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Corporate Governance and Risk Disclosure in Emerging Countries

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Abstract
The study examines the influence of corporate governance attributes on the corporate risk disclosure in the emerging countries. Board size, non-executive directors, independent directors, board diversity and CEO-duality are the important board of director's composition that is considered as corporate governance variables for this study. The study focuses on South Africa and Nigeria as these countries are among major players in the African emerging market. The sample comprises 42 financial and non-financial firms listed in Nigerian Stock Exchange and Johannesburg Stock Exchange. The data was drawn from 192 annual reports for the year 2014–2018. The analytical tools employed are manual content analysis and regression. The empirical results show that operational risk disclosure outweighs environmental and strategic risk disclosure. Meanwhile, past information, non-monetary and good news are considered less relevant, however dominate future, monetary and bad news which are more valuable to diverse stakeholders. Moreover, in considering the important factors that impact on the risk confession, that board size, independent director and diversity have greater influence in driving the risk disclosure upward. Nevertheless, non-executive director and CEO-Duality are statistically insignificant in determining the movement of risk information to divulge. The persistence of contemporary corporate risk practice jam-packed with irrelevant information might promote greater agency cost. The implication for the current practice might increase investors' uncertainty which in turn would raise the company cost of capital. This issue could be addressed by regulating risk disclosure in emerging countries instead of allowing corporate managers to report risk related information at their discretion. Corporate manager are also encourage to appreciate all the potential risk disclosure drivers in the African emerging countries.

Keywords: corporate risk disclosure, corporate governance, board composition, risk management, emerging countries

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Introduction

The advocacy of risk disclosure is extensively increasing in recent years as many businesses are exposed to diverse risks. Risk disclosure is a technique of tracking, computing, managing, and revealing business prospects and challenges that may shake existing or imminent firm value to the users of corporate reporting. The advocacy was commenced for more than two decades and still very few nations in the world responded by regulating corporate risk disclosure in their jurisdictions. Nevertheless, some companies operating in non-regulating countries consider risk disclosure appropriate and are more enthusiastic to divulge their risk voluntarily. The academic community has studied several factors that affect the extent of information to be disclosed. One of the factors that were pinpointed in the literature is corporate governance. A corporate governance system is regarded as one of the crucial culprits in the financial crisis and as the power which may facilitate the economic recovery [1]. Good governance is considered as bedrock that might shape the accomplishment of organizational objectives. The code of corporate governance in many nations describes the manner in which good governance could be actualized in the organizational setting. The code that stimulates good governance and corporate disclosure would yield dynamic management that would improve profitability and firm value. However, the concept of corporate governance is highly broad and encompasses connection amongst corporate managers, board members, investors and other stakeholders [2]. Hence, several previous studies [3–16] have articulated different corporate governance mechanism and examine their impact on the quantity of risk information unveil by firm. These studies were conducted in both developed and emerging countries. Meanwhile, many prior studies [17–23] have called on the comparative studies among emerging countries and [24] emphases the study should focus on emerging countries that are situated in the African region. This study is responding to this request and would provide further insight on the risk disclosure and corporate governance literature. The study is aimed to assess the effect of board of directors' composition on corporate risk disclosure in emerging countries. The paper consists of five sections. The first is introduction, literature is reviewed in the second section, the methodology employed are described in section three, results are presented and discussed in section four, and section five concludes the study.

Literature review

Corporate Risk Disclosure

In recent years, business organizations are requested to divulge their risk profile in any medium such as website, annual report, interim report or any other means by which users of accounting information can access the information. The critical evaluation of these kinds of information content might influence different stakeholders' decisions. "Disclosures have been judged to be risk disclosures if the reader of annual report is informed of any business opportunity or prospect, or of any hazard, harm, danger, threat or exposure, that has already impacted upon the company or may impact upon the company in the future or of the management of any such business opportunity, prospect, hazard, danger, harm, threat or exposure [25]. "The literature identifies numerous variables relative to corporate governance that influence risk disclosure behavior of corporate entities. These include corporate ownership structure, board independence and board composition". Moreover, agency theory, stakeholder theory and signaling theory are among the few theoretical frameworks usually researchers apply to explain the potential relationship between board composition (corporate governance) and risk disclosure practice by firms.

Corporate Risk Disclosure and Corporate Governance

The previous studies have sample different developed and emerging countries data and examine the influence of corporate governance variables on the quantity of risk confession. For example, a study [9] samples 424 banks among the gulf council nations and investigates their disclosure behavior. After scrutiny of 2008 annual reports of the sample companies, the findings demonstrate that Islamic financial firms divulged less risk information compared to conventional financial firms. Moreover, the greater risk confession defends on the greater quality of governance and the extent of risk confession pattern diverges across nations. In a similar study [13] explore the impact of bank governance on voluntary operational risk confession. The sample consists of 34 Islamic banks from different jurisdictions (United Arab Emirate, Dubai, Abu Dhabi, Saudi Arabia, Iran, Kuwait, Jordan, Qatar, Malaysia, and Bahrain) for the year 2008 to 2014. It is discovered that operational risk disclosure is pertinent for bank risk assessment. Moreover, auditor type, Independent directors and existence of sharia boards have positive effect on operational risk disclosure, while CEO-duality has negative effect. This indicated the CEO that chairs the board minimizes the amount of risk declaration. Meanwhile, it gives the impression that audit physiognomies presence in the bank are amongst the contributing factors on the amount of firm risk to divulge.

Moreover, the study [19] assesses the impact of banks' governance and the demographic conducts of uppermost governing gangs on the volume of risk disclosed voluntarily by Saudi Arabian banks. The analytical tool used in the measurement of quantity of risk disclosed in the listed banks annual reports is content analysis and the time span is from the year 2009 to 2013. The regression outcomes reveal that sizes of the board, gender, meetings of the audit committee and external ownership are extremely relevant on the volume of risk divulged. In a similar study, [16] evaluate the relevance of governance qualities on risk disclosure application amongst banks in Jordan. They sample 15 banks and accumulate the data from the annual report between the years 2008 to 2015. The information is analyzed as obligatory and voluntary risk disclosure. The content analysis and OLS regression display that board size and non-executive members, audit committee meetings and delegation of duties have a significant impact in escalating the size of voluntary risk disclosure, though management ownership is irrelevant. Nonetheless, Independent directors and the size of the audit committee are amongst the explanatory factors that explain the upward movement of mandatory risk disclosure.

In case of non-financial sector studies, scholars [26] conduct a research on corporate governance and risk in cross-listed and Canadian only companies. The sample comprises all Canadian companies included in the S and P/TSX Composite Index for the period 2009–2014. Results indicate that the effect of board characteristics such as size, independence and proportion of female directors remains the same in both cross-listed and not cross-listed firms. However, CEO duality and insider equity ownership impact firm risk only in cross-listed companies, while institutional shareholdings, environmental, social and governance disclosure and family control affect firm risk in Canadian only firms. Overall, the empirical results indicate that some governance mechanisms impact firm risks only in firms that cross-list, while others are well-suited for Canadian only firms. Meanwhile, researchers [10] examine the risk disclosures behavior in Spain. The study samples 35 annual reports of Spanish listed companies for the year 2009. The tools of analysis employed for the study were content analysis and regression. The empirical results demonstrate that no statistically significant relation was discovered between ownership structure, number of independent directors of the board and corporate risk disclosure.

In reference to emerging nations, the study [26] evaluates the determinants of risk disclosure behavior amongst listed companies in India. They sampled a total of 318 annual observations for the 6 years period and extracted the relevant data for the analysis. The statistical method reveals that higher size of the following: board, independent director, and gender diversity increase the volume of risk disclosure, though CEO who chairs the board contracts the extreme risk disclosure. Likewise, firms with slighter profitability, fewer liquidity and bigger in are enthusiastic to unveil superior risk information particularly old events. Furthermore, a similar study [7] investigates the role of firm governance in manipulating the degree of risk disclosure amid listed companies in South Africa. They sampled 169 firms' annual observations from the years 2002–2011. The findings reveal that significant ownership distributions in the hand of limited individuals and institutional investors' force corporate managers to release slighter risk information, nonetheless greater numbers of; non-executive, board members, and diversity of board are excited to upsurge firms' risk confession. Contrarily, the board chairman who is also the CEO is irrelevant on the amount of information to publicize.

In a similar research [12] conducted in Saudi Arabia examines the influence of board members who are from the royal family as well as the qualities of board on the volume risk to be unveiled by firms. The sample comprises 307 firms' annual observations between the years 2008 to 2011. The results uncovered the application of risk disclosures amongst companies are moderate. Besides, royal board members and size, board size, independence of board and frequency of board meetings have a substantial impact on the degree of risk divulged by firms.

Development of Hypotheses

Board Size

According to the agency theory, the greater board size has the potential of involving diverse expertise in the board; hence they would provide a significant role in influencing the information content of their annual reports. As noted by scholars [28], the higher board size, the greater the effectiveness in running the corporate affairs and that might improve corporate transparency with regard to risk. Likewise, the stakeholder theory reinforces that large boards tend to augment boards with different experts that can represent greater stakeholders' interest [27]. Large boards comprise mixed knowledge and diffused sentiments which toughens monitoring aptitudes and enriches company's disclosure strategy [29], although, different sentiments as well as non-integrated ideas are associated with bigger board size, thus reduced monitoring competences [27].The prior studies investigate the connection between risk disclosure and board size, and findings display diverse results. For example, the studies [30–31] have established that risk disclosure practices tend to increase provided firms have greater board size, whereas [28] find no significant effect amongst the explained and explanatory factors. Based on the aforementioned mixed findings, we proposed the following hypothesis as agency theory predicted:

H1: There is a positive association between board size and corporate risk disclosure.

Non-Executive Director

Non-executive directors are among the board composition and they are external to the company. Corporate managers could not exercise significant control or influence their behavior in the course of implementation of corporate strategic decision and risk divulging policy because they are not employees of the business. It is argued that non-executive members have to offer effective supervision that would ensure the success of a board especially by counseling, monitoring and disciplining superior managers [27]. Agency and stakeholder theories contend that the existence of non-executive members in the board composition is very crucial as their presence tends to reduce the agency cost [5]. They represent investors and other stakeholders in the board meetings especially in deliberations and executions of organizational objectives. Consequently, they are in a good position to monitor corporate managers and not to involve in any sort of conflict of interest that may arise [30]. This can be justified if they convince the board to divulge greater risk information in their annual reports for the consumption of all users [32]. The prior studies [30] confirm that volume of risk revelation increases with the proportion of non-executive members in the board. In contrast [32] does not discover any linearity amongst the two variables. However, consistent with the agency and stakeholder theoretical predictions the following hypothesis is considered:

H2: There is positive association between non-executive director and corporate risk disclosure

Independent Directors

The codes of governance have established a check and balance in the board due to leverage the corporate decisions and timely execution. Agency and stakeholder theories describe the association between independent members and the quantity of risk information to disclose. Agency theory suggests that the appointment of independent board members tends to shrink the agency conflict that may arise between corporate managers and investors as the level of transparency would decrease information asymmetry problems [33]. The existence of independent directors in the board might enhance corporate financial disclosures. Consistent with stakeholder theory prediction, independent board members serve as representatives to shareholders, employees, communities and other stakeholders, hence they have to monitor senior managers' activities and to ensure that the information demanded by various stakeholders are released [27].The prior studies hypothesize the possible connection between independent director and corporate risk disclosure. The studies [7] confirmed the potential linkage between the two variables, which means firms with greater independent members tend to raise their risk disclosure volume. In contrast, [34] contend that association does not exist. Despite the mixed conclusions from the literature, the hypothesis is proposed based on the agency and stakeholder theories prediction:

H3: There is positive association between independent directors and corporate risk disclosure.

Diversity of the board

Recently, scholars [35] argue that the advocacy to include a certain proportion of women in the board composition has received considerable attention". Women are anticipated to play a significant role towards actualizing the organizational objectives provided they are involved in the management teams. Nonetheless, [35] contend that agency theory does not give any explanation about the potential board effectiveness concerning gender diversity. In contrast, the other scholars [27] explained that agency theory advocates that boards with different genders can advance managerial monitoring and board independence. This assertion concurs with the signaling theory that the presence of women in the board is a good signal that might build firm reputation and increase corporate performance [27]. The women's presence in the board might create value to the firm owing to their different perspective on critical issues. There are few studies in the literature that assess the effect of gender diversity on risk disclosure. The findings of these studies [7; 27] reveal a positive association between the variables, while [26] reported non-existence of the association between diversity and risk confession. Considering the mixed result, we hypothesize based on theoretical support:

H4: There is a positive association between gender diversity and company risk disclosure

CEO Duality

The chairman of the board of directors is responsible to chair and preside over the board meetings. The code of governance proposed the division of duty between the person to chair the board and CEO. Duality exists whereby one person serves as CEO and chairman of the board. This action signals the absence of proper control in the corporate decision-making process [36]. The rationale behind segregating the two responsibilities is to promote the monitoring role and improve the quality of reporting [37]. Duality could be considered as amongst the contributing factors of quality disclosures [38] because it might influence a decision to conceal information he/she thought is detrimental to his/her position [39]. The agency theory suggests the separation between control of decision and decision management [27; 36]. However, the prior studies that investigate the potential association amongst CEO-duality and risk disclosures provide mixed results. For example, the study conducted by [39] reveals an inverse connection between CEO-duality and corporate disclosure, which indicated the volume of disclosure decreases provided the CEO is holding two responsibilities. In contrast, scholars [37] found a positive linearity between CEO-duality and corporate disclosure. The finding of [27] fails to establish any linkage between CEO-duality and corporate risk disclosure. Despite the above discussion and findings, the hypothesis is developed based on agency theory prediction. Thus:

H5: There is a negative association between CEO-duality and corporate risk disclosures.

Methodology

Sample and Data

The study samples 42 firms (see appendix 3) listed in the Nigerian Stock Exchange and Johannesburg Stock Exchange. The samples are taken from both financial and non-financial companies. In the process of selecting the financial firms, the study considers all the listed banks in both countries as a sample. However, the banks that have no adequate information are excluded from the sample. The prior studies [25] have suggested that there is no need to merge financial and non-financial firms as a sample because the financial firms are regulated by different regulations in a nation. However, the subsequent studies appear to show that there is no problem in constituting both sectors in the sample. Hence, this has motivated us to randomly select the non-financial firms operating in the manufacturing and incorporate them in the sample. Moreover, the study considers 5 years from 2014 to 2018. Therefore 210 annual reports are downloaded from the sample firms' websites. The sample was reduced to 192 due to missing data for some variable of interest. The data of all the independent variables were sourced from the Bloomberg data stream, while risk disclosure data was sourced from the annual reports of the sample companies. We performed manual content analysis on entire annual reports narratives including the note to account.

Content Analysis

Content analysis involves the analysis of annual report narrative sections and it is largely used in risk disclosure research. The use of this technique is consistent with previous studies [4; 6; 25]. In performing the content analysis, many studies coded the risk information by counting the relevant sentences, words, paragraphs, pages and percentage of pages. Consistent with prior studies [4; 6; 25], we coded the risk disclosure based on frequency of relevant risk sentences reported in the annual report narratives. These types of sentences were identified based on the content of the checklist (analysis instrument) adopted from erstwhile studies [4; 6; 25]. The checklist was designed to make a comprehensive insight on risk disclosure analysis. Initially, the risk sentence could be coded as environmental, operational or strategic risk disclosure. Secondly, risk disclosure sentences are also analyzed as quantitative (monetary) or qualitative (non-monetary) risk information. Thirdly, the sentence could be coded as good news, neutral or bad news. Finally, we should be able to understand the risk sentences disclosed are past, non-time or future information. The checklist is presented in Table A.1 of the appendix.

Measurement of Variables

There is a need to measure our variables, so that we can run the regression and test the research hypotheses. Corporate Risk Disclosure is a dependent variable, while board size, non-executive director, independent director, diversity and CEO-duality are the independent variables of this study. Table 1 displays the proxies used in measuring the variables.

Model

$$RD = \beta_{0it} + \beta_{1it}\left(Bsize\right) + \beta_{2it}\left(Nonex\right) + \\ +\beta_{3it}\left(Independent\right) + \beta_{4it}\left(Diversity\right) + \\ +\beta_{5it}\left(Duality\right) + e_{it} \quad . \qquad (1)$$

Table 1. Variable Description and measurement

Variable	Variable Description	Measurement Description
RD	Risk Disclosure	Number of risk sentences
Bsize	Board Size	Number of people in the board
Indirector	Independent Director	Percentage of independent director
Nonedir	Non-executive Director	The percentage of non-executive directors
Diversity	Women board member	The percentage of female in the board
Duality	CEO-Duality	1 if CEO is the Chairman and 0 otherwise

Results and discussion

The descriptive statistics, diagnosis and regression result are presented and discussed in this section. Table 2 shows many random variables used. The risk disclosure outcomes are presented based on the checklist adopted in the previous study and the procedures in its measurement were discussed in detail in section three of this paper. The summary statistics of all the discrete and continuous random variables are presented with their mean, standard deviation, minimum, maximum as well as the total number of observations used. Table 2 shows the descriptive statistics of overall risk disclosure and its diverse classifications. The total risk disclosure amounted to 2089.057, 763.269, 388 and 3585 sentences for the mean, standard deviation, minimum and maximum sentences disclosed by firms respectively. Initially, the risk disclosure is classified into four different categories. In the first category, there is environmental (744.245), operational (980.365) and strategic (366.01) risk disclosure. Based on the mean value depicted by the analysis, operational risk disclosure dominates environmental and strategic risk disclosure. In the second category, the risk disclosure sentences focused on time-horizon as either future, past or non-time information. The result indicated that non-time (920.224) is the most frequent risk sentence, whereas past information (804.385) dominates future information (366.01). This can be justified by their mean value reported in Table 2. Moreover, the third risk disclosure classified the sentences as quantitative (monetary) or qualitative (non-monetary). The mean for quantitative is 272.844 sentences, while 1817.776 sentences is peculiar to qualitative risk information. This shows that most of the disclosure is non-monetary. Meanwhile, the fourth and final risk disclosure focuses on the status of risk information as good, bad or neutral risk information. Neutral information recorded the highest mean value of 1174.641, while the mean value of good information (677.672) outweighs that of bad risk information (238.307).

Table 2. Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
Total RD	192	2089.057	763.269	388	3585
Environ RD	192	744.245	294.012	126	1501
Operational RD	192	980.365	407.545	142	1860
Strategic RD	192	366.01	141.431	74	973
Quantitative	192	272.844	103.837	60	710
Qualitative	192	1817.776	687.56	272	3201
Good news	192	677.672	281.804	88	1389
Bad news	192	238.307	103.812	63	467
Neutral news	192	1174.641	439.55	197	2355
Future info	192	366.01	141.431	74	973
Past info	192	804.385	383.284	99	1778
Non-time info	192	920.224	320.796	169	1667
Board size	192	12.526	3.152	5	20
Non-Executive	192	73.896	12.551	46.15	100
Independent	192	47.068	24.236	7.14	100
Diversity	192	20.016	10.145	0	62.5
CEO Duality	192	.016	.124	0	1

* RD – Risk Disclosure; Environ – Environmental.

Regression Result

The regression result is presented in Table 3, where total risk disclosure is regressed against five explanatory factors of the board of directors' composition. The board composition includes board size, non-executive directors, independent directors, diversity and duality. The overall P-value (0.000) is significant at 1% level. In addition, the F-test is 8.176, while R-squared is 0.180. Based on the R-square figure, the covariates included in the model explain the variation of total risk disclosure by 18%. Board size and independent directors are significant at 1%, diversity is also significant at 5% level, while non-executive directors and CEO-duality are not significant in explaining the corporate risk disclosure variation.

Table 3. Regression Result

Total RD	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Board size	64.028	16.505	3.88	0.000	31.466	96.590	***
Non-Executive	-1.928	4.963	-0.39	0.698	-11.719	7.863	
Independent	7.270	2.617	2.78	0.006	2.106	12.433	***
Diversity	13.434	5.172	2.60	0.010	3.230	23.638	**
Duality	183.544	412.098	0.45	0.657	-629.443	996.531	
Constant	815.601	429.774	1.90	0.059	-32.258	1663.460	*

*** p<0.01,** p<0.05,* p<0.1.

Table 4. Correlations

Variables	Total RD	Board size	Non-Executive	Independent	Diversity	Duality
Total RD	1.000					
Board size	0.286*	1.000				
Non-Executive	0.048	–0.161*	1.000			
Independent	0.267*	0.041	0.536*	1.000		
Diversity	0.240*	0.043	–0.014	0.211*	1.000	
Duality	0.058	–0.034	0.039	0.134	0.039	1.000

* Shows significance at the 0.05 level.

Table 5. Variance inflation factor

	VIF	1/VIF
Independent	1.567	.638
Non-Executive	1.511	.662
Diversity	1.072	.933
Board size	1.054	.949
Duality	1.023	.978
Mean VIF	1.245	.

Correlation

Table 4 shows Pearson's correlations due to understanding the potential relationship among our variables. All the computation was carried out at 5% level of significance. It is discovered that total risk disclosure is associated with non-executive, independent directors and diversity. This correlation result is similar with our regression outcome. In order to evaluate the possible multicollinearity problem, we focus on the association among explanatory factors. The results show non-executive directors (–0.161) are significant and negatively associated with company size.

However, the coefficient of independent directors (0.536) is significant and positively related to non-executive directors. Diversity reveals the significant coefficient of 0.211 and positively associated with independent directors. Nonetheless, it is noticeable that all the relationship concerning the independent variables is considerably beneath the 0.80 threshold. Therefore, the model does not suffer any multicollinearity problems.

Equally, Table 5 portrays the result of variance inflation factor (VIF) for the robustness of the multicollinearity assumption. The VIF result displays all the covariates values on which 10 are believed to be a threshold for multicollinearity problem. The figures depicted were less than the threshold and this has solidified our prior finding of non-existence of multicollinearity in the model.

Heteroskedasticity

The study computed Breusch-Pagan test to ensure the homoscedasticity assumption of our error term. The result produces 1.3 and 0.2539 for chi square and p-value respectively. This is a great indication that our model is free from heteroskedasticity problems as the p-value depicted is extensively above 5% level of significance. Furthermore, we perform the White test for the robustness of the findings. It reveals a chi square of 16.23 and a p-value of 0.5077 which is considerably more than 5% level of significance. Hence, the model complies with homoskedasticity assumption of error term (Table 5).

Discussion

The study analyses risk disclosure practice in emerging countries. The firms are constantly reporting all the risk disclosure categories, thus, environmental, operational and strategic risk disclosure. The greater frequency of operational risk disclosure above environmental and strategic is highly questionable about the quality of the disclosure. This is because, non-time and general risk management policy statement is required to classify under operational risk disclosure. This finding is consistent with the previous study [5]. The analysis instrument is designed to segregate quantitative and qualitative risk information; the result shows that lesser appearance of quantitative relative to quantitative risk disclosure has reduced the relevance to many stakeholders. This assertion has supported the earlier study [40] that reported similar results. Nonetheless, the future information is always more relevant to stakeholders. For example, analysts can use incorporated risk information to estimate future earnings and cash flow, however, the past information release is substantially higher than future risk information. This outcome is consistent with the prior study [25]. Despite the new dimension on how good news is considered as part of risk, nonetheless stakeholders appear more conservative by anticipating greater bad information than good one. Inappropriately, the study unveils that the good news are substantially higher than bad news. This practice might render the quality of disclosure inadequate and the result is in line with the prior findings [21].

Meanwhile, the study examines the influence of board composition on corporate risk disclosure. One of the factors to consider for the board composition is the number of people that would constitute the board, which is known as board size. Agency theory suggests that a bigger size of the board have the potential of including people with diverse knowledge in the board. Hence, they tend to influence the risk information to unveil. Based on our findings, board size is statistically significant at 1% level and influences the greater confession of risk information. The result is in line with erstwhile studies [21; 31] and backs the assertion that as board size increases, the effectiveness and corporate risk transparency is also increased. Therefore, consistent with agency theory prediction our hypothesis I is accepted.

Non-executive director is among the board composition that would improve the firm corporate governance. Including non-executive in the board composition could reduce the agency cost [36] as they are in a good position to monitor corporate managers in the event of conflict of interest [30]. The potential linkage we suggested between non-executive director and risk disclosure is not evidenced as our coefficient turnout to be insignificant. This finding is consistent with the previous study [19], however inconsistent with the study [30]. Hence, the results do not support the hypothesis 2 which postulated the positive association amongst the two variables.

Independent director is also another board of directors' composition. The code of corporate governance suggests the appointment of independent directors due to leverage the decision making process and maintains appropriate check and balance in the board. This process has strong implications by sliding agency conflict that might arise and also enhance transparency. Considering the potential association between corporate risk disclosure and independent directors, our findings have confirmed this proposition as the coefficient is significant at 1% confidence level. The board composition with greater independent members tends to report higher risk information. This supports the previous studies [5; 41]. Therefore, hypothesis 3 is accepted.

Diversity is one amongst the contemporary board composition. In recent years there is great activism to involve females in the board composition. Nevertheless, the relevance of diversity is ignored in the agency theory, however, the way females perceive things in the decision process might create further firm value. Diversity being one of the board compositions, the potential association is also studied. The findings suggest a positive association between diversity and corporate risk disclosure. This can be justified by a positive coefficient that is statistically significant at 5% level. The result supported the previous study [7] and also our hypothesis which postulated the positive relationship between the two variables. Hence, hypothesis 4 is accepted.

Duality is one of the board compositions where the CEO is the chairman of the board and saddles with responsibility to chair and preside over the board meetings. Ideally, the division of duty is more appropriate as suggested by corporate governance code. The rationale behind segregating the two responsibilities is to promote the monitoring role and improve the quality of reporting [37]. The possible influence of duality in relation to the risk disclosure was examined and the coefficient is not statistically significant which provides an absent of relationship between the two variables. This finding is inconsistent with the prior empirical studies [22]. Decisively, hypothesis 5 that suggests negative association amongst the variables is rejected as there is no sufficient evidence to establish it.

Conclusion

The paper evaluates the impact of board composition on corporate risk disclosure in the emerging countries. It is evidenced by greater board size; independent director and board diversity have great influence in moving risk disclosure upward. Nevertheless, non-executive and CEO-Duality have no effect on the magnitude of risk information disclosed. In addition, in terms of risk disclosure and nature, operational risk disclosures dominate environmental and strategic risk disclosures. Most of the information included in the operational risk disclosure is neutral, qualitative and non-time. The higher presence of general statement and risk definitions has reduced the relevance of risk disclosure to users. Quantitative, future and bad news are the most valuable risk information that could help stakeholders' decisions, however qualitative, past and good news are the most recurrent risks unveiled by firms. This development has shown a strong partiality in the selection of risk revelation. Likewise, the risk confession is greater for the financial sector and the overall disclosure is higher for South African firms. Despite the less pertinent risk information uncovered by firms, nonetheless, the overall companies' disclosure is increasing annually. Meanwhile, the absence of a comprehensive risk disclosure framework from the regulators has caused lack of uniformity on style corporate managers divulging risk information voluntarily. The findings posit that listed firms from emerging African countries divulge risk information in their annual report; however there is need to improve risk information that is more pertinent to users of accounting information. The company that constitutes their board with many people, independent directors and diversity tend to increase their risk revelation. These findings have implications to several stakeholders such as investors, regulators and African emerging markets.

The major limitation identified in this study was risk disclosure coding procedure. There is an element of subjectivity in all risk disclosure studies especially the manner in which the information is collected in the annual report narratives. However, in order to reduce the potential bias, we employ a manual approach which is the most hard and time consuming to execute by counting the relevant risk sentences based on the decision rule adopted from prior studies. Before coding any sentence, a reference has to be made to ensure that risk sentence is coded and recorded accordingly. This approach would improve the potential subjectivity earlier anticipated. The future studies could explore the potential influence or otherwise of board meetings and attendance on corporate risk disclosure. Secondly, the literature has highlighted the extent of risk associated with intangible asset and intellectual capital; therefore future studies could investigate if the firms with greater intangible asset or intellectual capital divulge greater risk information in both advanced and emerging countries.

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APPENDIX 1

Table A1. Risk Disclosure Categories Checklist

Risk Category	Disclosure Items
1 Environmental Risk	Environmental risk arises from factors essentially beyond the organization's control and comprises disclosure relating to: Economic risk (e.g., interest rate, currency risk, price and commodity, inflation, taxation, credit risk); Political risk; Social risk: such as kidnaping or murder of key staff, firm's asset vandalized by protesting citizens, pilferages, xenophobia, book haram, tribal and inter-religious crisis, fake currency, bad debts; Regulation and Legislation; Industry sources (e.g., competition, potential entrants, suppliers, substitutes, strategic partners, customers (e.g., changes in demand, changes in clients requirements and customers preferences); Climate and catastrophic.
2 Operational Risk	Operational risk is the probability of losses arising from the essential operation side of the firm. Operational risk covers such issues as: Internal control and risk management policies; Infrastructure risk; Liquidity and cash flow; Project failure; Product failure; Operational disruption; Operational problem; Employment practices and workplace safety (H and S); Environment risk (risks arising from the impact of companies' operations on the natural environment); Compliance and reputation; Legal risk.
3 Strategic Risk	Strategic risks arise from operating in a particular industry and are associated with the company's future business plans and strategies. Strategic risks encompass: Research and Development; Product market; Intellectual property right; Acquisitions, alliances, joint ventures; Management of growth; Derivatives; Investment; Technology.

APPENDIX 2

Table A2. Decision rules for risk disclosures

Decision Rules For Risk Disclosure
1. To identify risk disclosures a broad definition of risk is to be adopted as explained below.
2. Sentences are to be coded as risk disclosures if the reader is informed of any opportunity or prospect, or of any hazard, danger, harm, threat or exposure, that has already impacted upon the company or may impact upon the company in the future or of the management of any such opportunity, prospect, hazard, harm, threat or exposure.
3. The risk definition just stated shall be interpreted such that 'good' and 'bad' 'risks' and 'uncertainties' will be deemed to be contained within the definition.
4. Although the definition of risk is broad, disclosures must be specifically stated; they cannot be implied
5. The risk disclosures shall be classified according to the grid in Table 1, and by reference to the Appendix A risk categories
6. Sentences of general policy concerning internal control and risk management systems, corporate governance, employee health and safety shall be classified as 'non-monetary/neutral/non-time specific statements of risk management policy
7. Sentences of general policy concerning financial risk management shall be classified 'non-monetary/ neutral/non-time specific statements of risk management policy.
8. Monetary risk disclosures are those risk disclosures that either disclose directly the financial impact of a risk or disclose sufficient information to enable the reader to calculate the financial impact of a risk.
9. If a sentence has more than one possible classification, the information will be classified into the category that is most emphasized within the sentence.
10. Tables (quantitative and qualitative) that provide risk information should be interpreted as one line equals one sentence and classified accordingly.
11. Any disclosure that is repeated shall be recorded as a risk disclosure sentence each time it is discussed.
12. If a disclosure is too vague in its reference to risk, then it shall not be recorded as a risk disclosure.

Appendix 3.

Sample Firms

Stock Exchange Market	Sector	Sample
Nigeria Stock Exchange	Banking	8
Nigeria	Industrial	3
Nigeria	Consumer goods	6
Nigeria	Oil and Gas	2
Nigeria	Consumer Service	1
Johannesburg Stock Exchange	Bank	4
Johannesburg Stock Exchange	Financial Service 59	2
Johannesburg Stock Exchange	Life Assurance	2
Johannesburg Stock Exchange	Mobile Telecommunications	2
Johannesburg Stock Exchange	Construction & Materials	1
Johannesburg Stock Exchange	Mining	2
Johannesburg Stock Exchange	Industrial Metals & Mining	1
Johannesburg Stock Exchange	General Industrials	2
Johannesburg Stock Exchange	Oil & Gas Producers	1
Johannesburg Stock Exchange	Food & Drug Retailers	1
Johannesburg Stock Exchange	Tobacco	1
Johannesburg Stock Exchange	Media	1
Johannesburg Stock Exchange	Personal Goods	1
Johannesburg Stock Exchange	General Industrials	1

Source: URL: https://www.african-markets.com/en/stock-markets/ngse/listed-companies.

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The Impact of Corporate Social Responsibility on the Company's Financial Performance

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Abstract

This article empirically evaluates the impact of CSR behaviour on the financial indicators of 286 companies from Brazil, Russia, India, and China over six years from 2013 to 2018. Company information and CSR ratings were retrieved from the Bloomberg and RobetaSAM databases, and hypotheses were proposed based on a literature review. We constructed various analytical models that differ in dependent variables to better evaluate of distinct CSR metrics through different regression methods. Analyzed factors include: (1) the presence of women on the board; (2) the presence of a company in CSR ratings, and (3) various cultural aspects of the society where companies operate.

Our results support the conclusions of related research in this field of study. Among other consequences, our analysis indicates that CSR significantly influences financial performance, although this is also contingent on external factors. A company's presence in the CSR rating scale has a more substantial impact on profitability and market capitalization indicators than the actual score itself. CSR information disclosure has some effect on ROA and ROE, and the presence of women in the board of Directors showed a slight positive effect on market capitalization. Further, a high level of 'power distance' (i.e. the ostensible alienation of the general citizenry from political authority sources) in the society where company operates harms the relationship between the rating score and financial performance.

Keywords: corporate social responsibility, CSR behaviour, CSR ratings, regression method, gender diversity

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Introduction

Recent decades have seen a substantial rise in the popularity of corporate social responsibility (CSR) concept within both the business and scientific communities. There is also an emphasis on the research contributing to company CSR reporting, CRS definition and connections with financial result [1]. When it comes to decision-making, however, companies apply the principles of profit-maximisation and costs minimisation. But what should they do if the company's position concerning its impact on society and the environment influences its financial performance? The company's image and its recognition by rating agencies greatly influence the way investors, creditors, and employees perceive it [2]. Therefore, it is necessary to implement social, environmental, and managerial strategies in the corporate management's decision-making procedure. This necessity applies especially to those companies operating in the economic sectors which most adversely affect the environment or form a certain public sentiment. They comprise extractive industries, pharmacology, various industries that leave toxic emissions, and other sectors. However, the companies which operate in the above sectors and directly impact the environment and social medium, are not the only ones that preoccupy themselves with social responsibility. This is because CSR can directly and indirectly contribute towards a company's financial success. Investors perceive CSR as a positive signal from the company of a lower level of risk and a higher level of stability, not least because a socially responsible company has a lower probability of becoming a party to legal action [3].

Consumers are increasingly likely to question the products they purchase, their carbon footprint, the manufacturer's background, and a manufacturer's perceived level of goodwill. For example, suppose negative criticism is published about a company from environmental organisations, trade unions, or former employees. In that case, sales tend to fall because consumers are often reluctant to support a company with a perceived low level of social responsibility. CSR has several directions of influence upon a company's financial indicators.

F. Perrini draws on the assumption that corporate social disclosure can be considered as the most direct expression of the companies' attitudes and behaviors regarding social responsibility. If companies want to obtain their stakeholders' high-level reputation, they must show that they are interesting in continual, long-term improvement [4]. In developed countries, the trend towards more responsible investment and consumption has been increasing for many decades. For example, to attract investments and contribute towards building a positive reputation, companies disclose CSR information in non-financial reports, and participate in annual CSR evaluations carried out by rating agencies. In most cases, disclosure of CSR information is not mandatory. However, disclosure is necessary for a company to build up a 'sustainability rating' to strengthen its attractiveness.

It should be noted that the majority of CSR-related economic studies evaluate the same economic effects as studies that examine the implementation of sustainable development strategies or sustainable development goals (SDG). We will discuss this similarity in more detail below.

Theoretical Analysis of the Relation between CSR and Corporate Financial Indicators: Review of Existing Studies

The literature of CSR may be divided into three parts: 1 – study of the relation between CSR and financial indicators; 2 – detecting the influence on various CSR metrics (such as the level of information disclosure, and the impact of sustainability ratings on the corporate indicators); 3 – consideration of the cultural characteristics of the country in the analysis of CSR metrics and corporate performance.

CSR Influence on Corporate Performance

A large number of the research on CSR is dedicated to its relation with corporate financial indicators. The majority of such papers use data from developed countries and publicly traded companies. This topic is highly relevant for advanced economies in particular because a wide range of data is available for such companies. The methodologies of the considered papers are generally very similar. The authors study the influence of various CSR metrics on such financial indicators as return on assets or return on equity (ROA/ROE), market capitalisation, and Tobin's Q [5; 6].

The findings of the Aparna Bhatia and Binny Makkar study show that there is significant positive impact of international listing, industry, board size and board independence on CSR disclosure [7].

Profitability ratios are indicators of corporate fund management effectiveness and show the benefit of using assets and capital investments. The market capitalization level indicates the company's market value, which is also an important indicator for an investor showing stability and success. On this basis, we will use the profitability ratios and market capitalisation as dependent variables in our paper. To measure CSR, various indicators may be used, such as the CSR information disclosure score, as well as different sustainability ratings which will be described in detail. It should be noted that the most typical control variables included in the papers we investigated are those responsible for company size, financial leverage, and the rate of company growth. In addition, the authors used the percentage of women on the board of directors, capital expenditures and some other indicators as indicators of the company's stability.

The variable responsible for company size is the most frequently used control variable. Researchers most often choose the logarithm of the total assets as the indicator reliable for company size [8; 9]. This is because company size influences the existence of the company's resources, which cover non-operating expenses related to sustainable development activity. Also, company size influences the level of awareness of mass media about its operations. The more attention the company gets, the more resources its management is ready to create a positive reputation, including implementing CSR strategies. Companies with stable opportunities for growth are more likely to plan their activity with an eye toward a long-term perspective and invest in their reputation – and a steady increment in profit signals the company's business solvency and its opportunity to develop beyond operating activity. This informs the model by establishing a profit growth rate variable [10]. Regarding the papers' results considered in this subsection, it should be noted that the researchers studying this topic draw controversial conclusions. For example, some research concludes that the CRS implementation into company operations is a risk and an unnecessary set of expenses. Other research, on the contrary, obtains proof of the positive influence of CSR strategies on the corporate financial indicators. In this section of the review, we consider both points of view, and conclude about the reasons for such controversial results. It should also be noted that some authors emphasise that no influence of CSR metrics on financial indicators was revealed [11].

The authors of earlier note that high costs of CSR implementation often did not yield a positive tangible result because the market was not ready to perceive CSR as an essential characteristic for financial indicators. When there is no demand for social responsibility, the company has no incentive to invest [12; 13]. Therefore, the main question pertains to the practicality of such expenses concerning the obtained results. They also point out that more considerable expenses entailed by socially responsible behaviour cause deterioration in terms of competitiveness. As long as the funds are redistributed in favour of non-operating activity, the amounts used for the principal company activities are reduced [8]. However, this means that companies that do not invest in social responsibility think in terms of short-term prospects, choosing cost reduction in the current period. As a result, financial performance looks good in the short term, but worse over a longer interval because the benefits which may be obtained by a positive reputation and consumer confidence are absent [14].

Later papers reveal that together with the growth of public interest in CSR, the engagement of companies increases, and sustainable development strategies have become desirable (and mandatory in some cases) for businesses in various countries. Control of company's operations related to CSR plays an essential role in attracting large conscious investments due to creating a positive reputation and perception by society (for example, [10]). Holding the trust of consumers and shareholders allows a company to remain stable even in case of an economic decline; and establish business relationships with companies committed to similar values. Also, authors [15] assert in their paper that companies with a high level of social responsibility tend to surpass their competitors which have no CSR strategies over the long term. Additionally, according to the papers by Albuquerque et al. and Kim et al. [16; 17] the satisfaction of customers, employees and investors does not simply guide the company along the paths of growth, but also reduces its financial risks. This means that from an investor's point of view, a company investing in CSR is more attractive for investment due to a lower probability of judicial proceedings, scandals related to the environment, or misbehaviour towards customers or employees. A proactive social attitude from a company influences management decisions, leading them to the optimal level of riskiness that maximises the company value. Harjoto and Laksmana [18], come to this conclusion in their paper, emphasizing that CSR strategies may help a company avoid excessive risk acceptance or aversion, which positively impacts the investors' welfare. However, Fatemi et al. [19] in their paper point out that although under certain circumstances investments in CSR activity result in an increase in company value for shareholders, there is a chance that funds will be diverted from operations related to protection against competitors with the result in adverse consequences for the company.

The divergence of the research results may be due to various reasons. In the first instance, the choice of CSR metrics, financial indicators, and errors of measurement influence the results. Difficulties in obtaining and verifying information play their part too. As long as CSR activity in most countries and industries is left to company management' discretion (as well as information disclosure requirements), the systematisation of information for analysis may differ substantially from paper to paper. Besides this, as stated above, both company management and investors are changing their opinions on CSR, towards more awareness and understanding of its necessity. Therefore, the research conducted in the early 2000s evaluates corporate social responsibility as an activity diverting funds from the main corporate business and impairing the company's performance. The study from the past four years, on the other hand, addresses the positive effects of CSR and points out not just an understanding of the necessity of such effects, but also of legislative solutions for the implementation of elements of quality control of corporate non-financial activity. Considering all factors defining the positive or negative sign of the influence produced by CSR on corporate indicators, we expect to find a positive relation between CSR metrics and corporate financial performance.

Relation of CSR Information Disclosure with Financial Indicators

The second part of our paper is dedicated to studying the information on CSR strategies applied by companies, the level of its disclosure in non-financial reports, and the extent to which it corresponds to the facts. Standards of information disclosure differ not just for various countries, but also for the industry sectors in which companies operate. However, some standardised indicators are disclosed each year by companies in their annual reports, and in separate sustainability reports [20]. These indicators include the amount of various waste types per unit, participation in charitable endeavours and environmental projects, staff training costs, research and development, percentage of women on the board of directors, and other indicators [21]. The level of information disclosure and its reliability in such reports varies depending on the industry sector, company size, frequency of its mentioning by mass media, the level of development of political institutions in the country, and other factors [22]. Often companies state only that information that makes a positive impression, while failures are omitted from the reports. However, the research by [23] shows that such a behavioural model may result in drastic consequences for the company, such as adverse publicity, a buyers' strike, and an outflow of sales revenues. There is a popular point of view among scientists that companies engaging in greater social responsibility are more likely to actively disclose such information, as not doing so may cause shareholders' distrust. On the contrary, companies with low CSR levels are more likely to conceal information, avoiding the outflow of investments [24]. This is in line with the results of other research [25]. Point out that companies use CSR information disclosure as an instrument of influence on its perception by investors, furnishing only positive information, and avoiding negative details of the performed work. CSR information provided in the reports is among the risks and opportunities assessment tools for investors. For this reason, managers approach the preparation of reporting to demonstrate only positive results [26; 27]. It also means that companies intend to disclose information on CSR strategies only if such processes have improved financial indicators [28; 29].

Here, we can conclude that information disclosure does not eliminate contradictions related to corporate social responsibility and its implementation in corporate operations. A high level of CSR information disclosure does not necessarily signify that socially responsible behaviour will result in good corporate performance. On the contrary, companies, especially the large ones and those covered by mass media, should assess their risks when publishing any information. Excessive information and its concealment may cause a collapse in investors' confidence and financial losses. Moreover, discrepancies between disclosure and performance may arouse suspicion of unscrupulousness, and the same may happen in case of an absence of information when performing CSR activities. On the other hand, a high level of social responsibility, supported by high quality and verified disclosure, may result in positive financial indicators.

Many researchers use the disclosure score as a measure for CSR information disclosure in their models. They may be general or individual for each aspect: environmental, social or managerial. For example, analysts of the Bloomberg database, rating agencies or independent appraisers assign disclosure scores to companies based on assessment of the quantity and quality of the information disclosed in reports related to corporate social responsibility strategies. The information disclosure scores are only one aspect of the assessment of the way companies perform CSR activities. However, in aggregate (taking into consideration such indicators as the amount of hazardous waste per unit, participation in charitable endeavours and environmental projects, staff training costs, etc.) the information on disclosure offers an opportunity to evaluate the social responsibility level of a company comprehensively. However, analysis of such data often requires unique prerequisites that an investor a customer often lacks, e.g. knowledge of the nuances of CSR, and the industry sector within which the company operates. This makes it necessary to have outside evaluations performed by independent rating agencies and auditors. Such evaluations consider all CSR indicators at once (including the information disclosure level) and become a basis for creating ratings and sustainability indexes that are more convenient tools for evaluating CSR.

Companies strive to get into sustainable development ratings to obtain consumer confidence and attract new investments. For this purpose, companies spend funds not just for information disclosure, but also for its verification by auditors [30], which is an essential step toward recognition by rating agencies. Those papers which study the interrelations between CSR ratings and corporate financial indicators analyse the data on the companies which have various sustainability indices, such as the Dow Jones Sustainability Indices, FTSE4Good Index, the MSCI ACWI ESG Leaders Index, RobecoSAM Sustainability Yearbook, and other local indexes related to certain markets [5]. The ratings and sustainability indexes listed above are widely used as CSR metrics, *inter alia* in most papers considered at the beginning of section 1.1. Most commonly, the information analysed involves whether the company is included in a rating, and whether its score is stated in the Bloomberg or Thomson Reuters databases and is publicly available. It is rather convenient to include the rating scores into regression and analyse its influence on financial indicators, which is also an argument in favour of using the rating as a CSR metric in the majority of papers on this topic. One of the most popular ratings are the indices of the Dow Jones Sustainability Indices family. This tool is very convenient for most researchers, because the family comprises one global index, and individual regional indices related to various regions of Europe, Asia, North America, and South America. However, we cannot use it for our purposes, because it does not comprise a separate index for BRIC countries. Therefore, this paper uses the popular rating of sustainable development RobecoSAM, which evaluates various companies from different countries. The methodology of forming the applied rating is described in more detail in the section dedicated to variables.

Based on our literature analysis we put forward the following hypotheses:

Hypothesis 1. If a company is in the sustainability rating, this has a positive impact on its financial indicators.

This hypothesis was proposed based on the literature review described above and implies that we expect companies represented in the chosen sustainability rating to show better financial performance than their competitors who are not in the rating. The competitors from our sample have no CSR strategy, or fail to disclose information about it. There are also companies that are involved in CSR but disclose an insufficient amount of information for getting in the sustainable development rating. Making the selection is described in greater detail below.

Even though a hypothesis is made regarding a positive relation, it is impossible to assume faultlessly that the hypothesis will be confirmed, as the selection made for this paper consists of companies operating in emerging markets. According to previous research on the topic, the outcome of the analysis depends more on the chosen rating and some unobservable factors representative of the considered markets but not included in the models.

Hypothesis 2. There is a relation between the sustainability rating score and corporate financial indicators.

This hypothesis is a more detailed development of the previous assertion. If the first hypothesis compares the financial performance of socially responsible companies with that of their competitors, Hypothesis 2 is proposed to correlate companies' indicators inside the rating. For our analysis, we chose the sustainability rating RobecoSAM which assesses companies from 0 to 100 points. This process will be described in detail in the section dedicated to methodology. On this basis, we generated the hypothesis in order to define how the rating scores influence the corporate performance, and to what extent a company with a higher rating is more financially successful. To verify this hypothesis, we will include in the analysis only the companies from the sustainable development rating.

Hypothesis 3. There is a positive relationship between indicators of CSR information disclosure and the company value.

As was considered in one of the literature review sections a rather important aspect of social responsibility is information disclosure. Therefore, we assume that there is a positive dependence of the company profitability indicators and company capitalisation on the rating score related to the disclosure of sustainable development information. When verifying this hypothesis, we will use the rating score related to general CSR information disclosure assigned to the company by analysts of the Bloomberg database as an explanatory variable.

The next section of the paper is dedicated to the research studying how the cultural characteristics of the country where a company operates may influence the relation between CSR ratings and financial performance.

Relation of CSR ratings to corporate financial performance taking into consideration the cultural characteristics of a country

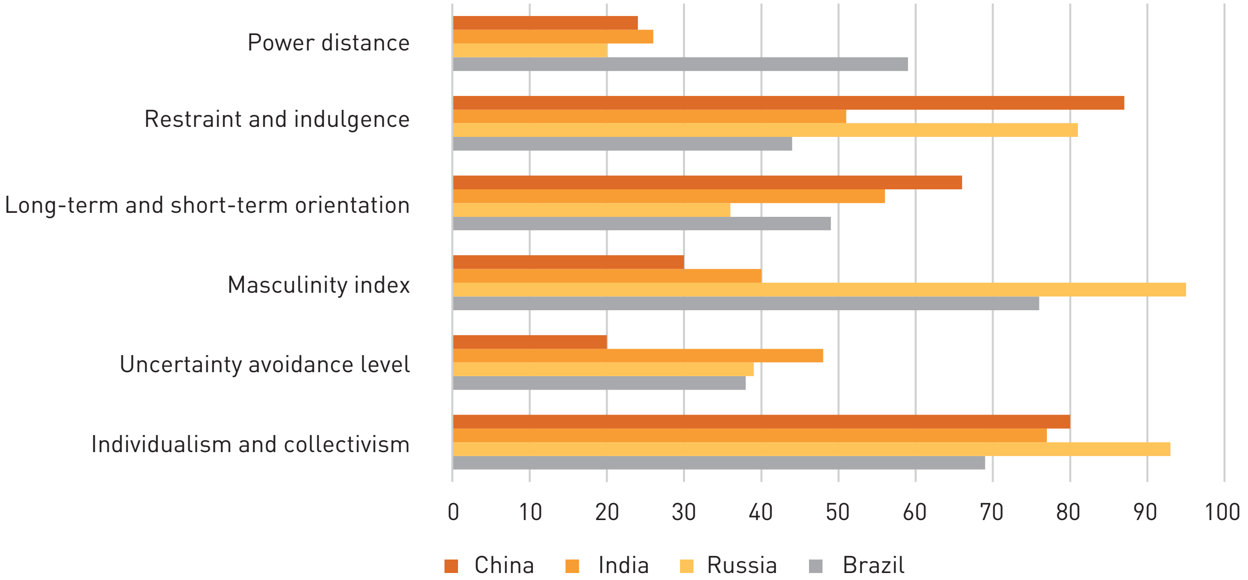
The influence of ratings in the actual circumstances of developed markets has been actively studied for a long time, and we have considered the papers dedicated to it in sections 1.1 and 1.2. As mentioned above, the conclusions made by researchers are controversial. However, suppose in developed countries this controversy is most commonly explained by the factors related to corporate intrinsic characteristics, the specific nature of the selection, or the choice of CSR metrics. In that case, the situation is quite different in emerging countries.

As long as the CSR concept is related not so much to companies' behaviour as to the impact they exert on society and the environment, it is crucial when analysizing consider the context in which a company operates. On the one hand, in countries with underdeveloped institutions and more prominent corrupt practices, CSR may take a different turn from developed countries, and become a lobbying and manipulation tool [31]. On the other hand, the concept of CSR is relatively new for emerging markets and the benefits it implies are not always entirely comprehensible for managers and investors. However, in recent years an increased awareness of such markets has been observed [32]. It is also necessary to consider the fact that companies in emerging markets differ due to a weaker corporate management structure. First of all, it means that managers have a more comprehensive range of powers, enabling them to make decisions for their advantage. It is a potential hazard for shareholders' welfare, because it may reduce the efficiency of use of equity and borrowed capital, and decrease the company value [33]. Papers on this topic are usually focused on one region, country or group of countries [10; 15; 34].

All the characteristic features of emerging markets listed above entail the necessity to study which characteristics of individual cultures are correlated with some societal problems. As the authors of some papers written in recent years point out, the country's cultural characteristics are guidelines to understanding what is considered desirable in a certain society. As such, they profoundly influence the creation of the relation between CSR and corporate financial performance and the concept of CSR itself [35]. Moreover, the cultural values are decisive in the behaviour of consumers, investors, and managers, shaping their convictions as regards a certain situation [36]. The authors also conclude that decision-making, following CSR strategy and the cultural values of concerned parties, results in better financial performance than ignoring such values.

The most popular tool for measuring cultural characteristics used by the authors of the studied papers is the six-dimension model of cultural differences developed by Geert Hofstede and co-authors [37]. According to Karolyi [38] the explanatory power of the Hofstede model is greater than that of other similar tools such as the World Values Survey (*WVS Database*) and some others and for this reason it is more popular and more widely used. In this paper we also used the Hofstede model which evaluates the cultural characteristics of a country through six dimensions, which are power distance, individualism and collectivism, uncertainty avoidance, masculinity and femininity, long-term and short-term orientation, and restraint and indulgence [37]. Further, these measurements will be considered in general, and extracts from characteristics of the countries analysed in this paper (Brazil, Russia, India and China) will be presented. The specific values of each dimension of the considered countries are represented in Figure 1.

Figure 1. Score of measurement of cultural differences for each country



Source: 'Country Comparison', Hofstede insights.

The first component of the model is *power distance*, i.e. the extent to which members of society with less power accept and acknowledge unequal power sharing. A high level of power distance indicates highly developed hierarchical systems, widespread bureaucracy, and underdeveloped democracy in the country. This indicator is exceptionally high in Russia and China. All the four countries are characterised by a high level of the centralised authority' acceptance, which is concentrated in the hands of the upper segment of population, this inequality perceived as normal.

The next dimension of the model characterises the *ability* of culture to satisfy the *immediate wants and personal desires* of members of society. Those cultures that have a high evaluation such as Brazil, prioritize in living, the ability to be merry, and positive thinking despite hardships. It gives them a sense of a more positive vision of the future. The restrained societies, like China, Russia and India, are prone to control their true desires, pessimism, and a perception of their leisure and joy as something prohibited and wrong. Such overcontrol/excessive control position makes members of society have a negative mindset for the future and feel that they are unable to influence their own lives.

The *short-term and long-term orientation of the society* is defined by the extent to the societies look more to the past and traditions of its nation (short-term orientation) or is more interested in the future than in the present or past (long-term orientation). Among the four sample countries, Brazil and India have a small score in this dimension, due to the religious cultures of these countries and their traditionalism. On the other hand, China and Russia, are pragmatic societies that demonstrate a high level of adaptability to situations.

The next aspect of the model is responsible for the division of emotional roles between the sexes. In other words, the higher the *masculinity index* of the society, the more it appreciates traditionally masculine values and the more it strives to establish strict rules and laws. For example, in India and China, respect towards a person is contingent upon his/her success and power, which is characteristic of a masculine type society. Brazil shows no distinct manifestation of gender, while Russia belongs to the feminine type of society, because dominating behaviour is accepted from a superior, but it is not typical among people of the same level.

The next element of the model is the *uncertainty avoidance level,* which is responsible for how tolerant members of society are to unexpected deviations from the usual course of life. The higher this level, the more the society tries to exercise control events with customs, regulatory standards, and laws, although nevertheless it is open to changes. Russia and Brazil show a high level of this dimension because these societies have a pressing need for rules and the development of legal systems to structure their live, resulting in the creation of complex bureaucratic procedures. China and India, meanwhile, demonstrate endurance of eventualities and the ability to adapt to any circumstances.

The next dimension is *individualism versus collectivism,* which is defined by the extent to which individual members of a society attach more importance to their personal goals and desires than to public interests and welfare. Three of these four countries are prone to collectivism for various reasons, such as strong family connections (Brazil), a high self-awareness of the nation as a whole (Russia), or the collectivist foundation of the society (China). India combines the features of individualism through religion (in which each person is responsible for his/her own lot) and of collectivism due to a high preference of group affiliation, in which it is customary to act while taking into consideration the general welfare [37].

The papers in this section more often make an allowance for industrial and cultural differences when analysing the relation between CSR metrics and financial indicators.

The research we have considered presents conclusions that national peculiarities influence how a board of directors takes decisions, how a company assumes risks, and how a company participates in CSR strategies. Veenstra and Shi [36], in their inter-country analysis also conclude that a high level of individualism and indulgence in the country results in a negative relation between CSR and financial performance, while a long-term orientation and power distance yield a reverse effect. However, the influence of dimensions on the relation between CSR and financial indicators varies enormously depending on the data used for analysis. Halkos and Skouloudis [41], in their paper, come to a conclusion that the higher the level of uncertainty avoidance in a culture, the less the influence of CSR in corporate financial performance. Long-term orientation and a high indulgence, on the contrary, facilitate a positive influence of CSR strategies on indicators. However, this contradicts previous research, which reveals a significant influence of masculinity, individualism, and a high-power distance index on the level of CSR implementation.

Based on an analysis of the papers considered in this section we propose the following hypothesis:

Hypothesis 4. Cultural peculiarities of a country influence the relation between the CSR rating assigned to the company and its financial performance.

Based on previous papers in which similar analysis tools have been used, we expect both a positive and negative effect from various aspects of the Hofstede model. It is impossible to predict the influence, which a particular element of the model exerts on creating the studied relation. The results of our model may both confirm the conclusions of previous papers and opposite yield results. Based on the preliminary analysis of country differences, we assume that a high bureaucratisation and hierarchy in the societies under consideration may have the most significant impact, because a poor performance of institutions reduces the proactivity of members of society and interest in following global trends. Thus, it is crucial to verify this hypothesis to understand which aspects of the cultural peculiarities model result in a different influence of CSR on the corporate financial performance in the BRIC countries analysed.

Methodology and Database

Research Model

In a generic form, the model is as follows:

$$ROA_{i,t} / ROE_{i,t} / Marketcap_{i,t} = \beta_0 + \\ +\beta_1 \cdot CSR_{presence_{it}} / CSR_{score_{it}} / ESG\,disclosure_{it} + \\ +\beta_2 \cdot Total\_assets_{it} + \beta_3 \cdot D/E_{ratio_{it}} + \\ +\beta_4 \cdot Growth\_rate_{it} + \beta_5 \cdot Diversity\,of\,board_{it} + \\ +u_i + \varepsilon_{it} \quad , \quad (1)$$

where:

ROA is the natural logarithm of return on assets;

ROE is the natural logarithm of return on equity;

Marketcap is the natural logarithm of market capitalisation;

CSR_presence is the presence of a company in the sustainable development rating (1 – the company is presented in the rating, 0 – the company is not presented in the rating);

CSR_score is the score of the sustainable development rating RobecoSAM;

Total_assets is the natural logarithm of the total corporate assets;

D/E ratio is debt to equity ratio;

Growth_rate is the profit growth rate of the company;

Diversity of board is the percentage of women on the board of directors;

u_i is unobservable individual effects;

ε_{it} is residual disturbance.

The majority of variables are presented as logarithms. We did this to approximate the regression residual distribution to the normal value and to avoid inadequate models.

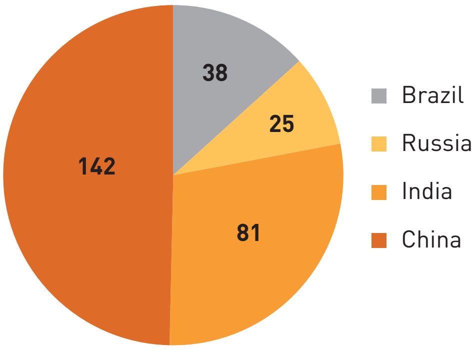
Description of the Selection

In this paper we use data concerning companies operating in Brazil, Russia, India and China collected using the Bloomberg database for six years from 2013 to 2018. The data was collected in two stages. At the first stage we collected information on the companies presented in the RobecoSAM rating. Then we chose competitors for companies from each industry sector commensurable in terms of size, country and primary business, which, however, are not presented in the sustainability rating. The majority of competitor companies are either not involved in CSR or fail to meet all criteria necessary to get into the rating. Some of them have no score concerning information disclosure.

The Bloomberg database, presents complete information on financial indicators necessary to build a model, and various aspects of CSR strategies are evaluated. After downloading the data, the selection comprised eleven sectors following the global industry classification standards of Bloomberg (GICS). The next stage of data processing was the elimination of observations related to the companies from the financial sector, because their activity structure and reports preparation differ drastically from other sectors which could cause errors and adversely impact the research findings [8].

Apart from that, the data was purged of empty values that were replaced with a mean value of the variable for each company. Thus, the final selection consists of 286 companies, which provides 1,716 observations. A breakdown of companies by their countries and industry sectors is represented in **Appendix 1**. Figure 2 shows the breakdown of companies by countries.

Figure 2. Breakdown of companies in the selection by countries



Source: the authors' calculations**.**

As we can see, most companies operate in the Chinese market and the smallest number of companies operate in the Russian market. The diversity of industry sectors in the Russian economy presented in the rating is the most meagre of the four countries. This may stem from the fact that the sustainable development concept has been developing in Russia recently. China and India have much more companies implementing it actively in their operations.

Hypotheses 1, 3, and 4 will be tested through the full selection. As long as the testing of Hypothesis 2 requires elimination from the selection of those companies not included in the RobecoSAM rating, it will be conducted using a separate sub-selection. This is necessary to reveal the influence of the rating score only on the financial performance of the companies in the rating.

Description of Variables and Descriptive Statistics

Before we proceed to our analysis of indicators of variables, let us consider the methodology for creating the sustainability rating.

As mentioned above, there are different methods of measuring corporate social responsibility. For our research, we chose the sustainability rating RobecoSAM as our CSR metrics system. RobecoSAM assigns points to companies from 0 to 100 based on whether their operations comply with those sustainable development parameters that influence company competitiveness. These comprise such indicators as the amount of hazardous waste per unit, participation in charitable endeavours and environmental projects, staff training costs, research and development, the percentage of women on the board of directors, support of minorities, the level of sustainable development information disclosure in the annual non-financial reports, and other information. The methodology applied to devising the rating is as follows. Over 7,500 companies across the globe take part in the annual corporate sustainability assessment (SAM) where they are evaluated against the criteria of CSR. Only those companies implementing CSR strategies as well as providing reports verified by an independent auditor are granted admittance to participation in the assessment. SAM considers industry characteristics, so the rating takes into account the specific character of the industry sector in which the company operates, and its susceptibility to CSR. This is one of the reasons that the rating was chosen: as long as the score initially reflects industry differences, the model will not be overloaded with variables (*Ranking | SAM Sustainability Yearbook*).

In order to verify hypotheses 1 and 2 we use the indicators of presence in the rating and the score assigned to the company, respectively, as explicative variables. To test Hypothesis 3, we chose the CSR information disclosure score (given to the company by analysis of the Bloomberg database) as an explicative variable. There are four kinds of such scores: the general disclosure score, and the scores related to disclosure of social, environmental and governance aspects. In this paper, where we are interested in more than a single component, the general disclosure score will be used in the model.

Descriptive Statistics

In this section we present descriptive statistics of the variables used in the analysis. To conducts a preliminary analysis, we provide descriptive statistics for the whole sample, and an analysis of indicators made separately for the companies included in the sustainable development rating, and for their competitors.

Table 1. Descriptive statistics, complete selection

	Number of observations	Mean	Standard deviation	Minimum	Maximum
ROA	1,716	.076	.077	–.49	.61
ROE	1,716	.014	.018	–1.07	1.23
Market cap (in millions of US dollars)	1,716	11,516.78	32,895.00	58.54	493,659.56
Rating	1,716	14,49	20,68	0	87
Assets (in millions of US dollars)	1,716	14,153.75	40,868.50	49.38	408,465.76

	Number of observations	Mean	Standard deviation	Minimum	Maximum
Leverage	1,716	1.48	3.74	–41.58	68.25
Growth rate (in %)	1,674	11	12	–149	99
ESG disclosure	1,394	30.57	15.24	0.83	72.73
Women on board (in %)	1,411	9.87	9.48	0	50

Source: the authors' calculations.

Table 1 above presents the descriptive statistics of the complete sample. There is a large spread of values for each indicator. For the variables of market capitalisation and total assets, this spread is explained by the diversity of the selection. We analysed large corporations and small companies because comparability of companies by size was not a precondition whenselecting. Also, well-marked differences in values are mitigated during analysis using transforming variables into logarithms.

ROA and ROE in the selection are alternatively positive and negative. Despite a wide spread between the minimum and maximum the mean values for both variables are positive: 7.5% for ROA and 14% for ROE, which is indicative of the selected companies' competitive ability and attractiveness for investors. The fact that return on equity is twice as large as the return on assets shows that on average, the companies from the selection use not only their equity capital, but borrowed funds as well (and it follows that the greater the borrowed funds, the higher the ROE and lower the ROA).

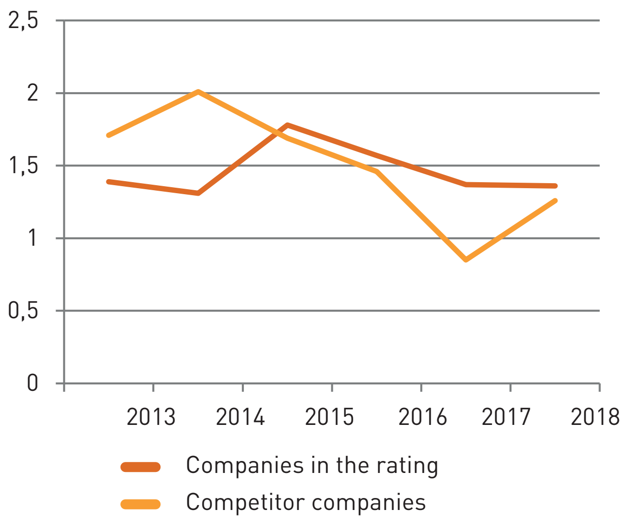
The financial leverage values confirm the assumption that companies from the selection have large amounts of borrowed funds. We use the ratio of borrowed funds to equity capital as the leverage variable. This ratio shows the extent to which a company finances its activity using borrowed funds (or its own funds) and is indicative of the ability of the equity capital to cover all undischarged debts in case of an economic crisis. The regulatory value for this variable is the interval from 1 to 2; however, the value depends on the industry sector capital intensity. For some sectors, this value may substantially exceed 2. In our case, we consider a wide spread between the minimum and maximum values of the financial leverage variable as the indicators related to the volatility of the markets we are analysing. A more detailed analysis of the selection showed that the majority of observations are in the interval of 0 to 10, and the threshold values of the variable are related to sudden drastic changes in the equity capital. As long as this data was collected from an official source and these values are not an error of measurement, we assume that they are related to external economic influences, or internal company challenges that have been subsequently resolved. Therefore, we decided not to eliminate these values as outlying data, and keep them in the analysis.

After we have considered the main control variables and analysed their values through the complete selection, we will compare descriptive statistics of two sub-selections: companies included in the RobecoSAM rating, and their competitors not presented in the rating.

The main difference revealed in the two sub-selections relates to the mean values for the variables of market capitalisation and total assets. On average, the capitalisation of the companies in the rating is 5–6 times greater than that of their competitors not present in the rating. The second sub-selection of companies also comprises large companies, however their number is much smaller. The observed distribution of values confirms that large corporations are involved in CSR much more, and as long as they have more significant financial opportunities, they are more likely to meet the criteria of ratings agencies. Thus, even after preliminary analysis, we can assert that a larger company size contributes towards overcoming barriers to entry into the sustainability rating.

Figure 3 illustrates the dynamics of the financial leverage indicator for two sub-selections. The mean value of the rated is at the level of the indicator's standard value (equal to 1.5) while the competitor companies' values are subject to more significant variations (in the range of 0.85 to 2) with every year. Thus, we can draw the conclusion here that companies not presented in the rating are, on average, more subject to sudden changes in the capital structure.

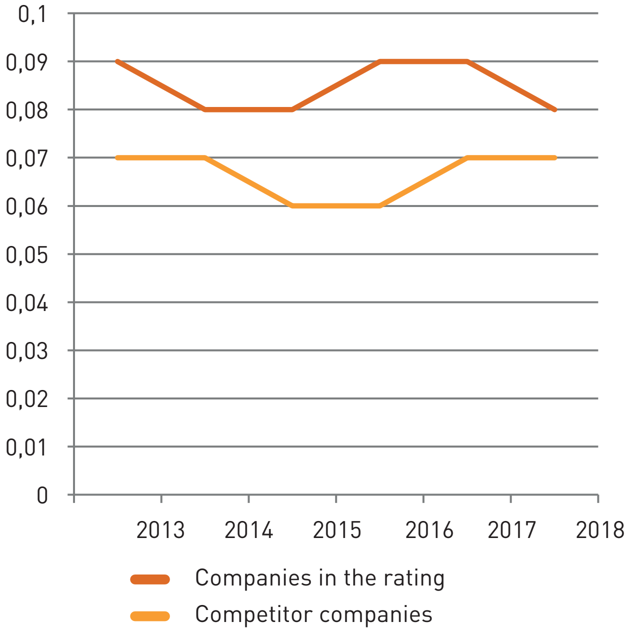
Figure 3. Dynamics of mean values of the financial leverage for two sub-selections of companies: those that are rated, and their competitors



Source: the authors' calculations.

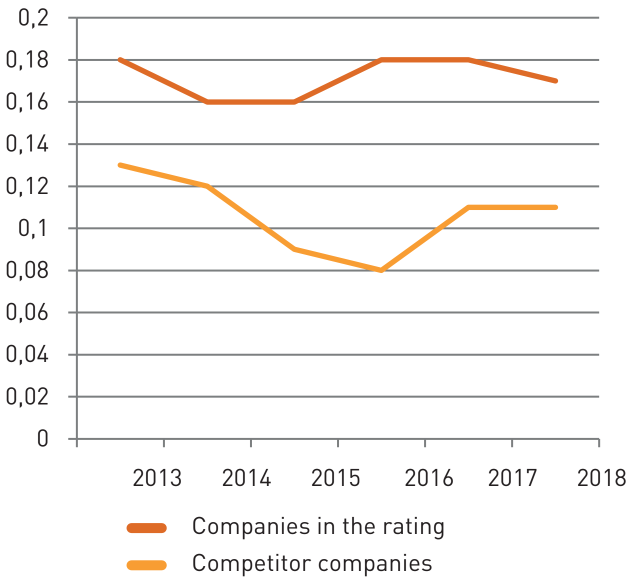
The mean values of return on assets for the companies from the rating are a little higher than those of the competitors, and both sub-selections show approximately the same dynamics of the indicator, which is represented in Figure 4.

Figure 4. Dynamics of mean values of return on assets for two sub-selections of companies: those that are rated, and their competitors



Source: author's own calculations.

Figure 5. Dynamics of mean values of return on equity for two sub-selections of companies: those that are rated, and their competitors



Source: the authors' calculations.

As for return on equity, this indicator is more volatile for competitor companies, and this may stem, as stated above, from drastic changes in the capital structure characteristics of less stable companies, especially in emerging markets (see the dynamics of the indicator in Figure 5). However, as a general matter, we can draw the conclusion that companies presented in the rating show, on average, higher performance indicators and are less subject to changes in their capital structure.

Research Results

When verifying each hypothesis, we constructed three specifications of the model, which differ in dependent variables. This allows for evaluating which financial indicator is most subject to the influence of CSR metrics. In this chapter, all model specifications were assessed using three methods: pooled regression, regression with fixed effects, and regression with random effects. Based on these test results we chose the adequate models for verification of each hypothesis.

Hypothesis 1. The presence of a company in the sustainability rating influences its financial performance.

In order to verify this hypothesis, we need to establish whether a company yields better results than its competitors who are not included in the rating. For an explanatory variable to verify the hypothesis, we used a categorical variable of the company's presence in the rating, which is 1 or 0. As long as the variable of presence in the rating is time-invariant, it is impossible to assess its coefficients using the regression with fixed individual effects. For this reason, we constructed two models for each specification: the pooled one and the model with fixed effects. Before we interpret the assessment results, it is necessary to choose a more adequate model and test for potential problems, e.g. multicollinearity, heteroscedasticity, and autocorrelation. In order to choose from the two models, we conducted the Breusch-Pagan test, the zero hypothesis for which states that there is no random individual effect. We conducted the test for three models specifications and the zero hypothesis is rejected for each at a 1% significance level. This means that we choose the regression with random individual effects. The model is presented as follows:

$$ROA_{i,t} \,/\, ROE_{i,t} \,/\, Marketcap_{i,t} = \beta_0 +$$
$$+\beta_1 \bullet CSRpresence_{it} + \beta_2 \bullet Total\_assets_{it} +$$
$$+\beta_3 \bullet D/E_{ratio_{it}} + \beta_4 \bullet Growth\_rate_{it} + u_i + \varepsilon_{it}\,.$$

The next step involves testing for errors in the regression. In order to verify the regression for multicollinearity we calculated VIF coefficients (variance inflation factor). The factor values do not exceed the classical extreme value, which equals 6, which implies no multicollinearity in the model. In view of specific features of the selection (such as missing data), it is impossible to conduct tests for heteroscedasticity and autocorrelation and correct the model with fixed effects appropriately. Therefore, we assume that coefficient evaluations are not distorted.

See in Table 2 the results of three models specifications with random effects. It is impossible to assess the adequacy of the models with random effects using the determination coefficient (R^2) because they are evaluated by the generalised squares method. The fact that all three models show high values of the Wald statistic (over 2,000) is indicative of the models' adequacy and significance.

Table 2. Results of the random effects models assessment

	Market cap	ROA	ROE
CSR presence	0.6996***	0.3419***	0.3042***
Size	0.5383***	–0.0965***	–0.0665***
Leverage	–0.2385***	–0.3314***	0.0140
Growth	0.1448***	0.5546***	0.5748***
_cons	3.2135***	1.1874***	1.7462***
Number of observations	1,604	1,495	1,493
R^2	–	–	–

* p<0.05;** p<0.01;*** p<0.001.

Source: the authors' calculations.

It is evident that in all specifications, the variable of presence in the rating (CSR presence) is significant at a 0.1% significance level and has a positive effect on the financial performance variables. Therefore, the influence on return on assets and equity is approximately the same (0.3419 and 0.3042 respectively) while the influence of presence in the rating on market capitalisation is twice as much. This may stem *inter alia* from specific features of the used selection, namely a large capitalisation of companies in the rating, unlike that of the competitors. The corporate size and growth rate variables are significant in all specifications at a 0.1% significance level. However, the financial leverage variable does not influence on return on equity. The substantive interpretation of the models states that the presence of a company in the RobecoSAM rating has a positive impact on the corporate financial performance, especially on the amount of market capitalisation. Thus, the *hypothesis* of a positive influence of presence in the sustainable development rating on financial performance is *confirmed*.

Hypothesis 2. There is a relation between the sustainability rating score and corporate financial performance.

In order to verify this hypothesis, we used the sub-selection which comprises only those companies presented in the sustainable development rating. This is necessary to evaluate the distinct influence of the rating score on corporate financial performance. The major question is whether the rating leaders surpass companies with a lower score.

When verifying this hypothesis, we constructed three regressions for each model specification, and then conducted tests to make our choice. The Wald test, which zero hypothesis states that the model contains no unobservable individual effects, showed for all three dependent variables that the regression with fixed effects describes data better than the pooled regression. The Breusch-Pagan test indicates that we choose the letter between the pooled regression and regression with random effects. In order to make our choice between the models with fixed effects and random effects, we conducted the Hausman test and chose the regression with fixed effects.

The final model with fixed effects is as follows:

$$\frac{\dfrac{ROA_{i,t}}{ROE_{i,t}}}{Marketcap_{i,t}} = \beta_0 + \beta_1 \cdot CSR_{score_{it}} + \beta_2 \cdot Total\_assets_{it} +$$

$$+\beta_3 \cdot \frac{D}{E_{ratio_{it}}} + \beta_4 \cdot Growth_{rateit} + \beta_5 \cdot Diversity\,of\,board_{it} +$$

$$+u_i + \varepsilon_{it}.$$

Similarly, to the verification of Hypothesis 1, after choosing the adequate model, we conducted tests to reveal various errors in the model. VIF values for all three specifications are within the normal value, which is indicative of multicollinearity. We conducted the Wald test for heteroscedasticity, which was revealed foall three specifications. We also carried out the Wooldridge test for the first-order autocorrelation. We do not conduct the test for spatial autocorrelation because it may emerge only if the number of years exceeds the number of studied companies. The Wooldridge test showed autocorrelation in all specifications of the model. In order to eliminate these problems, we applied White's heteroscedasticity corrections and Rogers's adjustments for heteroscedasticity and autocorrelation. However, it is evident from Table 3 below that in spite of modifications, the coefficients of the variables preserve their significance levels and signs. Therefore, we can assume that the initial model with fixed effects appropriately evaluates the available data, and the existing errors do not change the evaluation results. So, we consider the model with fixed effects as the adequate one.

See the final results of the assessment below:

Table 3. Results of the assessment: rating score influence on financial performance

	Market cap	ROA	ROE
Rating	0.0093**	0.0097**	0.0078*
Size	0.7572***	–0.2597***	–0.1959***
Leverage	–0.1437***	–0.3005***	0.0147
Growth rate	0.1350***	0.4456***	0.4631***
Women on board	0.0106***	–0.0002	–0.0023
_cons	1.6278***	2.9584***	3.2523***
Number of observations	861	812	811
R^2	0.3575	0.5430	0.5434

* p<0.05;** p<0.01;*** p<0.001.

Source: the authors' calculations.

Table 4. Results of thr assessment: the influence of the CSR information disclosure score on financial performance

	Market cap	ROA	ROE
ESG Disclosure	0.0062*	0.0074***	0.0074***
Size	0.6245***	–0.2091***	–0.1556***
Leverage	–0.2483***	–0.3080***	0.0087
Growth rate	0.1187***	0.5005***	0.5177***
Women on board	0.0065**	0.0005	–0.0013
_cons	2.7647**	2.2884***	2.6334***
Number of observations	1,295	1,206	1,204
R^2	0.3076	0.5648	0.5664

* p<0.05;** p<0.01;*** p<0.001.

Source: the authors' calculations.

As we see from Table 3, neither a significant influence of diversity of the board of directors on return on assets and equity was found, nor the influence of the financial leverage variable on return on equity. The models show that the rating score has a minor positive impact on market capitalisation and return on assets at a 1% significance level, and even less influence on return on equity at a 5% significance level. The signs before control variables and their significance did not change compared to the model, which verifies Hypothesis 1. A substantive interpretation of the results states that in spite of a positive impact of the rating score on financial performance, a higher rating does not imply that a company will surpass the firms with a lower sustainable development rating score. Thus, the results partly confirm the proposed hypothesis on existence of the dependence between the rating score and financial performance.

Hypothesis 3. There is a positive relation between CSR information disclosure indicators and the company value.

The essence of this hypothesis is in the verification of the extent to which disclosure of the CSR information by a company in the annual non-financial reports influences financial performance. When we verified this hypothesis, we used the total score of CSR information disclosure as the dependent variable, assigned to each company by an analyst of the Bloomberg database. As long as the variable is time variant the choice of the model is similar to that of Hypothesis 2. Based on the Wald, Breusch-Pagan and Hausman tests we chose the model with fixed effects as the most adequate one. The final model is as follows:

$$\frac{\frac{ROA_{i,t}}{ROE_{i,t}}}{Marketcap_{i,t}} = \beta_0 + \beta_1 \bullet ESG\,disclosure_{it} +$$

$$+\beta_2 \bullet Total_{assets_{it}} + \beta_3 \bullet \frac{D}{E_{ratio_{it}}} + \beta_4 \bullet Growth_{rateit} +$$

$$+u_i + \varepsilon_{it}.$$

VIF calculation revealed no multicollinearity in any of the specifications. We discovered the first-order autocorrelation and presence of heteroscedasticity by applying the White and Wooldridge tests. Similar to the verification of the previous hypothesis, we used the White correction and Rogers's adjustment. In a similar vein to the previous hypothesis, the assessment of models after correction did not influence the sign and significance of the coefficients with influence on ROA and ROE. The significance of the disclosure score coefficient in the specification with market capitalisation decreased to 5% when corrections were applied. Such results may indicate that errors in the model, where the dependent variable is market capitalisation, influence the results, and it is necessary to choose the model with corrections as the most adequate one. Consequently, the influence of the disclosure score on market capitalisation is of low significance. The results of the assessment of the final models are presented below in Table 4. We chose as the adequate model for specification with market capitalisation the model with White corrections, for ROA and ROE – the model with fixed effects without corrections.

The model assessment results show a significant but low influence of the disclosure score on return on assets and equity. This result is rather logically sound because a high level of information disclosure does not imply a high level of social responsibility. In our selection some companies have a disclosure score but have no score of the sustainable development rating. As discussed in the first chapter of this paper, disclosure may contain errors and distortions and therefore is not a reliable indicator as the rating score. Nevertheless, the obtained result confirms a higher financial performance of the companies with high disclosure than that of the companies without disclosure. However, a high information disclosure score does not entail rapid growth of return on capital.

At the same time, the influence of this indicator on market capitalisation is low and almost insignificant. This result may be interpreted substantively from the point of view that the disclosure score is assigned to all companies which one way or the other have CSR, and disclose information about despite their size, publicity in mass media, or reputation in the society. Therefore, there is almost no influence of this score on the amount of capitalisation. Moreover, the signs of the control variables' coefficients and their significance in comparison to models (2) and (3) have not changed.

Thus, we can conclude that the hypothesis on the positive relation between the disclosure score and the company' s financial performance is not rejected.

Hypothesis 4. Cultural peculiarities of a country influence the relation between CSR rating assigned to a company and its financial performance.

To verify the hypothesis that influence of country's cultural peculiarities on the creation of the relation between the CSR rating and financial performance exists, we used model (3) as the base. So, we studied the connection between the rating score and financial performance. Since the model with fixed effects was considered the most adequate one when verifying Hypothesis 2, we applied it again. In order to define which dimensions of the Hofstede model influence the studied dependence, we added variables of the intersection of the rating score with each dimension of the cultural peculiarities' model. We will further consider the results of models assessment for each specification, taking into account the cultural dimension.

Influence on the Relation Between the Rating Score and Return on Assets

When verifying the hypothesis, we found the influence of two out of six dimensions on the model results where return on assets, power distance, and indulgence are the dependent variable. See in Table 5 the results of an assessment of the models with cultural dimensions and model (3) without considering cultural differences. It gives a graphical representation of how the influence of rating on ROA changed.

Table 5. Influence of cultural dimensions on the relation between CSR rating and return on assets assessment results

	No cultural dimension	Power Distance	Indulgence
Rating	0.0097**	–0.2353***	0.0395***
Size	–0.2597***	–0.1680***	–0.1789***
Leverage	–0.3005***	–0.3310***	–0.3216***
Growth rate	0.4456***	0.5092***	0.5082***
Women on board	–0.0002	0.0007	0.0005
c.Rating#c.Power_dist		0.0031***	
c.Rating #c.indulgence			–0.0011**
_cons	1.6278***	2.0250***	2.1445***
Number of observations	861	1,224	1,224
R^2	0.3575	0.5731	0.5665

* p<0.05;** p<0.01;*** p<0.001.

Source: the authors' calculations.

It should be noted that when the power distance index was added to the basic model, the influence of the rating score on return on assets remained significant, but reversed its sign. The fact that the sign of influence of the CSR rating on financial performance reversed as a result of adding the power distance variable to the model may be indicative of the fact that a high level of hierarchy and bureaucratisation in the considered countries results in the situation that a company's rating score does not increase its competitive ability. This result is predictable in the case of emerging-economy countries. On the other hand, adding to the model the second dimension – indulgence level – altogether raised the influence of the rating score (from 0.0097 to 0.0384), and preserved the significance level. These results align with previous research considered in the literature review, which emphasises that a high level of this dimension gives members of society a more positive view of prospects.

Influence on the Relation Between the Rating Score and Return on Equity

Similarly, let us consider the assessment results of the models in which the return on equity is the dependent variable. As in verifying previous hypotheses, we did not include the financial leverage variable in the model due to the absence of a significant influence on the regression explanatory power. As in the case with ROA, one by one we added to the basic model variables of the intersection of the rating score with cultural dimensions. The assessment results show that the relation between the rating and ROE is under the influence of the same two dimensions that impact on return on assets: power distance and indulgence.

Table 6. Results of assessment of influence of cultural dimensions on the relation between CSR rating and return on equity

	No cultural dimension	Power Distance	Indulgence
Rating	0.0078*	–0.2158***	0.0354***
Size	–0.1959***	–0.1104**	–0.1203**
Leverage	0.0147	–0.0130	-0.0045
Growth rate	0.4631***	0.5254***	0.5246***
Women on board	–0.0023	–0.0011	–0.0013
c.Rating#c.Power_dist		0.0028***	
c.Rating #c.indulgence			–0.0010**
_cons	3.2523***	2.3658***	2.4751***
Number of observations	811	1,222	1,222
R^2	0.5434	0.5707	0.5652

* p<0.05;** p<0.01;*** p<0.001.

Source: the authors's calculations.

It is evident from Table 6 that taking the influence of cultural differences into account in the model increases significance of the variable of the rating score. The power distance index has the same effect upon the relation between the rating score and ROE as the link between the rating and ROA. The substantive interpretation of the results states that the higher the power distance in a country, the less the influence of the company's presence in the sustainable development rating on its financial performance. The influence of indulgence is also similar to that of the previous dimension. The higher the country's score for this dimension, the stronger is the influence of the company's presence in the rating on return on equity.

The potential impact of cultural dimensions *on the relation between the rating score and market capitalisation* was verified by applying the same principle as for profitability ratios. However, not a single dimension of the Hofstede cultural model showed a significant influence. For this reason, the results of corresponding regressions are not presented in this section. We conclude that there is no influence of cultural differences of countries on the creation of the relation between the RobecoSAM rating score and market capitalisation.

Thus, based on the analysis, we can conclude that the hypothesis of the influence of cultural differences on corporate financial performance is confirmed. Therefore, the results of the models align with previous papers. The power distance index has the most significant impact. This may stem from the following. If the index is high, the society accepts the hierarchy and bureaucracy of the governmental system, which gives rise to a weakening of personal responsibility. Weak personal responsibility, in its turn, reduces the importance of CSR for the society. Hence, the greater the power distance, the less the society members need and understand the CSR concept.

The fact that indulgence positively affect the relation between the rating score and profitability ratio may be attributable to the inverse logic. The freer members of society are to express their desires and interests, the greater each individual' personal responsibility for the implementation of such interests. It also shapes a more positive attitude to the future prospects of management and investors. This indirectly results in an easier integration of CSR strategies into conventional business operations.

Conclusions

Our analysis showed that despite the limitations caused by volatility and imperfection of emerging markets, CSR influences corporate financial performance, which is in line with the results of such authors as Cho et al. [10], Yan et al. [15] and Peng [33]. A company's presence in the CSR rating scale has a more substantial impact on profitability and market capitalisation indicators than the actual rating score itself. Therefore, we may postulate that investors and consumers perceive presence in the rating as a positive signal, while the response to the quantitative indicator of the rating is weaker. Also, based on a partial confirmation of Hypothesis 3 we can conclude that CSR information disclosure is not an indicator that defines corporate financial efficiency, although it has some impact on return on assets and return on equity.

Our research proves the conclusions of the Nina and Valdemar Smith and Nina Metter Verner, that had the proportion of women in top management jobs tends to have positive effects on firm performance. The presence of women on the board of directors showed no significant influence on profitability indicators; however, a slight positive effect of this indicator on the amount of market capitalisation was discovered.

Adding cultural differences to the model revealed the influence of two out of six dimensions on the relation between the CSR rating score and profitability indicators. Our analysis showed that a high level of power distance, which entails such problems as a complex hierarchical governmental system, corruption, reduction of personal responsibility, and acceptance of centralised authority, all harm the relation between the rating score and financial performance. When power distance dimension was added to the model, the sign of the coefficient of the rating score variable changed from positive to negative. The second dimension, which influences the studied dependence, is indulgence. As mentioned above, a high score of this dimension characterises members of society as positive-minded and able to satisfy their need for joy and fun. Such behaviour entails a calmer perception of the future and an ability to have a positive attitude towards changes. Therefore, the obtained result, represented by a positive influence of this dimension on the relation between CSR and profitability indicators, is expected and logically sounds. Thus, all the hypotheses we have proposed were entirely or partially confirmed (none were rejected).

The available corporate sustainability reporting guidelines, even the best ones, still have some lacks concerning non-financial coefficients disclosure. We sure that need to test more non-financial indicators on the corporate financial performance. We actively look for the new inter-linking issues and dimensions between CSR and income, in order to gain new insights with a view to reducing conflicts among issues.

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Abbreviations used in the Study:

CSR – corporate social responsibility;

GICS – global industry classification standards of Bloomberg;

SDG – sustainable development goals;

ROA – return on assets;

ROE – return on equity;

Tobin's Q – measures whether a firm or an aggregate market is relatively over- or undervalued.

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Appendixes

Appendix 1. Breakdown of Companies by Countries

Country	Brazil	Russia	India	China	Total
Communication services	2	2	3	15	**22**
Discretionary consumer goods	5	1	8	30	**44**
Fast-moving consumer goods	4	3	10	7	**24**
Power industry	2	6	3	8	**19**
Health care	4	0	20	9	**33**
Industry	4	2	8	25	**39**
Materials	7	6	19	26	**59**
Information technology	0	0	6	16	**22**
Utilities	10	5	4	6	**25**
Total	38	25	81	142	286

Appendix 2. Description of Variable

Variable	Description	Resource
Ln_markcap	Natural logarithm of corporate market capitalisation	Bloomberg
Ln_roa	Natural logarithm of return on assets (net profit/total assets)	Bloomberg
Ln_roe	Natural logarithm of return on equity (net profit/equity)	Bloomberg
CSR presence	Presence of a company in the RobecoSAM rating	Bloomberg
Rating	Score assigned to a company by the RobecoSAM rating	Bloomberg
ESG disclosure	General score of CSR information disclosure assigned by Bloomberg analysts	Bloomberg
Size	Natural logarithm of corporate total assets	Bloomberg
Leverage	Natural logarithm of corporate financial leverage (long-term liabilities/equity)	Bloomberg
Growth rate	Corporate profit growth rate	Bloomberg
Women on board (div_board)	Percentage of women on the board of directors	Bloomberg
Power_dist	Power distance index	Hofstede insights
Indulgence	Indulgence	Hofstede insights

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Bankruptcy Prediction for Innovative Companies

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Abstract

The main purpose of this article is to identify the best neural network model algorithm and relevant set of variables for predicting financial distress/bankruptcy in innovative companies. While previous articles in this area considered neural network analysis for large companies from primary sectors of the economy, we take the novel approach of examining the less-explored area of innovative companies.

First, we complete a comprehensive review of the relevant literature in order to define the best configuration of factors which can influence bankruptcy, network architecture and learning methodology. We apply our chosen method to a sample of companies from around the world, from industries which are considered innovative, and identify the dependence of bankruptcy probability on a set of factors which are reflected in the financial data of a company.

Our evaluation is based on the financial data of 300 companies – 50 of them are bankrupts, and 250 are 'healthy'. Our results represent the set of relevant factors for bankruptcy prediction and the appropriate neural network. We have applied a total of 19 factors characterising efficiency, liquidity, profitability, sustainability, and level of innovation. Our proposed analysis is appropriate for all sizes of companies. We provided two models in order to cater for the most confidence in terms of obtained results.

The total predictive ability of the model developed in our research is almost 98%, which is extremely efficient, and corresponds to the results of the most modern methods. Both approaches demonstrated almost the same level of influence of factor groups on final bankruptcy probability.

Keywords: bankruptcy, innovative companies, multivariate discriminant analysis, bankruptcy prediction, efficiency, liquidity, profitability, sustainability, innovation

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Introduction

At the beginning of the twentieth century, the world economy was faced with a large number of crises. This fact is obviously related to the rapid development of different branches of the economy. World GDP and technological innovation is growing faster than at any previous time in history. As a result, business cycle recessions have destroyed many companies and driven many more to bankruptcy. There are several causes of corporate financial distress and it is a difficult concept to define, but it is possible to reveal factors which can be a signal to impending bankruptcy. The definition of the pre-bankrupt condition is a crucial issue for the timely prevention of distress. There are several models which predict bankruptcy with very high accuracy, however, as we consider in greater detail below, such models are oriented on the basis of large industry sectors such as oil, gas, trading, or the entire economy as a whole. Such models are not effective predictors for companies from the most unsustainable economic sectors, e.g. companies to innovative industries. These companies have the highest bankruptcy risks because they necessitate the exploration of unknown economic areas and the creation of new products without any guarantee of profit. High expenditure in terms of research and development (R&D) decrease the free cash flow of innovative firms, and can leads to financial unsustainability and higher distress risk, although not necessarily. The high levels of R&D expenditure can also lead to successful strategic decisions which can improve the company's financial condition. Such expenditure is, in principle, warranted in the innovative sector, as innovative companies invent new technologies, which can improve life quality worldwide. Currently, there are no research studies which contain an adequate model for bankruptcy prediction of innovative companies. This is the reason why the current research is so relevant. The pre-bankrupt condition can be identified by the combination the presence of a set of formal financial factors, and defining this, particularly for innovative companies, is crucial to our task. As such, our research aims to help such innovative companies identify the relevant factors defining a pre-bankrupt condition in their sector.

The *main purpose* of this article is to choose the best neural network model algorithm and relevant set of factors for predicting the financial distress of innovative companies. Our proposed analysis is appropriate for all sizes of companies. It was conducted because the sample is rather small, and division can spoil the network studying.

To complete our task, it is necessary to address a set of issues: to analyse the research studies of previous years from the earliest to the latest, and to trace the development of knowledge in this sphere; to gather the relevant data for so-called 'healthy' companies and for bankrupt companies and identify an appropriate point indicating the beginning of financial distress; to convert this raw data to a data set which is convenient for analysis, to delete the missing values and to calculate the financial ratios and other variables which constitute factors of innovative corporate bankruptcy; to construct neural networks with different settings (e.g. according to architecture, factors, learning algorithm) and choose the most relevant algorithm with the highest forecasting accuracy and the lowest error; and finally, to construct a financial distress prediction model.

The object of this research is a sample of companies from around the world, from industries which are considered innovative. The subject of this article is the dependence of bankruptcy probability on the set of factors which are reflected in the financial data of a company.

The novelty of current research is that the previous articles in this area considered neural network analysis for large companies from primary sectors of the economy. These tend to be complicated models, which mix different tools such as neural network, regression analysis, multivariate discriminant analysis (MDA), and genetic algorithms, but innovative companies, being the most affected by market fluctuations, have not been adequately considered. On a related note, we selected a global sample of companies, because when restricted to the Russian economy alone, there are not enough companies to run the appropriate analysis.

We will analyse the provided data of 300 companies. 50 of them are bankrupts, and 250 are 'healthy'. Our results represent the set of relevant factors for bankruptcy prediction and the appropriate neural network.

Literature review

Since 1968, when the first and the most famous research paper in financial distress forecasting appeared [1–2], methodological approaches in this sphere have run in two directions: market-based methods and accounting based methods.

The market-based models

The market-based approach usually applies the Black – Scholes formula [3] in terms of call-option as a foundation for further analysis. The assumptions behind this method involve a classical version of option valuation theory: i.e. the value of the main variable corresponds to the Brownian motion value of dependent variables as normally distributed. The main factors for market-based models include: firm value, equity value, debt value, volatility of firm value, risk-free rate, and dividend payments.

As can be noticed all the variables can be seen by all people from the financial market. This is the reason such models are titled 'market-based'. The mathematical apparatus can be very complicated for such models, but the idea of defining the financial condition of a company is very straightforward. Quite simply, there is some threshold combination of variable values which gives the estimation of bankruptcy probability. Merton [4] created the first model with a minimal factor set, and subsequently many researchers improved upon this model by imposing new factors [5–9].

The main advantages of this group of methods are the necessity for small amounts of inputted information, availability for almost all people and also presence of a large number of special computer programs, which allows to calculate financial distress probability very quickly. The disadvantage of such methods is a low predictive ability and an incapability to vary according to different external conditions.

The accounting-based models

The second type of bankruptcy prediction model is accounting based. Two scientists developed this forecasting direction almost at the same time: Beaver [10] and Altman [1]. Altman's article became so popular that modern researchers often refer to it. Altman's approach used multivariate discriminant analysis (MDA) and ran a regression with five factors. The main factors for accounting-based models includes: profit / total assets; profit + taxes / total assets; sales / total assets; equity /liability; working capital / total assets.

After estimating the coefficient for each of these factors, Altman calculated the Z-score and compared it with critical statistics to make a conclusion about financial sustainability of a particular company. This article has motivated other financial distress experts to create predictive models [11]. Extended models have been in development for a long time, and many additional factors were included in MDA. Different factor combinations have been tested, but the predicting accuracy has not exceeded 75–80%.

The described methods have the advantage of simplicity in calculating bankruptcy score and interpreting results. They can be applied across a range of company types, industries, or economic conditions and can accommodate the inclusion of new factors for multivariate discriminant analysis. Some disadvantages of this method are that different samples can show very different results and on average demonstrate quite low predictive ability. However, this does not mean that such models are useless- in fact, the factors used to build them can be used to develop more advanced predictive approaches. The same factors are used in almost all papers devoted to financial distress prediction with neural network analysis as they give the highest accuracy in forecasting. In this paper, the development of artificial network analysis is considered the most effective method to approach evaluation.

The neural network models

The usage of neural networks for analysing financial distress prediction began with the article of Odom and Sharda [12]. The researchers built a neural network with 2-layer perceptron (MLP) and applied the learning algorithm of backpropagation. The input factors were the same as in the modified Altman model. The factors used in the modified Altman's bankruptcy model include: EBIT / total assets; equity / debt; sales / total assets; working capital / total assets; retained earnings / total assets.

The purpose of Odom and Sharda's article was to compare the predictive ability with the factor set of described neural network and classical MDA model. The data sample was not so large. It comprises 129 large companies from Moody's database, one half of which are bankrupts, with the rest being 'healthy'. The empirical study results demonstrate the superiority of neural network-based analysis to the MDA model in such aspects as prediction accuracy (79% against 75%), and the robustness of received estimations.

This research showed that there is a more efficient method than the MDA. For the next five years, scientists experimented with changing the factor combination and adding factors to improve the neural network model [13–15]. As a result, the authors managed to increase the predictive accuracy to approximately 80–83%.

It was obvious that corporate bankruptcy prediction required innovative, more convenient approaches to neural network analysis, and the thrust of the research focused on the integration of existing forecasting methods. Lee, Han & Kwon [16] combined neural networks, MDA, and decision trees in their research. They distinguished and compared the predictive ability of five models: MDA, decision trees, neural network with factor selection algorithm based on MDA, neural network with factor selection algorithm based on decision tree, and neural network with a self-organising Fisher's maps (SOFM). MDA and decision trees demonstrate very poor accuracy, about 70–75%. The main interest of their research is the comparison of the quality of three neural network models. The novelty of the research paper is its introduction of an unsupervised learning algorithm. It is widely recognized that in general there are two types of learning algorithm – supervised and unsupervised. The supervised algorithm is the most popular for forecasting. The backpropagation (BP) and learning vector quantisation (LVQ) are related to the supervised method. While SOFM is unsupervised. Lee, Han & Kwon invented a new methodology, combining the SOFM and LVQ, and this model has demonstrated its superiority in comparison to MDA and decision trees-based neural networks. The algorithm of this innovative approach is rather complicated. At the first stage, the neural network with SOFM algorithm factors are allocated to clusters which can reflect almost the same influence on financial sustainability according to input data. The second stage is the neural network analysis with an LVQ learning algorithm. This is needed for choosing the most appropriate variables inside each cluster. The third stage of analysis entails constructing the neural network for defining the most relevant clusters for the sample. The last stage of empirical analysis involves drawing conclusions about whether the company is bankrupt or not. This research was based on a sample of Korean firm data from 1979 to 1992. All companies were arranged according to size and by the value of assets. 58 factors were taken from six spheres: profitability, firm growth, cash flow, stability, activity, and credibility. As a result, the forecasting accuracy of 80.5% was identified, which is greater than other approaches.

The research of Jo, Han and Lee [17] once again proved the superiority of neural networks. They provided a comparison of MDA, case-based approach and neural network. Where previous researchers used linear or hyperbolic tangent activation function, Jo & Han used sigmoid, which is known today as the greatest resource for predicting bankruptcy. Another novelty is that authors have constructed 36 samples with the data from 1991–1993 for Korean companies. They vary in terms of forecasting period from one to three years. This represents the first research study taking in account the number of years before bankruptcy. As a result, the best forecasting accuracy was rated at a level of approximately 84%.

Yang, Platt and Platt [18] proposed a new type of neural network prediction architecture for financial distress. If all previous authors use multilayer perceptron (MLP) and varied only the learning algorithm, Yang, Platt and Platt used probabilistic neural network (PNN) which is one of a kind of radial basic function (RBF). This type of network is known to be better suited for classification issues. The data sample consists of gas and oil industry companies from the USA over the period of 1984–1989. This methodology exceeds the predictive power of MLP neural networks and especially MDA.

A significant research study which answers questions about the best existing neural network model is the paper of Charalambous, Charitou & Kaourou [19]. They built neural network to define the influence of 7 factors. Factors from the Charalambous, Charitou & Kaourou model include current liabilities / total assets; cash / total assets; long term debt / total assets; operating income; change in cash flow from operations / equity value, change in account receivables; working capital / equity value.

These factors include a comparison of a feedforward neural network architecture with a backpropagation learning algorithm, with a conjugate gradient algorithm, the radial basis function architecture (RBF) with the backpropagation algorithm and the MLP architecture with a combination of SOFM and LVQ. As a result, almost 90% accuracy was obtained for this neural network type. According to the authors, this approach is the most accurate currently in existence.

A number of other research studies approve the fact of superiority of neural network prediction against MDA and other approaches. A Spanish sample was used by Olmeda and Fernandez [20] for predicting financial distress by MDA, decision trees, and an MLP neural network. The latter showed the greatest forecasting power, with 83%. The same accuracy was obtained by Piramuthu, Raghavan and Shaw [21] which analysed the financial sector with MLP. Zhang [22] created the MLP with three hidden layers to predict bankruptcy for Korean firms with Altman's factors. They managed to produce results at 88% accuracy.

Koh and Tan's research [23] studies MLP neural network and profit regression analysis. This concludes that the predictive power is the same for both methods at a 92% level. Hybrid neural network models were constructed in papers of Yang [18] and Yim and Mitchell [24]. Both research studies obtained 95% accuracy. Data from Hungarian companies was introduced in the paper by Virag and Cristofs [25] in the context of a model quality comparison, using a neural network and a math statistical model. The neural network showed superior results.

Tsai and Wu [26] considered the use of an MLP neural network with one hidden layer. Researchers tested different nodes on this layer, numbered from 1 to 13. The analysis result demonstrates superiority of the 3-nodes MLP to other cases.

Kim and Kang [27] provided a comparison of an MLP neural network with three different learning algorithms: backpropagation, boosting, and bagging. The data sample was composed of Korean companies, and more than 30 factors were selected from seven types of firm's information, including: size, liquidity, leverage profitability, debt coverage, activity, and capital structure. As a result, the bagging algorithm produced the best quality results.

Zhou, Lai and Yu [28] included macroeconomic indicators beside a firm's financial ratios in their analysis. They compare MLP neural networks in the presence of macroeconomic variables. The set of variables are show in Table 1. The extended model demonstrated superior results in accuracy.

Table 1. Factors from Zhou, Lai and Yu model

Equity / Total Assets	Dividend	Sales / Cash
Net Income / Net Sales	Total Debt / Total Assets	Current Liabilities / Total Assets
Cash Flow / Total Assets	Current Assets / Total Assets	Long Term Debt / Total Assets
Cash Flow / Total Debt	Retained Earnings / Total Assets	ROA
Current Ratio	Working Capital / Total Assets	Current Assets / Current Liabilities
Cash / Total Assets	Total Assets	Net Income / Equity
Net Income / Sales	Current Assets / Sales	Working Capital / Sales
Fixed Assets / (Equity + Long Term Debt)	GDP	Consumer Price Index
Personal Income Index	Money Amount	

Kasgari et al. [29] conducted another comparison of an MLP neural network with a probit-regression model. They use only four factors, including sales divided by current ratio, operating income divided by sales, current assets divided by total assets, and total debt divided by total liability. The neural network correctly predicted 87% of bankruptcies, which is higher than the figure for the probit model.

Makeeva and Bakurova [30] compared a neural network with logistic regression using factors from four spheres, including financial leverage, profitability, liquidity, and turnover with a sample of Russian oil and gas industry companies. The most important parameters reflected profitability. As a result, the neural network gave 98% accuracy, better than the logistic model.

Yasnitsky et al. [31] ran a neural network analysis checking the probability of bankruptcy in banks. There were 15 qualitative and quantitative parameters. The accuracy of this model is higher than 90%, which is a great result for such an inconsistent industry.

Azayite and Achchab [32] used data from Moroccan companies and a factor set from a modified Altman's model to construct a hybrid model. The MDA regression helped to identify the best factors for a neural network. An MLP with a backpropagation learning algorithm helped to build the financial distress function, and the neural network calculated the bankruptcy probability with an SOFM algorithm. The distinguishing feature of this research is that the failure of firms has been predicted in 1, 2 and 3 years before the initial moment of bankruptcy. The hybrid model allowed for obtaining the best result for the Altman's factor set. The final prediction accuracy is approximately 95%.

Azadnia, Siabi and Motameni [33] tested the fuzzy neural network approach on a data sample of gas and oil companies from Tehran, and produced a prediction accuracy of 99%. They run an MLP with 3 hidden levels. More than 15 factors from four areas (productivity, asset quality, profitability, and sustainability) were selected.

The main research studies in neural network bankruptcy prediction were considered above. The summary of models, data samples, and results are introduced in Table 2.

Table 2. Summary of existing models

Year	Authors	Approach	Data set	Results
1990	Odom & Sharda	MDA vs. MLP neural network	129 companies from Moody's database	MLP (79%) is better than MDA
1996	Lee, Han & Kwon	MDA vs. decision tree vs. MLP based on MDA and decision tree with SOFM and LVQ learning algorithm	140 Korean companies	MLP with SOFM and LVQ is better (80.5%)
1997	Jo & Han	Case-based vs. MDA vs. MLP network	Korean companies (1991–1993)	MLP is better (83.8%)
1998	Yang & Platt	PNN with backpropagation vs. MLP network based on MDA	122 oil companies from USA (1984–1989)	PNN is better (84.1%)
2000	Charalambous & Charitou	MLP with SOFM and LVQ vs. RBF vs. Feedforward network with backpropagation vs. Feedforward network with conjugate algorithm	139 pairs of USA companies	Feedforward network with conjugate is better (89.6%)
2012	Kasgari & Divsalar	MLP	Iranian data set	(87%) accuracy
2012	Makeeva & Bakurova	MLP network vs. logistic regression	Gas & oil sector	MLP is better (98%)
2016	Azayite & Achchab	MLP with MDA and SOFM algorithm	Moroccan companies	(95%) accuracy
2017	Azadnia & Siabi	Fuzzy MLP network	Tehran companies	(99%) accuracy

The 'innovativeness' factor

As was mentioned above, the distinguishing feature of the present paper is the forecasting of bankruptcy, and the application of this forecast to innovative companies. It is very important to explain the rationale behind company selection. In this research, only innovative industries were selected for analysis. The following list of relevant industry sectors were taken from the article by Makeeva and Khugaeva [34] and standard industrial classification: drugs; computer and office equipment; electric transmission and distribution equipment; electrical industrial apparatus; household appliances; electric lighting and wiring equipment; household audio and video equipment; communication equipment; electronic components and accessories; miscellaneous electrical machinery and equipment; telephone communication; and computer programming, data processing and other computer related services; research, development and testing services.

The next question concerns the determination of some special factors, which can be significant for innovative companies in particular. Unfortunately, there are no research studies which look at the bankruptcy of innovative companies' using a neural network, but some do exist which use an MDA and costs of financial distress as analytical tools. The first mention of innovative firms in terms of bankruptcy probability was made by Opler and Titman [35]. They examined the financial distress of innovative companies, but there were no special factors which distinguished high-tech companies.

A more relevant research method is offered by Zhang [22]. He tried to answer the question about the presence of relationship between the R&D expenditure and bankruptcy probability. The Altman's Z-score was used for this purpose. Authors estimated four regressions with four different innovative company's indicators, including R&D expenditure divided by total assets, by sales, by number of employees, and by R&D capital. R&D capital was also used in the paper by Jo, Han and Lee [17]. The formula for R&D capital is following:

$$R\,\&\,DCap = R\,\&\,D_t + 0.8R\,\&\,D_{t-1} + 0,6R\,\&\,D_{t-2} + \\ +0,4R\,\&\,D_{t-3} + 0,2R\,\&\,D_{t-4}$$

As can be seen here, the R&D capital is the sum of R&D investments in the current year, and in the previous four years with defined weights.

Bulot also analysed the factors of innovative companies' bankruptcy. Besides the classical factors like liquidity and firm size, he used the R&D investments and change in investment policy like specific innovative factors. As a result, R&D investments makes sense in terms of a firm's sustainability.

The major research study which contains the analysis of almost 300,000 firms was described in by Buddelmeyer, Jensen and Webster [36]. This investigated the dependence between a firm's sustainability, investment in innovation, and other company characteristics. The model factors from [36] includes: market factors, which characterise the economy's growth and the environmental conditions; technical efficiency which also includes innovative factors like R&D expenditure and short-term investment activity; relative profitability of a company within the industry; salary in the company scaled by total assets is a proxy of variable costs; firm's access to finance.

There is no reason to consider these factors in detail, but it is important that innovativeness is used as a bankruptcy factor. The higher the investment in R&D, the more stable the company, according to the research results.

Makeeva and Khugaeva [34] estimated the costs of financial distress of innovative companies. They faced the problem of bankruptcy probability evaluation. Four factors for innovative companies were selected, including R&D expenditure divided by total assets, R&D expenditure divided by sales, R&D expenditure divided by number of employees, and R&D capital, which is defined as the sum of R&D expenditure of previous years, multiply by some coefficient, which was described above.

To sum up, there are a lot of research studies which investigate the impact of a firm's innovativeness on its sustainability and bankruptcy probability, but all of them use regression or MDA analysis, or focus on the costs of financial distress evaluation. The present research, by comparison, mixes a focus on innovativeness with the more powerful neural network analysis.

The different research studies into bankruptcy probability were discussed above. There are a lot of different methodologies for running the neural network analysis, and many factors from different areas of a company's financial results. We will consider the identification and choice of these factors and appropriate methods for empirical analysis.

Methodology and data

The bankruptcy factors

Several models were reviewed above, and in the framework of this research, the most relevant of those factors will now be outlined. Generally, this can be divided into five groups: effectiveness, profitability, sustainability, liquidity, and innovativeness (Table 3).

Table 3. Model factors

Factor	Reason for inclusion in the model	Research studies which used this factor	Anticipated influence sign on distress probability
Effectiveness			
Growth rate of net sales	The positive mean of this variable means the firm has growing demand on its product or service, and is a good sign that the company has a great financial sustainability	Tudor (2015), Piramuthu & Raghavan (1998), Olmeda & Fernandez (1997)	–
Sales / Total assets	This ratio reflects the effectiveness of assets usage	Ligang & Lai (2010), Olmeda & Fernandez (1997), Charalambous & Charitou (2000)	–
Profitability			
Net profit / Equity	These two variables reflect how much money the assets and equity generate	Charalambous & Charitou (2000); Ligang & Lai (2010); Azadnia & Siabi (2017); Makeeva & Bakurova (2012)	–
Net profit / Total assets			–
Gross profit / Sales	This is another group of profitability indicators, and demonstrates which fraction comprises the cost of goods and other productive expenditure in total revenue		–
Net profit / Sales			–
Sustainability			
Equity / Fixed Assets	This parameter demonstrates the coverage of fixed assets by equity, and is associated with lower sustainability and higher bankruptcy probability	Ligang & Lai (2010), Kim & Kang (2009), Piramuthu & Raghavan (1998), Charalambous & Charitou (2000)	+
Working capital / Total assets	Greater working capital related to assets, and is associated with greater ability to close the budget gaps and greater stability	Azayite & Achchab (2016), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Total liability / Total equity	Less debt in relation to assets and equity, usually associated with greater sustainability of a company and, consequently, with less probability of financial distress	Makeeva & Bakurova (2012), Olmeda & Fernandez (1997), Charalambous & Charitou (2000)	–
Total liability / Total assets		Kasgari & Divsalar (2012), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Liquidity			
Cash / Current liabilities	The most liquid asset is cash, which means that greater value of these two ratios associated with greater liquidity and less bankruptcy probability	Azadnia & Siabi (2017); Tsai & Wu (2008), Piramuthu & Raghavan (1998)	–
Cash / Total assets			–

Factor	Reason for inclusion in the model	Research studies which used this factor	Anticipated influence sign on distress probability
Curent assets / Current liabilities	This parameter group demonstrates the coverage of quick liabilities, total debt and total revenue by liquid assets. A greater mean of these ratios is associated with less bankruptcy probability	Kasgari & Divsalar (2012); Ligang & Lai (2010), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Current assets / Total liabilities			–
Current assets / Sales			–
Current liabilities / Equity	Thus parameter has negative influence on financial sustainability of a company		+
Innovativeness			
R&D / Total assets	The main criteria of innovativeness is R&D expenditure, to eliminate the influence of firm's size, this variable are scaled to total assets and sales	Makeeva & Khugaeva(2018), Liu (2011), Zhang (2005), Bulot (2015)	+/–
R&D / Sales			+/–
RD Capital / Total Assets	RD Capital = R&DExp(t) + 0,8R&DExp(t-1) + 0,6R&DExp(t-2) + 0,4R&DExp(t-3) + 0,2R&Dexp(t-4) This is a cumulative variable of R&D expenditure also scaled by the size		+/–

The above analysis on the anticipated impact of each factor on bankruptcy probability allows us to make a hypothesis about the total influence on each factor's group on final forecasting.

Hypothesis 1. *The effectiveness of a company is negatively related to distress probability for innovative firms.*

Hypothesis 2. *The profitability of a company has the same impact sign.*

Hypothesis 3. *Sustainability has a negative impact on financial distress probability.*

Hypothesis 4. *The liquidity of a company has the same impact sign.*

The innovativeness of a company does not have an obvious impact on performance indicators. Higher R&D expenditure usually affects free cash flow, and as a result the company can become incapable of making necessary payments and can face bankruptcy. On the other hand, greater R&D expenditure may help the firm's management to invent some new product or make some improvements in production processes which can enable growth in the firm's market position and, as a result, outperform its financial variables. Consequently, the probability of bankruptcy can decrease. In the framework of this paper, the following hypothesis is proposed:

Hypothesis 5. *Higher innovativeness is positively related to bankruptcy probability, particularly for companies from innovative industries.*

The neural network's learning

This section is considers different neural network methodologies. The neural network is a model of the neural system of a living organism. In contrast to parametric approaches to forecasting, when the connection between different elements is obvious, the network can identify dependence in cases where it is not straightforward. The network has the ability to learn based on real data in order to successfully forecast further work. Neural networks can be divided into two groups: 'supervised' and 'unsupervised'. The majority of articles considered above used the supervised method. The most popular are the backpropagation (BP) algorithm and learning vector quantisation (LVQ). As the unsupervised algorithm is usually self-organising, Fisher's map is used (SOFM). Several other learning algorithms exist besides these, but they are usually used for other issues, and rarely for forecasting bankruptcy. Moreover, they demonstrate less predictive ability and less robustness in terms of result. The classic BP algorithm was used in terms of network construction because the data have been taken for different sizes and company types. There is one danger in the use of the BP algorithm, which is overlearning. This situation is where the model becomes too formal and inflexible and can only classify bankruptcy according to one factor (whereas it is necessary to take all factors into account). The network usually tries to minimise the error, but while searching for the minimum error point it can overlearn. To eliminate this issue, it is necessary to restrict the learning time and check the model quality according to independent data.

Types of neural network architecture

The multilayer perceptron (MLP)

Another issue which should be taken into account is network architecture. There are several types, but the most popular is multilayer perceptron (MLP). It has at least three layers: input, output, and hidden. The input layer consists of factors and take a data with some weight. The next step involves transferring this weighted data to the hidden layer with an activation function. The neurons involved in the hidden layer can then connect with the output layer with another activation function. The output layer calculates the final mean, and a researcher can make a decision about the financial condition of a company. Neural networks usually contain one hidden layer, but in some cases two of them are needed. Three or more layers are used very rarely. The MLP can use BP, conjugate gradient, or delta-delta as a learning algorithm. The most common is BP. It can use four common activation function types: sigmoid, hyperbolic tangent, threshold, and linear function. The most popular is sigmoid function. This methodology has the main disadvantage of tending towards overlearning, but is consistent in application. This means that MLP greatly analyse the data with large number of input factors.

Radial basis function (RBF)

This function type has exactly one hidden layer with radial function, which produces a Gaussian function. The advantages of RBF are that it has only one hidden layer and it is not necessary to select the number of these layers, also such network entails less learning time, which substantially decreases the possibility of overlearning. The main disadvantage of this architecture type is the sensitivity to the number of factors on input layer. As a result, the network quality usually falls.

Probabilistic neural network (PNN)

Yang, Platt and Platt [18] used the PNN and compared its effectiveness with MDA and MLP. They conclude the superiority of the PNN. This neural network type looks like on RBF – it also has only one hidden level and has the same radial function as activation. PNN has a probability of belonging to some category in contrast to RBF. This architecture is the best for solving the classification issues. It seems this network type is the best for our current research, but poses the disadvantage that PNN can result in low forecast quality because the great number of factors mitigates against the choice of MLP, which is universal and more suitable for current issue.

Other network architecture types

It is necessary to consider other widespread neural network types, including general regression (GRNN), linear (LNN) and the self-organising Kohonen's network. The GRNN is not suitable for bankruptcy prediction. LNN is very simple for this issue. The Kohonen's algorithm was used in some papers on this topic but it is very difficult to apply, and not needed for the present research framework.

It is quite challenging to construct the best neural network for a particular issue. Because of this, several types of architecture and activation functions were used to build the most appropriate network. MLP perceptron was tested with 1 or 2 hidden layers with different numbers of neurons, as well as various activation functions: sigmoid, hyperbolic tangent, and the Softmax function from SPSS. To run the network, the computer program IBM SPSS Statistics 24 was used.

Data description

For our neural network analysis, we examined data from 300 companies around the world from the innovative sectors. The sample is divided into two groups: bankrupts and 'healthy' companies. There are 51 bankrupts (17%) and 249 'healthy' firms (83%).

In previous studies an equal proportion of company types was used, but it decreases the model's robustness depending on the choice of sample. Neural networks can predict bankruptcy only where there is an obvious feature of a bankruptcy available to identify. The greater fraction of non-bankrupts with increasing number of observations provide a higher model quality. This is true, because a neural network that can properly classify a bankrupt by a large number of unauthorised bankruptcies is more preferable. Data has been collected for a 6 year period. Thus, we have data on bankrupts for the period of 2012–2017. This long duration was selected because there are not so many companies in these innovative industries which faced with financial distress. The division of companies by bankruptcy is as follows: 2012 – 15, 2013 – 1, 2014 – 8, 2015 – 4, 2016 – 5, 2017 – 8, non-bankrupts – 249.

The division by country is as follows: 126 companies (42%) are from the USA, 66 (22%) – from Canada, 36 (12%) – from China, 21 (7%) – from Japan, 15 (5%) – from South Korea, 36 (12%) – from other countries.

The data sample is divided between 10 industries: computer programming – 117 companies, drugs – 90 companies, communication equipment – 30, electric transmission and distribution equipment – 18, electronic components and accessories – 15, electrical industrial apparatus – 9, R&D and testing services – 6, computer and office equipment – 6, electric lighting and wiring equipment – 6, and household audio and video equipment – 3 (Figure 1).

The observations above are used for our neural network learning and testing sample construction. A total of 37 factors were selected that could affect the likelihood of bankruptcy. The data were taken for two years: a year before the bankruptcy and a year of bankruptcy. Variables and their descriptive statistics are demonstrated in Table 4.

Figure 1. Data sample division by industries

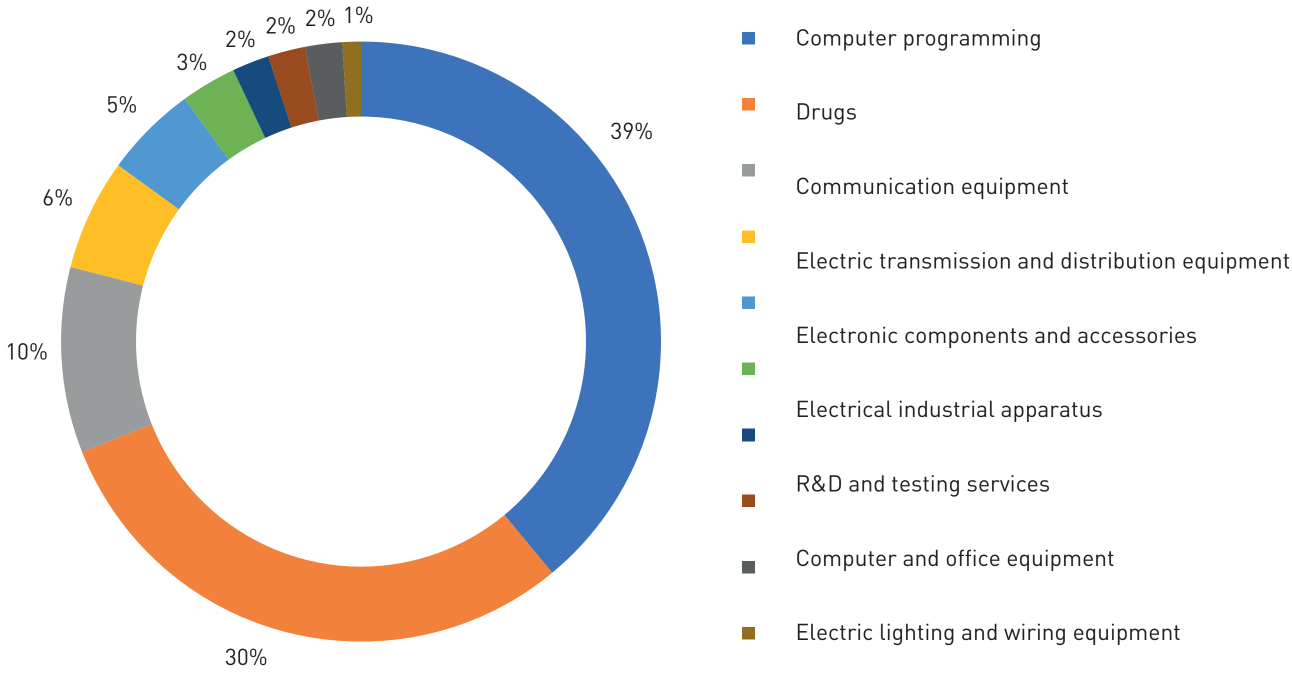


Table 4. Descriptive statistics

Descriptive statistics						
		N	Min Value	Max Value	Mean	St. deviation
BANKRUPT	Bankruptcy	300	0	1	.17	.376
GROW_NS	Growth rate of net sales	295	–.88	11.55	.1524	.79154
GROW_NS1	Growth rate of net sales – 1	295	–3.68	4.93	.0867	.49046
SAL_TA	Sales / Total assets	300	.00	8.06	.8303	.85799
SAL_TA1	Sales / Total assets – 1	300	.00	18.48	.8905	1.31510
NP_E	Net profit / Equity	300	–683.0	210.37	–5.688	55.04891
NP_E1	Net profit / Equity – 1	300	–172.6	11.71	–.7521	10.30278
NP_A	Net pofit / Total assets	300	–11.92	3.63	–.2875	1.23403
NP_A1	Net pofit / Total assets – 1	300	–19.19	3.63	–.3107	1.53507
GP_SAL	Gross profit / Sales	295	–2.90	5.65	.4087	.47648
GP_SAL1	Gross profit / Sales – 1	295	–2.90	5.65	.4154	.47369
NP_SAL	Net profit / Sales	299	–357.8	1.61	–2.606	22.14058
NP_SAL1	Net profit / Sales –1	299	–357.8	1.61	–2.529	21.88535
E_FA	Equity / Fixed assets	295	–2485	433.33	1.0213	153.47650
E_FA1	Equity / Fixed assets – 1	295	–195.5	433.33	9.8318	42.83228
WC_A	Working capital / Total assets	300	–12.00	.86	.1071	1.21998
WC_A1	Working capital / Total assets – 1	300	–17.36	.86	.0302	1.63675
L_E	Total liability / Total equity	300	–171.4	52.28	.4164	10.80219
L_E1	Total liability / Total equity – 1	300	–12.50	55.87	1.2758	5.06943

Descriptive statistics		N	Min Value	Max Value	Mean	St. deviation
L_A	Total liability / Total assets	300	.01	14.13	.7313	1.60268
L_A1	Total liability / Total assets – 1	300	.01	18.05	.7952	1.92696
CASH_CL	Cash / Current liabilities	300	0	19.61	1.0662	1.94487
CASH_CL1	Cash / Current liabilities – 1	300	0	25.57	1.1635	2.18065
CASH_A	Cash / Total asset	300	0	.88	.1984	.17610
CASH_A1	Cash / Total asset – 1	300	0	.88	.2091	.18456
CA_CL	Current assets / Current liabilities	300	.02	31.99	2.7156	3.15632
CA_CL1	Current assets / Current liabilities – 1	300	.01	26.51	2.7648	2.93711
CA_A	Current assets / Total assets	300	.04	1.00	.5876	.22893
CA_A1	Current assets / Total assets – 1	300	.04	.99	.5844	.23206
CA_SAL	Current assets / Sales	299	.03	81.79	1.7277	5.49972
CA_SAL1	Current assets / Sales – 1	299	.01	113.89	1.7283	6.90768
CL_E	Current liabilities / Equity	300	–171.4	36.32	.0948	10.32491
CL_E1	Current liabilities / Equity – 1	300	–5.52	36.32	.8132	3.16743
RD_A	R&D / Total assets	298	0	2151.26	15.768	139.76863
RD_A1	R&D / Total assets – 1	298	0	2204.48	14.413	137.25719
RD_SAL	R&D / Sales	297	0	79061.1	272.77	4587.37140
RD_SAL1	R&D / Sales – 1	297	0	81017.0	282.31	4700.93926
RDCAP	RD Capital / Total assets	297	0	23282.0	439.22	2200.31142
N valid	Bnkrpty File Dt	286				

The minimum and maximum values for each variable for bankrupts and non-bankrupts are presented in Table 5.

Table 5. Minimum and maximum values separately for bankrupts and non-bankrupts

Variable	Bankrupt		Non-bankrupt	
	Min	Max	Min	Max
GROW_NS	–0.88112	4.926324	–0.56961	11.5467
GROW_NS1	–3.67774	4.926324	–0.88024	3.094905
SAL_TA	0	5.685619	0.02721	8.061818
SAL_TA1	0	18.48214	0.007803	8.061818
NP_E	–683.041	11.7094	–172.632	210.3704
NP_E1	-14.813	11.7094	–172.632	0.873351
NP_A	–11.9189	3.63125	–3.24752	0.323625
NP_A1	–19.188	3.63125	–3.24752	0.323625
GP_SAL	–2.9	5.647026	–0.11614	0.966102
GP_SAL1	–2.9	5.647026	–0.11614	0.960938

Variable	Bankrupt		Non-bankrupt	
	Min	Max	Min	Max
NP_SAL	–357.835	1.607192	–50.2368	0.613509
NP_SAL1	–357.835	1.607192	–56.362	1.027454
E_FA	–2485	311.5442	–195.592	433.3333
E_FA1	–161.481	311.5442	–195.592	433.3333
WC_A	–11.9957	0.726	–9.10191	0.859479
WC_A1	–17.3644	0.706875	–9.10191	0.855117
L_E	–16.1891	22.6082	–171.481	52.2807
L_E1	–12.4957	22.6082	–1.07746	55.86709
L_A	0.037827	14.12834	0.011731	13.56984
L_A1	0.096296	18.05416	0.011434	13.56984
CASH_CL	0	13.36595	0.006046	19.60759
CASH_CL1	0	7.490566	0.006046	25.57322
CASH_A	0	0.840932	0.004492	0.882122
CASH_A1	0	0.840932	0.005389	0.882122
CA_CL	0.019171	16.64209	0.049778	31.99091
CA_CL1	0.01245	10.16735	0.049778	26.51117
CA_A	0.040431	0.99894	0.059751	0.972441
CA_A1	0.040431	0.987842	0.047756	0.978232
CA_SAL	0.030588	81.78959	0.059144	9.214689
CA_SAL1	0.007488	22.4529	0.059144	113.889
CL_E	–16.161	12.12195	–171.481	36.31579
CL_E1	–5.51718	12.12195	–0.76056	36.31579
RD_A	0	4.174721	0	2151.261
RD_A1	0	4.174721	0	2204.482
RD_SAL	0	77.4717	0	79061.15
RD_SAL1	0	77.4717	0	81017.09
RDCAP	0	892.4	0	23282

All factors which have the negative anticipated relationship with bankruptcy probability demonstrated less minimum values for bankrupts than for non-bankrupts. Variables which have the positive connection: L_A and L_E have less value for non-bankrupts, which is logically reasonable. There is not the same regularity as for the maximum means, but overall non-bankrupts has a higher value for the factors which have a negative anticipated impact on financial distress probability (with the exception of such variables as CA_SAL and CA_A, which represent liquidity). It is also necessary to notice that non-bankrupts have much greater values for parameters which characterise R&D expenditure. This may constitute the signal that R&D has a negative impact on bankruptcy probability.

Econometric analysis and results

Data treatment

Our empirical analysis began with data processing. The raw data contains a lot of missing values. The data division between the bankrupts and non-bankrupts of each year of the analysing period have also been provided. The next step is the calculation of financial ratios for the year of bankruptcy and a year earlier. Only R&D capital scaled by total assets was calculated for the current year, because this parameter has already contained information about the R&D expenditure of previous years. The emission data analysis does not make sense, because the neural network methodology does not require it. The final sample contains 286 valid observations: 14 were excluded by the algorithm. For the data analysis, the computer program IBM SPSS statistics has been used.

Neural network configuration selection

Two architecture types have been tested in the article: RBF and MLP. The first step was to define the best architecture type or its combination to solve the particular problem. The main parameters which aid in selecting the model are the percentage of correctly predicted bankrupts, non-bankrupts, and the error function value. We analysed the following combinations of network architectures:

The classical **MLP** network for all factors described in chapter II, which have been automatically set by the program. Predictive results are outlined below. The model quality is very high: the cross-entropy function produced a very low value; the percentage of correctly predicted companies is high: 98.8% for non-bankrupts and 87.5% for bankrupts on the tested sample (Table 6).

Table 6. Classical MLP model results

Model Results		
Learning	Error: cross entropy	6.596
	Incorrect prediction	0.5%
	Learning time	0:00:00.08
Testing	Error: cross entropy	4.523
	Incorrect prediction	2.2%

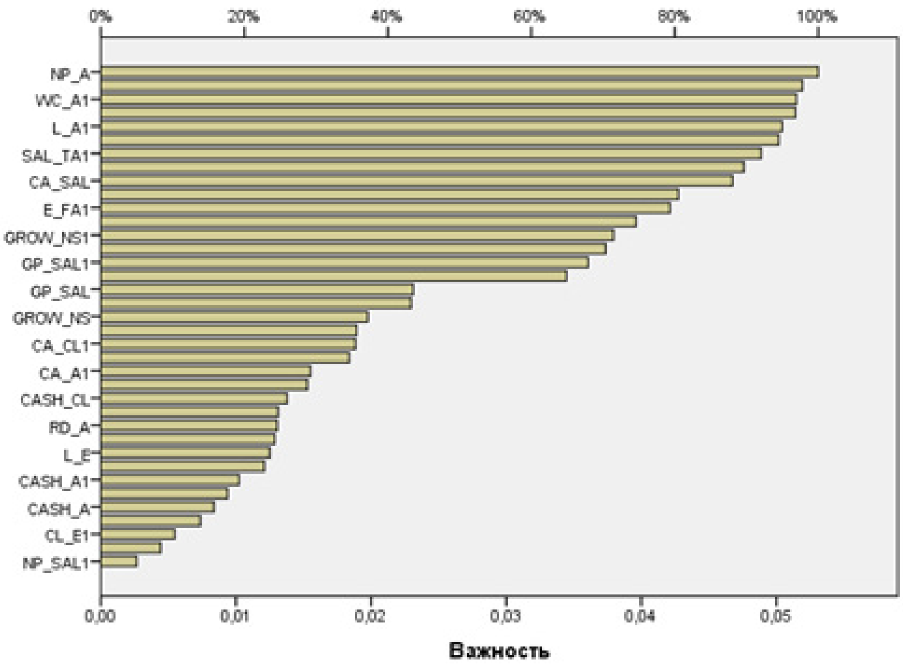
The radial basis function algorithm **(RBF)** was also run for all factors. The 8-neurons RBF demonstrated a lower predictive ability: 93.8% for non-bankrupts and 72.7% for the bankrupts on the tested sample with more prevalent errors than in the previous case. It may be noted that this model is worse overall in terms of all the applied parameters (Table 7).

Table 7. RBF results

Model Results		
Learning	Error: sum of squares	15.662
	Incorrect prediction	11.3%
	Learning time	0:00:01.69
Testing	Error: sum of squares	4.864[a]
	Incorrect prediction	8.7%

The MLP with only important parameters **(2-step MLP)**. According to this model the most important factors showed by the first MLP model were included in the network. They are introduced below. The program has automatically selected the optimal algorithm, but the accuracy is lower than in case 1 above: 100% accuracy for non-bankrupts and 67.5% for bankrupts. The model quality is also lower than for MLP with all factors (Figure 2).

Figure 2. Normalised Importance for RBF



The RBF with the most important factors, selected by MLP **(MLP-RBF)**. It is known that RBF can predict better with low quantity of input variables. As was stated below, the high dimension dramatically decreases the model quality of RBF. To improve this model, the selection algorithm based on MLP was used. This network demonstrated the lowest result from all models. The error function value is also very large (Table 8).

Table 8. MLP_RBF results

Model Results		
Learning	Error: sum of squares	18.878
	Incorrect prediction	11.8%
	Learning time	0:00:00.85
Testing	Error: sum of squares	7.435[a]
	Incorrect prediction	13.0%

The MLP and RBF, using separate factors for the year of bankruptcy and one year before the bankruptcy. There are 4 different models in total. We do not need to describe all these neural networks in detail because all of them demonstrated a much lower quality of model and predictive accuracy. It is necessary to check the decreased dimension models, because in some cases this can improve the result, but according to analysed data it did not produce a positive result.

The analysis which has been run above allows us to conclude that the MLP neural networks are better than the RBF for this particular issue. The main reason is that the number of the factors is rather large, while the methods of dimension decreasing did not improve the results. Another question is the usage of probabilistic neural network (PNN), which was created for solving classification issues. This approach has an RBF framework, and consequently is inappropriate for the present study, which involves a great number of input factors.

MLP architecture selection

It was decided that simple MLP is the best approach to analysing innovative company bankruptcy probability. MLP can have different kinds of architecture, and for this study all combinations were tested, and the best performing were selected. We can vary the following parameters: the activation function on the hidden layer, on the output layer, the number of the hidden levels, the quantity of neurons on each level. The activation function on the hidden level can be the hyperbolic tangent or sigmoid. The choice of activation function on the output layer is wider, and to that end, to the previous two functions were added identical and softmax functions. For the sake of convenience, all these functions are introduced in Table 9.

Table 9. Activation function types

Activation function	Description
Identical	$F(x) = x$
Sigmoid	$f(x) = \left(1 + e^{-x}\right)^{-á}$, α > 0, The most common function of this type is logistic function
Hyperbolic tangent	$f(x) = \frac{\left(e^{x} - e^{-x}\right)}{\left(e^{x} + e^{-x}\right)}$
Softmax	$f_i(x) = \frac{e^{x_i}}{\sum_{i=1}^{J} e^{x_i}},\ i = 1,\ldots,J$ This is generalised for multidimensional case of sigmoid function. In some case it can help to maintain better model quality.

It may be supposed that the identical function is worse than others for output layer activation function because of non-trivial dependence. For the completeness of the analysis all these functions have been tested.

Another parameter which can be variable in its effects is the layer quantity. For the purposes of forecasting, one or two hidden layers are used. After more than 200 iterations, two optimal configurations of architecture were defined.

MLP with one 4-neuron hidden layer, activation function for hidden layer is hyperbolic tangent, and for output layer Softmax is used. The correctly predicted variables are presented in Table 10. The cross-entropy value is 6.6 for the testing sample and 4.5 for tested. This small error value indicates that the quality of the model is excellent. Moreover, reducing the error value is an excellent feature of network power prediction.

Table 10. One hidden layer MLP results

	Observed	Predicted		
		0	1	Correctly
Learning	**0**	167	1	99.4%
	1	0	29	100.0%
	Total	84.8%	15,2%	99.5%
Testing	**0**	80	1	98.8%
	1	1	7	87.5%
	Total	91.0%	9,0%	97.8%

The most important factors are from all the main divisions of economic parameters of a company: profitability, effectiveness, sustainability, liquidity and innovativeness. They are arranged in descending order of importance in terms of predictions, but all of them are included in the top set of values. The neuron weights for the most significant factors are presented in Table 11.

Table 11. One hidden layer MLP estimations

Predictor	Predicted					
	Hidden layer 1				Output layer	
	H1:1	H1:2	H1:3	H1:4	[BANKRUPT=0]	[BANKRUPT=1]
Input layer	**GROW_NS1**	–.098	.126	.642	.293	
	NP_E	–1.07	1.00	.823	.737	
	NP_A	–1.02	.122	–.168	.345	
	NP_SAL	–.877	.255	.142	–.147	
	E_FA1	.496	–.201	.338	–.753	
	L_A1	.785	–1.02	–.343	–.305	
	CA_SAL	–.022	–.467	.162	–.738	
	RD_A	–.613	.382	.706	.071	
Hidden layer 1	**H1:1**					–1.153
	H1:2					1.540
	H1:3					1.237
	H1:4					2.018

The negative mean of neuron weight means that the increasing value of input mean decreases the output value. On the other hand, it reflects negative relationships between the dependent variable and a covariate. The positive value indicates a positive relationship. We shall here explore in detail the defining of dependence between NP_E and bankruptcy probability. The neuron on the hidden layer, which has a positive relationship with higher financial distress probability is H (1:1), because of its positive value, other neurons have a negative impact. The NP_E has a strictly negative correlation with neuron H (1:1). It can be concluded that NP_E has a negative connection with bankruptcy probability. It means that the variable NP_E and the company's profitability is the factor which decreases the bankruptcy probability. NP_A and NP_SAL, which also reflect profitability, have the overall effect of decreasing distress probability. The GROW_NS1, which reflects the firm's effectiveness also has the negative relationship with bankruptcy probability. L_A and E_FA1 are the variables from the sustainability sector, but the higher mean corresponds to lower sustainability. The dependence of these factors on bankruptcy probability is positive, and consequently the higher sustainability decreases such dependence. CA_SAL is the liquidity factor. Correspondingly to neuron weights it does not have definite influence, but the total impact is more likely positive than negative on bankruptcy probability. Nevertheless, the influence of liquidity is much less than the impact of profitability. RD_A variable is the innovativeness factor. It has a definite impact on distress probability, which is negative. To sum up, according to this model of the neural network, hypotheses 1, 2 and 3 are not rejected, while hypotheses 4 and 5 are rejected.

MLP with 2 hidden layers, 5 neurons in layer one and 4 in layer two, activation function for hidden layer is sigmoid, and for output layer Softmax is used. The cross entropy is 9.128 for the learning sample and 5.097 for testing sample. It is not significantly higher than in the previous network. The total accuracy is also less overall, but the main advantage of this model is that it has the highest value for correctly predicted bankrupts – 91.7%. The results of all samples are presented in Table 12.

Table 12. Results for MLP with two hidden layers

	Observed	Predicted		
		0	1	Correct
Learning	**0**	181	3	98.4%
	1	0	25	100.0%
	Total	86.6%	13.4%	98.6%
Testing	**0**	64	1	98.5%
	1	1	11	91.7%
	Total	84.4%	15.6%	97.4%

The variables from profitability, liquidity, sustainability, effectiveness and innovativeness are among the most important factors in terms of prediction accuracy, but the order of importance has a different sequence than in previous models. The table listing the influence coefficients on bankruptcy for the main variables is introduced in Table 13.

Table 13. Two hidden layers MLP factor impact

Factor	Influence
NP_E	35.80942
NP_A	54.17096
L_A	–102.832
RD_A	28.66417
GROW_NS1	27.67251
NP_SAL1	25.55392
WC_A1	40.76026

As can be noticed, profitability again negatively correlates with distress probability: NP_E, NP_A and NP_SAL1 have positive coefficients in relation to the output neurons for non-bankrupts. L_A has a negative coefficient, meaning unsustainability has a negative effect. Consequently, sustainability has a positive impact. Efficiency, Liquidity and innovativeness has also negative influence on bankruptcy probability. To sum up, profitability, effectiveness, and sustainability have a negative impact on bankruptcy probability, as was assumed in our hypothesis. Liquidity has been demonstrated to have a strictly negative impact in the second model, and to not have a strictly defined effect in the first model. As such, we can conclude that there is an overall negative impact on the likelihood of distress. The innovation hypothesis was rejected by both models, and it also has a negative connection. The representation of diapasons for the most important factors for bankrupts and non-bankrupts is presented in Table 14.

Table 14. The ranges for bankrupts and non-bankrupts for the most important variables

NP_E				
Range	Bankrupt		Non-bankrupt	
	Frequency	Percent	Frequency	Percent
–3.67773696	18	35,3	2	0,8
–1.95692485	1	2,0	5	2,0
–0.23611274	8	15,7	25	10,1
1.48469937	16	31,4	215	86,7
3.20551148	4	7,8	0	0,0
4.92632358	4	7,8	1	0,4
	51		248	

CA_SAL				
Range	Bankrupt		Non-bankrupt	
	Frequency	Percent	Frequency	Percent
0.03058824	1	2,0	0	0,0
16.3823882	45	90,0	249	100,0
32.7341881	2	4,0	0	0,0
49.085988	1	2,0	0	0,0
65.4377879	0	0,0	0	0,0
81.7895879	1	2,0	0	0,0
	50		249	

L_A				
Range	Bankrupt		Non-bankrupt	
	Frequency	Percent	Frequency	Percent
0.01173083	0	0.0	1	0.4
2.83505311	44	86.3	247	99.2
5.6583754	3	5.9	0	0.0
8.48169768	0	0.0	0	0.0
11.30502	1	2.0	0	0.0
14.1283422	3	5.9	1	0.4
	51		249	

RD_A				
Range	Bankrupt		Non-bankrupt	
	Frequency	Percent	Frequency	Percent
0	8	16.3	49	19.7
430.252101	41	83.7	197	79.1
860.504202	0	0.0	1	0.4
1290.7563	0	0.0	1	0.4
1721.0084	0	0.0	0	0.0
2151.2605	0	0.0	1	0,.4
	49		249	

GROW_NS1				
Range	Bankrupt		Non-bankrupt	
	Frequency	Percent	Frequency	Percent
–3.67773696	1	2.2	0	0.0
–1.95692485	0	0.0	0	0.0
–0.23611274	2	4.3	22	8.8
1.48469937	42	91.3	226	90.8
3.20551148	0	0.0	1	0.4
4.92632358	1	2.2	0	0.0
	46		249	

.

The distribution of observations across all ranges is almost the same for all the most important factors. The L_A factor which characterises a company's unsustainability is more likely greater for the bankrupt, which is logically explainable. CS_SAL presents the liquidity and it can be noticed that all non-bankrupts have almost the same level of this parameter, while for the bankrupts means are variously distributed across the ranges. We may conclude that profitability is the most important factor for NP_E as the distribution of values for bankrupts are closer to the lowest range, while healthy firms indicate a higher average mean.

Checking model quality

In the framework of this research, our model's validity needs to be approved. What are the major arguments that these two models can strongly predict distress? First, the demonstration by two different neural networks of practically identical results in terms of influence and importance allows us to conclude that the model is of high quality. Second, the values of the error function and the prediction accuracy are at a high level. But it is not enough to be confident in the quality of the model. There is one problem that remains: that dependence is obvious and a neural network is not needed to predict bankruptcy. In many articles, for example Lee, Han & Kwon (1996) a decision tree analysis was imposed in order to exclude this possibility. In this paper the random forest analysis is provided to prove the model quality. The results are shown in Table 15.

Table 15. The random forest prediction results

Model Results			
Observed	Predicted		
	0	1	Correctly
0	249	0	100.0%
1	51	0	0.0%
Total	100.0%	0.0%	83.0%
Approach: CHAID			

As can be seen here, 83% is the final accuracy level for the decision tree, against more than 98% by both neural networks. The quantity of correctly predicted bankrupts is zero. This fact lends credence to the argument that the neural network is a quality model with great predictive power for both categories. The final question is the choice of the most powerful model among those provided above. Both networks have great predictive power, as well as advantages and disadvantages. To receive a more accurate result for non-bankrupts the first model is preferable, while the second network is more appropriate for predicting bankruptcy.

Conclusion

In recent years, research studies on financial distress predicting have been devoted to increasing forecasting power. Many new combined methods have been invented: MDA with a neural network, more complex network configuration algorithms, networks based on a genetic algorithm, and many others. The total predictive ability of the model developed in the present research is almost 98%, which corresponds to the results of the most modern methods. The multilayer perceptron gave a great result due to the correctly selected factor set and network architecture. The most important factors have been taken from the best models of the earliest research which we have analysed. Moreover, extra factors have been added which reflect the 'innovativeness' of companies, because the paper's purpose was the prediction of financial distress for innovative companies. We have applied a total of 19 factors characterising efficiency, liquidity, profitability, sustainability, and level of innovation. All these factors have been analysed over two specific years: the year before bankruptcy, and the previous one, with the exception of R&D capital, which was examined only for one year. We provided two models in order to cater for the most confidence in terms of obtained results. The 3-layer MLP is greater for predicting all of a company's conditions, while the 4-layer MLP is greater for bankruptcy forecasting (91% correctly predicted bankrupts). Both approaches demonstrated almost the same level of influence of factor groups on final bankruptcy probability. The first model demonstrates a negative impact in terms of sustainability, profitability, effectiveness, and innovativeness, and an inconclusive result in terms of liquidity. The second model demonstrates a negative influence for all factor groups. The most important factors are profitability, sustainability, and innovativeness. Additionally, the variables NP_A, NP_E, L_A, L_A1, L_E, RD_A, CA_SAL and GROW_NS1 demonstrate the highest importance.

It would be very interesting to continue the development of models for innovative companies. Possible improvements involve the following: the expansion of the sample by adding additional years before bankruptcy, the use of dynamic neural networks to analyse this data sample and the introduction of special algorithms for selecting the most appropriate factor. More accurate predictions were possible only with the use of genetic algorithms and fuzzy neural networks, but previous studies used these approaches only for data samples from non-innovative companies. It would be interesting to apply such approaches on the forecast of financial distress of an innovative company.

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ESG-Risk Factors and Value Multiplier of Telecommunications Companies

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Abstract

The paper is devoted to the study of the impact of environmental, social responsibility and corporate governance (ESG) risk factors on the value of telecommunications industry enterprises expressed through the EV_EBITDA multiplier. The main goal was to assess the elimination of ESG risks from the standpoint of increasing the competitiveness of the company. The methodological basis of the study was the coordination of non-financial information of companies with their financial results. The paper implements the construction of a regression model within the framework of econometric modeling, the direction of which was proposed by A. Damodaran. The authors did not limit themselves to corporate information from one country, but identified five regions, such as the USA, the European Union, the UK, the rest of the developed countries (DEV), as well as the markets of developing countries (EM). The database was compiled on the basis of non-financial business activity parameters of 57 of the world's largest telecommunications companies as of 2021, where financial information is taken from the Bloomberg database, and the ESG risk coefficient of the rating of these companies is used from the Sustainalytics research center. The result of the study was that there is a stable relationship between the risk of the ESG rating and the EV/EBITDA parameter characterizing the cost of capital – that is, the lower the risk, the greater the cost of capital. For different country groups, the result was obtained with varying degrees of confidence: for "other developed countries" with a high 5% significance level, for European countries with a 10% level, for the USA, the insignificance of the coefficient is associated with a small sample size, and for developing country markets the coefficient is insignificant. The novelty of the results obtained lies in the use of a metric approach to confirm the stable dependence of ESG risk factors on the EV/EBITDA cost multiplier. The results obtained allow us to make a generalized conclusion that the elimination of ESG risks contributes to the growth of the company's competitiveness, where the results of the study are able to encourage companies to consider the disclosure of non-financial information as an important indicator of long-term sustainability. When ESG is considered as an integral factor in the future activity of the company, the end result is its higher evaluation by stakeholders.

Keywords: ESG risk factors, value multiplier, telecommunications companies, sustainable development, firm competitiveness

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Environmental, social responsibility and corporate governance factors become integral to operating of both large and small enterprises (SME). At the same time the above factors involve rather tangible risks and opportunities which may influence corporate operations directly in the short and long term. In general, it is necessary to deal with corporate social responsibility (CSR) of an economic entity where ESG is not an abstract set of non-commercial aspects of corporate operations, but rather provisions stated in various CSR standards (voluntary at the moment) which a company has to follow and add to non-financial reports if it aims at sustainable development. It is not surprising that at present the notion of ESG occurs when dealing with consumers as well as investors and a wide range of concerned parties.

In each national economy the telecommunications industry is defined as a special segment of the service industry [1]. This industry is characterized by a high competition and rapid growth of telecommunication networks which makes companies pertaining to this industry rethink constantly their role in the market and implement up-to-date profit generating business models. Our survey of academic literature dedicated to the research topic which included use of information from ResearchGate shows lack of academic research of influence of such relevant factors as ESG factors on the telecommunications industry and risks related to it [2]. Risks in the telecommunications industry are also difficult to assess because there are no methodologies which forecast the threats for such services, and it costs billions of dollars to communications providers [3].

The types of risks from the point of view of their management (ERM) have been classified before for the telecommunications industry in paper [4] where the authors distinguish the following risks: reputational risk, competition risk, requirements compliance risk, technical risk, health risk, country risk, asset impairment risk, liquidity risk, currency risk, counterparty risk, interest rate risk, equity risk, corporate governance risk, human resource risk, repayment risk, market risk, weather risk, fraud risk. As we see, ESG risks have not been classified into a separate group before. It was assumed that although unconventional risks could have an actual impact on corporate financial performance they were considered to be incidental risks, consequently, non-financial ones [5].

Nevertheless, risk management becomes increasingly important for ensuring a long-term efficiency based on protection of interests of concerned parties, integration of economic, competitive, social and environmental achievements and sustainable development [6; 7]. So, McShane [8] uses the finance services industry to analyze the best practices in risk assessment methods while Monda and Giorgino [9] point out limitations in searching for the methods of risk quantitative evaluation in other industries, such as telecommunications. The matter is that recent studies show that companies which meet the ESG requirements have a better management, take more care of the environment and sustainable development, have a lower income volatility and have access to cheaper cash funds [10].

The paper by Friede [11] investigated over 2,000 empirical studies dedicated to disclosure of ESG information and corporate operations and revealed that 90% of studies pointed out a positive relation between ESG compliance and operational performance. As part of proving the interrelation between ESG factors and operational performance a sample of 6,151 observations from the Chinese stock market from 2007 to 2015 showed that social contribution improves response to share prices while an additional analysis shows that corporate governance also improves the extent of disclosure about social contributions of companies [12].

In another research Buallay [13] studies banks in developed and emerging markets and obtains mixed results of ESG influence on performance. It has been established that environmental disclosure has a positive impact on such performance while CSR disclosure in general shows a negative similar relation. Besides, ESG implementation solely for the purpose of reduction in expenditure on loans may eventually contradict the sustainable development concept if companies fail to understand the synergy of their own ESG efforts and the way in which such synergy creates value for their shareholders [14].

At the same time the results on the basis of data on 104 transnational enterprises from Peru, Columbia, Brazil, Chile and Mexico from 2011 to 2015 indicate that a negative relationship between ESG evaluation and financial performance is observed even when analyzed separately [15]. The results obtained on a sample of French companies pertaining to the SBF 120 index from 2003 to 2011 are illustrative of a negative relation between ESG and Tobin's Q for the industries sensitive to the environment [16]. The results of a sample comprising developed countries from a study of 882 banks for the period of 2008 to 2019 show that ESG evaluations are associated negatively to the banks' performance indicator. Apart from that, banks have a smaller competitive advantage when they use their resources for social programs and initiatives (ESG and Tobin's Q) [17].

However, few studies are dedicated to the relation of competitive advantages of a company and its ESG compliance. Some researchers consider competitive advantage as company's ability to gain more economic profit in comparison to its competitors [18]. Results of a recent research of 20 largest pharmaceutical companies for 2014 and 2016 allowed to make a generalized conclusion that useful information obtained on the basis of reconciliation of structured data of financial and non-financial reports (from the Global Initiative database related to reports) facilitates improvement of business activity [19]. As a result of the research the general position of 5 socially responsible companies moved up to the 8th and 6th position in the Index of access to medicines. The results of comparing the growth rate of their total revenue, capitalization and long-term capital was positive in comparison to the growth rate of the quality of disclosure of non-financial indicators by them. Such interrelation was the strongest for raising long-term capital followed by growth of capitalization and at the same time it was the weakest for revenue growth.

Taking into consideration Russian achievements and western studies of fundamental and applied sciences it should be noted that a modern financial expert is increasingly integrated in the Big Data technology. Use of Big Data not just in the financial sector but in general is a logical consistent pattern of technical and scientific advance of recent decades. It is important to state that in spite of a significant change of situation in the recent years the companies still aim at increase of their value, improvement of their investment attractiveness, development and business expansion [20].

Further, we analyze a wide range of complex financial and non-financial parameters of business activity of 57 world top telecommunications companies. We took financial information from the Bloomberg database. We used the ESG risk coefficient of the rating of these companies from the Sustainalytics research center as a parameter characterizing social and environmental responsibility [21].

In order to establish the dependence of the cost of capital of companies on their ecological parameters we used the model offered by A. Damodaran according to which the regression equation is as follows:

$$EV\_EBITDA = a1 \cdot EBITDA\_3Y\_GROWTH + a2 \cdot DEPR\_EBITDA + a3 \cdot CAPEX\_EBITDA + a4 \cdot NWC\_EBITDA + a5, \quad (1)$$

where the variables EV_EBITDA = EV / EBITDA are the cost multiplier which shows the value of business in EBITDA. The matter is that EBITDA (earnings before interest, taxes, depreciation and amortization) is indicative of estimated cash profit which accrues to and may be distributed among shareholders and debtholders. EV is the market value of business where the Enterprise value = market capitalization + net debt value. This multiplier is the most stable and accurate one for assessment of telecommunications companies' value because it does not depend fundamentally on the debt load level unlike, for example, on Price/Earnings (P/E). In the multipliers DEPR_EBITDA = Depr/EBITDA, Depr is depreciation, CAPEX_EBITDA = CAPEX//EBITDA, CAPEX is investment in fixed assets, NWC_EBITDA = delta NWC/EBITDA, delta NWC is investment in working capital.

As long as companies operate in various parts of the world this factor has to be taken into consideration as well. For this purpose, we introduced slack variables which equal 1 if a company operates in a certain region (or country) and 0 – otherwise. The matter is that a limited number of observations prevents us from taking into consideration all country-related differences, therefore we defined five regions: the USA (US), the EU (EU), Great Britain (UK), other developed countries (DEV), markets of emerging countries (EM).

Thus, new variables were added to equation (1) and the final regression equation is as follows:

$$\begin{aligned} EV\_EBITDA = {} & b1 \cdot EBITDA\_3Y\_GROWTH + \\ & + b2 \cdot DEPR\_EBITDA + b3 \cdot CAPEX\_EBITDA + \\ & + b4 \cdot NWC\_EBITDA + b5 \cdot ESG\_Risk\_RTG + \\ & + b6\_us \cdot COUNTRY\_GROUP\_US + b6\_eu \cdot \\ & \cdot COUNTRY\_GROUP\_EU + b6\_uk \cdot \\ & \cdot COUNTRY\_GROUP\_UK + b6\_dev \cdot \\ & \cdot COUNTRY\_GROUP\_DEV + b6\_em \cdot \\ & \cdot COUNTRY\_GROUP\_EM. \end{aligned} \quad (2)$$

The constant is eliminated because all slack variables are used (to simplify interpretation of possible results). Then we eliminated the lines which did not contain all necessary data for calculation and the data related to the companies which shares' value fluctuated greatly or which had implemented large transactions of purchase and sale of shares. The results of calculations of model (2) applying the one-step least square method were obtained in an application software package for econometric modeling GRETL (Table 1).

Table 1. One-step least square method, GRETL package

Model: least square method, observations 1-57 were used
Dependent variable: EV_EBITDA
Robust estimators of standard errors (adjusted to heteroscedasticity), version HC1

	Coefficient	Standard error	t statistics	P value
EBITDA_3Y_GROWTH	−0.810515	0.386598	−2.097	0.0414**
DEPR_EBITDA	−0.185089	2.85702	−0.06478	0.9486
CAPEX_EBITDA	2.17957	1.65215	1.319	0.1935
NWC_EBITDA	0.149444	0.991101	0.1508	0.8808
COUNTRY_GROUPED_DEV	13.1554	1.77483	7.412	1.94e-09***
COUNTRY_GROUPED_EM	13.5044	2.07343	6.513	4.48e-08***
COUNTRY_GROUPED_EU	12.7619	1.64695	7.749	6.05e-010***
COUNTRY_GROUPED_UK	11.7424	1.88479	6.230	1.21e-07***
COUNTRY_GROUPED_US	16.0704	2.08792	7.697	7.25e-010***
ESG_RISK_RTG	−0.181865	0.0756335	−2.405	0.0202**

	Coefficient	Standard error	t statistics	P value

Mean of dependent variable 6.968421
Sum of squared errors 216.7565
R square 0.329665
F (9, 47) 105.6198
Loglikelihood −118.9476
Schwarz criterion 278.325

Standard deviation of the dependent variable 2.402957
Standard error of the model 2.147519
Corrected R square 0.201303
P value (F) 4.17e-28
Akaike criterion 257.8952
Hannan-Quinn criterion 265.8352

A low p value was obtained for variable 6 (DEPR_EBITDA)

The Ramsey test (RESET) –
Null hypothesis: adequate specification
Test statistics: F (2, 45) = 1.37988
p value = P (F(2, 45) > 1.37988) = 0.262048

Results of the test of equation significance: P value (F) = 4.17e-28 is low, consequently, the equation is significant. The Ramsey test shows that the null hypothesis is correct and the model specification is not rejected. As long as the model has no constant, in order to ensure that the obtained value of the correlation coefficient R^2 is correct we are going to verify what happens if we eliminate the parameter b6_uk·COUNTRY_GROUP_UK and introduce a constant. The values of R^2 and corrected R^2 have not changed.

The calculation results show that the variable ESG_RISK_RTG is significant at a 5% level and negative. This variable is interpreted as a risk and the lower its value the "greener" (environmentally benign) and socially more responsible is the company. A negative value of b5 means that the "greener" and socially more responsible the company the greater EV/EBITDA is, i.e. the bigger the company value with the same profit.

The assumed model shows just 21% of the corrected correlation coefficient R^2, i.e. it explains the behaviour of the dependent variable EV_EBITDA just by 21%. In light of this we made calculations of the model by regions, i.e. separately for emerging markets, other countries, the EU and Great Britain. At the same time the data set comprises only companies of the abovementioned regions while slack variables have not been introduced (in actual fact, b6 is equivalent to the constant).

See the calculation results for all companies and emerging markets in Table 2.

Table 2. Least-squares estimate of the modified model, GRETL package

Variable	Dependent variable: EV_EBITDA			
	Complete data set		Only emerging markets (COUNTRY_GROUPED_EM = 1)	Others
	(1) Model without the constant	(2) Model with the constant	(3)	(4)****
EBITDA_3Y_GROWTH	−0.81**	−0.81**	−0.8	0.47
	(0.39)	(0.39)	(0.6)	(0.95)
DEPR_EBITDA	−0.19	−0.19	−3.6	2.4
	(2.857)	(2.857)	(2.6)	(4.5)
CAPEX_EBITDA	2.2	2.2	−0.9	5.5*
	(1.7)	(1.7)	(1.4)	(2.8)
NWC_EBITDA	0.15	0.15	2.9	−0.01
	(1.00)	(1.00)	(2.8)	(1.2)

Variable	Dependent variable: EV_EBITDA			
	Complete data set		Only emerging markets (COUNTRY_GROUPED_EM = 1)	Others
	(1) Model without the constant	(2) Model with the constant	(3)	(4)****
COUNTRY_GROUPED_EM	13.5***	−2.6***		–
	(2.1)	(0.8)		
COUNTRY_GROUPED_EU	12.8***	−3.3***		−2.7***
	(1.6)	(0.9)		(0.7)
COUNTRY_GROUPED_UK	11.7***	−4.3***		−4.1***
	(1.9)	(0.9)		(0.8)
COUNTRY_GROUPED_US	16.07***			–
	(2.088)			
ESG_RISK_RTG	−0.18**	−0.18**	−0.46***	−0.11
	(0.08)	(0.08)	(0,14)	(0.09)
const		16.1***	20.8***	12.6***
		(2.1)	(3,3)	(1,6)
n	57	57	24	33
R^2	0.33	0.33	0.52	0.38
Corrected R^2	0.21	0.21	0.39	

Standard errors are specified in parentheses.

* significant at a 10 percent level.

** significant at a 5 percent level.

*** significant at a 1 percent level.

**** model with the constant and slack variables COUNTRY_GROUPED_DEV, COUNTRY_GROUPED_EU, COUNTRY_GROUPED_UK, the variable COUNTRY_GROUPED_US is eliminated.

For other regions, individually and collectively, the calculations indicate that all coefficients (except for the constant) are insignificant. For emerging markets the risk variable ESG_RISK_RTG is significant at a 5% level and negative. The value of the correlation coefficient R^2 increased a little while the absolute value is greater than in the general model.

The interpretation of the obtained results is ambiguous. On the one part, the result indicates that the "greener" and socially more responsible the company the greater EV/EBITDA is, i.e. the bigger the company value with the same profit. On the other part, the extent of explanation of changes of the dependent variable in the model is rather low and is explained by a rough division into groups which still have differences. A more serious group detailing as well as testing of the variables of ESG_RISK_RTG·COUNTRY_GROUP_... were not performed because it results in increase of the number of variables while the data set is highly limited. Besides, incompleteness of data should be taken into consideration because we tested only the companies in the ESG rating compiled by Sustainanalitics and a large number of companies have been eliminated because data was unfit for calculations.

The calculations indicate that everywhere the constants characterizing country differences become consistently significant coefficients while the coefficients characterizing components of corporate cash flow are mainly insignificant. In this case there may be a significant role of the fact that identical total cash flows may be divided into components in different ways. This may result in a wide scatter of regression coefficients, on the one hand, and, on the other hand, it is insignificant from the point of view of the explained variable. Therefore it is reasonable to introduce such variable as theoretically defined total cash flow or theoretically defined cost of capital. But we may simplify the problem as follows: probably, dependence of the cash flows components is not so important because the explained variable EV/EBITDA has the meaning of the period within which the cost of capital returns (actually it is the payback period) which should correspond to some mean values for a certain economy and industry.

We used for calculations a changed data set with an adjusted distribution by countries: we combined European countries (EU) with Great Britain, a part of countries representing emerging and risky markets was transferred to developed markets (New Zealand, South Korea, Taiwan). For this model we made calculations taking into consideration and not taking into consideration the variables which are components of cash flow (Table 3).

Table 3. Least-squares estimate of the changed model, GRETL package

Model: least square method, observations 1-57 were used

Dependent variable: EV_EBITDA

Robust estimators of standard errors (adjusted to heteroscedasticity), version HC1

	Coefficient	Standard error	t statistics	P value
ESG_RISK_RTG	−0.16	0.06	−2.8	0.0083***
COUNTRY_GROUPED_DEV	13.2	1.5	8.6	3.1e-011***
COUNTRY_GROUPED_EM	11.6	1.6	7.1	4.6e-09***
COUNTRY_GROUPED_EU	11.7	1.4	8.3	8.1e-011***
COUNTRY_GROUPED_US	14.9	1.7	8.6	2.3e-011***
EBITDA_3Y_GROWTH	−0.5	0.32	−1.7	0.099*
DEPR_EBITDA	0.03	2.8	0.01	0.99
CAPEX_EBITDA	2.6	1.6	1.6	0.16
NWC_EBITDA	0.013	0.97	0.013	0.99

Mean of dependent variable 6.968421 Standard deviation of the dependent variable 2.402957

Sum of squared errors 202.4249 Standard error of the model 2.053579

R square 0.373986 Corrected R square 0,269650

F (8, 48) 96.55249 P value (F) 6.36e-27

Loglikelihood −116.9981 Akaike criterion 251.9961

Schwarz criterion 270.3836 Hannan-Quinn criterion 259.1421

The biggest p value was obtained for variable 4 (DEPR_EBITDA)

Redundant variables test-

Zero hypothesis: regression parameters are zero parameters for the following variables:

EBITDA_3Y_GROWTH

DEPR_EBITDA

CAPEX_EBITDA

NWC_EBITDA

Test statistics: F (4, 48) = 4.34434

p value = P (F (4, 48)> 4.34434) = 0.00444162

Redundant variables test –

Zero hypothesis: regression parameters are zero parameters for the following variables:

DEPR_EBITDA

CAPEX_EBITDA

NWC_EBITDA

Test statistics: F (3, 48) = 4.99359

p value = P (F (3, 48)> 4.99359) = 0.00428354

Redundant variables test –

Zero hypothesis: regression parameters are zero parameters for the following variables:

DEPR_EBITDA

Test statistics: F (1, 48) = 0.000139819

p value = P (F (1, 48)> 0.000139819) = 0.990615

Redundant variables test -

Zero hypothesis: regression parameters are zero parameters for the following variables:

DEPR_EBITDA

NWC_EBITDA

Test statistics: F (2, 48) = 0.00250273

p value = P (F(2, 48) > 0.00250273) = 0.997501

Redundant variables test -

Zero hypothesis: regression parameters are zero parameters for the following variables:

EBITDA_3Y_GROWTH

DEPR_EBITDA

NWC_EBITDA

Test statistics: F (3, 48) = 1.03322

p value = P (F (3, 48) > 1.03322) = 0.386329

Redundant variables test –

Zero hypothesis: regression parameters are zero parameters for the following variables:

NWC_EBITDA

Test statistics: F (1, 48) = 0.000166512

p value = P (F (1, 48) > 0.000166512) = 0.989758

Redundant variables test –

Zero hypothesis: regression parameters are zero parameters for the following variables:

CAPEX_EBITDA

Test statistics: F (1, 48) = 2.57559

p value = P (F (1, 48) > 2.57559) = 0.115084

The test of the changed model for redundant variables – cash flow components – was negative: the zero hypothesis that coefficients of the variables EBITDA_3Y_GROWTH, DEPR_EBITDA, CAPEX_EBITDA, NWC_EBITDA equal zero simultaneously should be rejected (Table 4). Consequently, the assumption that the EV/EBITDA variable does not depend on components of cash flow was not confirmed.

But the redundant variables test shows that 3 variables DEPR_EBITDA, NWC_EBITDA and EBITDA_3Y_GROWTH may be considered redundant. Therefore, we are going to consider a model with 3 less variables. Reduction in the number of variables allows to refine the model replacing such variables as ESG_RISK_RTG and CAPEX_EBITDA with xx·COUNTRY_GROUPED_yy variables where xx is ESG_RISK_RTG or CAPEX_EBITDA, COUNTRY_GROUPED yy is a slack variable denoting a group of countries (COUNTRY_GROUPED_DEV, COUNTRY_GROUPED_EM, COUNTRY_GROUPED_EU, COUNTRY_GROUPED_US).

Regression equation:

EV_EBITDA =
c11· COUNTRY_GROUPED_DEV + c12·COUNTRY_GROUPED_EM + c13·COUNTRY_GROUPED_EU
+ c14·COUNTRY_GROUPED_US + c21·CAPEX_EBITDA·COUNTRY_GROUPED_DEV +
c22· CAPEX_EBITDA·COUNTRY_GROUPED_EM + c23·CAPEX_EBITDA·COUNTRY_GROUPED_EU (3)
+ c24·CAPEX_EBITDA·COUNTRY_GROUPED_US + c31·ESG_RISK_RTG·COUNTRY_GROUPED_
DEV + c32·ESG_RISK_RTG·COUNTRY_GROUPED_EM + c33·ESG_RISK_RTG·COUNTRY_
GROUPED_EU + c34·ESG_RISK_RTG·COUNTRY_GROUPED_US.

Table 4. Least-squares estimate of a new changed model, GRETL package

Model 15: least square method, observations 1-57 were used

Dependent variable: EV_EBITDA

Robust estimators of standard errors (adjusted to heteroscedasticity), version HC1

Coefficient	*Variable*	*Coefficient value*	*Standard error*	*T statistics*	*P value*
c11	COUNTRY_ GROUPED_DEV	15.7	3.1	5.1	<0.0001***
c12	COUNTRY_ GROUPED_EM	10.1	4.3	2.4	0.02**
c13	COUNTRY_ GROUPED_EU	13.2	3.1	4.2	0.0001***
c14	COUNTRY_ GROUPED_US	11.0	3.0	3.6	0.0007***
c21	CAPEX_EBITDA_DEV	1.5	1.0	1.6	0.1
c22	CAPEX_EBITDA_EM	0.6	1.8	0.3	0.7
c23	CAPEX_EBITDA_EU	5.9	2.4	2.4	0.02**
c24	CAPEX_EBITDA_US	5.8	1.6	3.7	0.0006***
c31	ESG_DEV	−0.31	0.14	−2.2	0.03**
c32	ESG_EM	−0.159	0.157	−1.0	0.3
c33	ESG_EU	−0.18	0.09	−1.9	0.06*
c34	ESG_US	0.05	0.14	0.34	0.74

	Mean of the dependent variable	6.968421	Standard deviation of the dependent variable	2.402957
	Sum of squared errors	195.0347	Standard error of the model	2.081851
	R square	0.396841	Corrected R square	0.249402
	F (11, 45)	128.9302	P value (F)	3.22e-30
	Loglikelihood	−115.9381	Akaike criterion	255.8762
	Schwarz criterion	280.3928	Hannan-Quinn criterion	265.4042

Calculation of this model shows that there is dependence between the risk value of environmental, social responsibility and corporate governance factors of the considered ESG rating and the EV/EBITDA parameter which characterizes the cost of capital, i.e. the lower the risk, the greater the cost of capital (a coefficient preceding the ESG_yy variable is negative).

For various country groups the abovementioned result was obtained with different degrees of reliability: for "other developed countries" (DEV) with a high 5% significance level, for European countries – with a 10% level. For the USA insignificance of the coefficient is associated with a small sample size. For developing country markets (EM) the coefficient is insignificant. A difference for the EM group from the results obtained in the previous model (equation (1)) is ostensible because in the new model the key players representing New Zealand, South Korea and Taiwan are transferred to the group of "other developed countries" DEV. Other countries pertaining to the group are diverse. This, together with the reduced number of observations in the group after transfer of a part of countries to the DEV group, leads to greater values of the standard error and as a result – to insignificance of the c32 coefficient.

On the basis of the results of this research it is shown that taking of ESG risk factors into consideration by a company helps to make a more accurate business evaluation by means of using the EV/EBITDA parameter which is confirmed by empiric results for telecommunications companies. This may be useful from the economic point of view to concerned parties in developed markets, in particular, in European markets. Thus, the fact that enterprises pay increasingly more attention to the environment and the influence they produce on the society becomes undeniable. In light of this, the present research should enhance investors' confidence in companies with an actual progress in ESG.

Our research conclusions indicate that companies' efforts of ensuring a sustainable development facilitate a successful conduct of business, providing solution of social problems at the same time. Thus, elimination of ESG risks increases corporate competitive strength. As long as in some countries companies are under no obligation to disclose ESG information results of this research may encourage companies to consider non-financial disclosure as an important indicator of long-term sustainability. When ESG is considered as an integral factor of corporate future operations the final outcome is a higher evaluation of the company by stakeholders.

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Approaches to Building Default Probability Models for Financial Instruments of Project Financing at Long Time Horizons

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Abstract

Project financing is one of the priority tools for stimulating the country's economic growth around the world, which allows the implementation of large-scale and capital-intensive projects, providing favorable credit conditions with insufficient creditworthiness of the project beneficiaries.

As a rule, project financing instruments are long-term (10–30 years, depending on the type of transaction), so this asset class is interesting for the implementation of the task of building long-term models for assessing credit risk associated with the introduction in 2018 of the new international financial reporting standard IFRS 9 "Financial Instruments".

The new standard requires financial institutions to calculate their expected credit loss (ECL) at the time of granting loans and other banking products exposed to credit risk, taking into account different time horizons, which significantly changes the traditional approaches to assessing credit risk by commercial banks.

As part of this work, a model was built to assess the long-term probability of default for the portfolio of assets of a Russian commercial bank belonging to the project finance segment in accordance with the requirements of the International Financial Reporting standard IFRS 9 "Financial Instruments". At present, the topic of this work is extremely relevant and may be of interest both for commercial banks that are faced with the problem of improving credit risk assessment models

Keywords: IFRS 9, expected credit losses, credit risk assessment stages, project finance, pdlife-time

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Introduction

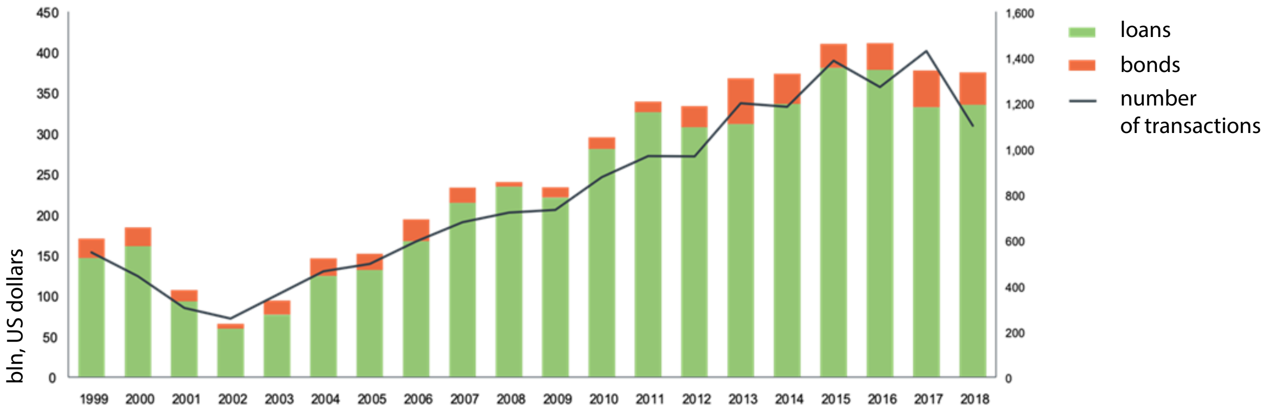
Project financing (PF) is a method of long-term borrowing for large projects by means of "financial engineering" based on loan on cash flow created only by the project without recourse to the borrower. The fundamental feature of project financing is that for implementation of a certain project a special project enterprise is established (SPV, SPE) which attracts resources (not only funds) for project implementation, implements the project and squares accounts with creditors and project investors using the funds (cash flows) generated by the project itself [1]. For decades project financing was a preferable way of financing of large-scale infrastructure projects all over the world. A series of studies emphasized its importance, especially for the countries with emerging market economies and accentuated the correlation between investment in infrastructure and economic growth.

Long-termness is a distinctive feature of project financing transactions – implementation of some projects takes 30 years. Large-scale capital-intensive projects usually require significant initial investments and generate the revenue sufficient only to cover expenses in the long-term. Thus, some authors point out in their papers that on average loans aimed at financing projects have a longer maturity than other syndicated credits [5–7]. This distinctive feature makes this assets class an interesting research object as a part of the task of constructing long-term models of assessing credit risk according to requirements of IFRS 9.

In the recent 15–20 years investors' interest to transactions of project financing has been growing across the globe. First of all, it is due to financing of infrastructure facilities' construction under public-private partnership (PPP): from 1999 through 2019 the volume and number of performed transactions increased more than twice (Figure 1). Projects are increasingly financed by issue of bonds backed by cash-flows from implementation of infrastructure projects based on PPP. According to international practices default of this tool occurs less frequently even in economic turbulence periods [8].

As on September 2020 over 3,000 PPP projects were implemented in Russia. Their total value exceeds 4.5 trillion roubles and the share of private investments amounts to 3.1 trillion roubles (69%). The total value of PPP projects amounts to 44% of expenses for infrastructure which have been planned for implementation of national projects in 2019 [8].

Figure 1. Global Volume of the Project Financing Market



Source: Moody's, ACRA.

Review of Methods and Models of Assessment of Credit Risk of Assets at a Long Time Horizon

On the basis of PD estimates MPD values are calculated for each life period of an agreement. Then they are used to calculate ECL for the whole lifetime of the agreement.

The model is calibrated on the basis of the PIT (point in time) principle:

$$PD_t^{PIT} = \beta_t \cdot PD_t^{TTC}, \quad (1)$$

where PD_t^{PIT} – default probability on the basis of the PIT calibration;

PD_t^{TTC} – default probability on the basis of the TTC calibration;

β_t – scaling coefficient defined on the basis of data about the current default rate of the portfolio

The following methods are applied to evaluate PD:

a) Use of external data about defaults;
b) Methods based on the migration matrix;
c) Methods based on approximation of historic default levels;
d) Approach based on exponential curve extrapolation (a simplified approach).

Use of external data on defaults. This method implies a PD assessment based on migration of ratings information on which is provided by external rating agencies (S&P, Moody's, Fitch Ratings, ACRA).

In case the Bank has no statistics to build a migration matrix using internal data the migration matrix built on external data is used. Depending on the purpose of modelling statistics of one or several rating agencies may be applied.

In case of inversion in the data of external matrices the matrix is adjusted (by experts or applying mathematical methods of reducing the function to a monotone function) PD assessment on the basis of migration matrices. The migration matrix is a square matrix which elements contain probabilities of change (transition probabilities) of the rating category of a corresponding Borrower.

$$M = \begin{bmatrix} p_{11} & \cdots & p_{1,n} \\ \cdots & \cdots & \cdots \\ p_{n-1,1} & \cdots & p_{n-1,n} \\ 0 & 0 & 1 \end{bmatrix}, \quad (1)$$

where p_{ij} – probability of transition to the j rating category in a certain period of time provided it belongs to the i rating category.

The Bank uses the rating scale of internal credit ratings to build the migration matrix (Appendix 1).

The Bank does not set upper and lower bounds of the values of the probability of default. According to IFRS 9 assessment of the probability of default is unbiassed. Subsequently, the conservatism concept enshrined in the model of probability of default assessment as per IRB Basel II [10] cannot be used to calculate PD in accordance with IFRS 9 and as part of upgrade of IRB of PD models in order to meet requirements of IFRS 9 such material adjustments are excluded (adjustment "PG not less than 0.03%" established in accordance with 483-P is also excluded) [4].

This is with the exception of the RF rating adjustment (the borrower's rating is not higher than the RF rating): this adjustment is preserved.

Depending on availability of data when constructing a migration matrix enlarged or initial rating categories may be used (for example, combining of ratings 7–, 7, 7+ into one category).

Assessment of probabilities of transition is determined by cohort analysis:

$$\widehat{p_{ij}} = \frac{N_{ij}(t)}{N_i(t-1)}, \quad (2)$$

where $N_{ij}(t)$ – number of migrations from state I into state j in the t period;

$N_i(t-1)$ – number of transactions in state I in the t – 1 period.

The probability of default at a 1-year horizon.

A one-year migration matrix $\boldsymbol{M}_0$ is constructed on the basis of statistics of observations for 12 calendar months. Shorter periods may be used in order to take into consideration the most relevant information.

An average one-year migration matrix is calculated by computing the arithmetic mean of one-year migration matrices obtained every quarter (month).

A one-year probability of default (PD_t) for each rating category is defined as the likelihood of transition into the state of "10-default". In the migration matrix (PD_t) is indicated in the last column of the one-year transition matrix.

If statistical frequency of defaults does not correspond to the probability of default in each rating grade in the Bank's master scale scaling is performed.

The adjustments performed are recorded in the Report on the Model Development.

When assessing the PD indicator on the basis of migration matrices the following main assumptions are contemplated:

- further transitions to rating grades depend only on the current rating but not on previous ratings (property of Markov process);
- probabilities of migration do not depend on a certain time point, i.e. the transition rates are unchanged in time (homogeneity) [9].

A formular to calculate the probability of default for the lifetime of a financial instrument:

$$M_T = M_1{}^T, \quad (3)$$

where T – lifetime of a financial instruments.

The column in the multiyear matrix which shows a probability of transition into default is the cumulative probability of default of a certain period (cPD). Use of the migration matrix allows to take into consideration complete information on migration of ratings when calculating the probability of default for the lifetime.

Profiles of cumulative PDs are made by evaluating parameters of cumulative DR distribution.

On the basis of the Weilbull distribution:

Parameters of the Weilbull distribution k and λ are assessed using a linear regression of double logarithm of the survival function. The survivorship function is defined by the following formula:

$$S(t) \bullet 1 - F(t;k,\lambda), \quad (4)$$

where $F(t;\kappa,\lambda)$ is a two-parameter Weilbull distribution function.

$$F(t;\kappa,\lambda) = cDR(t;\kappa,\lambda) = \begin{cases} 1 - e^{-\left(\frac{t}{\lambda}\right)^{\kappa}}, t > 0 \\ 0, t \le 0. \end{cases}, \quad (5)$$

where $k > 0$ defines the shape of the distribution function. $k < 1$ is indicative of a decrease of default rate in time, $k = 1$ points at stability of default rate in time, $k > 1$ is indicative of increase of default rate in time;

$\lambda > 0$ is a scale parameter which regulates survivorship time [11].

On the basis of the modified Weilbull distribution:

- Modeling of cumulative PD is made by selecting such distribution parameters which describe most accurately the behaviour of cumulative default rates.

A two-parameter modified Weibull distribution function is as follows:

$$F(t,\alpha,\beta) = cDR(t,\alpha,\beta) = \begin{cases} \dfrac{1-e^{-\left(e^{-(\alpha\cdot t^{\beta})}\right)}}{\left(1-e^{-1}\right)}, & t > 0, \\ 0 & , t \le 0 \end{cases} \quad (6)$$

where α and $\beta < 0$ are parameters of the modified Weibull distribution;

$cDR(t,\alpha,\beta)$ is the cumulative default rate per year [11].

Construction of the model for the project financing segment

The target segment of this model is customers pertaining to the area of applying the Project Financing models in accordance with the bank's methodology.

When developing of the present model the default definition stated in the section Terms and Definitions was used. The fact of assigning to a borrower of the "10-default" rating was taken into consideration as default characteristic.

At the date of developing the model Lt PD of the Project Financing segment 1,171 observations were available (key "TIN + reporting date", 325 default observations) for 116 borrowers since April 2009. In the segment of Project Financing (Developers) 1,334 observations were available (key "TIN + reporting date", 565 default observations) for 141 borrowers since April 2009. Moreover, the sample contains observations concerning 15 borrowers pertaining to both segments.

In view of the above the approach to modeling of Lt PD on the basis of the migration matrices constructed of consolidated internal data on changing ratings for both segments was considered for the segments of Project Financing and Project Financing (Developers).

When combining rating groups the number of observations in a rating group amounted from 292 to 890 observations (the largest number of observations was in the "default" rating group and the smallest number of observations was in "good" rating groups). As long as it is important for the segments with the borrowers characterized by credit risk above average to have a number of observations in "bad" ratings sufficient for rating migration analysis we made the conclusion on applicability of the approach to modeling of Lt PD by means of constructing the rating migration matrix on the basis of internal data.

The approach to getting multiyear PD using rating migration matrices. Computation of an average one-year migration matrix.

The migration matrix is indicative of the likelihood that a borrower with a certain rating as at the beginning of the year will have the following:

- the same rating (shown on the principal diagonal);
- rating with a higher probability of default (in the migration matrix such values are indicated above the principal diagonal);
- rating with a lower probability of default (in the migration matrix such values are indicated under the principal diagonal);
- rating of default state (in the migration matrix such values are indicated in column D, default).

When computing a one-year rating migration matrix using the data for a period exceeding 1 year probabilities of migration of the final one-year migration matrix are obtained by averaging probabilities of migration of several matrices. Averaging is performed by calculating the arithmetic mean.

A one-year migration matrix with averaged probabilities of migration is applied as the basic matrix to compute multiyear matrices.

When empiric default rates deviate from model ones (PD of the master scale) PD of the basic migration matrix (the last column – an average one-year default rate, DR) is adjusted to harmonize with PD of the Bank's master scale.

PD adjustment of the basic migration matrix is also necessary in case of inversions (PD of "bad" ratings is lower than PD of "good" ratings).

Adjustment may be performed both by means of calculating the coefficient by which the actually obtained DR is to be multiplied / divided and by means of permutation of PD of a corresponding master scale into the last column of the basic migration matrix. If the basic migration matrix is constructed on the basis of rating groups the weighted average of the number of observations in the rating group of PD of the master scale is calculated for the last column.

After adjustment of the values of the last column the transition probabilities of the basic matrix are adjusted in such a way that the sum of probabilities of transition of each line was 100% (by proportional change of probabilities of rating transitions of each line).

Adjustment example

Table 1. Values before adjustment

	1	2	3	4	5	Default
…	…	…	…	…	…	…
2	15.75%	78.91%	4.94%	0.40%	0.00%	0.00%
…	…	…	…	…	…	…

Table 2. Values after adjustment

	1	2	3	4	5	Default
…	…	…	…	…	…	…
2	15.55%	77.89%	4.88%	0.39%	0.00%	1.29%
…	…	…	…	…	…	…

Sum of probabilities of transition (except for default) before adjustment = 100%, sum of probabilities of transition after adjustment (except for default) = 98.71%.

Adjusted probability of transition from rating 2 to rating 1 is calculated by the following formula:

15.55% = 15.75% · (98.71% / 100%).

Other probabilities in the line are adjusted in the same way.

Calculation of cumulative PD estimates

Estimates of cumulative PD are obtained using migration matrices by means of raising a one-year migration matrix to the corresponding power. For example, in order to get a cumulative PD for N years it is necessary to raise the matrix to the N power in accordance with the Formula (1):

$$\mathrm{M} = \mathrm{M}_0^{\mathrm{N}}, \quad (7)$$

where M is a migration matrix for N years;

M_0 – a one-year migration matrix.

The column in the multiyear matrix indicating a probability of transition to the default state is the cumulative probability of default of a corresponding period (cPD).

Advantages of use of a complete migration matrix as opposed to use of just the column indicating the probability of default when calculating the cumulative probability of default consist in recording of complete information on rating migration when the probability of default is calculated for several years [12–15].

Adjustment of Probabilities of Transition of Ratings of the Basic Migration Matrix

A probability of rating transition should decrease monotonically when moving from the principal diagonal to extreme columns of the migration matrix. It means that the probability of transition of ratings to neighboring rating groups is higher in comparison to the probability of rating transition “skipping” 2 or 3 ratings.

Probabilities of transition are adjusted using mathematical methods (for example, approximation of nonmonotonic data series by a monotone function).

In practice parameters of the function (exponential, logarithmic) used for adjustment may be selected applying Excel (“search for solution” package, trend adding).

After obtaining the cumulative probability of default for consolidated rating groups it is converted into the conditional probability of default to calculate conditional PD for each rating inside rating groups applying logarithmic interpolation.

On the basis of the conditional PD obtained at the previous stage final marginal PD is calculated (exclusive of forecasting information).

The above transitions of the probability of default profiles are performed by the following formulae.

The cumulative PD is determined as:

$$\mathrm{cPD_t} = \begin{cases} \mathrm{cPD_{t-1}} + (1 - \mathrm{cPD_{t-1}}) \cdot \mathrm{PD_t}, t > 0 \\ 0, t = 0. \end{cases} \quad (8)$$

The marginal PD is determined as:

$$\mathrm{MPD_t} = \mathrm{PD_t} \cdot (1 - \mathrm{cPD_{t-1}}) = \mathrm{cPD_t} - \mathrm{cPD_{t-1}}. \quad (9)$$

Due to a non-linear character of change of PD ratings when moving along a rating scale it is not recommended to apply the linear approach to interpolation. See below the approach to interpolation which takes into consideration the non-linear character of PD.

Interpolation consists of several main stages.

1st stage.
Each rating is assigned a numerical value (Table 3).

Table 3. Numerical values of ratings

Rating	Numerical value
1+	1
1	2
1–	3
2+	4
2	5
2–	6
3+	7
3	8
3–	9
4+	10
4	11
4–	12
5+	13
5	14

Rating	Numerical value
5–	15
6+	16
6	17
6–	18
7+	19
7	20
7–	21
8+	22
8	23
8–	24
9	25
10	26

2nd stage.

Average-weighted ratings and PD corresponding to them expressed in terms of numerical values are calculated. Weights are the number of observations in each corresponding rating (Table 4).

Table 4. Example of calculated actual ratings and cPD corresponding to them

Actual average numerical value of the rating group	PD-1	PD-2	PD-3	PD-4	PD-5	PD-6
19.7	11.74%	11.10%	10.88%	10.53%	10.11%	10.11%
23.9	31.97%	29.02%	25.34%	21.64%	18.22%	18.22%

Table 5. cPD of the "8+" rating obtained by interpolation

Numerical value of the rating	PD-1	PD-2	PD-3	PD-4	PD-5	PD-6
22	19.37%	18.69%	17.21%	15.56%	13.91%	13.91%

3rd stage. PD is calculated for each rating on the basis of corresponding PD of rating groups.

For the j rating $PD_{j,t}$ for the period of t ($t \in [1, N]$, $t \in \mathbb{N}$) is calculated as per the following formula:

$$PD_{j,t} = PD_{i,t} \bullet \frac{PD_{i+1,t}}{PD_{i,t}}^{\left(\frac{b_j - a_i}{a_{i+1} - a_i}\right)}, \quad (10)$$

where b_j is a numerical value of the j rating which is between the numerical values of the rating groups i and $i+1$;

a_i, a_{i+1} are numerical values of rating groups i and $i+1$ respectively;

$PD_{i,t}$, $PD_{i+1,t}$ are conditional probabilities of default calculated applying migration matrices for the t period for rating groups i and $i+1$ respectively (Table 5).

At the next stage adjustment is performed: PD of the first year is set equal to PD of the master scale.

Forecasting macroeconomic information is taken into consideration by adjusting conditional PD of the 1st and 2nd year with consideration to the forecasted one-year default rate for 2 years (2 values of DR) from the date of reports.

TTC PD is the probability of default average for the whole economic cycle which assessment is based on all information available about the borrower. TTC PD is stable in time and is not correlated to the economic cycle. The calculated transition probability and default probability obtained after multiplication of the one-year migration matrix according to art. 7.1.3 are mean values computed on the basis of rating results for approximately 8 years (01.04.2009–01.07.2017) which covers various stages of the economic cycle, i.e. they are TTC PD estimates.

In order to take into consideration forecasting macroeconomic information it is necessary to adjust estimates of TTC PD ratings obtained for the model with consideration to the forecasted default rate.

PIT calibration is performed on the basis of Bayes' formula where the rating PD is scaled according to the forecasted default rate and CDT.

In order to convert one-year PD values Bayes' formula is applied.

$$PD_i^{New} = \frac{(1-CDT)*DR_{New}*PD_i}{CDT*(1-DR_{New})*(1-PD_i)+(1-CDT)*DR_{New}*PD_i}, \quad (11)$$

where PD_i^{New} – PIT PD of the i rating which corresponds to a new forecasting default rate DRNew;

PD_i – conditional PD of rating grade i;

DR_{New} – forecasting default rate;

CDT – average default rate calculated by the economic cycle.

The data source for developing the model is the corporate data warehouse (area of corporate data warehouse which stores the information of the data warehouse of CRM) with a set of presentations which contain data from various points of view (loan portfolio, agreement information etc.).

Data from the segments of Project Financing and Project Financing (Developers) was used for analysis.

Analysis comprises 114 customers from the model of Project Financing (994 observations, 315 of them are default ones) and 128 customers from the model of Project Financing (Developers) (1,082 observations, 506 of them are default ones).

Data from the segments of Project Financing and Project Financing (Developers) was used for analysis (hereafter – the PF portfolio). Due to a significant reduction in the number of borrowers in the PF portfolio in 2015–2017 in comparison to 2009–2013 we decided to analyze the PF portfolio as one segment without division into PF and PF (Developers).

See detailed information on the model in the Table 6. The first 4 lines are the models developed after October 2011, the last 2 lines are the models developed before October 2011 (in 2009).

Table 6. Number of unique records with a breakdown into models (PF portfolio)

Grouping of observations

No.	Model	Number of records
	Project Financing (Developers) v.2.0 (archive)	625
	Project Financing v.2.0 (archive)	527
	Project Financing (Developers) v.2.1	69
	Project Financing v.2.1	55
	Project Financing (Developers) v.1 (archive)	640
	Project Financing v.1 (archive)	563

Due to insufficient number of observations for individual ratings we made rating groups of 1 to 9 ratings in order to construct migration matrices.

When making rating groups we took into consideration the following:

- rating groups comprise ratings close in terms of risk level;
- the number of observations in a rating group should be sufficient to model probabilities of ratings transition (Table 7).

Table 7. Number of observations related to grades/groups

Rating group	Rating grade	Number of observations in a rating grade	Number of observations in a rating group
345	1+	–	330
	1	–	
	1–	–	
	2+	–	
	2	–	
	2–	–	
	3+	–	
	3	1	
	3–	–	
	4+	9	
	4	12	

Rating group	Rating grade	Number of observations in a rating grade	Number of observations in a rating group
345	4–	38	330
	5+	91	
	5	97	
	5–	82	
6	6+	139	401
	6	165	
	6–	97	
7	7+	115	292
	7	110	
	7–	67	
89	8+	57	593
	8	266	
	8–	73	
	9	197	

Analysis of data in terms of assigning to a stage of the project

As a part of model development we studied existence of dependence between the default rate and a project stage. When assessing borrowers' projects assigned to the segments of Project Financing and Project Financing (Developers) in the Bank the basic rating defining module comprises the factor of the Project Stage. Since the wording of factors changed in re-development of models we decided to combine the observations data in three groups: 1) A (initial financing); 2) B (work performance); 3) C (completion) (Table 8).

Analysis showed that over 65% observations pertain to the C stage (completion) and 18% – to the B stage (work performance). Apart from that, 84.3% of projects were at the completion (C) stage out of 312 observations as at 2015–2017 (Table 9).

Table 8. Description of values of the factor of the Project Stage model depending on the model version

Project version	Values of the factor of the Project Stage model	Designation of the factor of the Project Stage model
Project Financing v.1	A: Initial financing – <idea> level	A
	B: Preparation and beginning of work – <planning> level	
	C: Work performance	B
	D: Ready business – <completion> level	C
Project Financing v.2	A: Initial financing – <idea> level	A
	B: Preparation and beginning of work – <planning> level	
	C: Work performance	B
	D: Ready business – <completion> level	C

Project version	Values of the factor of the Project Stage model	Designation of the factor of the Project Stage model
Project Financing (Developers) v.1	A: Construction "from greenfield"	A
	B: Ditch / foundation	B
	C: House case constructed	
	D: Finishing	C
	E: Finishing constructing / restructuring of an existing building	
	F: Repairs of an existing building for further use	
Project Financing (Developers) v.2	Development project's stage (in percent)	
	< 20%	A
	> 20% < 70%	B
	> 70%	C

Table 9. Number of observations by the type of the project stage

Project stage	Number of observations	Share of observations in the total amount, %
A	134	5.6
B	459	18.3
C	1,632	65.2
(Empty)	280	11.2
Total	2,505	100

On the basis of the results of studies we took the decision not to divide the initial sample into project stages and not to determine individual models for various stages for the following reasons:

1) The major part of observations pertain to the stage of project completion (65%).
2) The rating calculated on the basis of the one-year default probability model takes into consideration the fact of project affiliation to a certain stage.
3) A single sample will allow to develop a stable PD Lifetime model.

Results of modeling of TTC LT PD before taking into consideration forecasting macroeconomic information

Basic Prerequisites

When constructing one-year migration matrix we adopted the following prerequisites:

- default is an absorbing state, i.e. getting out of the default state is not considered;
- in case of several ratings calculated on the basis of the same reports we used for calculation the rating with the last date of calculation;
- within the period (one year) we eliminated migrations into the state of "no rating (no re-rating)", i.e. if as at the beginning of the considered period a customer was assigned a rating and at the end of the year there was no information on the calculated rating such rating was considered in the calculation as remaining in the same rating. The prerequisite was introduced to meet the modeling purposes – the event of "no re-rating" was not simulated, change of the rating while the borrower is in the Bank's portfolio is simulated.
- assigning of "10" rating to the borrower was considered as an event of default (provided it did not equal 10 as at the previous date).

Average (Basic) One-Year Migration Matrix

Calculation of the basic migration matrix

One-year matrices were calculated as follows:

- a one-year probability that a borrower with a certain rating as at the beginning of the year will in one year have the same or a different rating was calculated per quarters for a one-year interval (one-year matrices were calculated per quarters);
- data was analyzed from 01.04.2009 to 01.07.2017 (30 matrices in total);
- the matrix obtained by averaging of 30 matrices was taken as the basic one-year matrix;
- for the PF portfolio the data was combined in rating groups 345 (3, 4+, 4, 4–, 5+, 5, 5–), 6 (6+, 6, 6–), 7 (7+, 7, 7–), 89 (8+; 8; 8– and 9). It was necessary to consolidate ratings into groups due to an insufficient number of observations in individual rating grades (Table 10).

Adjustment of the Last Column of the Basic Migration Matrix

Due to an insufficient number of default observations we adjusted probabilities of default on the basis of weighted PD of corresponding ratings in the master scale of the Bank. PD are weighted by the number of observations in each rating (Table 11 and 12).

Table 10. Average one-year migration matrix

Risk category	345	6	7	89	10
345	77.6%	13.5%	4.4%	1.3%	3.2%
6	18.3%	41.5%	23.9%	9.8%	6.5%
7	2.8%	13.7%	45.6%	30.5%	7.3%
89	3.7%	2.0%	6.6%	72.5%	15.2%
10	0.0%	0.0%	0.0%	0.0%	100.0%

Table 11. Weighted PD for rating groups

Rating group	Rating grade	Number of observations in the rating grade	Rating PD	PD* number of questionaries	PD of the rating group
345	1+	–	0.01%	–	2.42%
	1	–	0.02%	–	
	1–	–	0.04%	–	
	2+	–	0.08%	–	
	2	–	0.16%	–	
	2–	–	0.32%	–	
	3+	–	0.45%	–	
	3	1	0.58%	0.006	
	3–	–	0.75%	–	
	4+	9	0.96%	0.086	
	4	12	1.23%	0.148	
	4–	38	1.58%	0.600	
	5+	91	2.03%	1.847	
	5	97	2.61%	2.532	
	5–	82	3.36%	2.755	

Rating group	Rating grade	Number of observations in the rating grade	Rating PD	PD* number of questionaries	PD of the rating group
6	6+	139	4.31%	5.991	5.50%
	6	165	5.54%	9.141	
	6–	97	7.12%	6.906	
7	7+	67	9.14%	10.511	11.48%
	7	110	11.74%	12.914	
	7–	115	15.08%	10.104	
89	8+	73	19.37%	11.041	30.60%
	8	266	24.89%	66.207	
	8–	57	31.97%	23.338	
	9	197	41.06%	80.888	

Table 12. Basic one-year migration matrix (after reducing the master scale to PD)

Risk category	345	6	7	89	10
345	78.3%	13.6%	4.4%	1.3%	2.4%
6	18.5%	42.0%	24.2%	9.9%	5.5%
7	2.7%	13.1%	43.6%	29.2%	11.5%
89	3.1%	1.6%	5.4%	59.3%	30.6%
10	0.0%	0.0%	0.0%	0.0%	100.0%

Reducing the Basic Migration Matrix to the Monotone Type

The basic matrix is reduced to the monotone type against the principal diagonal by using smoothing functions. Values of transition probability are adjusted line-by-line except for the values in the last column and the principal diagonal.

In order to eliminate zero probabilities of transition and non-monotonic values above the principal diagonal we used the decreasing function $y = a \cdot \exp(-b \cdot t)$. Its parameters were selected applying the Search for Solution package in Excel (Table 13).

Table 13. The basic one-year migration matrix
(after reducing to PD of the master scale and reducing to the monotone type)

Risk category	345	6	7	89	10
345	78.3%	13.6%	4.3%	1.4%	2.4%
6	18.5%	42.0%	24.2%	9.9%	5.5%
7	0.0%	15.7%	43.6%	29.2%	11.5%
89	2.0%	3.1%	5.0%	59.3%	30.6%
10	0.0%	0.0%	0.0%	0.0%	100.0%

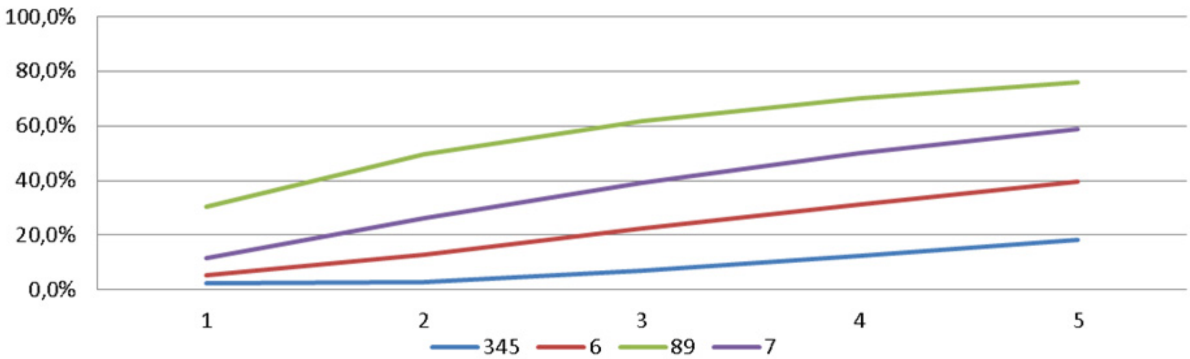
Results of calculation of cumulative PD

The cumulative PDs were calculated by raising to power of the adjusted basic one-year migration matrix (Table 14 and Figure 2). Multiyear matrices were calculated for the period not exceeding 5 years.

Table 14. The cumulative probability of default

Risk category	1st year	2nd year	3rd year	4th year	5th year
345	2.4%	6.0%	10.8%	16.7%	23.2%
6	5.5%	14.0%	23.7%	33.1%	41.6%
7	11.5%	26.3%	39.6%	50.5%	59.2%
89	30.6%	49.6%	61.9%	70.2%	76.2%
10	100.0%	100.0%	100.0%	100.0%	100.0%

Figure 2. Cumulative probabilities of default calculated on the basis of the basic matrix after adjustments



Reducing to the Master Scale, Results' Interpolation

Cumulative probabilities of default were transformed into conditional probabilities of default in accordance with dependence [12] for further reducing of TTC PD for the first year to the Bank's master scale and calculation of the conditional PD for each rating inside rating groups by means of logarithmic interpolation.

$$PD(t)=\frac{cPD(t)-cPD(t-1)}{1-cPD(t-1)}. \qquad (12)$$

The conditional PDs for rating categories 345, 6, 7, 89 were calculated by means of logarithmic interpolation.

The conditional PDs for ratings 1+, 1, 1–, 2+, 2, 2–, 3+, 3, 3– were fixed at the Bank's master scale level.

Table 15. The conditional probabilities of default obtained after reducing to the master scale and interpolation

Risk category	1st year	2nd year	3rd year	4th year	5th year
1+	0.01%	0.01%	0.01%	0.01%	0.01%
1	0.02%	0.02%	0.02%	0.02%	0.02%
1–	0.04%	0.04%	0.04%	0.04%	0.04%
2+	0.08%	0.08%	0.08%	0.08%	0.08%
2	0.16%	0.16%	0.16%	0.16%	0.16%
2–	0.32%	0.32%	0.32%	0.32%	0.32%
3+	0.45%	0.45%	0.45%	0.45%	0.45%
3	0.58%	0.58%	0.58%	0.58%	0.58%
3–	0.75%	0.75%	0.75%	0.75%	0.75%
4+	0.96%	1.06%	1.15%	1.21%	1.26%

Risk category	1st year	2nd year	3rd year	4th year	5th year
4	1.23%	1.51%	1.76%	1.96%	2.11%
4–	1.58%	2.14%	2.70%	3.17%	3.53%
5+	2.03%	3.65%	5.17%	6.58%	7.76%
5	2.61%	4.16%	5.77%	7.20%	8.32%
5–	3.36%	5.44%	7.28%	8.67%	9.63%
6+	4.31%	7.11%	9.17%	10.44%	11.15%
6	5.54%	9.05%	11.28%	12.33%	12.72%
6–	7.12%	11.40%	13.47%	14.24%	14.35%
7+	9.14%	14.04%	15.81%	16.23%	16.02%
7	11.74%	16.72%	18.07%	18.09%	17.56%
7–	15.08%	19.39%	19.79%	19.18%	18.23%
8+	19.37%	22.02%	21.40%	20.17%	18.83%
8	24.89%	27.31%	24.42%	21.96%	19.89%
8–	31.97%	28.40%	25.02%	22.30%	20.09%
9	41.06%	32.26%	27.05%	23.45%	20.76%

Marginal PDs were calculated on the basis of the conditional PDs (Table 15).

For ratings 1+, 1, 1–, 2+, 2, 2–, 3+, 3, 3– mPD were fixed at the Bank's master scale level.

For ratings 7, 7–, 8+, 8, 8– and 9 values of marginal PDs were adjusted in order to eliminate intersections (mPD should not decrease when the rating moves from 1+ to 9).

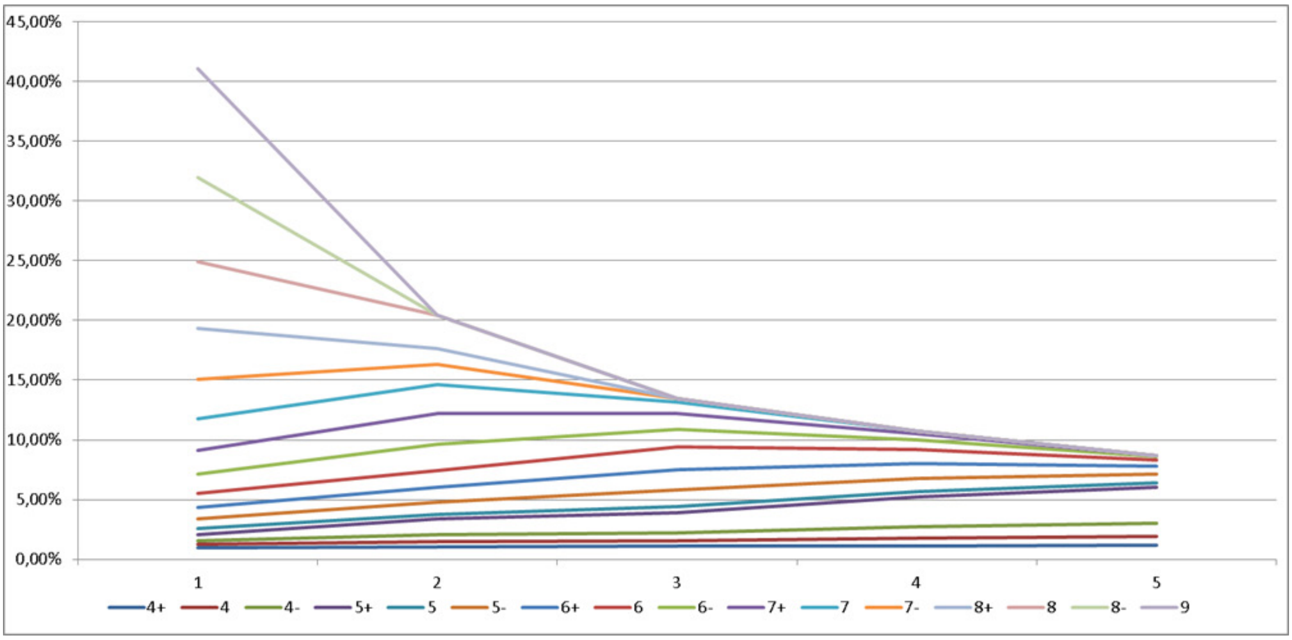
The final values of mPD (without regard to forecasting information) are presented in Table 16 and Figure 3.

Table 16. Marginal TTC profiles of multiyear default probabilities for the PF portfolio (adjusted)

Risk category	1st year	2nd year	3rd year	4th year	5th year
1+	0.01%	0.01%	0.01%	0.01%	0.01%
1	0.02%	0.02%	0.02%	0.02%	0.02%
1–	0.04%	0.04%	0.04%	0.04%	0.04%
2+	0.08%	0.08%	0.08%	0.08%	0.08%
2	0.16%	0.16%	0.16%	0.16%	0.16%
2–	0.32%	0.32%	0.32%	0.32%	0.32%
3+	0.45%	0.45%	0.45%	0.44%	0.44%
3	0.58%	0.58%	0.57%	0.57%	0.57%
3–	0.75%	0.74%	0.74%	0.73%	0.73%
4+	0.96%	1.05%	1.13%	1.17%	1.20%
4	1.23%	1.49%	1.71%	1.87%	1.97%

Risk category	1st year	2nd year	3rd year	4th year	5th year
4–	1.58%	2.11%	2.60%	2.97%	3.21%
5+	2.03%	3.58%	4.88%	5.89%	6.49%
5	2.61%	4.05%	5.39%	6.33%	6.79%
5–	3.36%	5.25%	6.65%	7.34%	7.46%
6+	4.31%	6.81%	8.15%	8.43%	8.06%
6	5.54%	8.55%	9.69%	9.40%	8.50%
6–	7.12%	10.58%	11.08%	10.14%	8.77%
7+	9.14%	12.76%	12.35%	10.67%	8.82%
7	11.74%	14.75%	13.28%	10.90%	8.82%
7–	15.08%	16.46%	13.55%	10.90%	8.82%
8+	19.37%	17.75%	13.55%	10.90%	8.82%
8	24.89%	20.51%	13.55%	10.90%	8.82%
8–	31.97%	20.51%	13.55%	10.90%	8.82%
9	41.06%	20.51%	13.55%	10.90%	8.82%

Figure 3. The marginal default probabilities (adjusted) for the PF portfolio



Comparative analysis of the results of development of the basic model for the Construction and Rental Business segments with the results of development of the basic model for project financing

Comparison of obtained mPD estimates for project financing (exclusive of forecasting information) to estimates for the Construction and Rental Business segments revealed that for "good" rating grades (3+, 3, 3–, 4+, 4, 4–, 4+, 4, 4–, 5+, 5, 5–) the obtained estimates are better (the probability of default is lower) than for the Construction and Rental Business segments. This may be due to the fact that the PF portfolio contains a third less observations in "good" rating grades (Table 17).

For "average" and "bad" rating grades the obtained estimates are a little worse (the probability of default is higher) than for the Construction and Rental Business segments. It should be noted that the PF portfolio contains 2.5 times as much observations in "bad" rating grades (8+, 8, 8–, 9) as in the Construction and Rental Business segments. It is important to take this feature into consideration when assessing the final mPD value in order to calculate ECL.

Table 17. Number of observations for rating grades

Rating grades	Number of observations for the PF portfolio	Number of observations for the Construction and Rental Business segments
2–, 3+, 3, 3–, 4+, 4, 4–, 4+, 4, 4–, 5+, 5, 5–	274	979
6+, 6, 6–	278	457
7+, 7, 7–	228	258
8+, 8, 8–, 9	475	178
10	821	414
Total	2,076	2,286

The effect of adding the obtained mPD estimates of the PF portfolio (instead of the estimates for the Construction and Rental Business segments) to calculation of ECL for the corporate portfolio as of 01.01.2018 amounted to 0.9 million roubles (or + 0.1 %).

Thus, the computed estimates do not lead to overvaluation of the ECL amount and show the specific character of the PF portfolio in the best way. Therefore, they should be used in ECL calculation in the Bank.

Adjustment of one-year PD values taking into consideration a Macro forecast

Table 18 represents the final one-year conditional PDs which indicate the probability of default taking into consideration influence of macroeconomic information.

Table 18. The final conditional PDs which indicate the probability of default taking into consideration influence of macroeconomic information (PF portfolio)

Scale	PD TTC	Forward PD (PD PIT for the 1st and 2nd year, PD TTC for the 3rd to 5th year)				
		1st year	2nd year	3rd year	4th year	5th year
1+	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
1	0.02%	0.01%	0.02%	0.02%	0.02%	0.02%
1–	0.04%	0.03%	0.04%	0.04%	0.04%	0.04%
2+	0.08%	0.06%	0.08%	0.08%	0.08%	0.08%
2	0.16%	0.12%	0.16%	0.16%	0.16%	0.16%
2–	0.32%	0.24%	0.31%	0.32%	0.32%	0.32%
3+	0.45%	0.33%	0.44%	0.45%	0.45%	0.45%
3	0.58%	0.43%	0.57%	0.58%	0.58%	0.58%
3–	0.75%	0.55%	0.74%	0.75%	0.75%	0.75%
4+	0.96%	0.71%	1.05%	1.15%	1.21%	1.26%
4	1.23%	0.91%	1.49%	1.76%	1.96%	2.11%
4–	1.58%	1.17%	2.11%	2.70%	3.17%	3.53%

Scale	PD TTC	Forward PD (PD PIT for the 1st and 2nd year, PD TTC for the 3rd to 5th year)				
		1st year	2nd year	3rd year	4th year	5th year
5+	2.03%	1.50%	3.60%	5.17%	6.58%	7.76%
5	2.61%	1.93%	4.09%	5.77%	7.20%	8.32%
5–	3.36%	2.49%	5.35%	7.28%	8.67%	9.63%
6+	4.31%	3.21%	7.00%	9.17%	10.44%	11.15%
6	5.54%	4.14%	8.91%	11.28%	12.33%	12.72%
6–	7.12%	5.34%	11.23%	13.47%	14.24%	14.35%
7+	9.14%	6.89%	13.84%	15.81%	16.23%	16.02%
7	11.74%	8.92%	16.48%	18.07%	18.09%	17.89%
7–	15.08%	11.56%	19.13%	19.79%	19.84%	20.05%
8+	19.37%	15.02%	21.73%	21.55%	22.09%	22.96%
8	24.89%	19.61%	26.98%	24.82%	26.54%	29,26%
8–	31.97%	25.70%	29.80%	28.51%	32.07%	38.24%
9	41.06%	33.89%	34.42%	35.26%	43.79%	63.11%

Table 19 represents the final one-year marginal PDs which indicate the probability of default taking into consideration influence of macroeconomic information and participate in ECL estimate.

Table 19. The final marginal PDs which indicate the probability of default taking into consideration influence of macroeconomic information (PF portfolio)

Scale	PD TTC	MPD				
		1st year	2nd year	3rd year	4th year	5th year
1+	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
1	0.02%	0.01%	0.02%	0.02%	0.02%	0.02%
1–	0.04%	0.03%	0.04%	0.04%	0.04%	0.04%
2+	0.08%	0.06%	0.08%	0.08%	0.08%	0.08%
2	0.16%	0.12%	0.16%	0.16%	0.16%	0.16%
2–	0.32%	0.24%	0.31%	0.32%	0.32%	0.32%
3+	0.45%	0.33%	0.44%	0.45%	0.44%	0.44%
3	0.58%	0.43%	0.57%	0.57%	0.57%	0.57%
3–	0.75%	0.55%	0.73%	0.74%	0.73%	0.73%
4+	0.96%	0.71%	1.04%	1.13%	1.18%	1.21%
4	1.23%	0.91%	1.47%	1.72%	1.88%	1.98%
4–	1.58%	1.17%	2.08%	2.61%	2.98%	3.22%
5+	2.03%	1.50%	3.54%	4.91%	5.93%	6.53%
5	2.61%	1.93%	4.01%	5.43%	6.38%	6.84%

Scale	PD TTC	MPD				
		1st year	2nd year	3rd year	4th year	5th year
5–	3.36%	2.49%	5.22%	6.71%	7.42%	7.53%
6+	4.31%	3.21%	6.78%	8.25%	8.54%	8.17%
6	5.54%	4.14%	8.54%	9.85%	9.55%	8.64%
6–	7.12%	5.34%	10.63%	11.32%	10.36%	8.95%
7+	9.14%	6.89%	12.89%	12.68%	10.96%	9.06%
7	11.74%	8.92%	15.01%	13.75%	11.28%	9.13%
7–	15.08%	11.56%	16.92%	14.16%	11.38%	9.22%
8+	19.37%	15.02%	18.47%	14.33%	11.52%	9.33%
8	24.89%	19.61%	21.69%	14.57%	11.71%	9.49%
8–	31.97%	25.70%	22.14%	14.87%	11.96%	9.69%
9	41.06%	33.89%	22.75%	15.29%	12.29%	9.96%

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Appendix 1.

Master scale of the bank

Scale of PJSC Bank XXX	Probability of default (PD)	Lower bound of the probability of default	Upper bound of the probability of default
1+	0.01%	0.00%	0.02%
1	0.02%	0.02%	0.03%
1–	0.04%	0.03%	0.07%
2+	0.08%	0.07%	0.14%
2	0.16%	0.14%	0.27%
2–	0.32%	0.27%	0.38%
3+	0.45%	0.38%	0.49%
3	0.58%	0.49%	0.63%
3–	0.75%	0.63%	0.81%
4+	0.96%	0.81%	1.04%
4	1.23%	1.04%	1.33%
4–	1.58%	1.33%	1.71%
5+	2.03%	1.71%	2.20%
5	2.61%	2.20%	2.82%
5–	3.36%	2.82%	3.63%
6+	4.31%	3.63%	4.66%
6	5.54%	4.66%	5.99%
6–	7.12%	5.99%	7.69%
7+	9.14%	7.69%	9.88%
7	11.74%	9.88%	12.69%
7–	15.08%	12.69%	16.30%
8+	19.37%	16.30%	20.93%
8	24.89%	20.93%	26.89%
8–	31.97%	26.89%	34.54%
9	41.06%	34.54%	100%
10	100%	100%	100%

Appendix 2.

Substantiation of the Approaches Chosen for PD Modeling

Method	Advantages	Drawbacks	Application
Weilbull distribution	The model approximates the simulative DR to the observed ones significantly better than migration matrices Simplicity of use	Requires a large amount of data on defaults	Applied in case of a large amount of data on defaults (to build DR for several years)
Migration matrices	Use existing information of the segment more heavily and therefore may be built with a smaller number of defaults A convenient mathematical apparatus Opportunity to make adjustments (for example, in the master scale)	At long periods of time (over 9 years) the results are exaggerated significantly but this may be disregarded due to discounting	Applied in case of insufficient data on defaults (for the Weilbull distribution)
Generator matrix	Use existing information of the segment more heavily and therefore may be built with a smaller number of defaults A convenient mathematical apparatus Convenient mathematical methods of adjustment Opportunity to obtain cPD estimates for nondiscrete time periods Opportunity to obtain nonzero PD for high ratings even in the absence of observed defaults	Highly complex including use No intuitive explanation when introducing adjustments in the master scale At long periods of time (over 9 years) the results are exaggerated significantly but this may be disregarded due to discounting	May be used instead of migration matrices if: Adjustments in the master scale are not necessary and Use of the generator matrix decreases the number of adjustments introduced by experts / manually

Source: [9].

Appendix 3.

Terms and definitions

Probability of default	–	The probability (in percent) of default in relation to customer's obligations within one year defined by means of the model of default probability assessment
Internal credit rating	–	an indicator which provides a complex characteristic of the customer's/project's solvency and is calculated on the basis of risk factor indicators
Default	–	failure to fulfill obligations of repayment of borrowings by the borrower (default is recorded in accordance with bank's rules)
Cumulative probability of default (cPD)	–	the probability of default at any point within the T period (accumulated probability of default, cumulative probability of default)
Marginal probability of default, mPD (t)	–	an unconditional probability that default will occur within the future t period which is a part of the T period (marginal probability of default)
Observation	–	a block of data about the customer/project as of a certain date
Rating	–	In accordance with Reports on Development of the Internal Model of Default Probability Assessment "Project Financing v.2.1", "Project Financing (developers) v.2.1".
Rating group	–	an aggregate of several rating grades placed in the neighboring positions in the rating scale which are consolidated in order to provide a sufficient number of observations for statistical analysis
Risk segment	–	a group of rating objects determined in accordance with the Rules for Classification of Bank's Credit Requirements to which the same model of default probability assessment is applied
Rating scale	–	gradation of rating estimates in accordance with Appendix 1
Conditional probability of default, PD (t)	–	a conditional probability that default will occur within the future t period which is a part of the T period provided default does not take place before the t period (conditional probability of default)
Lifetime probability of default, Lt PD	–	a probability of default within the contractual term of a financial instrument (lifetime probability of default)

Appendix 4.

Abbreviations

cDR	–	cumulative default rate
cPD	–	cumulative probability of default
Dpd	–	days past due
DR	–	default rate
mPD (t)	–	marginal probability of default, unconditional probability of default in the t period
PD	–	probability of default
PD for 12 months	–	probability of default in the following 12 months
PIT	–	point-in-time calibration
TTC	–	through-the-cycle calibration
IFRS 9	–	International Financial Reporting Standard (IFRS) 9 Financial Instruments
ECL	–	expected credit losses
SP AACR	–	software package Accounting and Analysis of Credit Risk

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Innovations Creation Process: CEO and Board of Directors Roles

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Abstract

There are innovation creation process, innovations' classifications, and measures considered in the paper. Recently focus on the literature moving from innovations relationship with financials to the role of people. This review considers board of directors group characteristics and CEO individual characteristics (the part of which impacts only firms from innovative industries) significant for innovation creation. The paper predicts investment in innovation, innovation outcome, and optimal for shareholders' wealth board of directors' type in dependence on CEO individual characteristics.

Keywords: innovations, corporate governance, behavioral finance

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Introduction about innovation creation process

What is innovation? The famous Austrian scientist, Josef Schumpeter, coined the term "innovation" in the 1930s and defined it as "new combinations" [1, p. 89]. The author suggested the next innovation process order: invention, innovation, diffusion, and imitation. As we can see from this sequence, the invention differs from innovation, and it is important for the current paper topic because it is devoted to innovation creation. Maclaurin (1953) [2] developed Schumpeter's innovation creation process by adding 'propensities': the propensity to invent, the propensity to innovate, the propensity to finance innovation, and the propensity to adopt innovations. Many authors later used these terms in researches [3–7]. Also, the term propensity to imitate is in use (Singh, 2006) [5].

Companies' innovative activities have a significant impact on the long-term development of the world economy. It requires investments that lead to the development of financial markets, increases the level of competitiveness that impacts consumers welfare, and drives the technological development of the world. Stimuli for companies to innovate are the opportunity of extra-profit receiving. Schumpeter considered profit as a risk premium, however, Knight (1921) [8] thought that profit exists due to uncertainty. But there are some problems with profit receiving from innovations. The thing is that in comparison with the trading business there is a much higher loss probability in innovation activity. An important role in innovation creation plays people, especially those of them who have significant decision-making power such as top managers and members of the board of directors [9–10]. Thus, studying their personal characteristics is useful, both for science and the companies investing in innovations.

Considering board members' and top managers' innovativeness we should look at the innovation creation process at the individual level. According to Schweizer (2006) [11], there is some type of mess in the literature regarding different innovation terms such as innovativeness, novelty-seeking, creativity, and innovative performance. To order terms, she suggested the novelty generation model (NGM). The starting point in the model is the "need for cognition", which is converted to novelty seeking (Figure 1).

Figure 1. The key idea of the novelty generation model (NGM)

Source: [11].

Schweizer (2006) [11] used the term "novelty seeking" based on information that 'novelty-seeking genes' gens were found: "DRD4, DRD2-A2, SLC6A3-9" [12–14]. Novelty seeking is often considered as a concept relevant to the need to seek out new information, and to exploratory activity in response to novel stimulation [15]. But there is also another concept called 'sensation-seeking' developed by Zuckerman et al. [16–19]. He defined sensation seeking as: "...a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience" [17, p. 26]. According to these 2 definitions, we can conclude that the term sensation seeking is wider and includes novelty-seeking.

The second step in the model is "creativity". Schweizer (2006) [11] divided it into novelty-finding and novelty-producing. Creativity according to Yagolkovskiy (2019) [20] is the ability to create new. According to Schweizer (2006) [11], creativity depends on 3 main traits: low levels of cortical and frontal-lobe activation [21], associative capabilities [22], and latent inhibition – the ability to keep many things on the mind at the same time [23]. West (2002) [24] and Cropley et al. (2011) [25] agree that an innovative process includes not only the generation of new ideas but also their possible modification and subsequent application, which are taken into the model as the third step – innovative performance. Schweizer (2006) [11] highlighted the main determinants of innovative performance: achievements need, self-confidence, perseverance, assertiveness, proactivity, extraversion, and cooperativeness. Many authors used these components in the research as explanatory variables for innovations [6, p. 26–27]. Interesting that Nambisan et al. (1998) [3] in their research about IT users' propensity to innovate also highlighted almost the same three components of innovativeness: technology cognizance, ability to explore, and intention to explore a technology.

Also, there is a lot of literature about innovations from technological, marketing, micro, and macro points of view [28]. Moreover, the branch of literature considered the collaborative effect on innovation is quite popular [29; 30]. Authors showed the importance of communication between people with opposite backgrounds for the creation and development of new ideas, for the invention step according to Schumpeter [1], and creativity according to Schweizer (2006) [11]. However, it was proven by Coskun et al. (2000) [31], that group creativity is higher when the group consists of 2–3 members, and the group loses its efficiency with an increase in the number of participants. So, the highest innovation output can be reached in the case of numerous contacts with people from different backgrounds developing an idea, and subsequent work in small teams to bring it to production.

The literature review consists of four main parts: 1) classification and measurement of innovation, 2) the board of directors' role in innovation creation; 3) the CEO impact on innovations; 4) influence of the relationship between the CEO and the board on innovations.

Classification and measurement of innovation

Before moving to the board and the CEO roles in innovations' creation it is important to overview how innovations are classified and how innovations' input and output can be measured to be able to discuss innovations' efficiency.

There are some classifications of innovation. Damanpour (1996) [32] highlights 4 dimensions of innovation: administrative and technical, product and process, radical and incremental, initiation and implementation [33]. Administrative innovations relate to human resources, technical – to the technologies. Rogers (2010) [34] and Zaltman et al. (1973) [35] classification for the initiation of innovation and implementation looks like not types of innovation, but different stages in the innovation creation process considered earlier. Product and process, radical and incremental classifications are more widespread than others [36; 37]. Radical innovations which are also called disruptive, lead to fundamental changes in firm activity and contain a high degree of new knowledge [38; 39]. Incremental innovations refer to a small knowledge increase [38; 40]. This classification is close to the division of innovations on exploratory (when a firm creates new technological knowledge in comparison with the existing one) and exploitative (when technological knowledge was created from existing knowledge) [41]. There is also the term innovations 'ambidexterity' used in the literature that reflects organizational ability to manage both types of innovations [42].

Utterback and Abernathy (1975) [43] were one of the first who used product and process innovations classifications. Product innovation is "the commercialization of new goods or services to meet an external user need" [37, p. 306]. Process innovation is "the introduction into the organization's production process or service operations of new elements" [32, p. 698]. Product and process innovation classification was used in numerous studies [36; 37; 44–47]. Relatively recently this classification was modified by adding business model innovations by Amit and Zott (2012) [48]. The business model innovation changes firms' value creation channels [37]. This wider innovations' classification gathers popularity in research and was used, for example, in Johnson et al. (2008) [49], Crossan and Apaydin (2010) [50], Foss and Saebi (2017) [51], Snihur and Wiklund (2019) [37]. Also, innovations may be classified according to implementation areas: technological, administrative, marketing, etc.

There are two ways how a company can get innovative technologies: develop them by themselves or acquire them from outside [27]. This paper concentrates on the development of innovations inside a company. The most common method of innovation input measurement is the amount of research and development expenditure (R&D) – so-called R&D intensity, which is usually calculated as "R&D to total sales", "R&D per employee" or R&D-to-market equity (R&D/ME) [52–56]. However, there is a problem with R&D recognition from an accounting point of view. According to IFRS (IAS 38) [57] expenditure can be recognized as R&D and capitalized only in cases when it can be proved that this expenditure will bring profit in the future. Also, firms are more interested not in investment in innovations, but in their outcomes. So, there is a necessity to evaluate it. There is a methodology to estimate innovations' output as the share of innovation product sales to total sales [58]. The main deficiency of this approach is the unavailability of data about innovative product sales. This information may be received only using survey methodology. Also, scientists use a number of patents and patent citations that may be scaled on R&D expenditures, the number of employees involved in R&D activity [59], or R&D capital [53] to measure innovations outcome [60; 61]. However, this approach also has a disadvantage: it does not take into account the fact that patents have different values for a company (is this innovation radical or incremental?). That is why the patents' value "weighted" approach [62] is considered as the best measurement for innovation outcome nowadays.

There is also a problem with an accounting of R&D accumulated, so-called R&D capital, and especially with its depreciation. Lev et al. (2005) [63] noticed that "companies with a high R&D growth rate relative to their profitability (typically early life-cycle companies) report conservatively, while firms with a low R&D growth rate (mature companies) tend to report aggressively" [63, p. 977]. And found "undervaluation of conservatively reporting firms and overvaluation of aggressively reporting firms" [63, p. 977]

Chan et al. (2001) [52] and Lev et al. (2005) [63] suggested the next way of R&D capital estimation: the 5-year cumulative R&D expenses assuming an annual depreciation rate of 20%

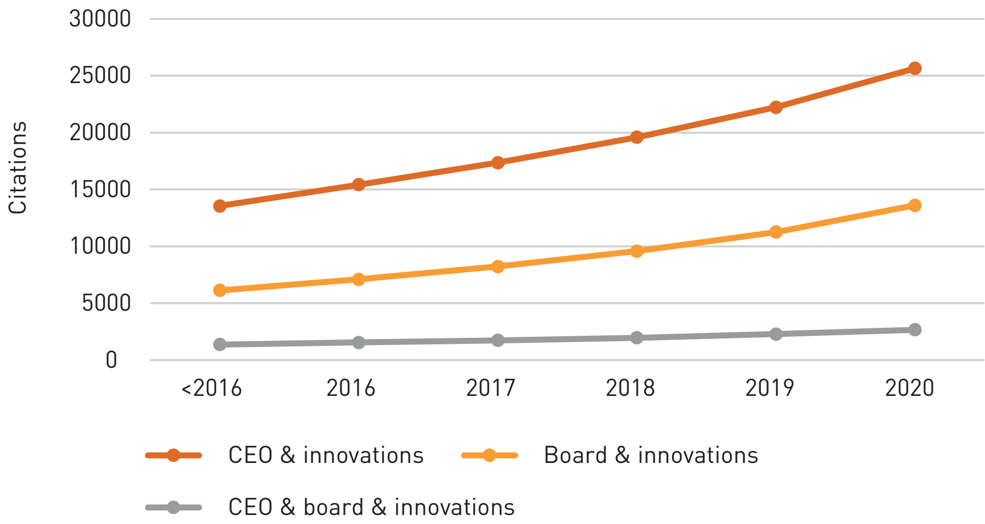
$$R\,\&\,D\,Capital_{i,t} = R\,\&\,D_{i,t} + 0{,}8 \bullet R\,\&\,D_{i,t-1} + $$
$$+0{,}6 \bullet R\,\&\,D_{i,t-2} + 0{,}4 \bullet R\,\&\,D_{i,t-3} + 0{,}2 \bullet R\,\&\,D_{i,t-4}.$$

This approach was used in some studies [53]. R&D capital depreciation rate is a separate question studied by many authors [64–66]. Recently Li and Hall (2020) [67] suggested a non-linear approach to R&D capital amortization and found that "the rates are in general higher than the traditionally assumed 15 percent and vary across industries" [67, p. 161].

Also, as R&D expenditures are exogenously dependent on past years' financial results its estimation requires the usage of instrumented variables [27]. Laursen et al. (2012) [27] used current ratio (CA/CL), equity – noncurrent assets, and gearing ratio (owner's equity over-borrowed funds) as instrumental variables for RD intensity. For external R&D acquired they used membership of a commercial consortium, labor flexibility (number employees on short-term contracts over the total number of employees), and gearing ratio as instruments.

Considered innovations measurements were used in 2 main branches of study: determinants of innovation input and estimation of innovations output and effectiveness [53; 68–69]. In 21 century these researches were extended by including additional variables, for example, intellectual capital [7] (13 359 documents in Scopus) and corporate governance characteristics [9; 53; 61] (27 797 documents in Scopus).

Figure 2. Cumulative citations in Scopus about CEO, board, and innovations in 2016–2020



Source: Scopus database search.

Especially scientists are interested in the CEO role in the innovation creation process. Figure 2 represents cumulative citations in Scopus in management and economics during 2016–2020 (Figure 2).

In this paper board of directors' group characteristics and CEO personal characteristics significant for innovations are considered.

Board role

Only the board of directors' characteristics relates to the board as the group of people will be discussed in this section as individual characteristics considered in the first and next sections may be applied for every board member.

External directors are historically considered as stabilizers and people who are responsible for corruption prevention in the company [70]. However, how do they impact innovations? From the first point of view, they bring a lot of information into the company, including information about recent innovations [71]. Balsmeier et al. (2014) [72] and Helmers et al. (2017) [73], highlighted the importance of independent and cross-board directors for R&D investment growth and the number of patents. But, from another point of view, external directors' "stabilization function" prevents them from risky investment in innovations [74; 75] in comparison with internal directors. Balsmeier et al. (2017) [70] found that companies with a higher percentage of external directors on the board are concentrated on innovations in some technological areas in which they already had some success. It leads to an increase in citations, but the numbers of uncited and highly cited patents remain at the same level, which confirms the idea about independent directors' risk-aversion. **Womens' presence** on the board is traditionally considered as a source of gender diversity that, as every diversity should increase creativity [76] and, as an instrument for a reduction in risk appetite [77]. However, some recent studies, for example, Adams & Ragunathan's paper "Lehman Sisters" (2017) [78], show that women in top management careers should be less risk-averse than men, so it's difficult to predict the direction of their impact on a firm's risk-perception level and innovations.

The **board size** role in innovation creation processes is still not identified clearly. On the one hand, the larger the board the more information and resources it has to manage. As proven by Mednick (1962) [22] information diversification increases creativity and an opportunity to create innovation consequently. On the other hand, there is an opinion that large boards are less efficient, due to the necessity to spend more time for negotiation [79], and do not have any significant impact on patents' creation [71]. Another debatable board of directors' characteristic is the number of **board meetings** per year. According to Vafeas' (1999) [80] study, more frequent board meetings make the board more efficient in the long term, but this is caused, usually, by a bad state of affairs, at some stage in the company. However, Chen (2012) [79] did not find any significant relationship between the frequency of board meetings and R&D.

Regarding **board tenure,** we can also anticipate two factors. On the one hand, according to Ben Amar et al. (2013) [81], the longer tenure, the easier board members can make decisions, but, on the other hand, they lose their independence and there is a smaller number of new idea sources which can come to the company and push innovations. So, according to Bravo & Reguera Alvarado (2017) [55] study, there is no relationship between board tenure and R&D intensity. Numerous authors noticed the important roles of board members' **education and work experience** for innovation creation. For example, according to Chen (2012) [79], board members' education increases R&D investment, due to a higher ability to understand and manage complex, innovative projects. Also, it was shown in Allemand et al. study (2017) [10], that if board members have scientific degrees, engineering education, marketing, and research experience, a firms' innovation activity is higher. Sun et al. (2020) [82] proved that a higher level of a firms' human capital correlates with a greater number of patents.

CEO duality is a quite widespread phenomenon, when the CEO simultaneously acts as the Chairman of the Board. CEO duality has positive and negative effects. Classically, CEO duality is considered as an unfavorable factor for shareholders' wealth [54]. CEO duality reduces the board's opportunity to control R&D expenditure to an efficient level [83]. According to Li & Yang (2019) [84], "CEO tenure is positively related to the percentage of exploitative innovation" [84, p. 539]. In the next block of the literature review, it will be considered in detail, how and why CEO personality is so important for innovation.

CEO role

The CEO is often considered as the face of the firm, and his or her actions highly impact company strategy and organization at all levels. That is why CEO individual characteristics and experience are very important for a company's investment in innovations and its output, both in the form of patents and citations, and in the form of financial indicators [60; 85; 86]. Later in the text, CEO characteristics-affected innovations are considered in three dimensions: 1) innovativeness, 2) risk preferences, 3) overconfidence (including mitigation of negative effects).

CEO innovativeness

Islam and Zein, from Australia, in their article "Inventor CEOs" (2020) [61], studied the CEO propensity to innovate, measured as the number of patents belonging to the CEO. They divided the sample from S&P 1,500 high tech innovative companies, from 1993 to 2005, for five main categories: active inventor CEO, passive inventor CEO, non-inventor CEO, high-impact inventor CEO, and low-impact inventor CEO. The Active CEO is a CEO whose number of patents increased after becoming CEO, passive CEOs received all their patents before becoming CEO. The CEO with the highest number of patents in the sample is Steve Jobs, with 222 patents. The high-impact inventor CEO is a CEO who holds 2 or more highly cited patents.

The authors found a positive correlation between CEO's propensity to innovate and innovations in the company [61]. However, there are 2 possible explanations: 1) An innovative company recognizes its potential and invites an inventor CEO type; 2) The Inventor CEO plays a key role and increases company innovations. To resolve an endogeneity problem authors used a difference in difference model and found that inventor CEO replacement for non-inventor leads to a decrease in the number of patents by 20% and citations by 36% [61]. The authors concluded that CEO individuality is more important than a firm's innovative opportunities [61]. Also, they found that the inventor CEO invests in innovations more than the non-inventor, and that the founder effect, CEO overconfidence, and general managerial skills don't incur any significant impact on innovations [61].

Another important part of the research of the "Inventor CEOs" [61] is devoted to **CEO experience**. According to empirical results, there is a positive correlation between CEO experience in some technology classes and the number of firm's patents in the same technology class. And the more active the inventor CEO, the higher number of firm patents in the CEO-experienced-technologically class. Moreover, patents from the CEO-experienced-technologically class are more valuable: "$10.6 million higher average value per patent" [61, p. 516]. And the probability to create a radical patent in a class is higher when the CEO has "in-class inventor experience" [61, p. 516]. However, the authors found that investing in different technological classes leads to a lower number of patents in each class [61].

Following Mukherjee et al. (2017) [87], Islam and Zein (2020) [61] tested inventor CEO impact on firm financial outcomes and found that the stock market reacts more positively to announcements about a breakthrough new product made by the inventor CEO. Using different propensity to innovate measurement, the authors found that active and high-impact inventor CEOs are associated with a 70% higher number of patents, citation, and patents value than non-inventor CEOs. Bostan and Mian (2019) [88], also proved that companies, under the direction of inventor CEOs, have a higher number of both cited and uncited patents. It is interesting, also, that, according to the research results, the stock market undervalued inventor CEO-run companies, which allowed the firm to have abnormal stock returns during the first years after the appointment of the inventor CEO.

There is a widespread opinion that management **education** and **work experience** also impact his or her behavioral specificities, like risk-preferences and overconfidence [89]. According to Custódio et al. (2019) [90] research, CEOs who have management experience, will lead to an increase in the number of patents, however, some authors suggest that research experience will be the most valuable for CEOs in innovative companies [89]. The question about education consists of two parts: quality and specialization. Gottesman & Morey (2006) [91], found that the quality of education doesn't affect any significant impact on future innovation activity, including having an MBA degree. Islam and Zein (2020) [61] found that **age** doesn't incur any impact, however other authors, such as Acemoglu et al. (2014) [92], wrote that age is an important factor. I can suggest a possible explanation: maybe age is correlated with inventor CEO experience, measured as the number of patents, because the older the person is, the more years he or she has to create more patents.

CEO risk-preference

One of the first relationships between risk and creativity was found by the psychologist. Martindale (1999) [21], who demonstrated that creativity is positively correlated with cortical activation (arousal), which has an inverse U-shape form. When the complexity of the task increases, optimal arousal decreases. More simple tasks require a higher level of arousal. In other words, stress reduces creativity. The same result was observed by Kandasamy et al. (2014) [93], that in stress situations, the cortisol level increases, which reduces risk-appetite.

On the contrary, Eisenman (1987) [94] was one of the first who claimed about the positive correlation between creativity and risk-taking, studying firstborn white males. Subsequent authors supported Eisenman's point of view [95] and developed it, especially regarding intrinsic motivation [96; 97]. The solution to this contradiction, according to Loch (2017) [98] and Shen et al. (2018) [99], is that risk-taking is a prerequisite of creativity. It means that inventors are ready to take some degree of risk, due to the high expected value of the innovations created, both for society and for themselves.

It is interesting, in the context of the current study, how to measure top-management risk preferences? One recent breakthrough research was made by Sunder et al. (2017) [9]. The authors investigated the presence of CEO pilot licenses as a proxy for *sensation seeking*. It is important to note that sensation seeking slightly differs from risk attitude and represents openness to new ideas, which is positively correlated with innovativeness [100]. It was found that a lower risk-aversion is positively correlated with innovations' output. Grinblatt & Keloharju (2009) [101] found that people with a higher number of speeding tickets may be considered as sensation seekers and they are more active on the stock exchange.

There are also investigations devoted to risk perception proxy, like Fischer et al. (2007) [102]. It was proven that online racing games increase the probability of car accidents in real life and risk level in other actions. Also, a positive correlation between extreme sports and risk-taking was found by Self et al. (2007) [103]. However, Brymer (2010) [104] has the opposite view. The author thinks that extreme sportsmen understand risks quite well, both extreme sport risks and everyday risks (e.g. driving a car), they prepared carefully to eliminate the probability of a negative outcome from doing extreme sports, and should not be considered as sensation seekers. It should also be noted that risk is subjective – a motorcyclists' speed may seem excessive to a car driver, but not to another, experienced motorcyclist.

Another factor that impacted risk attitude is "early life exposure to fatal disasters" [105, p. 169] according to Bernile et al. (2017) [105] study. The authors showed that there is a positive relationship between firm risk level and CEO risk attitude formed through negative events in childhood. It is interesting that, if the effects from an early life disaster were low to moderate, a person becomes riskier in the future in the CEO role. At the same time, if a disaster led to dramatic negative consequences, a person chooses a conservative risk minimization strategy in the CEO role. Moreover, Serfling (2014) [106] and Brooks et al. (2018) [107] showed that older investors have higher risk-aversion and lower willingness to invest.

One more interesting research is devoted to the cultural role in risk perception. Frijns et al. (2013) [108] studying M&A practice across the world, noticed that companies from counties with high risk-aversion, avoid international and cross-industry deals and require a higher premium. Thus, we can conclude that there are some different ways to estimate CEO creativity and innovativeness, using one of the considered sensation-seeking or risk-aversion measures.

CEO overconfidence

According to Griffin and Tversky (1992) [109], overconfident individuals tend to overestimate the net discounted expected payoffs from uncertain endeavors. When the CEO of the company is overconfident, it leads to both positive and negative effects for the firm. Before detailed overconfidence consequences consideration, let us review some approaches to CEO overconfidence measurement:

1) Stock options in CEO hands "after the vesting period in which an exercise becomes permissible" [60, p. 1459]. Malmendier & Tate (2005, 2008) [110; 111] created an options-based methodology, but Hirshleifer et al. (2012) [60] noticed that data inability does not allow researchers to recalculate 67% of the value in options, in a clear way, because CEO wealth was unknown;
2) Verbal analysis. For verbal analysis, Hirshleifer et al. (2012) [60] used 2 groups of words in the CEO's speech in the press: confident and cautious. CEO was considered as overconfident if the number of confident phrases exceeds the cautious ones each year;
3) One other methodology that is applicable for overconfidence estimation uses debt inflow because overconfident CEOs value equity more than debt. It is based on the idea that overconfident CEOs tend to overinvest, according to Galasso & Simcoe (2011) [112];
4) Moreover, there is a methodology that allows researchers to track R&D profitability – through CDSs (credit default swaps) improved by Chang et al. (2019) [113]. This methodology directly relies on debt financing which allows us to connect it with overconfidence measurement.

Also, it's very important that CEO overconfidence does matter only for risky innovation industries and doesn't incur any significant influence both on R&D amount and a firm's value in other ones [60; 89; 112]. There are also some interesting findings regarding overconfidence. The first one is that companies with overconfident CEOs should have higher costs, in the form of investments, because the CEO believes in a project's success too much and increases its scale. Malmendier and Tate (2005) [110] demonstrate that overconfident CEOs spend more available internal funds on capital expenditures. Chen et al. (2013) [114] concluded that SG&A decrease is not desirable for overconfident CEOs because they believe in "future growth prospects and SG&A needs". The second conclusion is that the overconfident CEO prefers external debt financing, instead of shares issuing, to avoid dilution of equity capital as the CEO values it too high and because the overconfident CEO considers external equity financing as costly [115]. And last, but not least, a finding shows that overconfident CEOs may be slightly aggressive in acquisitions which often cause a negative market reaction [116].

It was found that companies with overconfident CEOs have higher stock volatilities and R&D expenditures which leads to higher patents and citations. However, this innovations' activity, unfortunately, does not always increase a company's value [60; 117; 118]. CEO overconfidence leads to an increase in the number of patents and patent citations, but the correlation is lower than 1. Moreover, only an extremely overconfident CEO can increase a firm's value through increased patents' citations due to "radical" innovation invention.

CEO vs Board of directors

Another block of literature proves that CEO overconfidence is not the unique company risk and innovations source. Let's not forget about board and decision-making power distribution across **board** members, CEO, and other top management (for example, CFO). To evaluate risk correctly, it's necessary to consider board members' risk preferences. Leng et al. (2018) [119] proved that large boards can eliminate the negative effects of CEO overconfidence. Moreover, Kolasinski and Li (2013) [116] showed that well-balanced boards of directors can help overconfident CEOs to avoid mistakes during M&A deals. One more interesting article was written by Wong et al. (2017) [41] about ambidextrous innovation. They found that "an independent board and dedicated institutional ownership mitigate the positive relationship between CEO overconfidence and a firm's ambidextrous imbalance" [41, p. 414]. Leng et al. (2018) [119] found that overconfident CEOs increase the likelihood of bankruptcy, however, larger boards decrease the probability. Li & Tang (2010) [120] noticed that the presence of independent directors on the board decreases overinvestment caused by CEO overconfidence. Nakano & Nguyen (2012) [121] think that a large board can outargue the overconfident CEO in the decision-making process. Using a sample consisting of 940 non-financial UK firms, listed on the LSE, and 1,304 CEOs during 2000–2015 years, the authors proved that the risk of failure is higher in firms managed by overconfident CEOs. At the same time just confident – not overconfident CEOs, reduce the probability of bankruptcy.

One more interesting paper about CEO behavioral bias mitigation by the board is written by Banerjee et al. in 2015 [122]. The authors studied whether independent directors on the board can restrain the negative effects caused by CEO overconfidence such as "extreme risk-taking and overinvestment" [122, p. 2813] on the example of the Sarbanes-Oxley Act (SOX), 2002. Based on O'Conor (2002) [123] the authors suggested that Enron's troubles were not overcome in good time because of the "permissive board that exhibited groupthink and inadequate oversight" [122, p. 2813]. According to Graham et al. (2013) [124] "CEOs tend to be more optimistic, and less risk-averse, than the lay population is" [122, p. 2813]. Banerjee et al. (2015) [122] showed that capital expenditures to total assets made by overconfident CEOs decreased after SOX adoption. Also, they found that the process of SOX led to a significant drop, both in systematic and firm-specific risks, for firms with overconfident CEOs, but was it beneficial for shareholders? The authors demonstrated that SOX adoption leads to an increase in shareholders' wealth in companies with overconfident CEOs, instead of "hinder value creation by these CEOs" [122, p. 2815].

The article, "Board composition and CEO power" by Baldenius et al. printed in the "Journal of Financial Economics" in 2014 [125] studied the board of directors and CEO relationship impact on shareholders' wealth. The authors described 2 types of board: 'centralized' when the board makes a decision, and 'delegated' when the board delegates decision-making power to the CEO. Also, the board has 2 functions: to monitor management activity and to advise. It is interesting to note that board members with a financial background prefer to monitor, while former CEOs and people with technology, marketing, and consulting experience are more involved in advising. In general, CEOs prefer delegation instead of advising from the board side. It's noticeable that the authors assumed that the board fully represented shareholders' interests. Using modeling, the authors showed that "the CEO, at times, has incentives to appoint a board that is excessively focused on monitoring" [125, p. 64]. This result is surprising, on the one hand, because CEOs are less willing to be monitored, however, it revealed that the monitoring board prefers to delegate decision-making power to the CEO, which increases his power. The second surprising result is that CEOs can make projects more difficult to reinforce themselves as a company's leader. To counter the threat of entrenchment, shareholders nominate more advisor-biased boards instead of monitoring and advising to the same degree. According to the results obtained, "the less biased the CEO, the more the board delegates" and that "to increase shareholders value, CEO bias has to be small".

Story et al. (2015) [126] showed that the relationship between a firm's value and product innovations looks like an inverse U-shape, both in developed (UK) and developing (Ghana) counties. It is interesting that, for the developing country, an increase in access to financial sources leads to higher innovation output, and there is no such relationship in the developed market. It may be explained through a stable supply of the financial market in a developed country. Moreover, firms from a developing country are less able to compete with their competitors under more dynamic market conditions.

Based on the reviewed information we can formulate hypotheses about R&D amount, innovations types, and optimal for shareholders' wealth board of directors' types in innovative industries in dependence on two CEO characteristics: innovativeness and overconfidence (Table 1). As overconfidence and innovativeness have a stronger impact in innovative industries [60; 61] we take it into account. Risk-taking was not considered separately as it is a prerequisite of innovativeness both in form of creativity (inventor CEO) and innovative performance (overconfidence) [11; 98; 99].

Table 1. R&D amount, innovation output, and optimal board of directors' type prediction in dependence on CEO characteristics in innovative industries

Inventor CEO	Overconfident CEO	R&D expenditures	Innovations output	Optimal board type
Non-inventor	Non-overconfident	The lowest	No	Centralized *risky* board
	Overconfident	Low	Incremental	Centralized *moderate* board
Inventor	Non-overconfident	High	Incremental	Delegated board
	Overconfident	The highest	Radical	Centralized *conservative* board

Source: author's hypotheses based on Islam and Zein (2020) [61]; Hirshleifer et al. (2012) [60]; Hirshleifer et al. (2013) [53]; Baldenius et al. (2014) [125].

Inventor CEO is based on Islam and Zein (2020) [61] and may be measured as the presence of CEO patents. On the one hand, the inventor CEO has all the personal traits required for innovations: the need for cognition, creativity, and innovative performance, however, there is a question will he be able to manage employees as managed themself? That is why we considered Inventor CEO as a person who exactly has the need for cognition and creativity [11], so this person will invest more in R&D than a non-inventor [61]. Overconfident CEO is considered as a person able to succeed in innovative performance [11]. Only an inventor overconfident person can make radical innovations [37; 60; 61]. But overconfidence according to the literature also impacts R&D expenditures [60; 61], so for overconfident CEO, it is higher than for non-overconfident both for inventor and non-inventor CEO types.

Optimal board types were chosen based on Baldenius et al. (2014) [125] between delegated and centralized. We add three levels of risk attitude for a centralized board: risk-averse (conservative board), risk-neutral (moderate board), and risk loving (risky board). Inventor non-overconfident CEO was considered as optimal for innovative industry, because based on his innovativeness we can conclude that he is confident (but not overconfident) [11; 124], that's why his innovative performance may be profitable and stable. So, the best board for such a CEO is delegated board that just monitors the results of the firm activity. For inventor overconfident CEO centralized conservative board will be the better bankruptcy risk-reducing agent [67; 120–122]. A moderate board would fruitfully control non-inventor overconfident CEO, because it will mitigate negative overconfidence effects, but will not interfere with the development of the company. And the risky board will compensate non-inventor non-overconfident CEO.

Conclusion

According to the review prepared innovations are studied in the literature from many points of view. Innovation creation may be on individual [11] and firm levels [1]. Innovations' input is measured as R&D which is connected with firm financials in two ways: firstly, like expenditures, secondly, as investments that may be profitable or not. That is why usually an inverse U-shape relationship between innovations inputs and share prices is tested [56]. R&D output may be measured as a share of innovative sales, patents and citation, and using patents' value-weighted approach. Successful innovations require not only the financial base but also sufficient human capital in the company at all levels (from developers to the top management and board members) [7]. Big companies have an advantage in innovation creation due to their ability to concentrate a huge number of resources, and it also was noticed that big companies produce most of the innovations nowadays [61].

On the one hand, the firm innovation output positively depends on BoD's and CEO's low risk-aversion level, overconfidence, and innovativeness, but on the other hand, bankruptcy risk simultaneously increases. Also, it is noticeable that firms in which CEOs have a high propensity to innovate, provide more innovations, but only in innovative industries. Moreover, only extremely overconfident CEOs increase a firm's value through higher innovation output, while firms with moderately overconfident CEOs have lower stock volatility and bankruptcy risk. Large boards and the presence of external directors can mitigate the negative effects of CEO overconfidence. It seems that there is an optimal point corresponding with innovation efficiency: balance between BoD and CEO innovativeness (including different degrees of confidence, low risk-aversion, open-mindedness, proactivity, resistance, and creativity) and financial discretion. So, we can see that profit in innovative industries is analog of Schumpeter risk premium [1] and Knight payment for uncertainty [8].

Also, where is an interesting question that remains unresolved - who is more important for company innovativeness: the CEO or the board? According to my point of view, which is supported by Islam and Zein (2020) [61], the CEO plays a more important role in the innovation creation process than the board of directors, because the CEO is the manager and has a direct impact on business processes in the company when the board of directors – indirect. As a continuation of the study, it would be interesting to test predicted in Table 1 relationships on real data. There are also some limitations of the study. Firstly, we did not consider the full range of personal traits such as narcissism or short-termism, and characteristics like CEO power, etc.

that also may be valuable for innovations prediction. Secondly, it seems that it is not possible to predict innovation impact on shareholders wealth based only on CEO and the board characteristics.

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