

# **Assessing Corporate Credit Risk Transitions and Bankruptcy Prediction on SMEs As A Result of the COVID-19 Pandemic**

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## **Abstract**

We estimate the impact of the COVID-19 pandemic on credit risk changes on a large sample of Polish 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 analyze rating transitions under multiple potential scenarios, focusing on the deterioration of the SME firms' profits, working capital including an increase in current liabilities. Our modelling provides Bond Rating Equivalents (BREs) to capture changes in credit quality under the different scenarios. 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. We explain and comment upon this seemingly counter-intuitive result in our analysis.

Keywords: COVID-19, Altman Z"-Scores, bankruptcy prediction, credit risk, bond rating equivalents, recession, Polish SME firms

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

## Introduction

In the spring of 2020, the Covid-19 pandemic started to spread globally<sup>1</sup>. 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 the year, the pandemic situation was even worse and the key question that arose was whether companies that survived the first lockdown will 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 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. 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 was the financial health of the sample companies 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 favorable 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 the 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<sup>2</sup>. Although the situation of the Polish companies was very favorable, domestic banks tightened lending policy to the corporate

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<sup>1</sup> The COVID-19 epidemic was declared by the WHO as a public health emergency of international concern on January 30, 2020, and the Director-General of the World Health Organization (WHO), Dr. Tedros Adhanom Ghebreyesus, announced on 11 March 2020 that the new coronavirus disease 2019 (COVID-19) can be characterized as a pandemic; see: <https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020> (accessed 31.03.2021)

<sup>2</sup> Between 2017 and 2020 long-term bond issues on the domestic market by Polish companies amounted in total to PLN 58.2 billion (ca. EUR 13.5 billion). This form of financing is used mainly by large corporations. In the same period, the value of corporate loans increased by PLN 45.8 billion (ca. EUR 10.7 billion). The most important form of external financing was leasing. The value of new leasing agreements between 2017 and 2019 amounted to PLN 177.4 billion (ca. EUR 41.3 billion). For details see: Tymoczko D., Markowski K. [ed.], *Rozwój systemu finansowego w Polsce w 2020 r.*, National Bank of Poland, Warsaw, 2021, p. 45 and p. 99.

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<sup>3</sup>.

Here we ask the crucial question, what would happen to the financial and economic condition of Polish companies if distressed conditions negatively affected their performance. As the Polish financial market significantly differs from the US, not only by its size but also the popularity of financing via corporate bonds and especially the lack of credit ratings, which are still not common in Poland. Instead, we apply a Bond Ratings Equivalent (BRE) methodology, as proposed by Altman (1989)<sup>4</sup>. In our analysis, we use the ubiquitous Altman's Z''-score model which is one of the most powerful tools used in bankruptcy prediction<sup>5</sup>. 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.

### **Literature review**

The impact that the COVID-19 pandemic has had on the 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 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:

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<sup>3</sup> Altman, E. I. (2020). Covid-19 and the credit cycle. *Journal of Credit Risk*, June, 16(2), p. 67-99.

<sup>4</sup> Altman, E. I. (1989), *Measuring Corporate Bond Mortality and Performance*, *Journal of Finance*, 44(4), 909-922.

<sup>5</sup> For examples of articles on accuracy and importance of Altman Z-score models see: Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K. and Suvas, A. (2017); Das, S. R., Hanouna, P., Sarin, A. (2009) and Levy C., M. Mysore, K. Sneader and B. Sternfels (2020).

1. general issues of assessing the impact of the COVID-19 pandemic on the economy, evaluating its consequences and analyzing possible scenarios,
2. outbreak of the pandemic and its implications for specific industrial sectors,
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 et al. (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 modeled the shock based on an underutilization of labor 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, that 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 et al. (2020) analyzed the connections between the recent spread of COVID-19, 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 on the US. Moreover, the COVID-19 risk is perceived differently over the short and the long-run.

Bofinger et al. (2020) analyzed the impact of the coronavirus pandemic from the perspective of the real economy and financial market. They analyzed the potential shocks that it may have on the supply and demand side of the market. One of the observations is that currently many companies rely on just-in-time production schemes, and disruptions in the logistics channels can lead to shortages of goods. The supply shocks were partly mitigated by teleworking and working from home, options that started to be heavily used by many companies. The authors claim that one week during which an economy runs at 50% capacity amounts to a loss of output of up to 1% of its GDP. The demand shock in many countries may affect their demand for intermediate goods of such exporters as Germany. Direct negative effects from the security measures will massively restrict “social consumption” (restaurant visits, domestic tourism, and trade fairs) and is unlikely to be fully offset by a catch-up effect after the end of the crisis. Moreover, the demand contraction may be triggered by the financial sector’s reduction in the supply of credit.

Gössling et. al (2020) analyzed 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 impacts on air travel, cruises, and accommodations have been devastating.

Al-Dabbagh (2020) studied the role of the decision maker in crisis management, and analyzed the crisis decision-making process, its skills and strategies. Ratten (2021) examined the opportunity to utilize entrepreneurship in times of a 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) analyzed 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 analyzed 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 analyzed from a perspective of its vulnerability to downgrades over the expected downturn in the real economy. He also analyzed 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) and (2018)) 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 analyze 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 et al. (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 that 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 & Achsani (2020) use Altman's Z and Z''-score models to analyze potential bankruptcies of national airline companies in Asia after the onset of the Covid-19 pandemic. Swaliha et. al. (2021) perform a study of the financial soundness of Indian automobile industries. Buzgurescu & Elena (2020) use this model to estimate 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 analyzed assuming several possible scenarios of corporate sensitivity to the crisis. The data has also been analyzed 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.

McKinsey & Company's Levy et al. (2020) analyzed the resiliency 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 (2008-09) and the current one. They find that this model turns out to be a better directional indicator of post-downturn market performance than does 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.

## Methodology

In our analysis we use Altman's  $Z''$ -score model (Altman et. al (1995)), according to the formula:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (1.)$$

where:

$X_1 = (\text{Current Assets} - \text{Current Liabilities}) / \text{Total Assets}$

$X_2 = \text{Retained Earnings} / \text{Total Assets}$

$X_3 = \text{Earnings Before Interest and Taxes} / \text{Total Assets}$

$X_4 = \text{Book Value of Equity} / \text{Total Liabilities}$

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 et. al (2019). This approach is used since there is a lack of ratings of the companies in Poland, and no formal ratings of private 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<sup>6</sup>.

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<sup>6</sup> 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 these with  $Z''$ -scores higher than 7.55 and lower than 7.76 are assigned AA+/AA BREs. All intervals are right-closed.



**Table 1. Bond Rating Equivalents of U.S. 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: Author's calculations based on Altman et al. (2019), p. 207, updated to include 2020 data.

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<sup>7</sup>. Using formula 1., we calculate BREs to check how analyzed 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:

- 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.

<sup>7</sup> A 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.

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 (from AAA do CCC-) and for specific sectors.

It turns out that in all scenarios that we analyze, 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 Polish Central Statistical Office data shows that companies' net profits fell by 11.4% on average in 2020 in comparison with the previous year<sup>8</sup>. One should keep in mind that government stimulus packages were launched which moderated profit declines, and the impact of the pandemic and lock-downs was not the same for all sectors. Our analysis focuses on "what if" questions and we analyze what would be the financial condition of companies if the real economy shocks were more pronounced. Indeed, it was more severe for certain enterprises than the average declines.

### **Sample description**

The analyzed 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<sup>9</sup>. These seven sectors account for 88% of the nation's output (Table 2). The sample comprises data as of December 31, 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

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<sup>8</sup> According to data for three quarters of 2020. Central Statistical Office , Signalling Information, Financial results of non-financial enterprises in I-IX of 2020, [https://stat.gov.pl/files/gfx/portalinformacyjny/pl/defaultaktualnosci/5502/12/41/1/wyniki\\_finansowe\\_przedsiębiorstw\\_niefinansowych\\_w\\_okresie\\_styczen-wrzesi....pdf](https://stat.gov.pl/files/gfx/portalinformacyjny/pl/defaultaktualnosci/5502/12/41/1/wyniki_finansowe_przedsiębiorstw_niefinansowych_w_okresie_styczen-wrzesi....pdf) (accessed 31.12.2020).

<sup>9</sup> 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 Central Statistical Office publication "Financial results of non-financial enterprises 2019" Using sample size determination formula, the minimum sample size for the study was calculated such that: Necessary Sample Size =  $(Z\text{-score}) - \text{StdDev} * (1 - \text{StdDev}) / (\text{margin of error})$ . 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.

(SME's) according to the EU methodology<sup>10</sup>. 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.

**Table 2. Polish economy output in 2019, by sectors, in EUR millions**

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%
<b>Total output</b>	<b>1 057 358</b>	<b>88.4%</b>

The Polish Statistical Office 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)<sup>11</sup>. 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, *Quarterly national accounts of gross domestic product 2015–2019*, Warsaw, Poland, 2020.

The median value of the Total Assets for the analyzed companies equaled 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.

**Table 3. Summary statistics of selected financial accounts of the analyzed companies, as of December 31, 2019 (in EUR '000)**

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

Remark: 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.

<sup>10</sup> The category of micro, small and medium-sized enterprises consists of enterprises which: employ fewer than 250 persons; and have either an annual turnover not exceeding EUR 50 million or an annual balance sheet total not exceeding EUR 43 million. The EU recommendation 2003/361 of 6<sup>th</sup> May 2003 includes the definition of the SME's available at: <http://data.europa.eu/eli/reco/2003/361/oj>. In our study, micro-enterprises with less than 9 employees are not included in the sample.

<sup>11</sup> [https://stat.gov.pl/en/metainformation/classifications/#Polish%20Classification%20of%20Activities%20\(PKD\)](https://stat.gov.pl/en/metainformation/classifications/#Polish%20Classification%20of%20Activities%20(PKD)) (accessed 27.02.2021)

Source: Author's calculation based on data reported by the Polish Court Register [last access: 20.02.2021].

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. Similar conclusions can be drawn when we look at the median values for Total Revenues (Table 5)<sup>12</sup>.

### **Bond Rating Equivalent**

Based on the BRE methodology of the Altman Z"-score model (Table 6 and Figure 1) as of December 31, 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 were 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 vulnerability of those SMEs to potential insolvency in a downturn.

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<sup>12</sup> For more statistics please see the Appendix.

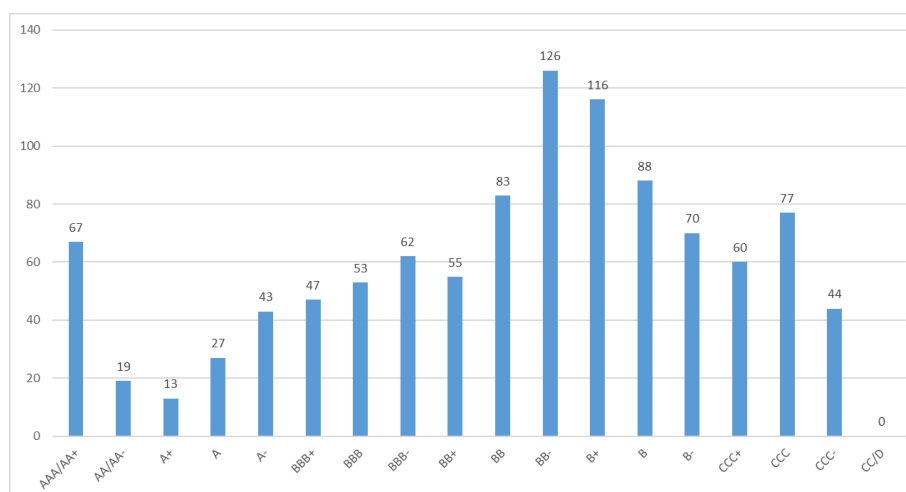
**Table 6. Bond Rating Equivalents for Polish SMEs as of December 31, 2019**

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			

\* Based on the Altman Z''-score model. See Altman et al. (2019).

Source: Authors' calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

**Figure 1. Bond Rating Equivalents for Polish SMEs as of December 31, 2019**



Source: Author's calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

### 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:

$$EBIT\ margin = \frac{EBIT}{Total\ Revenues} * 100\% \quad (1)$$

where:

- EBIT is the Earnings Before Interest and Taxes
- Total Revenues are revenues from sales and any extraordinary activities<sup>13</sup>

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 the more vulnerable are companies to sales decreases. Therefore, we assert that the EBIT margin is a good indicator of company's financial condition. Analyzing 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 the 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:

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<sup>13</sup> 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, we consider it as a good proxy for EBIT margins.

1. EBIT margin --->Retained Earnings--->Book Value of Equity--->Current Assets--->Total Assets---> Z''-score----> BREs
2. EBIT margin--->Current Liabilities & 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 lowering company's 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<sup>14</sup>. 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<sup>15</sup>. 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<sup>16</sup>.

In our sample, the actual average EBIT margin in 2019 equaled 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%<sup>17</sup> ((Figure 2).

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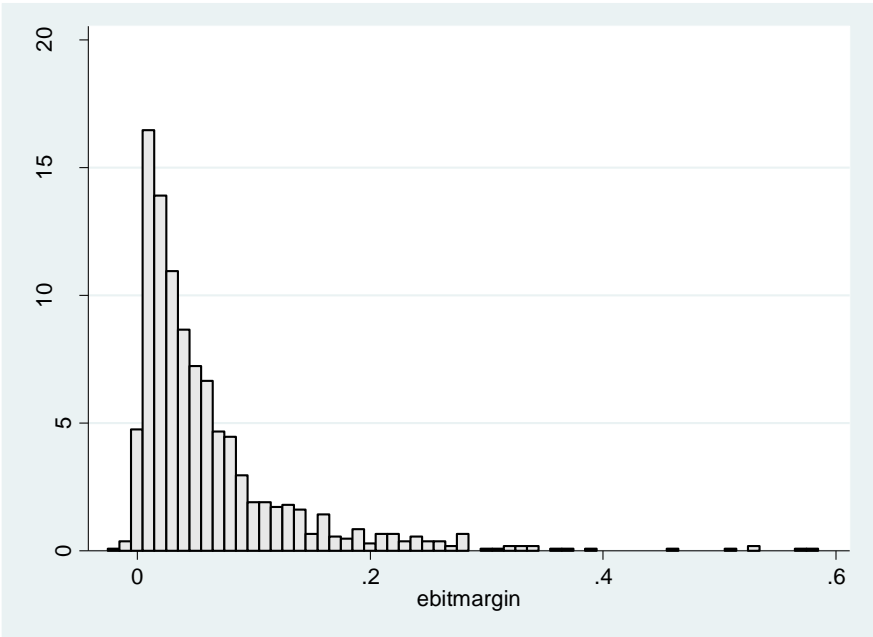
<sup>14</sup> Sales are included in the original Z and Z'-score models but not in the Z''-score (Altman et al. (2019)).

<sup>15</sup> 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.

<sup>16</sup> 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.

<sup>17</sup> 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.

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

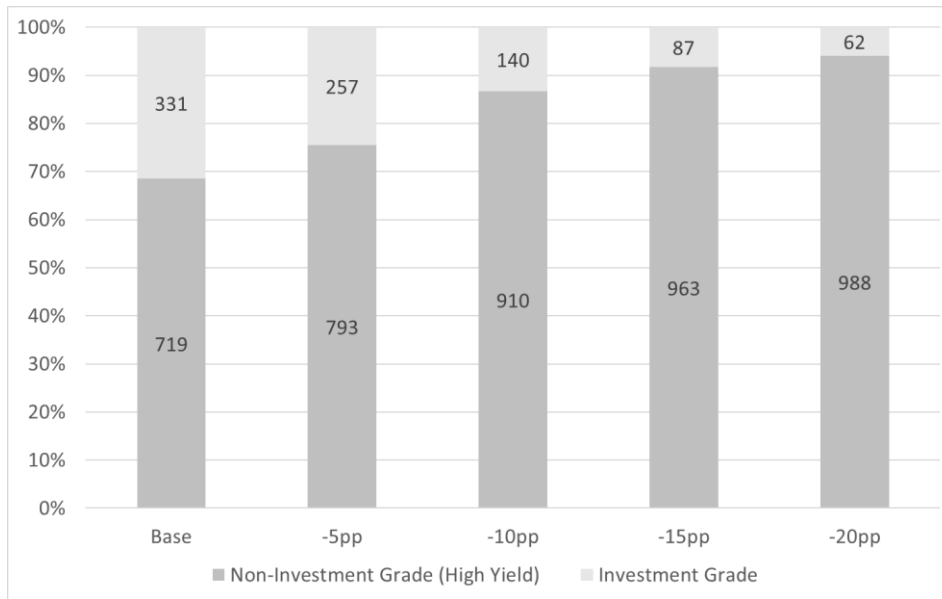


Note: EBIT margins are shown as decimals. The vertical axis shows a percent of the sample companies that reported certain levels of the EBIT margins. The bin size is 0.01 or 1%.  
 Source: Author’s calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

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 20 pp, still 62 companies (5.9% of the sample) 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 to 10 pp, 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.



**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.

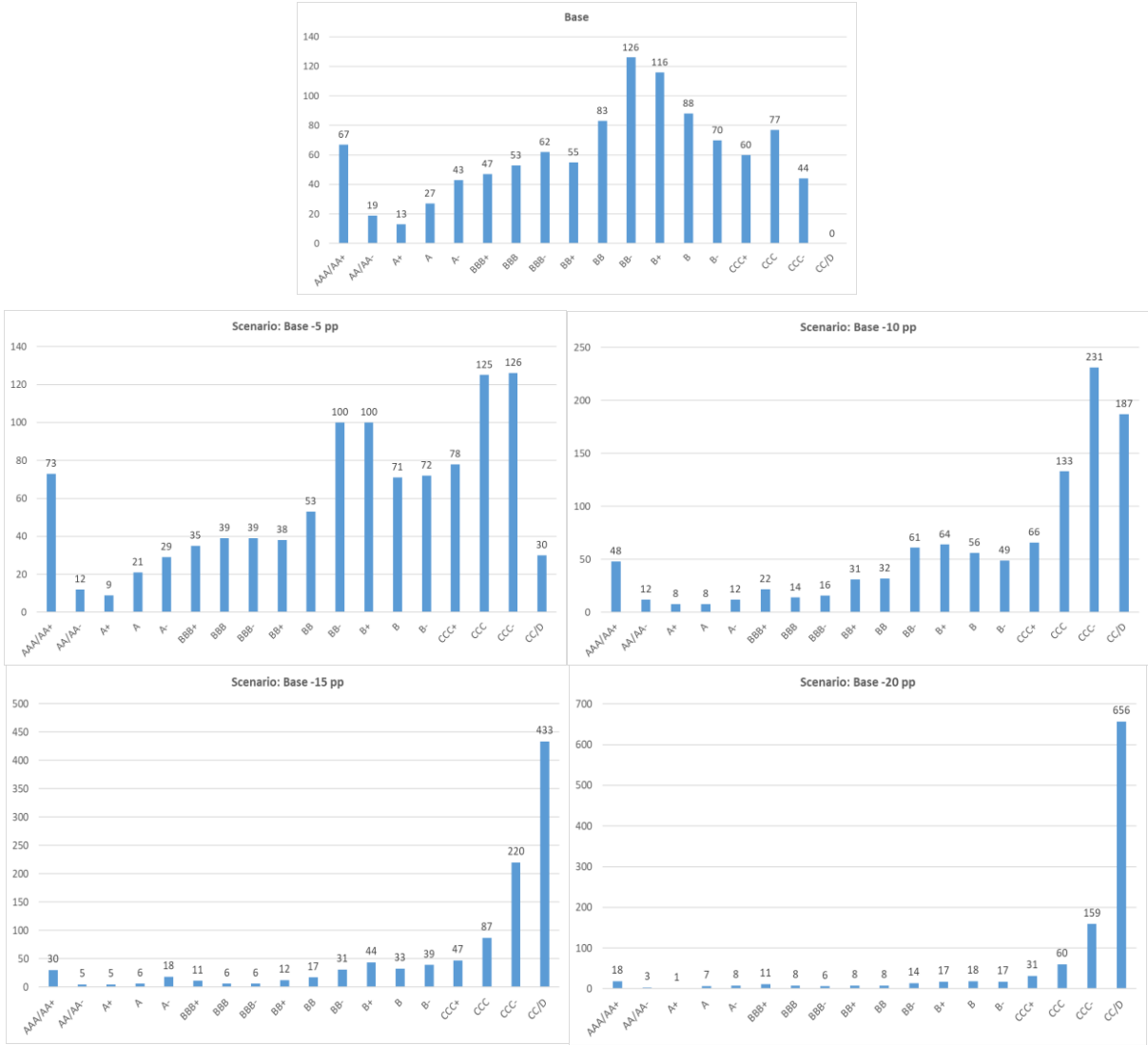
Source: Author's calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

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 (-20% pp), the most numerous resulting categories are D and all CCCs, together accounting for 86.3% of the total number of the analyzed 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 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 lock-downs due to the pandemic will have a devastating effect on companies' financial condition and are an important insight for a country's government. If the lock-down 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.

**Figure 4. Bond Rating Equivalents, Base and by Scenarios**



Source: Author's calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

**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 1.3 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 or even migrate up, but as the EBIT margins deteriorate more and more the latter’s number significantly falls. 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 analyzing 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 16 notches, going from AAA/AA+ to CCC-. The number of companies that improve their rating class is steadily declining and the migrations up are decreasing (Table 8).

**Table 8. Rating changes calculated as the number of notches and number of companies that migrate down, up or maintain their initial ratings, by scenarios**

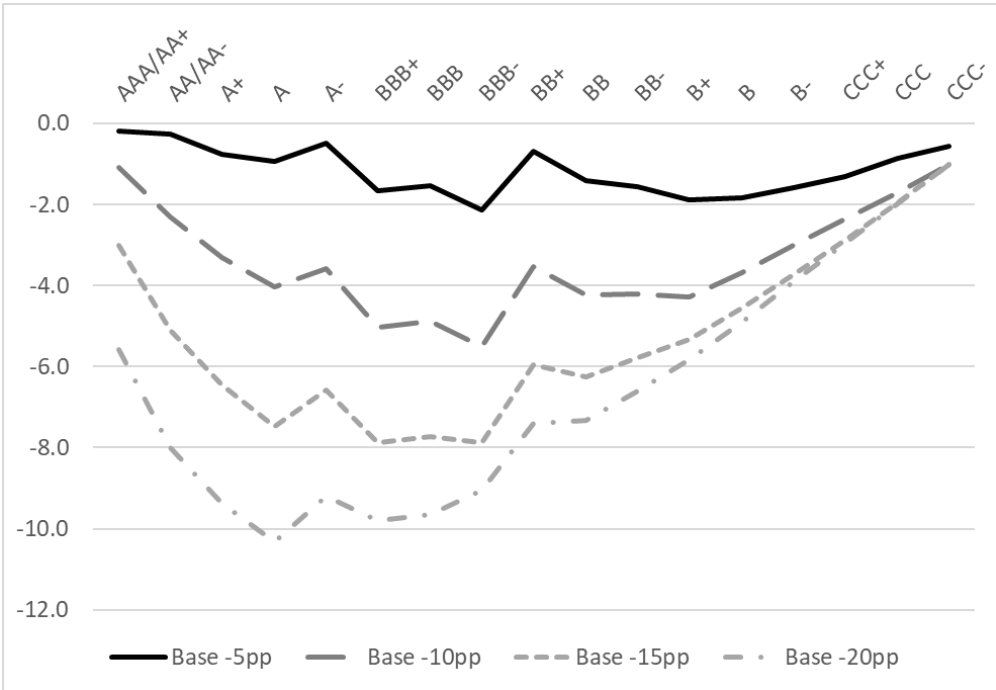
	Base -5pp	Base -10pp	Base -15pp	Base -20pp
Median	-1.0	-3.0	-5.0	-6.0
Average	-1.3	-3.5	-5.1	-6.2
Std.Dev	-1.6	-2.2	-2.7	-3.2
Minimum	-7	-11	-13	-16
Maximum	5	3	2	1
# of companies that migrate down	747	965	1013	1030
# of companies that maintain their initial rating	209	69	33	18
# of companies that migrate up	94	16	4	2

Source: Author’s calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

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 are companies 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<sup>18</sup>. In other words, to analyze 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, the average downgrade is 10 notches, which was observed only for the A+ to BBB- rated entities.

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



Source: Author’s calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

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

<sup>18</sup> The highest Z'-score in the sample was 11.61 and it must deteriorate by 3.86 to make this company fall to the AA rating class.

CC/D-rating, which is a maximum possible downgrade, i.e. to default. It can be calculated using Formula 2.:

$$\text{Default risk}_{BRE} = \frac{N_d}{N_{max}} \quad (2)$$

where:

$N_d$  - is a number of notches a company from a respective BRE class goes down in a scenario considered,

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

As can be seen from Formula 2., the values that we obtain fall within the range  $\langle 0,1 \rangle$ . 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 are 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<sup>19</sup>. 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 gives the opportunity to access 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)<sup>20</sup>. What is worth noting in the three most severe scenarios, all or nearly all CCC- rated entities fall into

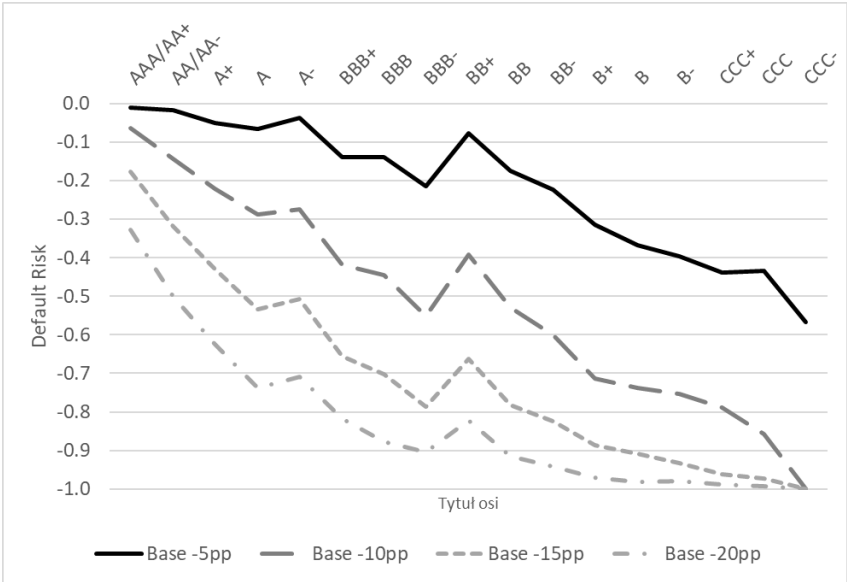
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<sup>19</sup> The differences between A and A- rating classes are in the range of 0.01 and 0.03 and are not statistically significant.

<sup>20</sup> If a 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.

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.

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



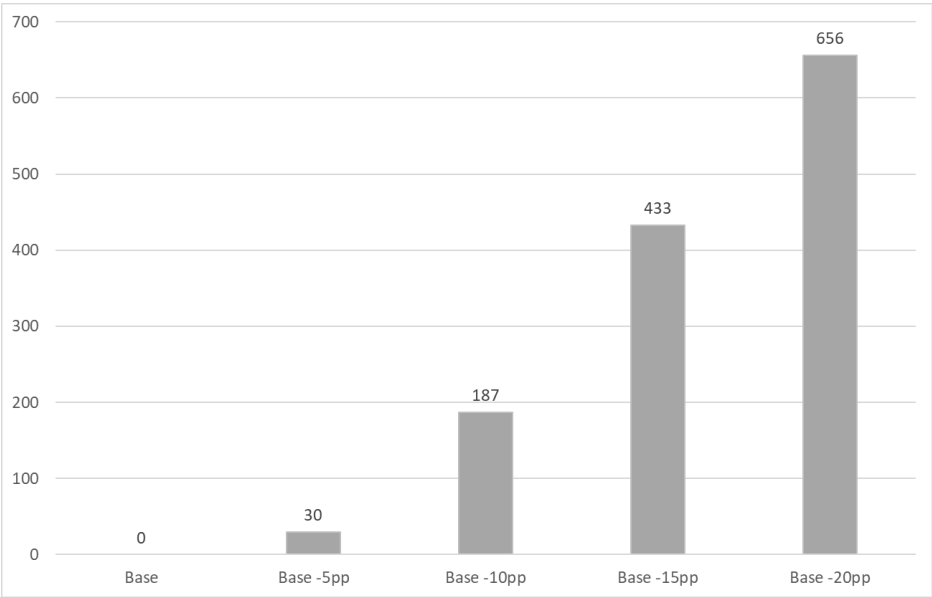
Note: the closer the value to -1, the higher the probability that companies from an individual BRE will fall to CC/D rating class.

Source: Author’s calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

**Default scenarios**

An important question is how many companies would be considered as defaulted based on every scenario that we analyze. Not unexpectedly, as the EBIT margins deteriorate, there are more and more companies that migrate to the D rating class (Figure 6). In the mildest scenario, only 30 entities (2.9%) of the sample fall into default, while in the most severe one, as many as 656 companies (62.5%) are classified as defaulted. We can comment with retrospect 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 form of the subsidies, direct lending, and tax relief were introduced.

**Figure 6. – The number of companies with CC/D BREs**



Source: Author’s calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

***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 10, Figure 8). Based on the available data, it is hard to point out what are the key factors behind the different migrations of the BREs 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.

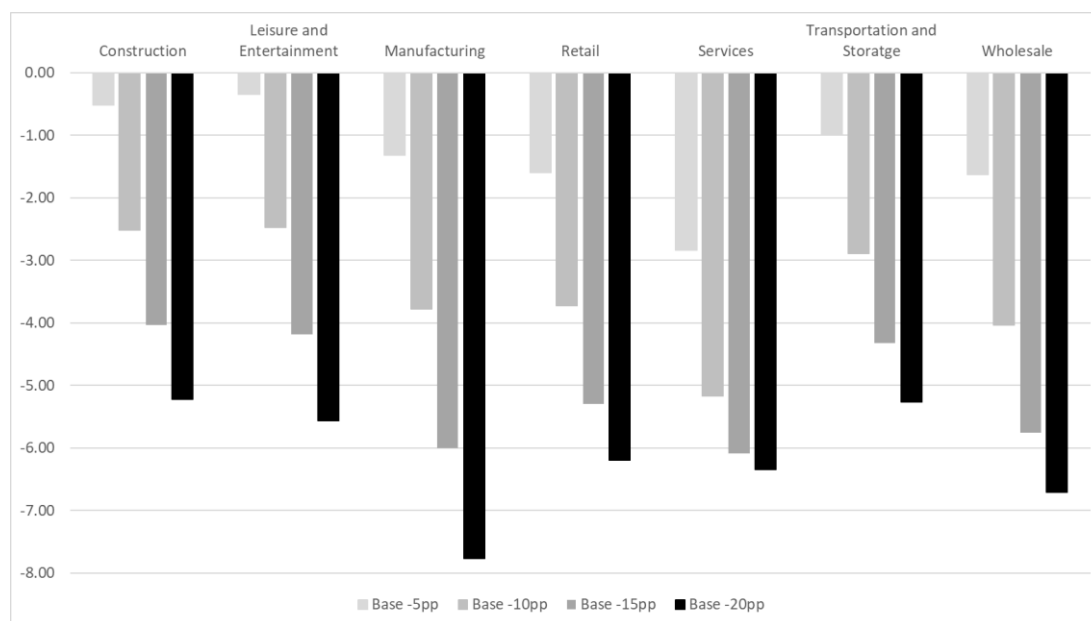
**Table 10. Average BRE change under different scenarios, by sector**

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

Source: Author's calculation based on data reported to the Polish Court Register [last access: 20.02.2021].

The difference in BRE changes between the lightest and the most severe scenarios equals to 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 (3.84) 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.

**Figure 8. BREs change under different scenarios, by economic sectors**



Source: Author's calculation based on data reported to the Polish Court Register [last access: 20.02.2021].



## Concluding remarks

Our simulations for the Polish corporate sector indicate that as the economic situation worsens, the new reality is reflected in a deterioration of profits margins at the EBIT level. In the scenarios considered, the Bond Rating Equivalents (BREs) calculated using the 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 26 percentage points less than in the base situation when we estimate that 32% of the population of the Polish 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 analyzed 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 a conclusion that excessive lock-downs may have serious consequences for the Polish companies, especially, if they are not accompanied by a systemic stimulus from the government in 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. 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 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 flatter than and the U- or W-shaped lines are less pronounced. 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 are the relative drops, which reflects a higher probability of default. In the most severe scenario (-20 pp drop), over 90% of BB and lower rated companies fall into the CC/D BRE class.

Further work in this field may be focused on the extension of the sample to companies from other emerging economies and also to advanced economies. International comparison should shed some 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.

## Appendix A for sector analysis

**Table A1. Summary data for the analyzed companies – total assets, by economic sector, as of December 31, 2019 (in EUR '000)**

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: Author's calculation based data reported to the Polish Court Register [last access: 20.02.2021].

**Table A2. Summary data for the analyzed companies – total revenues, by economic sector, as of December 31, 2019 (in EUR '000)**

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 A3. Summary data for the analyzed companies – number of employees, by economic sector, as of December 31, 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: Author's calculation based data reported to the Polish Court Register [last access: 20.02.2021].

**Table A4. Summary data for the analyzed companies – number of employees, by economic sector, as of December 31, 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: Author's calculation based data reported to the Polish Court Register [last access: 20.02.2021].

**Table A5. The asset turnover ratio, by economic sector, as of December 31, 2019**

Sector	Avarage	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: Author's calculation based data reported to the Polish Court Register [last access: 20.02.2021].

**Table A6. Standard Deviation for sample, by economic sector, as of December 31, 2019 (in EUR '000)**

	Construction	Leisure and entertainment	Manufacturing	Retail	Services	Transportation	Wholesale
Current Assets	9567.167	5175.569	8352.389	10666.176	3026.925	4319.866	11100.993
Current Liabilities	7256.123	4534.923	4929.924	10220.528	3067.653	3467.836	10280.035
Total Assets	13514.949	8215.832	12228.966	15041.235	4825.002	6113.340	14974.641
Retained Earnings	952.681	926.081	798.174	693.269	86.310	568.438	777.346
EBIT	1409.534	1224.854	1177.923	873.566	126.573	719.884	1057.704
Book Value of Equity	1837.404	1077.296	1901.691	421.872	231.527	1668.050	1147.285
Total Liabilities	10591.077	5935.909	7059.460	12906.357	3965.396	4373.533	13432.619
Total Revenues	14990.682	11502.670	13502.956	17573.693	5252.706	8628.531	18250.764

Source: Author's calculation based data reported to the Polish Court Register [last access: 20.02.2021].

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