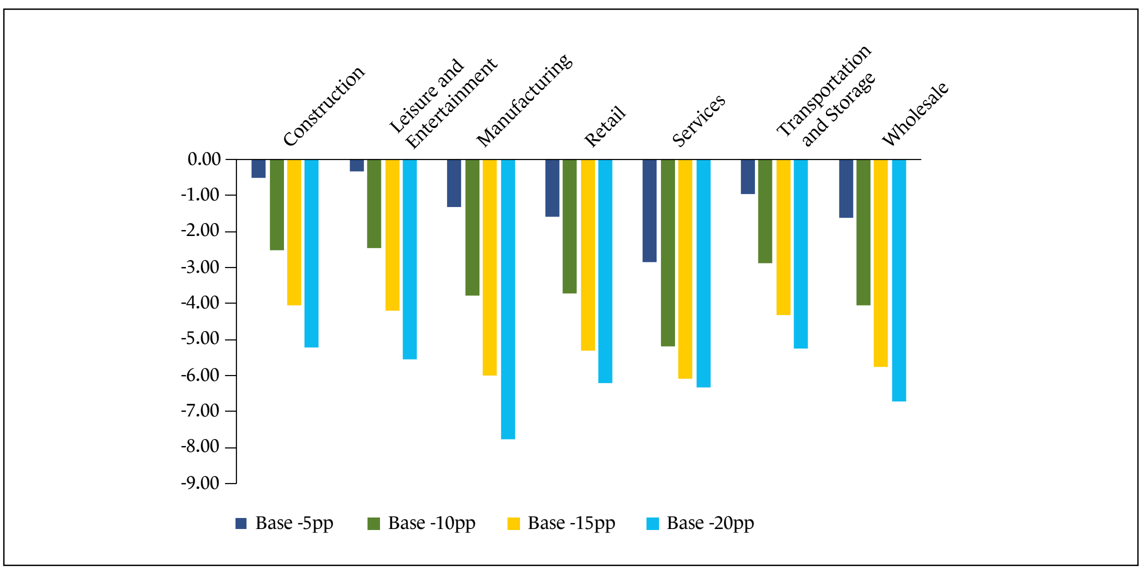
Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 7
Number of companies with CC/D BREs



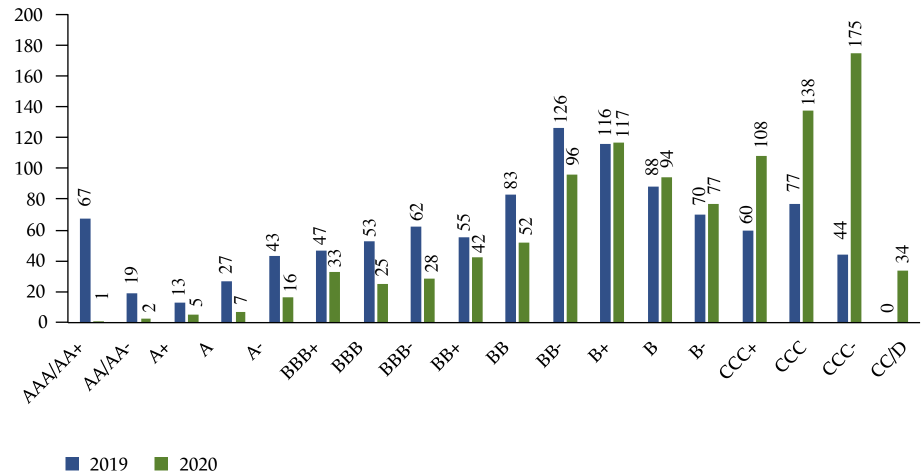
Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 8
BREs change under different scenarios, by economic sectors



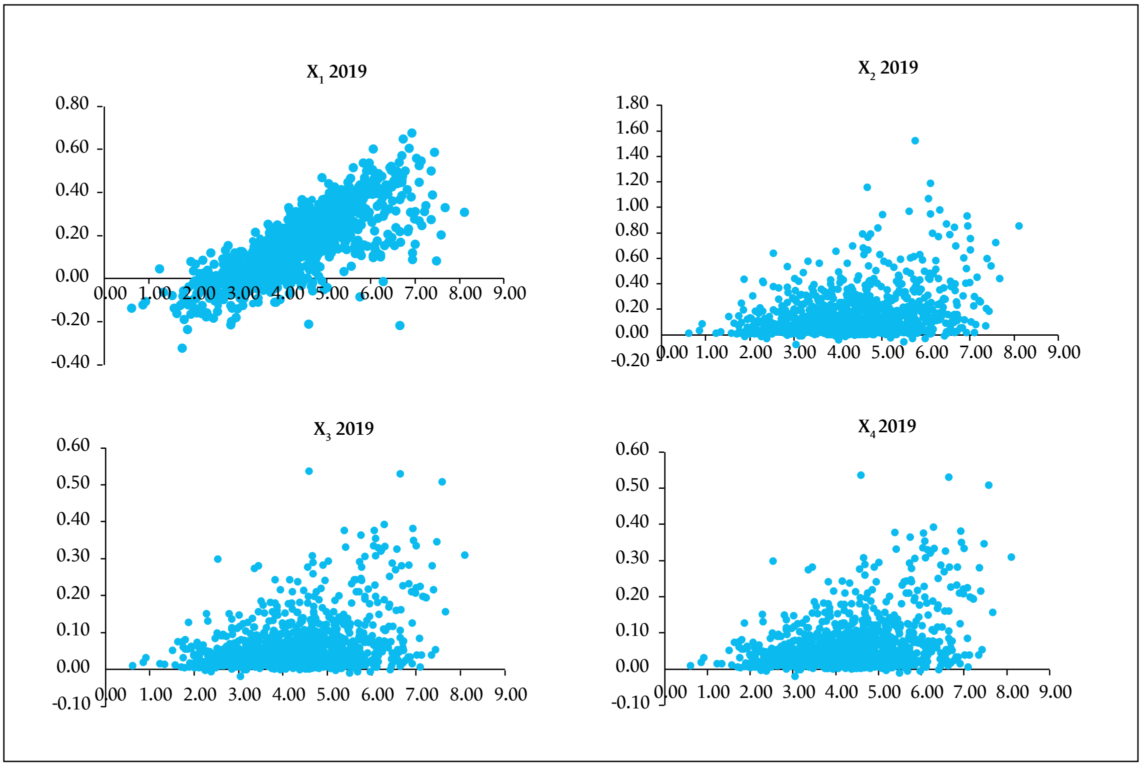
Source: own calculation based on data reported to the Polish Court Register (last access: 20.02.2021).

Figure 9
Bond Rating Equivalents for the sample companies, 2019 and 2020



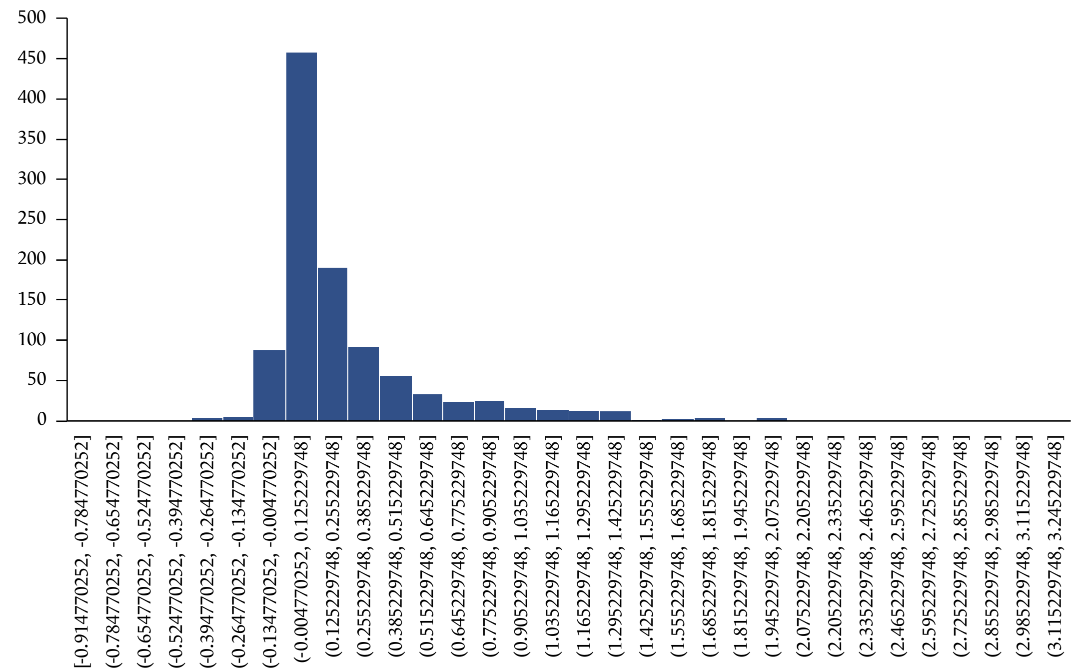
Source: own calculations.

Figure 10
Z”-Score in 2020 vs X_1–X_4 in 2019



Source: own calculations.

Figure 11
The distribution of the effect of the state aid in 2020 on the credit risk of the sample companies

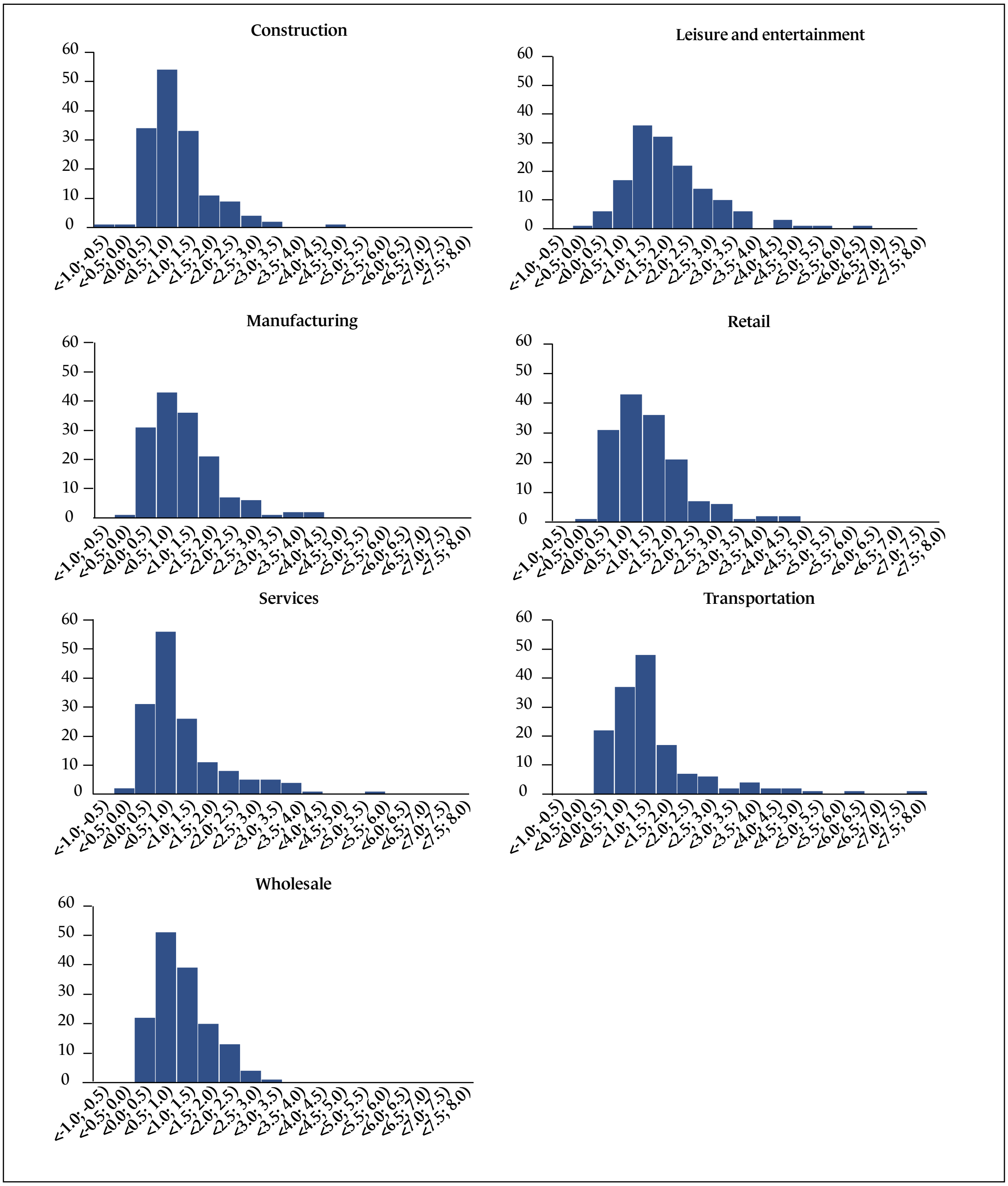


Note: the statistics are calculated for 2020 at the individual company level as the difference between Z"-Score and Z"-Score where EBIT is replaced by Profit from Sales. Positive values indicate that the effect was positive. The horizontal axis shows numbers, not rating notches, and the vertical axis shows the number of companies.

Source: own calculations.

Figure 12

The distribution of the effect of the state aid in 2020 on the credit risk of the sample companies, by sectors



Note: the statistics are calculated for 2020 at the individual company level as the difference between Z”-Score and Z”-Score where EBIT is replaced by Profit from Sales. Positive values indicate that the effect was positive. The horizontal axis shows numbers, not rating notches, and the vertical axis shows the number of companies.

Source: own calculations.

Ocena wpływu szoków ekonomicznych i finansowych na poziom ryzyka kredytowego segmentu MŚP: analiza scenariuszowa

Streszczenie

W artykule dokonano analizy wpływu pandemii COVID-19 na ryzyko kredytowe ponad 1000 przedsiębiorstw z sektora MŚP, należących do siedmiu kluczowych sektorów gospodarki. W badaniu wykorzystano model Z"-Score Altmana, który jest jednym z najlepszych narzędzi służących do oceny ryzyka kredytowego. W ramach przeprowadzonych badań oceniono skalę podatności badanych firm na obniżenie ratingu kredytowego, w tym prawdopodobieństwo niewypłacalności i złożenia wniosku o ogłoszenie upadłości, co wydaje się szczególnie istotne w obliczu pogorszenia koniunktury w gospodarce realnej, wywołanego skutkami pandemii COVID-19. Opierając się na analizie czterech scenariuszy, zbadano zmiany ratingów poszczególnych spółek, koncentrując się na pogorszeniu zysków przedsiębiorstw i obniżeniu poziomu kapitału obrotowego, wynikającego m.in. ze wzrostu zobowiązań bieżących. Na podstawie przeprowadzonych analiz stwierdzono, że ścieżki migracji ratingów są dość zróżnicowane i nie wiążą się z przynależnością sektorową poszczególnych spółek. Szczególny nacisk położono na migracje ratingów podmiotów, dla których pogorszenie ratingu powoduje konieczność złożenia wniosku o ogłoszenie upadłości. Zaskakującym wynikiem badania jest stwierdzenie, że najbardziej odporne na spadek ratingu kredytowego (poza podmiotami, które uzyskały oceny ryzyka kredytowego na poziomie AAA/AA+ i AA/AA-) są podmioty należące do najniższej grupy ratingowej (CCC). Wśród najmniej odpornych znalazły się natomiast podmioty, które należały do najniższych klas inwestycyjnych. W ramach przeprowadzonych analiz wyjaśniono i skomentowano ten pozornie sprzeczny z intuicją wynik badania. W pracy przeanalizowano także rzeczywiste zmiany poziomu ryzyka kredytowego poszczególnych spółek w czasie trwania pandemii COVID-19. Wykazano, że zdecydowanie najważniejszym czynnikiem wpływającym na odporność spółek na wystąpienie szoku jest stopień ich płynności finansowej przed kryzysem, reprezentowany przez zmienną X_1 w modelu Z"-Score.

Słowa kluczowe: COVID-19, Altman Z"-Scores, prwdopodobieństwo upadłości, ryzyko kredytowe, ekwiwalenty ratingu obligacji