4

2020 / Vol. 14
ISSN 2073-0438
cfjournal.hse.ru

JOURNAL OF CORPORATE FINANCE RESEARCH

Электронный журнал
«Корпоративные финансы»

www.cfjournal.hse.ru

New Research | Corporate Financial Analytics | Applied Financial Analytics | Methods | Reviews | Discussions

Корпоративные финансы

2020. № 4, т. 14
Электронный журнал
www.cfjournal.hse.ru
ISSN 2073-0438

Адрес редакции:
Высшая школа экономики,
факультет экономических наук,
Покровский б-р., д. 11, корп. S
Тел.: +7 (495) 621 9192 *27188
E-mail: *cf@hse.ru*

Электронный журнал «Корпоративные финансы» издается с 2007 г. Учредителями журнала являются Национальный исследовательский университет «Высшая школа экономики» и **Ирина Васильевна Ивашковская** (главный редактор).

Цель журнала – создание информационного ресурса, необходимого для развития корпоративных финансов как современной области исследований и преподавания, направленной на разработку и применение принципов финансовой теории для анализа и моделирования комплекса финансовых решений фирмы и их роли в создании ее стоимости, анализа и моделирования поведения агентов (менеджмента) и выявления роли их стимулов в создании стоимости компании, анализа финансовой архитектуры фирм и корпоративного контроля, а также других смежных направлений.

Электронный журнал «Корпоративные финансы» ориентирован на развитие исследований в новой для российской экономической науки области теоретических концепций финансовых решений современных компаний, апробацию и эмпирическое тестирование современных концепций корпоративных финансов на базе данных стран с растущими и развитыми рынками капитала, а также на распространение получаемых результатов.

Журнал выходит четыре раза в год (поквартально).

Доступ к электронному журналу постоянный, свободный и бесплатный по адресу: *https://cfjournal.hse.ru*.

Журнал «Корпоративные финансы» включен в список ВАК России, индексируется в Российском индексе научного цитирования (РИНЦ). С 2015 г. входит в топ-1000 лучших российских журналов Russian Science Citation Index (RSCI) на базе Web of Science.

Требования к авторам изложены на официальном сайте журнала: *https://cfjournal.hse.ru/auth_req.html*.

Все статьи, поступающие в редакцию, проходят анонимное рецензирование. Плата за публикацию статьей не взимается.
С публикационной этикой можно ознакомиться на официальном сайте журнала: *https://cfjournal.hse.ru/etika*.

Journal of Corporate Finance Research

2020. Vol. 14. # 4
e-journal

www.cfjournal.hse.ru
ISSN 2073-0438

Contacts:

Higher School
of Economics (HSE),

11 Pokrovsky Boulevard, Building S
Tel.: +7 (495) 621 9192 *27188
E-mail: *cf@hse.ru*

Journal of Corporate Finance Research (JCFR) was established in 2007. It is founded by the National Research University Higher School of Economics (NRU HSE) and **Irina Ivashkovskaya** (chief editor). The journal is included in Web of Science Russian Science Citation Index (RSCI).

Journal of Corporate Finance Research aims to publish high quality and well-written papers that develop theoretical concepts, empirical tests and research by case studies in corporate finance.

The scope of topics that are most interesting to JCFR includes but is not limited to: corporate financial architecture, payout policies, corporate restructuring, mergers and takeovers, corporate governance, international financial management, behavioral finance, implications of asset pricing and microstructure analysis for corporate finance, private equity, venture capital, corporate risk-management, real options, applications of corporate finance concepts to family-owned business, financial intermediation and financial institutions.

JCFR targets scholars from both academia and business community all over the world.

Frequency: 4 times per year

The Journal of Corporate Finance Research is committed to upholding the standards of publication ethics and takes all possible measures against any publication malpractices. Editors of the journal reserve the right to reject the work from publication in case of revealing any such malpractices.

Guidelines for authors:
https://cfjournal.hse.ru/en/for%20authors.html.

Содержание

Электронный журнал «Корпоративные финансы»
2020. №4, т. 14
www.cfjournal.hse.ru

Новые исследования

Корпоративная финансовая аналитика

Обзоры

Contents

Journal of Corporate Finance Research
2020. Vol. 14. # 4
www.cfjournal.hse.ru

New Research

Corporate Financial Analytics

Reviews

News Sentiment in Bankruptcy Prediction Models: Evidence from Russian Retail Companies*

Elena Makeeva
Associate Professor
ORCID
E-mail: emakeeva@hse.ru

National Research University Higher School of Economics, Moscow, Russia

Maria Sinilshchikova
Researcher
ORCID
E-mail: mariasinilshchikova@gmail.com

Corporate Finance Center, National Research University Higher School of Economics, Moscow, Russia

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 7-18 (2020)
DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.7-18
Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

* The research leading to these results has received funding from the Basic Research Program at the National Research University Higher School of Economics

**News Sentiment in Bankruptcy Prediction Models:
Evidence from Russian Retail Companies**

Abstract

This study is aimed at investigating the application of news sentiment analysis to bankruptcy prediction models in the context of the Russian retail sector.

We analyse 190 companies: 95 Russian retail companies that went bankrupt in 2015-2019, and 95 non-defaulting analogue companies. This figure was attained from a larger pool of 312 companies retrieved from the Spark database on the basis of analysis of relevant financial data and further validated by the presence of pertinent news media coverage within 3 years of default date. The methodological base of this analysis is the logistic regression approach, used as a benchmark model, and several machine learning models: random forest, support vector machine, and multilayer perceptron.

The predictor set applied consists of 34 financial variables and sentiment variables, aggregated using the 'bag-of-words' from a total sample of 4877 news articles, from more than 800 distinct online resource locations. We establish a set of hypotheses based on a review of existing literature in the area, and evaluate their accuracy on the basis of our technical analysis.

Our results show that sentiment variables are statistically significant, and that adding sentiment variables improves the performance of bankruptcy prediction models. Also, the results indicate some reference characteristics of companies in terms of word-choice and descriptions in the news, indicating word choices correlated with financially stability and those correlated with financially instability.

Keywords: news sentiment, bankruptcy prediction models, random forest, support vector machine, multilayer perceptron

JEL classification: G17, G33

Introduction

Accurate analyses of a firm's financial stability are essential for multiple aspects of a company's planning and strategic processes, and are relied upon by other market participants, particularly banks. The probability of default, along with loss given default and exposure at default, are essential components in credit risk modelling. The problem of forecasting bankruptcy on the basis of financial reporting is connected with the fact that analysing the actual results of company reporting is possible only in the year subsequent to publication, which means that bankruptcy forecast in the short term is more challenging. Using news media resources for forecasting purposes assists with short term predictions by providing more current and recent data for analysis.

The COVID-19 pandemic of 2020 has caused the largest global recession in history. The overall effects of COVID-19 are not yet apparent, but it is already becoming clear the number of bankruptcies will rise enormously. The most novel and accurate methods of bankruptcy prediction are especially relevant today.

One of the main trends in bankruptcy prediction today is the application of new sources of information, will leads to an increase in the accuracy of the models. One of the most promising sources of information is textual data, which can be obtained from corporate disclosures, news, and social networks [1]. News sentiment analysis has been successfully used to predict stock price dynamics [2], but at the time of writing only a very small number of articles have been published dedicated to its application to the bankruptcy prediction problem. The advantage of using the news as a source of information is the availability and frequency of updated data, in comparison with traditional financial data and corporate disclosures sources, which are mostly updated once a year or quarterly [3].

Unlike the studies about the impact of the news sentiment on stock prices (where sentiment directly affects the value of shares of companies), the impact of news on the financial instability of a company should be understood as a description of the event which led to certain consequences for the company. To clarify, in the latter event, the news does indirectly affect the probability of default.

The methodological base of this work includes machine learning methods such as the random forest (RF) method, support vector machine (SVM) method, multilayer perceptron (MLP) method, and the logistic regression approach, which is to be used as a benchmark model. For the sentiment variable aggregation, 'the-bag-of-words' model [4] is used, along with the Linis Crowd dictionary [5].

Literature review

Machine learning in bankruptcy prediction models

Machine learning methods have received more attention than statistical methods, and in comparison with linear models, machine learning models provides higher accuracy. As part of a review of 89 articles related to bankruptcy prediction models, Aziz [6] indicates an average accuracy ratio of 88% for machine learning and 84% for statistical models.

Also, machine learning methods do not have heavy restrictions on the entry data and thus are able to capture complex and non-linear patterns. On the other hand, the 'black box' results are not stable, have difficulties with interpretation, and trend towards overfitting [7]

According to Shi [8], the three most used methods of machine learning are:

1) Decision tree (DT). Unlike other machine learning methods, this is easy to interpret and can be displayed visually [9]. Tsai [10] claims that DT reaches the highest accuracy in comparison with other methods.
2) Artificial neural network (ANN), which shows a stable level of high performance in fitting nonlinear data, which in turn allows it to deal with very complex patterns. Ciampi [11] shows that ANN outperforms the Multiple Discriminant Analysis (MDA) and LR methods within a sample of 7000 companies, and is good for dealing with data omissions. However, ANNs tend to generalise results, which can lead to overfitting [12]. As such, Ding [13] claims that while ANN identifies only local optimum results, the support vector machine method (see below) succeeded in achieving global optimal results.
3) Support vector machine (SVM). Unlike ANN, SVM controls for errors with regard to generalising. SVM is successfully used in high dimensional nonlinear data and small datasets [14].

Sentiment analysis in finance

Sentiment analysis is a field of research based on methods of natural language processing, dedicated to identifying emotional attitudes either in relation to the subject under discussion in text to the object, or to a text as a whole.

One of the first studies about textual analysis in the field of finance belongs to Kohut [15]. The study suggests the content of the letters from companies' presidents letters differs between companies with high and poor financial performance.

According to Kearney [3], the sentiment analysis in finance can be divided into the following groups according to the source of information:

- Public corporate disclosures (annual reports and press releases) [16]
- The style and content of corporate disclosures signal as to the company's current situation and may contain useful information about future financial performance from the corporation's point of view. The limitation of this source of information is the low frequency of the data. The data is available only for the small number of the biggest companies and the disclosures are made on a quarterly or annual basis. Moreover, companies tend to try to manipulate public opinion to their benefit [17].

- Media, news articles and analysts' reports [2]
- Such compositions express observers' opinions about the overall financial and economic conditions, or about a particular industry or company. The advantage the news source is that news media and similarly published articles are available at all times and are frequently updated.
- Internet messages and social media networks [18]
- Social media networks are a potentially useful source of textual information because many people spend a considerable amount of time every day on the internet. However, internet messages, as opinions of common people, are among the noisiest sources of information because of the irrationality of such judgments and general unprofessionalism of internet users [3].
- Other or combined sources. [19]

The most common methods of sentiment analysis in finance are machine learning [16] and dictionary-based approaches [20].

According to the machine learning approach, the text is divided by tokens: e.g. by sentence, by word, or by combination of words. Each token is labelled with some category title. The machine learning algorithms predict these labels using the set of tokens.

The basis of the dictionary-based approach is a predefined dictionary with words arranged according to categories (e.g. positive and negative). Each word from the text is mapped with the dictionary word category. The dictionary-based method is associated with the 'bag of words' [4] because texts are considered to be unsorted sets of words.

The dictionary-based methods vary in how the dictionaries are defined and in how each word should be weighted.

The issue of the dictionary-based approach is that it is context-dependent: some words may have different tonalities in terms of different topics. This leads to the creation of topic-specific dictionaries, i.e. finance-specific dictionaries. Thus, the finance dictionary by [21] outperforms the traditional nonspecific Harvard dictionary in financial performance prediction and fraud detection [21].

Since the first wave of explosive interest in sentiment analysis, there has been a field of research on the sentiment of English language texts. However, no one has thus far succeeded in creating a successful multilanguage sentiment dictionary. The dictionary of Russian sentiment was created in 2016 by [5].

Each word found in such a dictionary may be weighted equally or have some weighting rule attached. The proportional scheme is called 'term frequency' (TF):

$$TF_{ij} = \frac{n_{ij}}{\sum_k n_{ij}}, \quad (1)$$

where – n_{ij} the frequency of the word i in the document j

k – number of documents

Another weighting is called 'inverse document frequency' (IDF):

$$IDF(w) = log\frac{N}{df_t} \quad (2)$$

where N– the number of all documents

df_t – the number of documents that contain the word w

Finally, term frequency – inverse document frequency (TF - IDF) is the result of multiplying (1) by (2):

$$TF\_IDF_{ij} = TF_{ij} IDF(w) \quad (3)$$

The main idea behind the IDF approach is that the most frequently occurring words are the least informative. [21] argues that the TF - IDF method outperforms the TF method. However, Azam [22] mentions that the TF method performs better on the smaller datasets. The article by Chen [23] suggests a more controlled term weighting method. Mai [24] uses TF - IDF weights for building a deep learning model.

Hypothesis

As a result of our literature review, the following hypotheses are thus articulated:

Hypothesis 1. *The TF - IDF word weights significantly increase bankruptcy prediction model performance in comparison with TF word weights.*

The TF - IDF is the more widely used weighting scheme [3], whereas TF weighting is more accurate in small datasets [22].

Hypothesis 2. *The number of news items has a statistically significant impact on the probability of default.*

To test how news items influence the probability of default, first we should check whether news coverage influences the probability of the default separately from the news content.

Hypothesis 3. *The news sentiment has a statistically positive impact on the probability of default. The application of the news sentiment variable significantly increases the model's performance.*

The evidence of the significance of textual sources other than news in financial insolvency predictions is provided in [25], and [24]

Hypothesis 4. *Negative news has a more significant effect on the probability of default than positive news does.*

The positive / negative influence of positive / negative news in the context of stock market activity is confirmed in articles [26], [27]. Leung [28] claims that positive news articles do have influence on the market. Apergis [29] shows that negative news articles influence the stock market more than positive ones.

Methodology and Data

For modeling bankruptcy in this study, we use four simple and effective methods that have already established in the above-mentioned literature: logistic regression (LR); random forest (RF); support vector machine (SVM) and multilayer perceptron (MLP).

To evaluate the predictive performance of the machine learning analysis, the AUC-ROC performance measurement approach is preferred due to the balance between the true positive and the true negative rate [30].

To reduce the effect of the high variation between different splits and provide robust results, a 5-fold cross validation was conducted. Firstly, the sample was randomly split into 5 equal parts (subsample 1 (S1), … subsample 5 (S5). Then, S2 + S3 + S4 is used as the training set, while S1 is used as the test set. By repeating this step 5 times, each subsample is used as the test set one time. Thus, we get 5 AUC-ROC values and can calculate the mean AUC-ROC and standard deviation.

To test the significance of the model performance change, we conduct paired sample t-tests on the AUC-ROC metrics on the different splits and models, following the methodology of [24] and [31].

The analysis is performed in Python using the "scikit-learn" library.

Textual analysis methods

For our Hypothesis 1 (Model 1), the matrices of TF and TF-IDF frequencies of 658 dictionary words as columns and articles as rows are calculated (the 'bag-of-words' method). This array of columns represents the set of predictor variables. The matrix dimension is presented as (number of articles) x (number of dictionary words mentioned in articles). The default flags are duplicated for company, with the number of news articles greater than 1.

For Hypothesis 2 – 4 (Models 2-4) the news articles are aggregated by company and TF and TF-IDF statistics for all dictionaries are calculated (again, the «bag-of-words» method). The matrix dimension is represented as (number of companies) x (number of dictionary words mentioned in articles). Next, sentiment variables are calculated as the column sum of the TF and TF-IDF weight arrays. For each company, positive sentiment is the column sum of the weights (either TF or TF-IDF) of positive words; and negative sentiment is the sum of weights (TF or TF-IDF) of negative words multiplied by (-1); sentiment is the sum of positive and negative sentiment. For TF it simply takes the form:

$$sentiment_t f_i = \frac{number\ of\ \ positive\ words\ \ for\ company\ i - number\ of\ \ negative\ words\ \ for\ company\ i}{number\ of\ \ positive\ words\ \ for\ company\ i + number\ of\ \ negative\ words\ \ for\ company\ i} = \\ = pos_s entiment_i + neg_s entiment_i \quad (4)$$

For the lexical base for Russian sentiment analysis, the dictionary is obtained from the Linis Crowd dictionary [5], being the first Russian sentiment dictionary. Linis Crowd is a HSE open-source project that contains a sample of internet texts on socio-political topics with user ratings, and a sentiment dictionary based on these texts. The sentiment for each word is based on the average score, which is scaled from -2 to 2. After processing all ratings and deleting neutral words, 2719 words were left. The words with positive sentiment are considered as positive, the words with negative sentiment are considered negative. The lexical base was expanded with 186 antonyms, synonyms, and single-root words. The final dictionary consists of 2906 words in initial form (1027 positive and 1878 negative).

Database

The sample of companies was assembled from the Spark database, based on the following criteria. Russian companies from the retail sector with a default between 2015-2019 (and their non-default pairs) were selected. Financial data from one year before the default was considered. News data was taken for the three year period prior to the default date. The 'size of companies' metric was established in terms of 'micro', 'small', 'medium' and 'big' companies, with revenues of more than 50 million RUB. As a result, a sample of 312 (156 default and 156 non-default) companies was collected.

Textual factors

As a source of textual data, Yandex News was preferred to other news aggregators [32], e.g. Google News, Yahoo News, or databases, e.g. Spark or Thomson Reuters [33], for the following reasons:

1) It covers the entire observation period (2012-2019). For example, Google News and Spark store news only for the last year.
2) Yandex News aggregates a lot of online journals, even small regional ones, which results in a high level of news coverage for both small and big Russian private companies.
3) Yandex's advanced algorithms ensure high search relevance for Russian-language queries.

For each company in the sample the following web search query is completed:

1) Query: full company's name in Russian. If there are several companies with a similar name, a key word is added to the company's name (place of the registration or industry).
2) Options: The time period from 3 years before the date of default to the date of default.

The total number of articles is 4877, from more than 800 different online journals. News items were found for 95 company pairs out of 156 pairs.

Figure 1. The most frequent negative (left) and positive (right) words.

Text preprocessing is done using Python libraries: Natural Language Toolkit NLTK 3.4.5 [34], Pymorphy2 0.8 [35], and base Python libraries.

After preprocessing, all words are matched with the 'positive' and 'negative' dictionary categories.

The most frequent negative words and the most frequent positive words are presented in Figure 1. The word clouds are made with the Python library 'word cloud' resource. From Figure 1, we may see that the most frequent negative words are related to crime and legal issues.

Results

In general, the results are satisfactory. A high average accuracy of bankruptcy prediction is achieved, and some significant information is extracted from the news.

The implications for our hypotheses are as follows:

Hypothesis 1. The data do not provide enough evidence towards Hypothesis 1

Hypothesis 2 The data do not provide enough evidence towards Hypothesis 1

Hypothesis 3 The hypothesis is not rejected. The news sentiment has a significantly negative impact on the probability of default and adding the news sentiment variable significantly increases the model performance.

Hypothesis 4. The hypothesis is not rejected. The negative news sentiment has greater impact on the probability of default than positive news does. Also, in case of SVM and MLP, adding the negative news sentiment variable results in a statistically higher average performance than adding a positive news sentiment variable does.

We use 34 financial control variables from Sample 2, and perform a one-factor analysis.

After all the transformations, the following factors are included in the model (Model 0):

Table 1. Model 0. The final set of control financial variables: Logistic regression

	Variable	Coefficient	p-value	Significance
X2	net income / revenue	-2.9022	0.0000	***
X25	cash and cash equivalents / current liabilities	-1.4209	0.0225	*
X30	payables / revenue	2.2413	0.0000	***
X33	revenue / mid-year inventories	2.728	0.0000	***

The variables that are included with negative coefficients reduce the risk of default (net income margin and cash ratio) and those that are included with a positive sign increase the risk of default (payables / revenue, and revenue / mid-year inventories).

For the benchmark performance, the machine learning analysis for Model 0 is performed:

The initial performance of the model is not very high (Table 2). This may be partly explained by the small sample size and the presence of both small and big companies. The articles with a comparably small dataset (e.g. of 240 variables and accounting-based variables [14]) and [36] with the sample of 107 default companies provide a comparable average AUC-ROC performance of 60-80%.

Table 2. Model 0. The final set of control financial variables. Machine learning analysis.

Model \ ROC-AUC	Mean	SD
Logit regression	0.75	0.06
Random forest	0.77	0.06
Support vector machine	0.76	0.06
Multilayer perceptron	0.76	0.03

Logistic regression analysis

The number of news items is not a significant variable (Table 3). So, **the data do not provide enough evidence in support of Hypothesis 2.** This model is excluded from further analysis in the next subchapter.

Table 3. Model 2. Logistic regression

	Variable	Coefficient	p-value	Significance
X2	net income / revenue	-2.9362	0.0000	***
X25	cash and cash equivalents / current liabilities	-1.5292	0.0154	*
X30	payables / revenue	2.1162	0.0000	***
X33	revenue / mid-year inventories	2.7295	0.0000	***
news_number	number of news article for each company	0.0054	0.1165	

Table 4. Model 3. Logistic regression

	Variable	Coefficient	p-value	Significance
X2	net income / revenue	-2.8297	0.0000	***
X25	cash and cash equivalents / current liabilities	-1.2658	0.0600	.
X30	payables / revenue	2.1130	0.0001	***
X33	revenue / mid-year inventories	2.5121	0.0001	***
sent*	Sentiment	-0.4778	0.0001	***

*sentiment variables are calculated for TF-IDF word weights due to the low statistical difference. For a more detailed explanation see the next subchapter.

Table 5. Model 4. The logistic regression

	Variable	coeff	p-value	coeff	p-value
X2	net income / revenue	-2.7874	0.0000***	-3.0572	0.0000***
X25	cash and cash equivalents / current liabilities	-1.1641	0.0728*	-1.6942	0.0109*
X30	payables / revenue	2.4754	0.0000***	1.5455	0.0064**
X33	revenue / mid-year inventories	2.8039	0.0000***	2.2797	0.0003***
pos_sent	Positive sentiment	-0.2789	0.1141		
neg_sent	negative sentiment			-0.7245	0.0003***

*sentiment variables are calculated for TF-IDF word weights due to the low statistical difference. For a more detailed explanation see the next subchapter.

News sentiment is a significant coefficient, so **the first part of Hypothesis 3 is not rejected** under the confidence level more than 99.99% (Table 4). The news sentiment has a significant negative impact on the probability of default, which corresponds to the supposition that the greater the number of positive words (as the characteristics of the positive events) and the less the number of negative words (as the characteristics of the negative events), the lower the probability of default.

Negative sentiment is a significant variable under the confidence level of 90%, whereas positive sentiment is not (Table 5). The absolute value of the coefficient in the logistic regression is more for the negative sentiment. The results of Table 5 permit us to infer that our **Hypothesis 4 is not rejected.**

One of the main challenges of bankruptcy prediction is the increase in explanatory power of the models. In the next subchapter, the issue of model accuracy changes when news sentiment variables are investigated.

Machine learning analysis

The first step of the analysis is to compare the TF (Model 1a) and TF-IDF (Model 1b) performance. For this purpose, 658 unique dictionary words mentioned in the text are tested as the default predictors with TF and IDF weights.

Table 6. Model 1a and 1b. Machine learning analysis.

	Model 1a		Model 1b		two-tailed t-test
Model \ ROC-AUC	Mean	SD	Mean	SD	p-value
Logit regression	0.60	0.07	0.59	0.07	0.8764
Random forest	0.62	0.06	0.61	0.07	0.9353
Support vector machine	0.64	0.04	0.64	0.04	0.9518
Multilayer perceptron	0.62	0.07	0.64	0.04	0.6715

A paired sample t-test (Table 6) shows that the mean difference between the performance of Model 1b and 1a is not statistically different from zero, which **does not provide any evidence for the acceptance of Hypothesis 1**. As TF-IDF statistics are more widely used, in the subsequent models the aggregated sentiment variable with TF-IDF weighting scheme is used.

The average AUC-ROC performance (Table 6), is relatively low: the resulting performance of analysis of the total word collection is comparable to one-factor analysis for financial variables. However, combined with aggregated control variables, the text variable could improve the performance of the model and, more importantly, could lead to the following findings concerning word significance:

Table 7. List of 100 most significant negative words by content group

Group	Negative
Legal	банкротство, иск, уголовный, банкрот, суд, следствие, отсудить, расторгнуть, арбитражный, прокуратура, расследование, арбитраж, обанкротить, преследование, правоохранительный, банкротить, следователь, арест, банкротит, взыскание, осудить, уголовка, преступление, неправомерный, обанкротиться, обвинительный
Crime	мошенничество, хищение, нарушитель, арестовать, сокрытие, наказание, коррупция, незаконно, угонять, умышленный, взятка
Accident	взрыв, погибнуть, пострадавший, жертва, аварийный, гибель, захват, пострадать, разрыв
Debt	долг, взыскать, задолженность, убыточный, коллектор, неуплата, просрочка
Conflict	обмануть, подозревать, недобросовестный, заподозрить, дискриминация, конфликт, недостоверный, пожаловаться, ложный, эксплуатировать, требовать,
Prohibition	ограничить, запретить, ограничение, изъять
Low-quality	проблемный, неисправный, испортить, задерживать, заглохнуть, износ, опасный, невыполненный, некачественный, задержать
Other	снести, расторгнуть, ликвидация, опоздание, пропасть, уходить, негативный, закрывать, отказываться, горелый, недостаток, заставить, ликвидировать, потерять, уйти, самовольный, закрыться, остановка, реорганизация, специфический, выброс, дефицит

The presence of legal issues, crime, accidents, debt, conflicts, prohibitions, and low quality of delivered products or services in news articles correlates with companies having some serious problems that may lead to bankruptcy (Table 7):

Table 8. List of 100 most significant positive words by content group

Group	Positive
Innovation& Research& Strategy	прогресс,технический, стратегический, стратегия, презентовать, запускать,исследование, обновить, запустить, технология, развитие, инновация, обучать, информационный, интеллектуальный, развиваться, инициатива, внедрение, обучение, блокчейн, реформа, запуск, преобразовать, осваивать
Awards& Success	рекорд,награждать, номинация, победа, выигрывать, премия, награда, успех, успешный, процветать, заслуга,
Social activities	церемония, фестиваль, фотовыставка, форум, социальный, искусство, выставка, творчество, оздоровительный, празднование
Career events	трудоустройство,профориентация, карьерный
Partnership	сотрудничество, сотрудничать
High-quality	удобный, продуктивный, комфортный, удобно, шикарный, соответствовать, удовлетворить, популярный, оригинальный, уникальность, исключительный, актуальный, универсальный
Improvement	стабилизироваться, открыть, расширение, открыться, предотвращение, реконструкция, расширить, реконструировать, улучшить, защитить, оснастить, восстановление
Voluntary	льготный, добровольно, добровольный, бесплатный, дарить, благотворительный,
Other	семейный, солнечный, инвестиция, застраховать, семья, динамично, уверенность, динамичный, помощь, инвестировать, вечный, сладкий, выгодно, субсидия, выгода, инвестиционный, неплохо, шустрый

On the other hand, mentions of innovation, research activity, awards, social and career events, high-quality products or services, and declarations of new partnerships are correlated with a company in circumstances of financial stability (Table 8).

The second step is to check whether adding the news sentiment variable (Model 3) may significantly increase the model quality in comparison with the benchmark model with only control variables (Model 0):

Table 9. Model 3. Machine learning analysis

	Model 3		Model 0		one-tailed t-test
Model \ ROC-AUC	**Mean**	**SD**	**Mean**	**SD**	**p-value**
Logit regression	0.84	0.03	0.75	0.06	0.0167**
Random forest	0.86	0.03	0.77	0.06	0.0072***
Support vector machine	0.82	0.02	0.76	0.06	0.0335*
Multilayer perceptron	0.86	0.01	0.76	0.01	0.0001***

Adding sentiment variable to the control variables allows us to significantly increase the average AUC-ROC performance (Table 9), which indicates that **the second part of Hypothesis 3 is not rejected**. The RF reaches its highest accuracy (at 90%) in this particular area of analysis.

The last step of our analysis involves checking whether negative news sentiment and control variables (Model 4b) are correlated with a higher increase in the model quality than the positive news sentiment and control variables (Model 4a) do:

Table 10. Model 4a and 4b. The machine learning analysis

	Model 4a		Model 4b		one-tailed t-test
Model \ ROC-AUC	**Mean**	**SD**	**Mean**	**SD**	**p-value**
Logit regression	0.82	0.04	0.84	0.04	0.3638
Random forest	0.82	0.04	0.86	0.03	0.1804
Support vector machine	0.81	0.03	0.84	0.03	0.0894·
Multilayer perceptron	0.80	0.02	0.84	0.03	0.0600·

The results of one-tailed paired sample t-test (Table 6) are ambiguous: under the significant level of 10% the mean difference between Model 4b and 4a performance is statistically greater than zero only for SVM and MLP.

All methods of performance are nearly on the same level of accuracy, which is a surprising fact for the LR. The first explanation for this result is that machine learning algorithms have a lower performance at small datasets. Another explanation is that data-preprocessing and feature selection is done according to the logistic regression assumptions and specifics, which may increase the LR performance. The final possible explanation concerns the specifics of the machine model. As such, RF may perform worse than LR if the formula in model training contains a high proportion of essential predicting factors [37]. According to Salazar [38], RF and SVM perform at nearly the same level when the number of predictors is small. Gaudart [39] claims that the neural networks do not outperform linear regression in the case of normality, and the presence of homoscedasticity, the independence of the errors, and our preprocessing methodology, brings our data very close to the normal distribution. The overfitting effect of the small sample size was minimised by application of the 5-fold validation. The small number of predictors is regarded as harmonising in terms of establishing the comparability of the logistic regression and the machine learning method results.

References

1. Wang G, Chen G, Chu Y. A new random subspace method incorporating sentiment and textual information for financial distress prediction. Electronic Commerce Research and Applications. 2018 May 1;29:30-49.
2. Gupta K, Banerjee R. Does OPEC news sentiment influence stock returns of energy firms in the United States?. Energy Economics. 2019 Jan 1;77:34-45.
3. Kearney C, Liu S. Textual sentiment in finance: A survey of methods and models. International Review of Financial Analysis. 2014 May 1;33:171-85.
4. Zhang Y, Jin R, Zhou ZH. Understanding bag-of-words model: a statistical framework. International Journal of Machine Learning and Cybernetics. 2010 Dec 1;1(1-4):43-52.
5. Koltsova OY, Alexeeva S, Kolcov S. An opinion word lexicon and a training dataset for russian sentiment analysis of social media. Computational Linguistics and Intellectual Technologies: Materials of DIALOGUE. 2016;2016:277-87.
6. Aziz MA, Dar HA. Predicting corporate bankruptcy: where we stand?. Corporate Governance: The international journal of business in society. 2006.
7. Alaka HA, Oyedele LO, Owolabi HA, Kumar V, Ajayi SO, Akinade OO, Bilal M. Systematic review of bankruptcy prediction models: Towards a framework for tool selection. Expert Systems with Applications. 2018 Mar 15;94:164-84.
8. Shi Y, Li X. An overview of bankruptcy prediction models for corporate firms: A Systematic literature review. Intangible Capital. 2019;15(2):114-27.
9. Kumar PR, Ravi V. Bankruptcy prediction in banks and firms via statistical and intelligent techniques–A review. European journal of operational research. 2007 Jul 1;180(1):1-28.
10. Tsai CF, Hsu YF, Yen DC. A comparative study of classifier ensembles for bankruptcy prediction. Applied Soft Computing. 2014 Nov 1;24:977-84.
11. Ciampi F, Gordini N. Managerial characteristics and default prediction modeling for small firms: Evidence from small Italian firms. In35 Convegno Annuale AIDEA-Management Senza Confini. Gli Studi di Management Tradizione e Paradigmi Emergenti 2012 (pp. 1-19). IT.
12. Chen N, Ribeiro B, Chen A. Financial credit risk assessment: a recent review. Artificial Intelligence Review. 2016 Jan 1;45(1):1-23.
13. Ding Y, Song X, Zen Y. Forecasting financial condition of Chinese listed companies based on support vector machine. Expert Systems with Applications. 2008 May 1;34(4):3081-9.
14. Chandra DK, Ravi V, Bose I. Failure prediction of dotcom companies using hybrid intelligent techniques. Expert Systems with applications. 2009 Apr 1;36(3):4830-7.
15. Kohut GF, Segars AH. The president's letter to stockholders: An examination of corporate

communication strategy. The Journal of Business Communication (1973). 1992 Jan;29(1):7-21.

16. Park S, Lee J, Kim K. Semi-supervised distributed representations of documents for sentiment analysis. Neural Networks. 2019 Nov 1;119:139-50.
17. Callison C, Zillmann D. Company affiliation and communicative ability: How perceived organizational ties influence source persuasiveness in a company-negative news environment. Journal of Public Relations Research. 2002 Mar 1;14(2):85-102.
18. Broadstock DC, Zhang D. Social-media and intraday stock returns: The pricing power of sentiment. Finance Research Letters. 2019 Sep 1;30:116-23.
19. Kothari SP, Li X, Short JE. The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. The Accounting Review. 2009 Sep;84(5):1639-70.
20. Loughran T, McDonald B. Measuring readability in financial disclosures. The Journal of Finance. 2014 Aug;69(4):1643-71.
21. Loughran T, McDonald B. When is a liability not a liability. Journal of Finance, forthcoming. 2009 May 6.
22. Azam N, Yao J. Comparison of term frequency and document frequency based feature selection metrics in text categorization. Expert Systems with Applications. 2012 Apr 1;39(5):4760-8.
23. Chen et al., "Turning from TF-IDF to TF-IGM for term weighting in text classification," Expert Systems with Applications, vol. 66, pp. 245-260, 2016
24. Mai F, Tian S, Lee C, Ma L. Deep learning models for bankruptcy prediction using textual disclosures. European journal of operational research. 2019 Apr 16;274(2):743-58.
25. Hájek P, Olej V, Myskova R. Forecasting corporate financial performance using sentiment in annual reports for stakeholders' decision-making. Technological and Economic Development of Economy. 2014 Oct 2;20(4):721-38.
26. Caporale GM, Spagnolo F, Spagnolo N. Macro news and stock returns in the Euro area: a VAR-GARCH-in-mean analysis. International Review of Financial Analysis. 2016 May 1;45:180-8.
27. Dzielinski M. News sensitivity and the cross-section of stock returns. NCCR FINRISK. 2011(719).
28. Leung DK, Lee FL. How journalists value positive news: The influence of professional beliefs, market considerations, and political attitudes. Journalism Studies. 2015 Mar 4;16(2):289-304.
29. Apergis N, Miller SM. Consumption asymmetry and the stock market: empirical evidence. Economics Letters. 2006 Dec 1;93(3):337-42.
30. Olson DL, Delen D, Meng Y. Comparative analysis of data mining methods for bankruptcy prediction. Decision Support Systems. 2012 Jan 1;52(2):464-73.
31. Gardner J, Brooks C. Statistical Approaches to the Model Comparison Task in Learning Analytics.
32. Lu YC, Shen CH, Wei YC. Revisiting early warning signals of corporate credit default using linguistic analysis. Pacific-Basin Finance Journal. 2013 Sep 1;24:1-21.
33. Papakyriakou P, Sakkas A, Taoushianis Z. Financial firm bankruptcies, international stock markets, and investor sentiment. International Journal of Finance & Economics. 2019 Jan;24(1):461-73.
34. Bird S, Klein E, Loper E. Natural language processing with Python: analyzing text with the natural language toolkit. " O'Reilly Media, Inc."; 2009 Jun 12.
35. Korobov M. Morphological analyzer and generator for Russian and Ukrainian languages. InInternational Conference on Analysis of Images, Social Networks and Texts 2015 Apr 9 (pp. 320-332). Springer, Cham.
36. Geng R, Bose I, Chen X. Prediction of financial distress: An empirical study of listed Chinese companies using data mining. European Journal of Operational Research. 2015 Feb 16;241(1):236-47.
37. Kirasich K, Smith T, Sadler B. Random Forest vs Logistic Regression: Binary Classification for Heterogeneous Datasets. SMU Data Science Review. 2018;1(3):9.
38. Salazar DA, Vélez JI, Salazar JC. Comparison between SVM and logistic regression: Which one is better to discriminate?. Revista Colombiana de Estadística. 2012 Jun;35(SPE2):223-37.
39. Gaudart J, Giusiano B, Huiart L. Comparison of the performance of multi-layer perceptron and linear regression for epidemiological data. Computational statistics & data analysis. 2004 Jan 28;44(4):547-70.
40. Engelberg J. Costly information processing: Evidence from earnings announcements. InAFA 2009 San Francisco meetings paper 2008.
41. Ahmadi Z, Martens P, Koch C, Gottron T, Kramer S. Towards bankruptcy prediction: deep sentiment mining to detect financial distress from business management reports. In2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA) 2018 Oct 1 (pp. 293-302). IEEE.
42. Beaver WH. Financial ratios as predictors of failure. Journal of accounting research. 1966 Jan 1:71-111.
43. Fulmer JG, Moon J, Gavin TA, Erwin M. A bankruptcy classification model for small firms. Journal of commercial bank lending. 1984 Jul;66(11):25-37.

44. Fedorova E, Demin I, Khrustova L, Osetrov R, Fedorov F. The influence of the tone of the CEO's letters on the company's financial performance. Russian Journal of Management. 2017;15(4).

45. Ohlson JA. Financial ratios and the probabilistic prediction of bankruptcy. Journal of accounting research. 1980 Apr 1:109-31.

46. Qu Y, Quan P, Lei M, Shi Y. Review of bankruptcy prediction using machine learning and deep learning techniques. Procedia Computer Science. 2019 Jan 1;162:895-9.

47. Bellovary JL, Giacomino DE, Akers MD. A review of bankruptcy prediction studies: 1930 to present. Journal of Financial education. 2007 Dec 1:1-42.

48. West RC. A factor-analytic approach to bank condition. Journal of Banking & Finance. 1985 Jun 1;9(2):253-66.

49. Merton RC. On the pricing of corporate debt: The risk structure of interest rates. The Journal of finance. 1974 May 1;29(2):449-70.

50. Feller W. An introduction to probability theory and its applications, vol 2. John Wiley & Sons; 2008.

51. Nilsson P. The influence of related and unrelated industry diversity on retail firm failure. Journal of Retailing and Consumer Services. 2016 Jan 1;28:219-27.

52. Gleason KC, Mathur LK, Mathur I. The interrelationship between culture, capital structure, and performance: evidence from European retailers. Journal of business research. 2000 Nov 1;50(2):185-91.

53. Ahmad Z, Abdullah NM, Roslan S. Capital structure effect on firms performance: Focusing on consumers and industrials sectors on Malaysian firms. International review of business research papers. 2012 Jul;8(5):137-55.

54. Gaur V, Fisher ML, Raman A. An econometric analysis of inventory turnover performance in retail services. Management science. 2005 Feb;51(2):181-94.

55. Akinboade OA, Mokwena MP, Kinfack EC. Estimating profit efficiency among South African retail firms using stochastic frontier approach. The International Review of Retail, Distribution and Consumer Research. 2008 Dec 1;18(5):511-20.

56. Makeeva E, Bakurova A. Forecasting bankruptcy oil and gas companies using neural networks. Journal of Corporate Finance Research. 2012(3 (23)):22-30.

57. Демешев ББ, Тихонова АС. Динамика прогнозной силы моделей банкротства для средних и малых российских компаний оптовой и розничной торговли. Корпоративные финансы. 2014;8(3).

58. Mselmi N, Lahiani A, Hamza T. Financial distress prediction: The case of French small and medium-sized firms. International Review of Financial Analysis. 2017 Mar 1;50:67-80.

59. Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance. 1968 Sep 1;23(4):589-609.

60. Altman EI, Sabato G. Modeling credit risk for SMEs: Evidence from the US market. InManaging and Measuring Risk: Emerging Global Standards and Regulations After the Financial Crisis 2013 (pp. 251-279).

61. Pradhan R, Pathak KK, Singh VP. A Study of Credit Lending and Prediction of Bankruptcy using Back-Propagation Neural Networks. IIMS Journal of Management Science. 2012;3(2):179-93.

62. Zhang W. R&D investment and distress risk. Journal of Empirical Finance. 2015 Jun 1;32:94-114.

The Influence of CEO Personal Characteristics on the Market Value of Russian Companies

Liudmila Ruzhanskaya

Doctor of Science in Economics, Associate Professor, Head of Academic department for International Economics and Management

ORCID

E-mail: l.s.ruzhanskaya@urfu.ru).

Graduate School of Economics and Management, Ural Federal University, Ekaterinburg, Russia

Anatoly Sizikov

Researcher

ORCID

E-mail: anatolysizikov@gmail.com

Graduate School of Economics and Management, Ural Federal University, Ekaterinburg, Russia

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 19-30 (2020)

DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.19-30

Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

The Influence of CEO Personal Characteristics on the Market Value of Russian Companies

Abstract

This paper analyses the impact of a CEO's demographic and professional characteristics on the market value of the company. The growth of company capitalisation involves the expectations of investors specifically their view of the personality of the CEO, including whether he will be able to maintain the proper level of the company's work and whether there is expediency in further investment. Therefore, it is extremely important to understand exactly what qualities of a top manager influence investor expectations.

This research is based on data from the 50 largest public Russian companies from non-financial sectors for the period 2011-2019, and iformation is included on 98 CEOs across this period. Herein we define the mechanism of the relationship between the personal characteristics of the CEO and the market value of the company.

Based on a pooled regression assessment, our results indicate that the level of education of the CEO is an insignificant variable, and practical experience is valued higher than academic qualification (this is consistent with the results of previous studies). The market responds positively to the appointment of executives with industry experience. The experience of a CEO in a prior governmental or state role impacts negatively on firm value, and the status of the company's founder is met with optimism by the market, seeming to assure an interest in strategic development. The status of an outside manager is rated higher by the market than a successful career inside the company. The optimal age of the head of the company from the point of view of positively influencing the value of the company was determined at 49 years.

We conclude that a portrait of the head of a large traded Russian corporation has been constructed in the present work, which contributes to the literature on optimal market perception for businesses and manager.

Key words: CEO, market value of the company, demographic characteristics of the CEO, professional characteristics of the CEO

JEL classification: G32, G34

Introduction

The personal characteristics of top managers play a role in any team, but for publicly traded companies, they also act as signals to financial markets about a firm's stability and possible strategic directions of development. What distinguishes top managers from the CEO is that the CEO is responsible for the company's activities in general and reports only to the owners of the company and their representatives. Unlike other managers he has more decision-making power which is accompanied by a higher degree of responsibility. The CEO represents the interests of the owner in relation to employees and joint organisations [1].

Research in the field of corporate governance uses the 'upper echelons' theory to substantiate the influence of demographic and professional characteristics of managers on the company's performance [2]. A counter-argument to this point of view is represented by the observation that managers, being limited by the actions of corporate monitoring mechanisms and the external business environment, are restricted in their actions. However, these circumstances do not significantly affect the company's activity [3–5]. As an alternative direction for studying the relationship between the personal characteristics of a manager and the performance of a firm, we will seek to identify the conditions wherein this relationship appears most significant. Where a final understanding hasn't been reached [6], this may be a result of differences in the institutional environment of different countries, in the economic situation, and in socio-cultural traditions. This article aims to make up for the lack of research on Russian data on this topic with the use of a wide range of demographic and professional characteristics of top managers. An additional task is to establish whether after 30 years of reforms the reaction of financial markets and the corporate governance model is still strongly influenced by the legacy of the "Soviet past", which leads to a significant difference between the results of domestic studies and the results of works on samples of other countries.

Thus, the purpose of this research is to evaluate the impact of the demographic and professional characteristics of the CEO of the largest traded Russian companies on their market value.

Literature review and research hypotheses

The dependence of financial indicators on the managerial abilities of the head of the company was substantiated in the 'upper echelons' theory [7]. As proxy variables to determine the managerial abilities of top managers, it is proposed to use the following series of observed characteristics: age, education, work experience, and career history. However, using only demographic variables leaves open the question about the impact of the real psychological and social processes that govern the behaviour of top management. Scientists call this challenge the 'black box problem' [8–9].

To explain the personal characteristics of the mechanism of the positive impact of the CEO on the effectiveness of a company, we used the analytical category of 'commitment to the organisation'. Emotional commitment is defined as "an emotional attachment to an organisation with which the person involved in membership in the organisation is clearly identified" [10]. Existing research shows that leaders with high levels of organisational commitment would like to see their company was doing well and shows good results [11–12].

The list and nature of the influence of each of the demographic and professional characteristics analysed in our model on the company's market value is given below.

1. Demographic characteristics.

1.1. *Gender CEO*. A positive relationship between female participation in the top management of a company and its gross profit was found [13]. However, the authors of the work cited at reference [14], conducting a similar study, used the Tobin's Q coefficient to represent the company's financial performance, and did not find a positive relationship. A meta-analysis of 140 papers led to the conclusion that female participation in the top management of a company has a positive effect on its balance sheet indicators; this relationship is most pronounced in countries with a higher level of shareholder protection [15].

1.2. *Age CEO*. Researchers in the paper cited at [7] suggested that young leaders are more inclined to take risks and take more strategically important actions. However, another work [16] found a positive effect of age on balance sheet indicators. The authors explained this by the fact that a top manager at a certain age pays more attention to profit maximisation, which affects the size of the bonus payments. The authors of another work [17] came to a similar conclusion. In research number [18] the authors concluded that firm success is positively correlated with increasing CEO age. This is explained by the fact that the younger the CEO, the more inclined to take risks, which does not always have a positive effect on the firm's performance.

1.3. *Citizenship CEO*. For companies in emerging markets, attracting top managers (expats) from foreign developed economies is associated with the transfer of effective management technologies and best practices. In addition, foreign executives can exercise independent control over Russian managers and have extensive business contacts abroad. The world labour market for top managers is much wider than the national one. This statement applies particularly in the case of Russia [1]. Nevertheless, attracting foreign leaders can be associated with a certain number of challenges, including difficulty in adapting to the socio-cultural characteristics of the country, and a lack of understanding of the specifics of the Russian market [19]. Also, the costs associated with finding, hiring and moving a foreign manager can be significant [20]. Studies analysing the effects of citizenship of top managers on the effectiveness of the company utilise not merely the fact of citizenship but the experience of management abroad

[3; 21]. A positive relationship was found between a CEO with foreign experience and firm performance, but a stronger relationship was observed for international companies. In the case of Russia, expats tend to have international experience, so foreign citizenship can be strongly correlated with international experience.

2. Professional characteristics.

2.1. *Tenure in current position.* In earlier works, scientists tried to find a linear relationship between these variables and determine the effect of the length of time the CEO has held their current position on the financial performance of companies [20]. A negative effect of longer duration for the company's management team was found with regard to company growth [22]. The negative effect is perhaps explained by the fact that managers who work for a long time within the same company adhere to regular and unchanging strategies, and they become adherents of their own static ideas. As such, they are less prepared to e.g. introduce fundamentally new technologies which negatively affects the expectations of investors but benefit the value of the company's shares. At the same time, some research [23] was able to identify a positive effect of the duration of the current position on the profit margin. The positive effect is that a long-serving CEO has already formed a successful company management strategy, and is aware of all internal processes and is well-versed in the industry. However, other studies failed to find a significant effect [19; 24].

2.2. *Work experience as a CEO: in the same industry, in a similar position, in this company.* One of the ways to accumulate human capital is to have work experience in a similar industry, which assumes that the manager knows the peculiarities of its functioning, successful and unsuccessful examples of business models of other companies in the industry, the specifics of interaction with the government, and potential counterparties [1]. Work experience gained in a similar environment can be quite valuable for a CEO, as it helps to accelerate the adoption of strategically important decisions [25]. From this point of view, there is reason to believe that experience in a similar industry can positively influence a company's performance. According to estimates obtained in earlier studies (see e.g. [26]) the share of cross-sectoral movements of the heads of Russian companies is only 8% of the total number of transfers. This means that CEOs are focused on developing industry experience, because this is a more successful hiring strategy.

2.3. *Experience in public service.* There is no consensus among researchers as to how political ties affect a company's performance. In some studies, it is concluded that the political connections of the CEO have a positive impact on the company's activities [27–28]. It is assumed that a leader with political connections has access to limited resources which provide a competitive advantage. Such resources include new sources of funding, tax cuts, etc. The authors conclude that executives with experience in the public service are less likely to be removed from their positions because owners value their contributions through political connections [28].

On the other hand, the political connections of a CEO reduce the incentives of the top manager to look for more effective ways to solve strategic problems [29]. For example, to optimise operating costs requires a reduction in the number of employees, but the leader could resist pursuing this measure since it is politically disadvantageous [30].

2.4. *CEO's membership on the boards of directors of other companies*. The literature provides analysis of the importance for the company of the share of independent directors on the board of directors of companies [31-32]. In turn, independent directors are often at the head of other enterprises [33]. It would be interesting to trace the opposite effect, that is, to determine how the representation of the leader on the board of directors of other companies can influence his activities in the context of the present study.

In-depth interviews with the directors of Russian companies conducted by Forbes in 2010 demonstrated that representation on the board of other companies contribute to self-fulfillment and professional experience in various spheres of the economy. Through participation in the board of directors of other companies, the head undergoes training, learns the specifics of other industries, and establishes business contacts at a high professional level [34]. Therefore, we can assume that the representation of the head of the board of directors of other companies has a positive impact on the financial performance of his company.

2.5. *CEO education level.* A high level of education allows managers to offer more optimal solutions [35]. Previous research findings point to the importance of management training. An analysis of data on the manufacturing sector in the United States revealed that the level of education of the CEO is directly related to the results of the company's performance [36]. For example, the research [37] provides evidence that the level of education of a person influences the development of the value systems of top managers in the USA. Directors who are highly qualified in accounting, finance, consulting, and law are more successful in making the right business decisions to ensure the company's success in the stock market. On the contrary, some studies have failed to establish a link between the education level of the CEO and the performance of the company [38]. Based on a sample of data from US firms, it found no significant association and the conclusion was made that business education is overrated.

There are not many works devoted to the study of the role of the leader in Russia. Among them are the works cited at [1] and [18] which examine the state of the labour market for managers in Russia, determine the degree of integration of the Russian market into the international market, and study the factors influencing the appointment of heads of enterprises (citizenship and experience in the industry). A. Chirikova, researching gender issues in the appointment of top managers in Russian companies, found that the problem of the 'glass ceiling' is relevant for Russia. This problem is especially widespread in the regions [39]. Based on the existing literature and economic intuition, it can be assumed that a woman's tenure as a CEO represents her accumulated work experience (e.g. in a managerial position, in the same industry, her taking part in the boards of directors of other companies, or in the public service), a high level of education in general (and business education in particular), as well as the fact that foreign specialists from developed economies were attracted to the management of the company. The age of the leader affects the market value of the company in a non-linear fashion.

Research methodology

From a methodological point of view, the analysis of the impact of personal characteristics of the CEO on the results of the company implies that solutions may be proffered in two areas: (1) methods of personal performance measurement and (2) the definition of performance indicators of the company that would reflect the perception of the financial markets and corporate signals. In addition, relevant articles differ in that they analyse either individual characteristics of managers or a whole set of characteristics.

CEO characteristics and model independent variables

Perhaps the largest number of personal characteristics of company leaders was analysed in the research cited at [40]. The authors included in the study 30 positions of personal characteristics of candidates for executive positions, dividing them into 5 thematic groups (leadership, personal, intellectual, motivational, and interpersonal). The study was based on personal interviews, which evaluated difficult to measure leadership characteristics such as self-confidence, diligence, and decisiveness. However, such assessments are largely subjective and may give distorted results. In addition, they entail significant costs for collecting and information is often not available for external analyst.

To the set of variables analysed (gender, age, work experience, citizenship), an 'ethnic' category can be added [41]. The authors of the mentioned study used ROA as a dependent variable. It was discovered that the variables of age, citizenship, and professional qualifications are significant in measuring company performance. A particularly efficacious profile in terms of efficiency proved to be the combination of a young CEO and an older chairman of the board. A significant disadvantage of this analysis is the omission of nonlinear forms of variables.

The study cited at [42] is devoted to issues of the impact of gender differences on the executives of the company. In addition to the extended parameters for the gender variable (e.g. the proportion of women on the board), the analysis included variables of age, the proportion of CEOs who combine several positions in the company, and the way in which these positions were obtained. As a result of the conducted event analysis it was found that female leaders are less inclined to take risks. Additionally, the authors pointed out that the appointment of a woman to the position of CEO had the same impact on the company's results as the appointment of a man.

Methodologies and results differ regarding the influence of the leader's experience and age. There are studies that have found a positive relationship between variables of managerial experience and company performance [43]. Somewhat less obvious, at first glance, were the results obtained in the study [44]: it turned out that a CEO with the existing experience in a related position in the first place tends to increase the amount of company debt, and secondly, these leaders increase the likelihood of bankruptcy. Moreover, firms that have hired ex-CEOs cannot financially catch up with more successful firms with CEOs without general managerial experience.

Some research uses non-linear relationships to assess the impact of experience and age on performance. The study cited at reference number [45] examined the issue of changes in the cost of transport companies. The authors wanted to explain the errors in the company valuation model built with financial indicators as regressors. To do this, they introduced quadratic forms for the variables of age and experience. As a result of the study, it was found that too long a tenure in the position of CEO leads to negative consequences (the real value of the company turns out to be less than the theoretical one). Similar findings were obtained for the variable of 'age'.

Justification of the dependent variables of the model

The Tobin's Q coefficient was chosen as a dependent variable as a measure of the company's market value which is an indicator of market attractiveness. However, a significant limitation of this ratio is that it does not always fully reflect the efficiency of the company, and may depend on external factors, rather than management decisions [46]. Despite this, most studies use the Tobin's Q-ratio as a measure of company value. The Tobin's Q-ratio provides the market opinion on the effectiveness of all strategic decisions of the company and the quality of the accompanying functional management policies (marketing, financial, personnel management, etc.). In other words, assuming the market is efficient, market opinion should reflect the company's fair value.

Tobin's Q is the most widely used market-based measure of performance [47]. Researchers often develop simplified formulas for Tobin's Q that do not require many sources, requires only access to information that may be in the public domain, or requires the calculation of the market value of the company's long-term debt. In practice, the following approximating formula is often used [48]:

$$\text{Approximate Q} = \frac{\text{MVE} + \text{PS} + \text{Debt}}{\text{TA}}, \quad (1)$$

where MVE – market capitalisation of a company;

PS – the value of preferred shares;

Debt – the amount of long-term and short-term liabilities;

TA – total assets.

In addition, the model includes the following control variables: company size (natural logarithm of total assets), financial leverage (the ratio of the sum of short-term and long-term debt to equity in %), capital expenditure (the ratio of capital expenditure to the total assets of the company in %), revenue growth rate (change in revenue compared to last year in %), state ownership (which takes the value 1 if the state's share in the authorised capital of the company is more than 50%, and 0 if the share is less than 50%). The state ownership variable also reflects the peculiarity of corporate governance in Russia. Binary variables allow you to consider the temporal structure of the data in the pooled regression.

The independent binary variabless take the value 'one' if the manager is a woman, has citizenship outside the CIS, is a member of boards of directors external to the company, previously worked in a managerial position, previously worked in the industry to which the company belongs, previously worked in government bodies, is the founder of the company, or previously worked in this company as an employee. Based on the existing system in Russia, the level of education of a leader is encoded by a rank variable that takes values from 1 to 5 with an increase in the level of education (value 1 – bachelor's / specialty degree, 2 – master's degree, 3 – Ph.D, 4 – master's degree and MBA, 5 – PhD and the presence of an MBA).

Data analysis

Our database was formed on the data of 50 largest Russian non-financial companies for the period from 2011 to 2019 during which 98 CEOs worked in these companies. Companies' market capitalisation data were obtained from the Moscow Exchange website. The financial information of companies was extracted from the annual reports of the companies analysed. Biographical information and professional characteristics of managers were collected from personal pages on the official websites of companies as well as other open sources. A brief description of the companies and personal characteristics of the sampled executives is presented in Table 1.

Table 1. Descriptive statistics of the sample

Variable (units)	Number of observations	Mean	Standard deviation	Minimum value	Maximum value
Tobin's Q (units)	434	0.74	0.76	0.02	6.43
Education (rank)	450	2.18	1.25	1	5
Age (years)	447	49.81	8.8	33	71
Tenure as CEO (years)	450	7.39	6.65	1	27
Company size (bn. rub.)	448	1150.38	2744.47	34.07	21882.35
Revenue growth rate, %	447	8.82	13.88	-58.59	68.7
Financial leverage, %	448	54.79	28.06	8.02	177.6
Capital expenditures, %	448	8.45	4.73	0.26	35.02

Variable (units)	Total	Number of observations where the variable is 1
CEO-woman (units)	98	1
CEO Citizenship outside the CIS (units)	98	6
Member of the external board of directors (units)	98	39
Industry experience (units)	98	72
Public service experience (units)	98	34
Work experience as CEO (units)	98	50
Intra-firm CEO career (units)	98	42
Company founder (units)	98	7
Companies with a controlling stake owned by the state (units)	50	18

The companies in the sample are heterogeneous in terms of financial and economic indicators. The average value of Tobin's Q is 0.74 which means that the market value of the company's assets is less than their book value and the market underestimates the company. The lowest values of the indicator corresponded to the crisis year of 2014. Tobin's Q, representing the dependent variable, was not correlated with any variable.

There is only 1 woman among 98 leaders in the sample. However, the results may be underestimated due to the relatively small number of companies in the sample. According to estimates obtained in the work cited at reference number [9], which analyses the movement of managers from 1997 to 2007, the proportion of women leaders is 6.2%. The author concludes that this result may indicate the presence of a "glass ceiling" problem.

Only 6 out of 98 executives are foreign citizens, including 2 which head a company with a controlling stake owned by a foreign strategic investor. 4 foreign executives work in retail chains. Large Russian business prefers to attract domestic managers, believing that they are better versed in a specific business environment. At the same time, the overwhelming majority have previous experience in the industry (72 out of 98) and a third of the sample also have experience in the public service (34 out of 98). The latter fact can be explained not only by the importance of relations with state governing bodies but also by the fact that in 18 companies out of 50 the controlling stake belongs to the state.

Almost 40% of CEOs are also members of other boards of directors. This reflects the integration process of large Russian businesses.

From public sources we managed to identify the presence of MBAs for only 19 people, mainly in the younger contingent of the sample. A quarter of CEOs hold a Ph.D. This may indicate that the owners of companies value the practical experience of the leader more than academic knowledge. The importance of experience as a marker for the choice of the head of the company is also emphasised by the fact that 42 representatives of the selected group have work experience in this company, and 50 have previous experience as a leader.

Most of the large Russian companies were founded back in the days of the USSR and the opportunity to found their own company arose after its collapse. In addition, almost 30 years have passed since the founding of large entrepreneurial firms. Hence, a small number of founders of the companies continued to work as CEOs (7 out of 98).

The average CEO age is 49.8, which is not very high compared to other countries. The average CEO tenure is 7.39 years, which means that the CEO often remains for 2 terms in office. The record-breaking CEO for the longest term is the CEO who has been in the position for 27 years, and who is one of the founders of the company, and also a shareholder. This situation is typical for all executives and co-founders of the companies in the sample.

Research results

The hypotheses were tested using pooled regression. Initially, the data contained 450 observations, however, after excluding observations with missing indicators, 431 observations remained in the sample. The results of the regression model are presented in Table 2.

Table 2. Results of regression analysis

Variables	-1 Tobin's Q	-2 Tobin's Q	-3 Tobin's Q	-4 Tobin's Q
CEO gender				−0.266** (0.089)
CEO citizenship outside the CIS	−0.453*** (0.094)	−0.426*** (0.096)	−0.401*** (0.097)	−0.405*** (0.099)
Member of the external board of directors	0.284*** (0.024)	0.259*** (0.023)	0.252*** (0.023)	0.251*** (0.023)
Industry experience	0.221*** (0.03)	0.206*** (0.033)	0.205*** (0.032)	0.202*** (0.031)
Education	−0.017 (0.011)		−0.025* (0.011)	−0.0255* (0.011)
MBA		−0.2 (0.033)		
Public service experience	−0.128** (0.041)	−0.104** (0.045)	−0.096** (0.043)	−0.098** (0.042)

Variables	-1 Tobin's Q	-2 Tobin's Q	-3 Tobin's Q	-4 Tobin's Q
Work experience as CEO	0.132** (0.046)	0.142** (0.047)	0.143** (0.049)	0.143** (0.048)
Intra-firm CEO career	–0.254*** (0.054)	–0.262*** (0.049)	–0.261*** (0.049)	–0.262*** (0.049)
Company founder	1.276*** (0.233)	1.209*** (0.233)	1.193*** (0.227)	1.189*** (0.229)
CEO change			–0.048 (0.071)	
Age	0.058** (0.019)	0.067*** (0.019)	0.068*** (0.019)	0.069*** (0.018)
Age2	–0.0006** (0.0001)	–0.0006** (0.0002)	–0.0006*** (0.0001)	–0.0006*** (0.0001)
Tenure as CEO	0.019 (0.016)	0.026 (0.015)	0.022 (0.018)	0.026 (0.015)
Tenure 2 as CEO	–0.002** (0.0008)	–0.002** (0.0008)	–0.002** (0.0009)	–0.002** (0.0008)
Company size	–0.104*** (0.017)	–0.084*** (0.016)	–0.081*** (0.017)	–0.081*** (0.017)
Revenue growth rate	0.007** (0.002)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Financial leverage	–0.006*** (0.001)	–0.005*** (0.0008)	–0.005*** (0.0008)	–0.005*** (0.0008)
Capital expenditure	0.033*** (0.005)	0.028*** (0.005)	0.0277*** (0.005)	0.027*** (0.005)
Companies with a controlling stake owned by the state	–0.617*** (0.05)	–0.659*** (0.049)	–0.645*** (0.052)	–0.648*** (0.053)
Years	Included			
Cons	–0.038 (0.728)	–0.351 (0.546)	–0.333 (0.533)	–0.368 (0.524)
R^2	0.547	0.509	0.511	0.511
N	431			

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

All control variables were statistically significant in all modifications of the model. The negative sign of the size of the company is explained by the fact that this variable is in the denominator of the independent variable which means that the larger the denominator, the lower the ratio of capitalisation to total assets is obtained. In turn the status of a state enterprise has a negative impact on the market value of the company.

Most of the studied independent variables turned out to be significant, which is consistent with the theory of the upper echelons and the theory of human capital. We did not test the hypothesis about the influence of gender due to a single observation that a woman was leading the company in the sample. It was not possible to confirm the hypothesis about the positive influence of the foreign citizenship of the head on the market value of the company, and the relationship turned out to be negative. On the one hand, it should be considered that only 6 foreign executives were included in the sample, and two of them represented a group of companies with a controlling foreign owner. Therefore, it would be wrong to make an unambiguous conclusion that the positive effect of a technology transfer by a foreign leader is less than the disadvantages associated with ignorance of the specifics of the Russian business environment. Rather, this hypothesis needs additional testing.

Membership of a CEO on the board of directors of other companies has a positive effect on the market value of the firm he heads. The market places a high value on top managers networking and strategic decision-making experience on the board of directors.

Our analysis revealed a positive impact of previous experience in the industry on the market value of the firm. Experience in the industry gives an idea of the specifics of its functioning, potential counterparties, methods of interaction with the state, etc., which in turn is positively met by the market. Descriptive statistics results also prove that the owners prefer to hire executives with experience in the industry.

Previous experience as CEO turned out to be a positively significant variable. This thesis is supported by the fact that the educational level was not a significant variable for the model considered. The practical experience gained by the leader is more important than academic knowledge for investors.

Our study found a negative effect of a CEO's work experience in state bodies on the company market value. It should be recalled that one of the ways to accumulate human capital in this case is to acquire connections at the state level. The result obtained may indicate that at a certain stage these advantages in terms of efficiency turn into disadvantages. A CEO with the support of the state has less incentive towards careful strategic planning and development of the firm [30]. For example, if the business contacts of a manager at the state level contribute to winning the tender for a contract, it is likely that the manager will not be involved in optimising production in order to fulfill the contract on terms that are more favourable to the customer. In turn, the optimisation of production could bring significant benefits in the conclusion and execution of other contracts. The obtained result indicates that the market values a CEO with more practical experience in market conditions, and who possesses the skills of a leader, than the ability to access and employ administrative resources.

The market apparently negatively perceives the fact of an internal promotion to CEO, fearing that a person has already formed a team for himself which may lead to selfish management of the company for his own purposes (and ignoring the interests of stakeholders). At the same time, a person from the outside can look at the company from a different angle, which may entail new ideas and strategies for the management of the company.

The status of the founder of the company has a positive effect on its market value. The market negatively perceives state-owned companies and state people, fearing that they will pursue other goals and motives for doing business while the market assesses private owners and founders positively, because they know the whole business from the inside and their goal is to further develop the business and strengthen the market.

Our analysis confirmed the presence of a nonlinear relationship between the age of the leader and the market value of the company, but the tenure of the CEO turned out to be insignificant. The results obtained support the assumption that after reaching a certain age, a manager begins to lose their business acumen, does not follow relevant trends, becomes conservative, and introduces fewer new ideas. According to the signs of the age variables, a maximum point is reached which corresponds to 49 years, after which the market starts to assess the age of the leader negatively.

Conclusion

Over the past decades the stock market continues its active development, which is the primary reason for paying close attention to the formation of a company's market value. There are many theories studying the issue. However, in an unstable business environment more and more attention are paid to the personal qualities of the top management of companies their ability to cope with non-trivial tasks, develop competent business strategies and compete in the modern market.

First of all, the growth of the company's capitalisation reflects the expectations of investors, which incorporates their view of the personality of the CEO: e.g. whether he will be able to maintain an appropriate level of the firm's work, and whether there is expediency in further investment. Therefore, it is extremely important to understand exactly what qualities of top management affect investor sentiment and the market value of the company accordingly.

Our research confirms the importance for investors of the personal characteristics of the top executives of companies belonging to the category of 'large traded companies'. According to the data, the Russian market prefers a new CEO to be a man around 49 years old, born in the CIS, and who has experience in the industry. A valuable characteristic of a CEO is the fact that he is on the board of directors of other companies, and is also a CEO in a separate company, with less emphasis on his experience in public service.

In conclusion, it should be noted that the study has some drawbacks. Firstly, due to problematic data access the sample time period is only 9 years, which does not allow for tracing the long-term effects of the influence of managers on the market value of companies. Secondly, our analysis can be expanded to include salary information in the model, to consider the impact of a CEO having a wife and children, and having a stake in the company he leads. Finally, the characteristics of managers may be dependent on the performance of the company. That is, whether the presence of certain characteristics can account for the problem of endogeneity, which is a difficult challenge to address due to the problematic search for instrumental variables. However, we should noted that these drawbacks may also be perceived as opportunities, and potential directions of future research.

References

1. Roshchin S., Solntsev S. The labor market of top managers in Russia. Moscow: NRU HSE Publ.; 2016. 252 p. (In Russ.).
2. Rumelt R. Good strategy bad strategy: The difference and why it matters. New York: Crown Business; 2011. 336 p.
3. Daellenbach U.S., McCarthy A.M. Commitment to innovation: The impact of top management team characteristics. *R&D Management*. 1999;29(3):199-208. DOI: 10.1111/1467-9310.00130
4. DiMaggio P.J., Powell W.W. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*. 1983;48(2):147-160. DOI: 10.2307/2095101
5. Haveman H.A. Follow the leader: Mimetic isomorphism and entry into new markets. *Administrative Science Quarterly*. 1993;38(4):593-627. DOI: 10.2307/2393338
6. Diaz- Fernández M.C., González-Rodríguez M.R., Pawlak M. Top management demographic characteristics and company performance. *Industrial Management & Data Systems*. 2014;114(3):365-386. DOI: 10.1108/IMDS-04-2013-0210
7. Hambrick D.C, Mason P.A. Upper echelons: The organization as a reflection of its top managers. *The Academy of Management Review*. 1984;9(2):193-206. DOI: 10.2307/258434
8. Brett J.F., Cron W.L., Slocum J.W. Jr. Economic dependency on work: A moderator of the relationship between organizational commitment and performance. *The Academy of Management Journal*. 1995;38(1):261-271. DOI: 10.2307/256735
9. Hambrick D.C. Upper echelons theory: An update. *The Academy of Management Review*. 2007;32(2):334-343. DOI: 10.2307/20159303
10. Allen N.J., Meyer J.P. The measurement and antecedents of affective, continuance and normative commitment to the organization. *Journal of Occupational Psychology*. 1990;63(1):1-18. DOI: 10.1111/j.2044-8325.1990.tb00506.x
11. Brealey R., Myers S., Allen F. Principles of corporate finance 11th ed. New York: McGraw-Hill Book Co.; 2014. 1341 p.
12. Chaganti R.S., Zimmerman M.A., Kumaraswamy A., Maggitti P., Arkles J.B. TMT characteristic, time-to IPO and firm performance. *Journal of Management & Public Policy*. 2016;7(2):37-56.
13. Smith N., Smith V., Verner M. Do women in top management affect firm performance? A panel study of 2,500 Danish firms. *International Journal of Productivity and Performance Management*. 2005;55(7):569-593. DOI: 10.1108/17410400610702160
14. Rose C. Does female board representation influence firm performance? The Danish evidence. *Corporate Governance*. 2007;15(2):404-413. DOI: 10.1111/j.1467-8683.2007.00570.x
15. Post C., Byron K. Women on boards and firm financial performance: A meta-analysis. *The Academy of Management Journal*. 2014;58(5):1546-1571. DOI: 10.5465/amj.2013.0319
16. Auden W.C., Shackman J.D., Onken M.H. Top management team, international risk management factor and firm performance. *Team Performance Management*. 2006;12(7/8):209-224. DOI: 10.1108/13527590610711778
17. Fischer H.M., Pollock T.G. Effects of social capital and power on surviving transformational change: The case of initial public offerings. *The Academy of Management Journal*. 2004;47(4):463-481. DOI: 10.2307/20159597
18. Brockmann E.N., Simmonds P.G. Strategic decision making: The influence of CEO experience and use of tacit knowledge. *Journal of Managerial Issues*. 1997;9(4):454-467.
19. Roshchin S., Khudenko K. Labor relations at foreign enterprises in Russia. In: Management. Century XX, century XXI. Moscow: Ekonomist; 2004:121-140. (In Russ.).

20. Balkin D.B., Markman G.D., Gomez-Mejia L.R. Is CEO pay in high-technology firms related to innovation? *The Academy of Management Journal*. 2000;43(6):1118-1129. DOI: 10.5465/1556340

21. Finkelstein S., Hambrick D.C., Cannella A.A. Jr. Strategic leadership: Theory and research on executives, top management teams, and boards. Oxford, New York: Oxford University Press; 2009. 480 p. DOI: 10.1093/acprof:oso/9780195162073.001.0001

22. Sørensen J.B. The ecology of organizational demography: Managerial tenure distributions and organizational competition. *Industrial and Corporate Change*. 1999;8(4):713-744. DOI: 10.1093/icc/8.4.713

23. Waldman D.A., Ramírez G.G., House R.J., Puranam P. Does leadership matter? CEO leadership attributes and profitability under conditions of perceived environmental uncertainty. *The Academy of Management Journal*. 2001;44(1):134-143. DOI: 10.2307/3069341

24. Iaquinto A.L., Fredrickson J.W. Top management team agreement about the strategic decision process: A test of some of its determinants and consequences. *Strategic Management Journal*. 1997;18(1):63-75. DOI: 10.1002/(SICI)1097-0266(199701)18:1<63::AID-SMJ835>3.0.CO;2-N

25. Finkelstein S., Hambrick D.C. Top-management-team tenure and organizational outcomes: The moderating role of managerial discretion. *Administrative Science Quarterly*. 1990;35(3):484-503. DOI: 10.2307/2393314

26. Solntsev S. CEOs in Russia: Who reaches the top? Working paper WP15/2009/09. Moscow: NRU HSE; 2009. 32 p. (In Russ.).

27. Faccio M. Politically connected firms. *The American Economic Review*. 2006;96(1):369-386. DOI: 10.1257/000282806776157704

28. Fisman R. Estimating the value of political connections. *The American Economic Review*. 2001;91(4):1095-1102. DOI: 10.1257/aer.91.4.1095

29. Boubakri N., Cosset J.-C., Saffar W. Political connections of newly privatized firms. *Journal of Corporate Finance*. 2008;14(5):654-673. DOI: 10.1016/j.jcorpfin.2008.08.003

30. Black B.S., Love I., Rachinsky A. Corporate governance indices and firms' market values: Time series evidence from Russia. *Emerging Markets Review*. 2006;7(4):361-379. DOI: 10.1016/j.ememar.2006.09.004

31. Ivashkovskaya I., Kukina E., Stepanova A. The impact of corporate financial architecture on economic profit: An empirical study of Russian companies in the crisis and pre-crisis periods. In: Proc. 12th Int. sci. conf. on economic and social development (Moscow, 5-7 Apr. 2011). (In 4 vols.). Vol. 4. Moscow: NRU HSE; 2012:39-48. (In Russ.).

32. Fan J.P.H., Wong T.J., Zhang T. Politically connected CEOs, corporate governance, and post-IPO performance of China's newly partially privatized firms. *Journal of Financial Economics*. 2007;84(2):330-357. DOI: 10.1016/j.jfineco.2006.03.008

33. Zhang Y., Rajagopalan N. CEO succession planning: Finally at the center stage of the boardroom. *Business Horizons*. 2010;53(5):455-462. DOI: 10.1016/j.bushor.2010.05.003

34. Filatov A.A. Why do managers become independent directors? Forbes. 2010. URL: http://www.forbes.ru/column/48736-zachem-menedzhery-idut-v-nezavisimye-direktora (accessed on 5.05.2020). (In Russ.).

35. Certo S.T. Influencing initial public offering investors with prestige: Signaling with board structures. *The Academy of Management Journal*. 2003;28(3):432-446. DOI: 10.5465/amr.2003.10196754

36. Rajagopalan N., Datta D.K. CEO characteristics: Does industry matter? *The Academy of Management Journal*. 1996;39(1):197-215. DOI: 10.2307/256636

37. Manner M.H. The impact of CEO characteristics on corporate social performance. *Journal of Business Ethics*. 2010;93(Suppl. 1):53-72. DOI: 10.1007/s10551-010-0626-7

38. Gottesman A.A., Morey M.R. CEO educational background and firm financial performance. *Journal of Applied Finance*. 2010;20(2):1-13.

39. Chirikova A. Woman at the head of the company. Moscow: Institute of Sociology of RAS; 1998. 358 p. (In Russ.).

40. Kaplan S.N., Klebanov M.M., Sorensen M. Which CEO characteristics and abilities matter? *The Journal of Finance*. 2012;67(3):973-1007. DOI: 10.1111/j.1540-6261.2012.01739.x

41. Amran N.A., Yosuf M.A.M., Ishak R., Aripin N. Do characteristics of CEO and chairman influence government-linked companies performance? *Procedia – Social and Behavioral Sciences*. 2014;109:799-803. DOI: 10.1016/j.sbspro.2013.12.546

42. Martin A.D., Nishikawa T., Williams M.A. CEO gender: Effects on valuation and risk. *Quarterly Journal of Finance & Accounting*. 2009;48(3):23-40.

43. Chi J., Liao J., Chen X. Political connected CEOs and earnings management: Evidence from China. *Journal of the Asia Pacific Economy*. 2016;21(3):397-417. DOI: 10.1080/13547860.2016.1176644

44. Elsaid E., Wang X., Davidson W.N. III. Does experience matter? CEO successions by former CEOs. *Managerial Finance*. 2011;37(10):915-939. DOI: 10.1108/03074351111161583

45. Ben Mohamed E., Jarboui S., Baccar A., Bouri A. On the effect of CEOs' personal characteristics in transport firm value? A stochastic frontier models. *Case Studies on Transport Policy*. 2015;3(2):176-181. DOI: 10.1016/j.cstp.2015.01.001

46. Pham P.K., Suchard J.-A., Zein J. Corporate governance and alternative performance measures: Evidence from Australian firms. *Australian Journal of Management*. 2011;36(3):371-386. DOI: 10.1177/0312896211413035

47. Al-Matari E.M., Al-Swidi A.K., Hanim F. The measurements of firm performance's dimensions. *Asian Journal of Finance & Accounting*. 2014;6(1):24-49. DOI: 10.5296/ajfa.v6i1.4761

48. Chung K.H., Pruitt S.W. A simple approximation of Tobin's q. *Financial Management*. 1994;23(3):70-74. DOI: 10.2307/3665623

Dynamic Mapping of Probability of Default and Credit Ratings of Russian Banks

Ella Khromova
Investment Director
ORCID
E-mail: epkhromova@gmail.com
Investment company LLC "Prima Capital", Moscow, Russia

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 31-46 (2020)
DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.31-46
Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

Dynamic Mapping of Probability of Default and Credit Ratings of Russian Banks

Abstract

Investors are interested in a quantitative measure of banks' credit risk. This paper maps the credit ratings of Russian banks to default probabilities for different time horizons by constructing an empirical dynamic calibration scale. As such, we construct a dynamic scale of credit risk calibration to the probability of default (PD).

Our study is based on a random sample of 395 Russian banks (86 of which defaulted) for the period of 2007-2017. The scale proposed by this paper has three features which distinguish it from existing scales: dynamic nature (quarterly probability of default estimates), compatibility with all rating agencies (base scale credit ratings), and a focus on Russian banks.

Our results indicate that banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned. As a result, a rising capital strategy was formulated: the better a bank's credit rating, the shorter the investment horizon should be and the closer the date of investment should be to the rating assignment date in order to minimise credit risk.

The scientific novelty of this paper arises from the process of calibration of a rating grade to dynamic PD in order to evaluate the optimal time horizon of investments into a bank in each rating class. In practical terms, investors may use this scale not only to obtain a desired credit rating, but also to identify quantitative measure of credit risk, which will help to plan investment strategies and to calculate expected losses.

Keywords: banks, credit ratings, probability of default, mapping, calibration

JEL classification: G21, G24, G33

Introduction

The sustainability of a country's financial system primarily depends on the performance of financial institutions. The key financial institutions are banks and credit organisations. The assessment of banks' credit risk is an important issue for governments, regulators and investors. All such economic agents are interested in having banks functioning well, as they serve as the main financial intermediaries on the market. The most commonly-used ways of assessing financial performance and controlling the level of credit risk of a bank are by evaluation of default probability and via credit rating. The probability of default (PD) is the likelihood of a bank failure over a fixed assessment horizon, and a credit rating (CR) determines the class to which a company belongs based on the PD.

CR is represented in symbolic form, which may lead to problems with the interpretation and quantitative assessment of potential losses of a bank's counteragent. However, a CR model itself usually has better forecasting power compared to a PD model with quantitative outcome. Therefore, the calibration scale of CR to PD will allow to obtain quantitative estimate of credit risk, based on a CR grade assigned by a rating agency (RA) or as forecast by a CR model.

The aim of this paper is to construct a dynamic scale of CR calibration to PD. Investors are interested in a quantitative measure of banks' credit risk. This goal is achieved with the help of default frequencies estimation for each group of credit rating grades. This scale is built on the basis of an extensive sample of Russian banks and can be used by both investors and internal management in credit risk assessment. The topic of this paper may be of particular importance in the current situation, which is critically close to a global economic crisis.

The topic of mapping CR to PD is frequently studied: many researchers and RAs propose their own calibration scales. However, the novelty of CR to PD calibration scale of this paper is supported by the following superior features. First, the scale has a high frequency dynamic nature that allows to estimate the change in PD of a particular CR class, with a quarterly periodicity after the rating assignment date. Second, this calibration scale provides a quantitative PD estimate for a CR assigned by any national or international rating agency, because it uses uniform CR scale in calibration. Third, this scale was constructed based on a data sample of Russian banks that accounts for the specific features of the country.

Additionally, while constructing the calibration scale, we notice several important patterns and try to explain their possible reasons and origins. A dynamic scale assessing the calibration of qualitative CR measures to quantitative PD measures showed that the better the credit rating of a bank, the higher the CAGR of PD is (PD increases in time at a faster rate in the better rating classes). As a result, the rising capital strategy was formulated. Investment in banks with a better credit rating is optimal right after the rating issue, and is efficient over a short term period. However, to achieve minimal credit risk for capital investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1-2 years after the rating assignment.

The paper is structured as follows. First, we introduce the literature review on CR and PD mapping. Next, the detailed data description and the methodological issues are discussed. Empirical results are provided in the main part, and the paper ends with our conclusions.

Review of related academic literature and hypothesis development

There are several literature streams that study the non-linear dependence between credit ratings and other fundamental risk parameters (PD, LGD and EAD). For example, Volk [1] in his paper linked the forecasted values of firms' PDs with credit ratings and identified disparities in firms' creditworthiness when estimated by these methods. Papers [2] and [3] study the phenomenon whereby a higher credit rating may lead to a higher LGD. Another literature stream focuses on the calibration of PD and CR to the same scale. The paper cited at [4] compares a variety of calibration approaches and concludes that a 'scaled likelihood ratio' approach is superior to the standard 'scaled PDs' approach. Pomasanov and Vlasov [5] introduce the model of credit ratings calibration on PD for Russian banks. Alternatively, paper [6] offered models for credit ratings and PD calibration in samples with small number of bankrupt firms. The proposed method is based on the idea of benchmarking and genetic algorithms. Moreover, paper [7] provides a calibration scale that takes into account the forecasted PD and has a forward-looking nature. Different methods of comparing the credit ratings and PD were used in the academic papers cited at references [8; 9; 10]. For example, Godlewski [8] compared banks' CR and PD in emerging countries and proved a partial divergence of ratings with the use of a PD scoring model, by finding out that CR tends to aggregate banks' default risk information into intermediate-to-low ratings grades. Most of the articles mentioned above offer an econometric model, which can be used for interpreting CRs with the help of PD (see, e.g. [1; 4; 5; 7; 11; 12]). Moreover, the tables with credit ratings and implied PDs are provided by RAs themselves: S&P (Annual Corporate Default and Rating Transition Study), Moody's (Corporate Default and Recovery Rates) and Fitch (Transition and Default Studies). However, one faces several limitations while applying these scales to Russian banks:

- First, RAs do not provide the corresponding scales of credit rating conversion for different countries and for different geographic groups. The data used by the RAs to prepare these calculations mostly include their home country (the USA) and the countries of major shareholders (developed countries such as Canada and the UK). Russian banks are not representative in such databases;

- Second, the values of annual historical default frequencies (estimates of default probabilities) for various credit ratings are calculated by each RA empirically (based on default statistics of banks with credit ratings of a particular RA), which leads to an inadequate comparison of the level of creditworthiness for the same rating class in different time periods;
- Third, the scales provided by each RA are not dynamic in nature, i.e. they provide only annual frequencies. An investor may not evaluate the possible losses which can occur in the short run (in a month/quarter after the investment is made).

Based on this literature review, we aim to construct a uniform calibration scale that simultaneously includes the CR of different RAs and allows to estimate the probability of default in different time frames after credit rating assignment. Following a time frame analysis, the following hypothesis was formulated.

Hypothesis 1. Banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time.

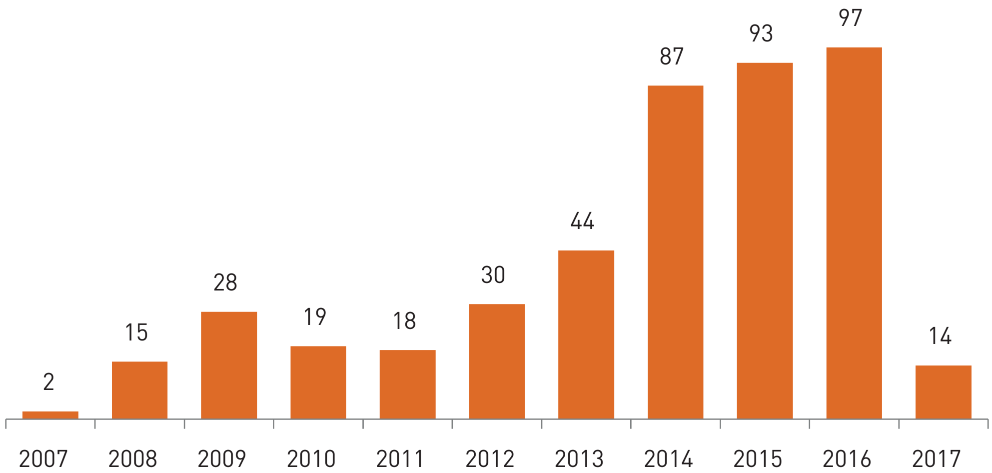
The intuition behind this hypothesis is that speculative banks that survive for a prolonged period are mainly small but stable, while banks with investment rating grades face huge competition and cannot fulfil regulatory requirements for a long period. Therefore, it is supposed that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned.

Data sample description

The empirical research of this paper is based on the dataset that was consolidated with the help of Matlab code from two separate databases. The first is the "Banks and Finance" database provided by the informational agency "Mobile", while the second is the database of Central Bank of Russia, which consists of the RAS statements of all Russian licensed banks. The data was gathered with a quarterly periodicity that allowed us to obtain a panel dataset of Russian banks. Initially, information about 2071 banks was extracted for the period from 2004 to 2017.

Some data filtration methods were applied in order to generate a representative sample. First, all state-owned banks (according to the definition of Vernikov and Bobkov [13]) were omitted, as we consider standalone ratings. The main reduction of the sample size appeared due to the fact that only a small share of banks (395 banks) was assigned a CR grade. The historical data of CR changes was taken from on-line aggregators of banking statistics Cbonds.ru and Bankodrom.ru. The data included CR grades of national RAs (NRA, RAEX, AK&M, Rus-Rating, Ria-Rating) and international RAs (Standard & Poor's, Fitch, and Moody's). The data on banks' defaults were collected from Cbr.ru and Banki.ru. During the extraction period, 86 Russian banks that got a CR assessment defaulted at least once. See Figure 1 below for the historical distribution of all Russian banks (before any filtrations) for the period from 2007 to 2017.

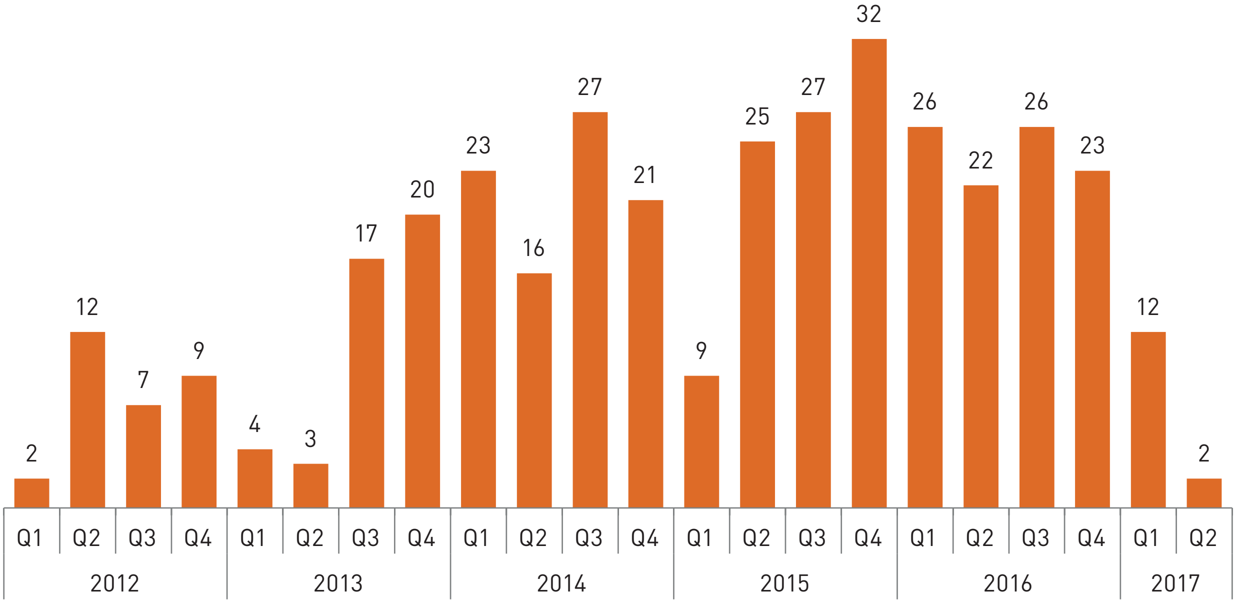
Figure 1. Historical annual distribution of defaults of Russian banks from 2007 to 2017



Source: Authors' own calculations.

From the graph above we can conclude that after the 2008 crisis there was an increase in the number of defaults. Moreover, since 2014 the banking regulation proposed by the policy of Elvira Nabiullina in the Central Bank of Russia has become sharper. We can see that the growth rate of defaults reached 98% in 2014. In Figure 2 below, one can see a more detailed version of the historical distribution of defaults provided by quarters.

Figure 2. Historical quarter distribution of defaults of Russian banks from 2012 to 2017



Source: Authors' own calculations.

A disproportional distribution of defaults can be seen in quarterly periodicity of data (Figure 2). However, one can notice that usually the highest number of defaults appear at the end of the year (Q3 and Q4). This tendency can be explained by the fact that at the end of the year the fulfillment of annual normatives can be easily compared to the previous behaviour of the bank.

The last step of filtration was a manual check on outliers and unrealistic data. In the case of absence of some date (which rarely happened) we averaged the value with reference to the nearest periods. The overall amount of observations remaining was 11,627. Due to the intrinsically imbalanced nature of default data sets, the amount of default-periods were lower than non-default ones (223 of defaults compared to 11 404 of non-defaults).

Methodology description

Calibration of CR to the base scale

As the first step of dynamic CR to PD mapping scale construction, rating grades of national and international rating agencies were calibrated into a single scale. In order to construct a base rating scale, symbolic rating grades were transformed into numerical values and then calibrated into the common (base) scale, derived from the methodology of Karminsky and Sosurko [14] which is often used in research on this topic [15; 16].

It was concluded by Karminsky and Sosurko [14] that the best results of mapping scales are obtained by using the class of linear-logarithmic transformations. In this case, the parameterisation of mappings implies finding a pair of coefficients for mapping each of the scales into a basic one (free term and coefficient in front of the logarithm of the described rating scale). Moody's international scale was chosen as a dependent variable for the base scale construction. Therefore, the following regression was run in order to fulfill the mapping procedure:

$$LN(M) = \alpha LN(R_i) + b_i \quad (1)$$

where M is a Moody's international scale and R_i is the scale of CR that should be calibrated to the base scale. In general, the specification of the model and the total values of the coefficients and characterise the function of converting the numerical values of ratings by the scales under consideration () to the base scale (). The estimated coefficients for international RAs like Standard & Poor's, Fitch, and Moody's (both international and national scales) and national RAs such as NRA, RAEX, AK&M, Rus-Rating, and Ria-Rating were calculated.

The results are summarised in Appendix 1.

The interpretation of this figure implies representation of symbolic CR into the numeric base scale, where smaller numbers are given to banks with the best CR, and the biggest numbers assigned to the worst of them. Therefore, in this paper 32 different grades of rating were considered.

Dynamic mapping of CR to PD

Taking into account all the above-mentioned limitations of the existing calibration scales, we aim to construct a uniform dynamic scale of the credit rating score conversion to PD. The credit rating scores used for calibration are calculated according to the base scale obtained after the credit rating mapping. Then, average default frequencies were taken as an empirical proxy of PD. Overall, to prepare a scale of credit rating score and PD compliance, the following steps were taken.

Step 1: We calculate the matrix for each credit rating score which shows the default frequency for the banks which were assigned a particular credit rating in each of the available time periods. To estimate the default frequencies, we create R code (Appendix 4), which helps us to calculate the following matrices for each rating score. Each cell in a matrix represents the default frequency (DF) which is calculated as:

$$DF_{l,q}^{(r)} = \frac{Default_{l,q}^{(r)}}{Banks_l^{(r)}}, \quad (2)$$

where r is a rating score;

l is the time quarter of a credit rating assignment, l = (1, 2, …, 48);

q is the time quarter of a bank's default, q = (2, 3, …, 49).

Default is the number of bankrupt banks, $Default_{l,q}^{(r)}$ is the number of banks that got credit rating r in period l and defaulted in period q;

Banks is the total number of banks, $Banks_l^{(r)}$ is the total number of banks that got credit rating r in period l.

Consider Appendixes 2 and 3, which present the default frequencies for credit scores r =17.5 and r = 15.5 from the second quarter of 2012 to the second quarter of 2017. In the columns, the periods of ratings assignment are presented (l = 29, …, 48). In the rows, the periods of default with ratings r = 17.5 and r = 15.5 are shown (q = 30, …, 49).

Step 2: We do not fix the quarter when the credit rating *r* was assigned. We estimate the period after which a bank goes bankrupt starting from the moment of rating assignment over the entire time horizon. Thus, to estimate the PD, we take the average values of the cells diagonally. For example, the PD after one period is found as an average default frequency:

$$DF^{(r)}(k=1) = Average\left\{DF_{1,2}^{(r)}; DF_{2,3}^{(r)}; \dots; DF_{48,49}^{(r)}\right\}, \quad (3)$$

where k is the number of quarters after which the bank went bankrupt.

Alternatively, the PD after two periods (quarters) is calculated as:

$$DF^{(r)}(k=2) = Average\left\{DF_{1,3}^{(r)}; DF_{2,4}^{(r)}; \dots; DF_{47,49}^{(r)}\right\}. \quad (4)$$

Hence, the default frequencies after τ periods are found as:

$$DF^{(r)}(k=\tau) =$$
$$= Average\left\{DF_{1,\tau+1}^{(r)}; DF_{2,\tau+2}^{(r)}; \dots; DF_{49-\tau,49}^{(r)}\right\} \quad .(5)$$

Step 3: We summarise the obtained results for each rating score r presented in the sample of Russian banks. The intermediate tables are constructed where we present the default frequencies which are used to estimate the PD in k time periods (quarters) of a bank with credit rating r.

Step 4: The estimated default frequencies for a set of rating grades are averaged for each rating class. This is done for a more logical representation of the obtained results and for keeping an approximately equal number of bank-periods in each class. We divide the rating scores on 5 rating classes: BBB [8-10], BB [12-13.5], B [14-15.5], CCC [16-17.5] and C [18.5-21] based on international scale. For example, the default frequency for a bank with credit rating from class CCC [16-17.5] after τ quarters is calculated as:

$$DF^{(CCC)}(k=\tau) =$$
$$= \frac{DF^{(16)} \times n^{(16)} + \dots + DF^{(17.5)}(k=\tau) \times n^{(17.5)}}{n^{(16)} + n^{(17.5)}} \quad (6)$$

where $n^{(r)}$ is the total number of bank-periods with rating r.

As a result of the procedure described above, a dynamic transmission scale which relates a rating score to average default frequencies of Russian banks was summarised in table format for each rating class (Table 1 below).

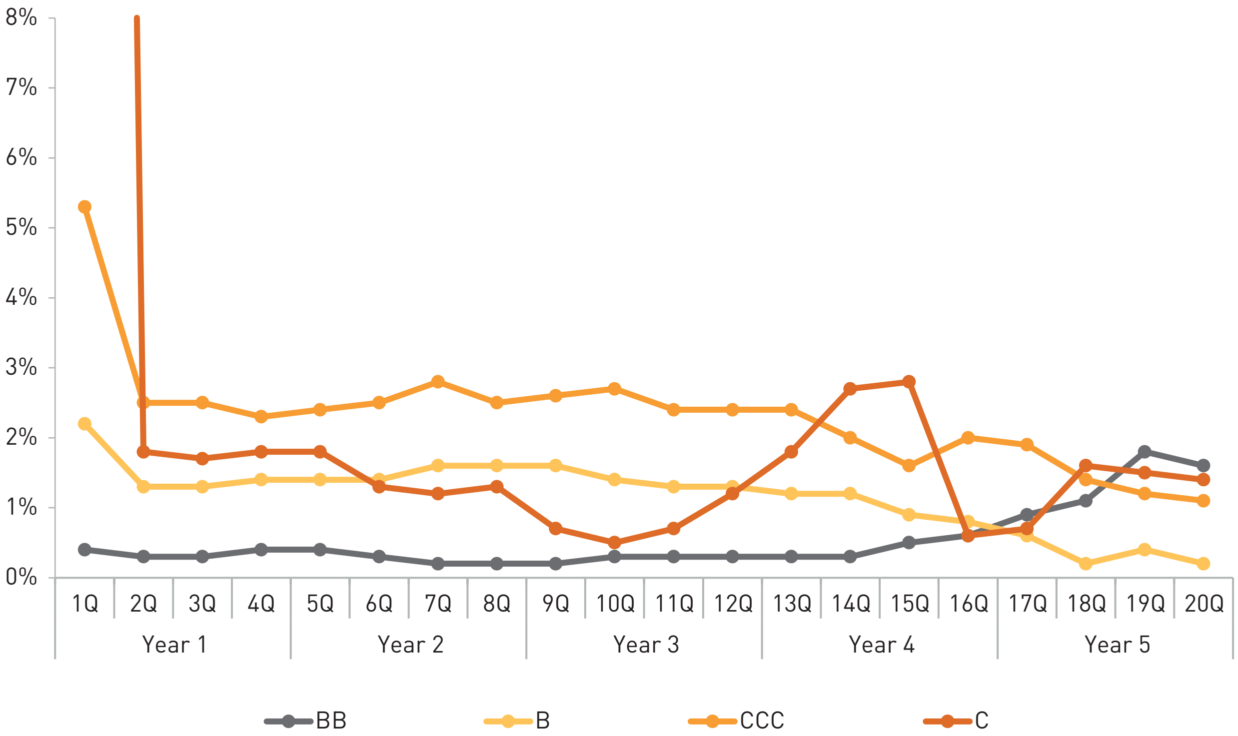
Table 1. Dynamic transmission scale of credit ratings and DF (%)

	BBB [8-10]	BB [12-13.5]	B [14-15.5]	CCC [16-17.5]	C [18.5-21]
1 quarter		0.40	2.20	5.30	56.10
2 quarters		0.30	1.30	2.50	1.80
3 quarters		0.30	1.30	2.50	1.70
4 quarter		0.40	1.40	2.30	1.80
Cum. DF in 1 year	-	1.30	6.30	12.60	61.40
5 quarters		0.40	1.40	2.40	1.80
6 quarters		0.30	1.40	2.50	1.30
7 quarters		0.20	1.60	2.80	1.20
8 quarters		0.20	1.60	2.50	1.30

	BBB [8-10]	BB [12-13.5]	B [14-15.5]	CCC [16-17.5]	C [18.5-21]
Cum. DF in 2 years	-	2.40	12.30	22.90	67.00
9 quarters		0.20	1.60	2.60	0.70
10 quarters		0.30	1.40	2.70	0.50
11 quarters		0.30	1.30	2.40	0.70
12 quarters		0.30	1.30	2.40	1.20
Cum. DF in 3 years	-	3.50	18.00	33.00	70.00
13 quarters		0.30	1.20	2.40	1.80
14 quarters		0.30	1.20	2.00	2.70
15 quarters		0.50	0.90	1.60	2.80
16 quarters		0.60	0.80	2.00	0.60
Cum. DF in 4 years	-	5.20	22.00	41.00	77.80
17 quarters		0.90	0.60	1.90	0.70
18 quarters		1.10	0.20	1.40	1.60
19 quarters		1.60	0.40	1.20	1.50
20 quarters		1.80	0.20	1.1	1.40
Cum. DF in 5 years	-	10.60	23.40	46.60	83.00

Source: Author's own calculations.

Figure 3. Comparison of quarterly default frequency increment for credit classes



Source: Authors' own calculations.

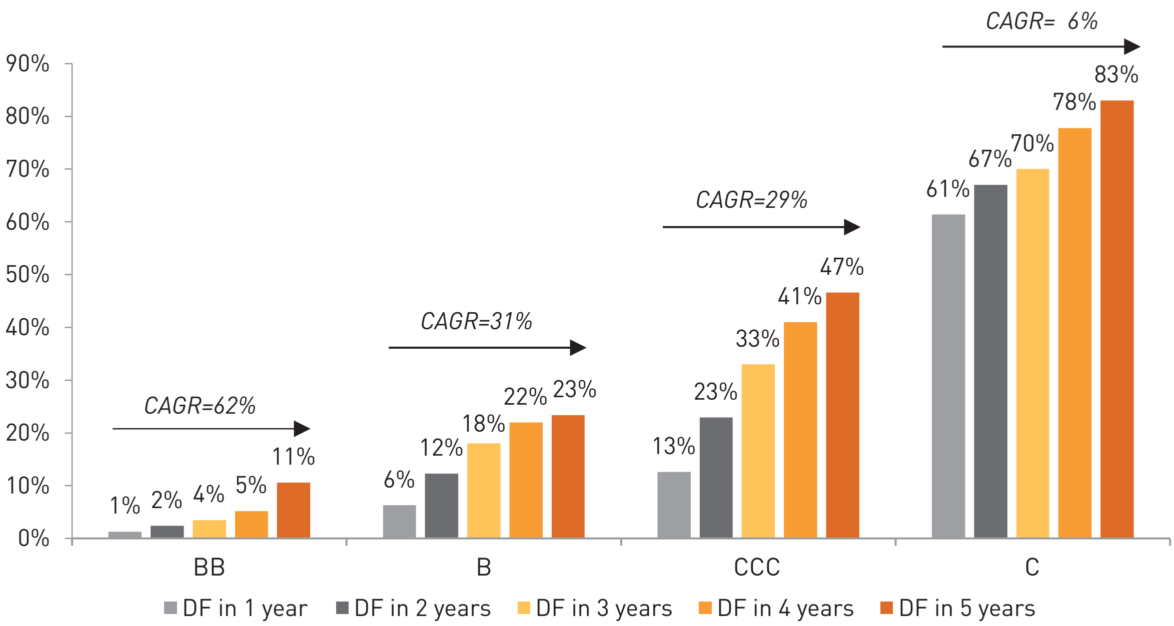
With the help of Table 1, an economic agent can understand the quantitative estimate of credit risk associated with a particular credit rating of Russian bank on the basis of default frequencies analysis. Each credit rating can be easily converted into a clear PD estimated by default frequency. The dynamic scale allows to evaluate the credit risk both annually and quarterly. Table 1 presents the annual cumulative DFs and an incremental DF per quarter. We notice that banks with newly assigned credit ratings tend to have a higher credit risk. This tendency sharpens for the lower-rating assignments. As an example, consider that a bank with credit rating B receives credit rating CCC, which is not a very dramatic downgrade. The probability that this bank defaults after one period is now 5.30%. The probability of default of the bank is significantly higher than of a similar one that has received credit rating CCC a year ago (it would have PD after one quarter of 2.40%).

Figure 3 illustrates the tendency explained above. We notice that banks with junk ratings (from class C) have a very high probability of failure after the first quarter of credit rating assignment (the default frequency is about 56%). However, the banks that survive after the first quarter have probabilities of default even lower than banks with ratings from a better class (class CCC) and for some periods the probabilities of default are even less than for credit ratings from class B. The intuition of this tendency is the following. The junk credit ratings are usually assigned to banks with very poor financial sustainability (these will hardly survive for more than two quarters) and small expanding banks (these have great chances to survive for a long period of time). Small banks have worse financial ratios than large and mature banks, but this does not mean that the probability of failure is extremely large for them. If they survive over the first quarters following receipt of a credit rating, their sustainability can be even better than those with ratings from a better class.

Moreover, from Figure 3 above we also notice that an increase in default frequencies is growing beginning from year 3 for almost each rating class. This pattern may be explained in two ways. Firstly, the competition in high rating classes is severe enough that it leads to a deterioration of financial stability for banks that do not prevail. Secondly, the internal management of banks with unchanged credit rating for several years may put less effort into development and innovations, which makes such banks less stable to external shocks.

This result does not allow us to reject the hypothesis of this paper, i.e. that banks with high ratings are more stable immediately following the rating assignment, while speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned.

Figure 4. Distribution of annual cumulative Default Frequencies for credit rating classes



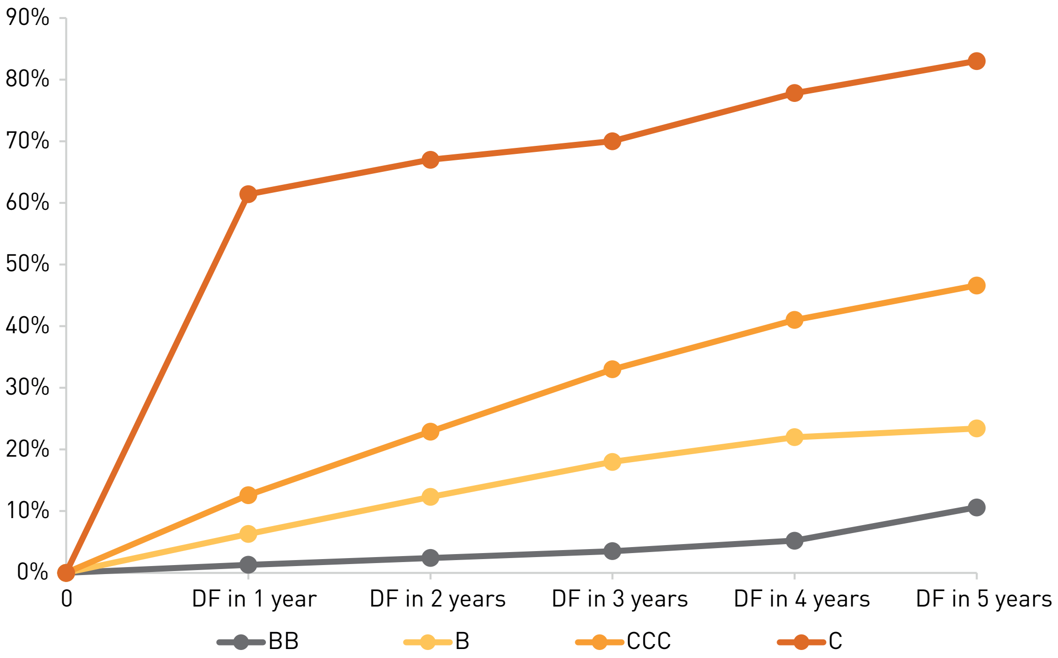
Source: Authors' own calculations.

Figure 4 illustrates the graduate cumulative increase in annual default frequencies for each rating class. As expected, lower probabilities of default are associated with a rating class BB [12-13.5] (the best class of ratings presented), while the PDs in the High Speculative Grade are larger for poorer rating classes. However, we can observe an interesting pattern: the cumulative annual growth rate (CAGR) of default frequencies decreases as credit ratings become lower. CAGR is calculated for each rating class as:

$$CAGR = \left(\frac{DF_{year5}}{DF_{year1}}\right)^{1/5} \quad (7)$$

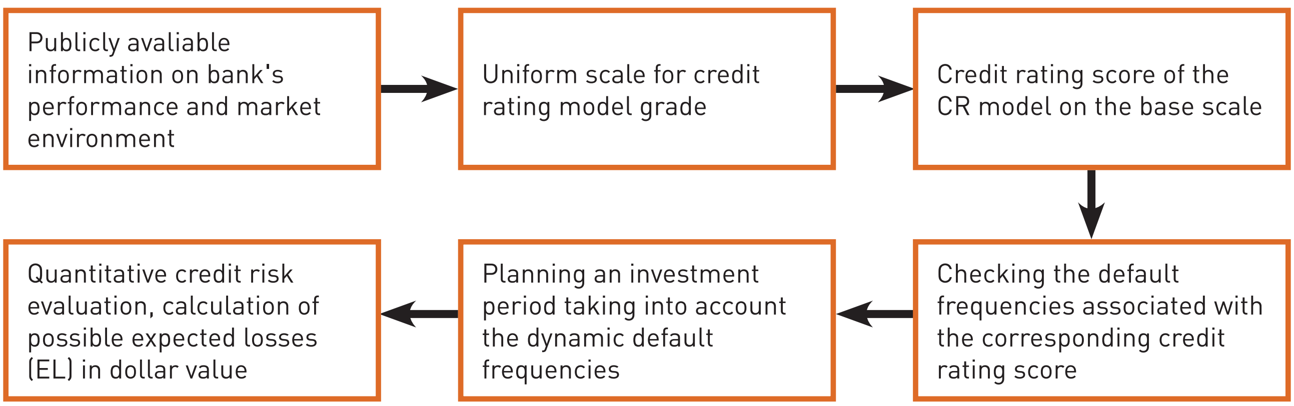
From the figure above, we can see that in the class C [18.5-21] (although it contains junk credit ratings), a bank which is able to survive for one year after the rating issue has a lower incremental PD on the horizon of the next five years (as CAGR value shows). We conclude that the better the financial sustainability of a bank, the higher the CAGR of PD is. An analysis of default frequencies shows us that PD increases in time at a faster rate in the better rating classes. We are able to formulate a capital rising strategy. Investment in banks with better credit ratings will minimise credit risk right after the rating issue and is efficient to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1 or 2 years after the rating assignment. This is demonstrated with the help of CAGR values in classes BB [12-13.5] and C [18.5-21]. In class BB, CAGR of PD equals to 62%, which is more than ten times higher than the value of CAGR in class C (6%). The intuition behind this is similar to that of the previous results. Banks from a better credit rating operate in a more competitive environment, so there is high probability (almost 11%) that within a 5 year time period a bank will shift to lower rating classes and even become defaulted. On the other side, banks form the worst rating class have a high probability to default immediately (within 1 quarter), but if they have survived for the longer period, there is a clear tendency of improvement in rating grade.

Figure 5. Average cumulative Default Frequencies for credit rating classes



Source: Authors' own calculations.

Figure 6. Method of credit risk assessment presented in the thesis



Source: Authors' own calculations.

Figure 5 above illustrates the graduated differences between the default frequencies of banks with ratings from classes BB, B and CCC. PD is much larger for credit class C, we notice that banks with credit ratings on the range from 18.5 to 21 are extremely unstable during the first year after the credit rating assignment compared even to the banks with very similar ratings from class CCC. However, if such banks can survive during this period, an incremental PD for them is not substantial and lower than for banks from better rating classes.

To sum up, it was concluded that the better the financial sustainability of a bank, the higher CAGR of PD is. Analysis of default frequencies shows us that PD increases in time at a faster rate in the better rating classes. As a result the capital rising strategy was formulated. Investment in banks with better credit ratings will minimise credit risk right after the rating issue and is efficient to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1 or 2 years after the rating assignment.

Therefore, our paper provides an algorithm which can be useful for investors for credit risk evaluation based on publicly available info on Figure 6.

If one wants to evaluate the credit risk of a Russian bank, and it hasn't been assigned a rating grade by any RA, one can estimate it using the CR model provided in the paper [11]. In order to do that, only publicly available financial info will be needed. Then the forecasted rating grade will be estimated in the terms of base scale. If initially a public RA grade was available, then this grade could be transformed to the base scale using the table in Appendix 1. Then, to assess the quality of information enclosed in the credit rating scores obtained, the calibration scale should be applied. This scale will help in planning an investment horizon taking into account the dynamic default frequencies, the obtaining of a quantitative credit risk evaluation, and calculation of possible expected losses (EL) in dollar value. This proves the significance of individual credit rating models, and shows the possibility of their practical use, as the forecasted credit ratings on a base scale are interdependent with estimated PD. Moreover, the following methodology can be used in increasing forecasting power of the existing PD models that are widely used in recent research: [17; 18; 19; 20; 21].

Conclusion

In this paper we present the method of credit risk estimation for banks. The forecasted CR score can be used to evaluate the credit risk of a bank using a dynamic transmission scale, which relates a rating score to average default frequencies of Russian banks. The uniform calibration scale that allows us to estimate probability of default in different time frames after credit rating assignment was empirically constructed using a random sample of 395 Russian banks (86 of them defaulted) for the period of 2007-2017. With the help of this scale, investors obtain not only the numeric credit rating, but also the quantitative measure of credit risk, which is more comprehensive. This helps them to plan their investment strategy and to calculate the expected losses (EL) in dollar value.

We fail to reject the stated hypothesis, as we discovered that banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned. We are able to formulate a capital rising strategy. Investment in banks with better credit ratings will minimise credit risk right after the rating issue, and is efficient enough to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long term investment 1 or 2 years after the rating assignment.

The novelty of this paper arises from the process of calibration of a rating grade to dynamic PD scale in order to evaluate the optimal time horizon of investments into a bank in each rating class. The proposed scale has three superior features compared to the existing scales: dynamic nature (quarterly PD estimates), compatibility with all RAs (base scale CR) and focus on Russian banks. This approach can be improved by the inclusion of additional information about rating migrations. Currently, the scale accounts only for the moment of a rating assignment but not for the period spent in a specific rating class. Additionally, in further research, it is possible and advisable to study the calibration of the credit ratings on the historic default frequencies of a developed country, and to compare the transition scale with the Russian one.

References

1. Volk M. Estimating Probability of Default and Comparing It to Credit Rating Classification by Banks. *Economic and Business Review*. 2013;14(4):5-23.
2. Shi B., Chi G., Li W. Exploring the mismatch between credit ratings and loss-given-default: A credit risk approach. *Economic Modelling*. 2020;85:420-428. DOI: 10.1016/j.econmod.2019.11.032
3. Shi B., Zhao X., Wu B. & Dong Y. Credit rating and microfinance lending decisions based on loss given default (LGD). *Finance Research Letters*. 2019;30:124-129. DOI: 10.1016/j.frl.2019.03.033
4. Tasche D. The art of probability-of-default curve calibration. *Journal of Credit Risk*. 2013;9(4):63-103. DOI: 10.21314/JCR.2013.169
5. Pomasanov M., Vlasov A. Calibration of national rating systems. *Rynok cennich bumag = Security market*. 2008;12(363):74-79. (In Russ.)

6. Pomasanov M., Hamalinsky A. Rating Model Calibration for Sectors with a Low Number of Defaults. *Financial risk management.* 2012;02(30):82-94.
7. Rudakova O., Ipatyev K. Some Approaches to the Calibration of Internal Rating Models. *Review of European Studies*. 2015;7(10):25-36. DOI:10.5539/res.v7n10p25
8. Godlewski C. Are Ratings Consistent with Default Probabilities?: Empirical Evidence on Banks in Emerging Market Economies. *Emerging Markets Finance and Trade*. 2007;43(4):5-23. DOI: 10.2753/REE1540-496X430401
9. Chan-Lau J. Fundamentals-Based Estimation of Default Probabilities: A Survey. *IMF Working Papers*. 2006;06(149). DOI:10.5089/9781451864090.001
10. Schuermann T., Hanson S. Estimating Probabilitites of Default. *Federal Reserve Bank of New York Staff Reports*. 2004;190.
11. Karminsky A.M., Khromova E. Increase of banks' credit risks forecasting power by the usage of the set of alternative models. *Russian Journal of Economics*. 2018;4(2):155-174. DOI: 10.3897/j.ruje.4.27737
12. Zhivaikina, A.D., Peresetsky, A.A. Credit ratings of Russian banks and reviews of banking licenses 2012-2016 yy. *Journal of the New economic Association*. 2017;4(36): 49-80. (In Russ.)
13. Vernikov A., Bobkov V. Quality of governance and bank valuation in Russia: an empirical study. *Journal of Corporate Finance*. 2008;3(7):5-16.
14. Karminsky A.M., Sosurko V.V. The unified rating mapping: a step from the myth to reality. *Bankovskoedelo = Banking subject*. 2011;6:58-63. (In Russ.)
15. Hainsworth R., Karminsky A.M., Solodkov V.M. Arm's length method for comparing rating scales. *Eurasian Economic Review.* 2013;3(2):114–135. DOI: 10.14208/eer.2013.03.02.002
16. Dyachkova N. The comparison of rating scales of russian and foreign agencies for industrial and financial companies. *Journal of Corporate Finance Research.* 2018;12(2):35-52 (In Russ.)
17. Demeshev B.B., Tikhonova A.S. Dynamics of Predictive Power of Insolvency Models for Russian Small-medium Enterprises: Wholesale and Retail Trade. *Journal of Corporate Finance Research.* 2014;8(3):4-22. DOI: 10.17323/j.jcfr.2073-0438.8.3.2014.4-22 (In Russ.)
18. Morgunov A.V. Modeling the Probability of Default of the Investment Projects. *Journal of Corporate Finance Research.* 2016;10(1):23-5. DOI: 10.17323/j.jcfr.2073-0438.10.1.2016.23-45 (In Russ.)
19. Totmyanina K.M. Assessment the probability of default for corporate borrowers given macroeconomic situation. *Journal of Corporate Finance Research.* 2014;8(1):19-31. DOI: 10.17323/j.jcfr.2073-0438.8.1.2014.19-31 (In Russ.)
20. Rybalka A.I. Modeling Probability of Default in the Construction Sector: Factors of Corporate Governance. *Journal of Corporate Finance Research.* 2017;11(3):79-99. DOI: 10.17323/j.jcfr.2073-0438.11.3.2017.79-99 (In Russ.)
21. Zakharova A.A., Telipenko E.V. Selection of risk factors of bankruptcy of an enterprise based on the method of main components. *Journal of Corporate Finance Research.* 2014;8(1):64-2. DOI: 10.17323/j.jcfr.2073-0438.8.1.2014.64-72 (In Russ.)

Appendix

Appendix 1. Mapping RA to the base numerical rating scale

Base	S&P			Fitch			Moody's			RAEX	Rus-Rating		AK&M	NRA	Ria
Rating	I/N*		N**	I/N		N	I/N		N	N	I/N	N	N		
Scale	$	RUB	RUB	$	RUB	RUB	$	RUB	RUB	RUB	RUB	RUB	RUB	RUB	RUB
1	AAA	AAA	-	AAA	AAA	-	-	Aaa	Aaa	-	-	-	-	-	-
2	AA+	AA+	-	AA+	AA+	-	-	Aa1	Aa1	-	-	-	-	-	-
3	AA	AA	-	AA	AA	-	-	Aa2	Aa2	-	-	-	-	-	-
4	AA-	AA-	-	AA-	AA-	-	-	Aa3	Aa3	-	-	-	-	-	-
5	A+	A+	-	A+	A+	-	-	A1	A1	-	-	-	-	-	-
6	A	A	-	A	A	-	-	A2	A2	-	-	-	-	-	-
7	A-	A-	-	A-	A-	-	-	A3	A3	-	-	-	-	-	-
8	BBB+	BBB+	-	BBB+	BBB+	-	-	Baa1	Baa1	-	A+	-	-	-	-
8,5	-	-	-	-	-	AAA(rus)	-	-	-	-	-	-	-	-	-
9	BBB	BBB	ruAAA	BBB	BBB	-	Aaa.ru	Baa2	Baa2	-	A	-	-	-	-
9,5	-	-	-	-	-	-	-	-	-	-	-	AAA	-	-	-
10	BBB-	BBB-	-	BBB-	BBB-	AA+(rus)	-	Baa3	Baa3	A++	A-	-	-	-	-
10,5	-	-	-	-	-	-	Aa1.ru	-	-	-	-	AA+	-	-	-
11	BB+	BB+	ruAA+	BB+	BB+	AA(rus)	-	Ba1	Ba1	-	BBB+	-	-	-	-
11,5	-	-	-	-	-	-	-	-	-	-	-	AA	-	-	-
12	BB	BB	ruAA	BB	BB	AA-(rus)	Aa2.ru	Ba2	Ba2	-	BBB	-	-	AAA	-
12,5	-	-	-	-	-	A+(rus)	-	-	-	-	-	AA-	-	-	-
13	BB-	BB-	ruAA-	BB-	BB-	A(rus)	Aa3.ru	Ba3	Ba3	-	BBB-	A+	-	-	-
13,5	-	-	ruA+	-	-	A-(rus)	A1.ru	-	-	A+	-	A	-	AA+	-
14	B+	B+	ruA	B+	B+	BBB+(rus)	A2.ru	B1	B1	-	BB+	A-	A+	-	AA
14,5	-	-	ruA-	-	-	BBB(rus)	A3.ru	-	-	-	-	BBB+	-	AA	-
15	B	B	ruBBB+	B	B	BBB-(rus)	-	B2	B2	-	BB	-	-	-	AA-
15,25	-	-	ruBBB	-	-	BB+(rus)	Baa1.ru	-	-	-	-	BBB	A	AA-	-
15,5	-	-	ruBBB-	-	-	BB(rus)	-	-	-	A	BB-	-	-	A+	A+
15,75	-	-	ruBB+	-	-	BB-(rus)	Baa2.ru	-	-	-	-	BBB-	-	-	-
16	B-	B-	ruBB	B-	B-	B+(rus)	Baa3.ru	B3	B3	-	-	-	-	A	A
16,25	-	-	-	-	-	-	-	-	-	-	-	-	B++	-	-

Base	S&P			Fitch			Moody's			RAEX	Rus-Rating		AK&M	NRA	Ria
Rating	I/N*		N**	I/N		N	I/N		N	N	I/N	N	N		
Scale	$	RUB	RUB	$	RUB	RUB	$	RUB	RUB	RUB	RUB	RUB	RUB	RUB	RUB
16,5	-	-	ruBB-	-	-	B(rus)	Ba1.ru	-	-	-	B+	BB+	-	A-	A-
16,75	-	-	-	-	-	-	Ba2.ru	-	-	-	-	-	-	-	-
17	CCC+	CCC+	ruB+	CCC	CCC	B-(rus)	Ba3.ru	Caa1	Caa1	B++	B	BB	-	BBB+	-
17,25	-	-	-	-	-	-	-	-	-	-	-	-	-	BBB	-
17,5	-	-	ruB	-	-	-	B1.ru	-	-	-	-	-	B+	BBB-	BBB+
17,75	-	-	-	-	-	-	B2.ru	-	-	-	-	-	-	BB+	-
18	CCC	CCC	ruB-	CC	CC	-	B3.ru	Caa2	Caa2	B+	B-	-	-	BB	BBB
18,25	-	-	-	-	-	-	-	-	-	-	-	-	B	BB-	-
18,5	-	-	-	-	-	-	Caa1.ru	-	-	-	-	-	-	-	BB+
18,75	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19	CCC-	CCC-	ruCCC-	C	C	-	Caa2.ru	Caa3	Caa3	B	CCC+	B	C++	-	C
19,25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19,5	-	-	-	-	-	-	Caa3.ru	-	-	-	CCC	B-	-	-	-
19,75	-	-	-	-	-	-	-	-	-	-	-	-	C+	-	-
20	-	-	-	-	-	-	Ca.ru	Ca	Ca	C++	C	CC	-	-	-
20,25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
20,5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
20,75	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
21	D	D	ruD	D	D	D(rus)	C.ru	C	C	E	D	C	C	-	-

* I/N – International rating scale, N – National rating scale
Source: [11].

Appendix 2.

Intermediate matrix with default frequencies for credit score 17.5 (for periods 29-48)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
30	0,10%																			
31	1,20%	2,00%																		
32	0,96%	0,96%	0,97%																	
33	0,96%	0,96%	0,97%	2,04%																
34	0,96%	0,96%	0,97%	1,02%	2,22%															
35	1,92%	1,92%	1,94%	1,02%	1,11%	1,11%														
36	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%													
37	2,88%	2,88%	3,88%	5,10%	5,56%	4,44%	3,45%	3,41%												
38	0,96%	0,96%	1,94%	2,04%	2,22%	2,22%	2,30%	2,27%	4,55%											
39	0,96%	0,96%	0,97%	1,02%	1,11%	1,11%	1,15%	1,14%	1,14%	2,50%										
40	0,96%	0,96%	0,97%	0,00%	0,00%	0,00%	0,00%	1,14%	1,14%	1,25%	2,50%									
41	0,96%	0,96%	2,91%	3,06%	3,33%	3,33%	2,30%	2,27%	3,41%	3,75%	2,50%	3,85%								
42	2,88%	2,88%	2,91%	3,06%	3,33%	3,33%	3,45%	2,27%	2,27%	2,50%	2,50%	2,56%	1,32%							
43	2,88%	2,88%	1,94%	2,04%	2,22%	2,22%	3,45%	3,41%	3,41%	2,50%	1,25%	1,28%	1,32%	2,53%						
44	2,88%	2,88%	2,91%	3,06%	2,22%	2,22%	2,30%	2,27%	1,14%	1,25%	1,25%	1,28%	2,63%	2,53%	3,70%					
45	0,96%	0,96%	0,00%	0,00%	0,00%	0,00%	1,15%	2,27%	2,27%	2,50%	2,50%	1,28%	1,32%	1,27%	1,23%	3,85%				
46	1,92%	1,92%	1,94%	2,04%	1,11%	1,11%	1,15%	1,14%	1,14%	1,25%	2,50%	2,56%	2,63%	2,53%	2,47%	2,56%	3,90%			
47	1,92%	1,92%	1,94%	2,04%	2,22%	2,22%	2,30%	2,27%	2,27%	2,50%	2,50%	2,56%	2,63%	2,53%	2,47%	2,56%	2,60%	3,95%		
48	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,14%	1,25%	1,25%	1,28%	1,32%	1,27%	1,23%	1,28%	1,30%	1,32%	4,35%	
49	0,96%	0,96%	0,97%	1,02%	1,11%	1,11%	1,15%	1,14%	1,14%	1,25%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,41%

Appendix 3.

Intermediate matrix with default frequencies for credit score 15.5 (for periods 29-48)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
30	0,00%																			
31	0,00%	1,14%																		
32	1,15%	1,14%	2,20%																	
33	1,15%	1,14%	1,10%	3,30%																
34	1,15%	1,14%	1,10%	1,10%	3,23%															
35	0,00%	0,00%	0,00%	1,10%	1,08%	4,35%														
36	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	3,19%													
37	4,60%	4,55%	3,30%	2,20%	2,15%	2,17%	3,19%	3,33%												
38	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	4,40%											
39	3,45%	3,41%	3,30%	3,30%	3,23%	3,26%	3,19%	3,33%	3,30%	4,30%										
40	5,75%	5,68%	5,49%	6,59%	6,45%	6,52%	6,38%	5,56%	5,49%	5,38%	6,67%									
41	3,45%	3,41%	3,30%	2,20%	2,15%	2,17%	2,13%	2,22%	2,20%	3,23%	3,33%	5,81%								
42	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	1,10%	1,08%	1,11%	1,16%	6,98%							
43	3,45%	3,41%	4,40%	4,40%	4,30%	4,35%	3,19%	3,33%	3,30%	4,30%	5,56%	5,81%	5,81%	8,75%						
44	3,45%	3,41%	4,40%	4,40%	5,38%	5,43%	5,32%	5,56%	6,59%	6,45%	6,67%	6,98%	5,81%	6,25%	12,33%					
45	1,15%	1,14%	2,20%	2,20%	2,15%	2,17%	1,06%	1,11%	1,10%	1,08%	1,11%	1,16%	1,16%	1,25%	1,37%	9,86%				
46	1,15%	1,14%	1,10%	1,10%	2,15%	2,17%	2,13%	2,22%	1,10%	1,08%	1,11%	1,16%	2,33%	2,50%	2,74%	2,82%	4,62%			
47	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,69%		
48	4,60%	4,55%	5,49%	5,49%	5,38%	5,43%	5,32%	5,56%	4,40%	4,30%	4,44%	4,65%	4,65%	5,00%	5,48%	4,23%	4,62%	5,08%	4,84%	
49	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	1,10%	1,08%	2,22%	2,33%	2,33%	2,50%	2,74%	2,82%	3,08%	3,39%	3,23%	8,33%

Appendix 4.

R code for default frequencies matrix calculations

```
getwd()
setwd(«/Users/romanmacbook/Desktop»)
install.packages(«openxlsx»)
library(openxlsx)
file <- read.csv2(«file.csv»)

file_matrix <- function(r) {
m <- matrix(nrow = 40, ncol = 40)
colnames(m) <- seq(1,40)
rownames(m) <- seq(2,41)

for (i in 1:40){
for (j in i:40){
a <- subset(file, bank %in% file$bank[file$rating == r & file$quarter == i])
sum_defaulted_quarter <- sum(a$fact_of._default[a$quarter == j])
sum_rated_quarter <- sum(ifelse(file$rating == 21
& file$quarter == i, 1, 0))
m[j,i] <- round(sum_defaulted_quarter/sum_rated_quarter, 2)
}
}
return(m)
}
View(file_matrix(21
))
write.xlsx(file_matrix(21
), '21.xlsx', row.names = T, colnames = T)
```

Source: Author's own calculations.

Approaches to Digital Profiling in the Financial Market

Tatyana Ilina
PHD, Associate professor in economic sciences
ORCID
E-mail: ilinatg@mail.ru
Tomsk State University, Tomsk, Russia

Elena Piatina
Assistant
ORCID
E-mail: pyatina_lenaa@mail.ru
Tomsk State University, Tomsk, Russia

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 47-60 (2020)
DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.47-60
Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

Approaches to Digital Profiling in the Financial Market

Abstract

Creating a "digital profile" is one of the points of the Russian national program Digital Economy [1]. A single biometric profile creation system is becoming the infrastructure basis for the digital transformation of the entire economy [2]. The process of forming a digital society is associated with the total digitization of all forms and types of relationships. At the same time, it is necessary to take into account the features, threats and trends of this process.

The purpose of this article was to study the essential features and application of digital profiling of the financial market, defining the applications of this method and methodological approaches by examining existing expertise in other areas, and industries.

The article summarizes information about the use of digital profiling in various industries. Areas of the financial market for the application of profiling were identified. The general characteristics are formulated and the features of the development of a methodological approach to profiling in the financial market are revealed. The criteria and principles of forming a digital profile of a market participant, relationships and patterns for improving the models of identification of participants and the market profile as a whole are presented.

Keywords: digital profile, financial market, profiling method, digital identity, identification, digitalization, financial market regulation

JEL classification: E58, G14, G21, G30

Introduction

In the circumstances of digital transformation the government role consists in arranging conditions for improving efficiency of advanced technology implementation in financial and non-financial economic sectors. Therein, during transformation it is necessary to ensure a high confidence of population and organizations in innovation technology and its safety. Based on this, the Central bank of the Russian Federation in cooperation with concerned government agencies and financial market participants implements common initiatives for creation and development of financial technology and a digital financial infrastructure.

The information infrastructure built now and represented in the national program Digital Economy gave rise to the notion of "digital profile" which implies a collection of information on individual persons and legal entities stored in the state information systems and furnished to such persons and entities at request and with their consent applying special-purpose digitalized information technology [3]. Thus, the digital profile of a citizen is one of the key components of the digital infrastructure. The Ministry of Digital Development and the Bank of Russia deal with conceptional preparation to its creation.

Development of a digital profile for a certain person or organization will grant access to any information on the profile subject to the user with access to the system which collects and provides data on various profiles. Public authorities act as the principal user of this system.

According to the concept, a digital profile is to consist of such components as: basic data on the profile subject (passport details, Tax Identification Number etc.); data from other national registers in the form of links; list of the profile subject's consents to personal data processing.

The draft legislation describing the digital profile concept takes into account the fact that the composition of information stored in the profile is to be determined by the Russian government taking into consideration the necessity to supply data. The digital profile data, first of all, will provide individual persons' and legal entities' identification and rendering of public services.

The single system comprising all profiles in its entirety will be a huge database which may also be used for various types of research and analysis including the financial market analysis.

In financial market studies the digital profiles of the market players performing the main functions will be of interest: direct participants of financial transactions (sellers and buyers of financial instruments, products and services), financial intermediaries and regulators.

The results of research of the financial market digital profile, presented by the authors earlier, addressed the issues of study of various indicators characteristic of the market participants directly involved in financial relations creating the market situation and exerting a significant influence on its development [4]. In the authors' opinion, all these indicators taken together give an opportunity to form a general approach to the digital profile of the whole market.

In view of the aforesaid, the financial market digital profile may be considered as the aggregate of digital profiles of this market participants.

Therefore, in this research we defined the following problems: study of distinctive features and possibility of application of the digital profiling method to the financial market and its participants; determining the scope of application of this method in the financial market after study of its use in other fields and industries.

Materials and Methods

The digital profiling method is the foundation of the offered methodological approach for creating of a digital profile for a financial market participant.

Profiling is a mix of methods specially developed to assemble and then assess a person's psychological profile. Such profile is made in order to have an opportunity to define fixed-action patterns which may be used in application tasks. Here is an example of application tasks for use of the profile: forecasting of management and HR risks, deception detection; development of models of economic, social, financial and elective behaviour [5]. Various tools used in profiling provide an opportunity to assess impartially human behaviour expressed verbally and non-verbally, evaluate a person's appearance, his / her behavioural preferences and characteristics which allow to predict such person's behaviour in a particular situation in future in other circumstances.

Accumulating experience in application of this method various experts added more tooling which made profiling variable. So, modern profiling methods comprise traditional profiling tools as well as tools related to digitalization.

A digital profile is information electronic media or a special service which stores all data on a person [6].

As a research method digital profiling is a new method derived from common profiling which emerged in the environment of total digitalization while digital economy was formed. Digital profiling stems from engineering sciences as a method of study of digital environment and work with big data which describe various aspects of human relations and society. Therefore, this method is widely applied in practice in social sciences.

Criminology was one of the first social sciences to use the digital profiling method. This method was applied to investigate the cases when one digital device could not be associated with a certain user (use of one device by several users). Later it was applied as a method of making an offender's digital profile by means of studying his / her behaviour, developing a model and analyzing digital footprints. Now, while digital technology is implemented widely, this method serves to counter threats which jeopardize national and public security [7].

Gradually the profiling method with different sets of tools including those implying use of digital technology gained popularity and was applied in other human life spheres: aviation and banking [8–10]; human resource management [11; 12]; marketing [13]; education [14–17]; ethnic issues [18–20].

The profiling method is used in management when dealing with human resources, in particular, in control of employment, dealing with psychological climate and personnel performance. Employee profiling implies screening and assessment of candidates as well as analysis of personal characteristics and competencies of the employees working in a company in order to ensure a better job performance in line with the corporate HR strategy. Profiling enables specialists to predict future behaviour of employees in case of emergency or under pressure. It provides an opportunity to define with maximum accuracy employee's "criminal propensity" and the factors which may encourage it.

At present the profiling method applying the tools based on information and digital technology is a new HR tool. Thus, HR professionals use extensively various digital tools such as job sites, social networks and messengers which help to collect and analyze information on a possible candidate in order to make his/her profile to define the job suitability by means of digital screening. So they obtain more unbiased information on the candidate and shorten the time of a job interview with him / her [21]. Also such digital tool as online testing is applied in digital profiling. It enables a candidate to evaluate his / her competencies necessary for the job in the company and the employer – to realize whether the candidate suits for the job on the basis of the testing results [22].

The profiling method in the commercial (banking) field is the basis for banking scoring technology and banking risk assessment. Bank profiling is also applied to reduce credit risks related to crediting losses. Bank profiling is founded on audit and business methodology. In this case on the basis of calculations profiling defines the degree of the credit repayment risk at the time of filing an application and conducting an interview with the borrower. Thus, in banking the profiling method helps to detect the borrower's criminal intent to commit a credit fraud and to define the banking risk degree expressed as a high uncertainty of implementability of the offered business project.

In banking the digital profiling method is applied by an extensive use of digital technology represented in a new format called data mining. This analysis is intended to reveal unknown relationships in the accumulated data, and it is especially important to ensure the bank's competitiveness: credit risk analysis on the basis of the accumulated information on borrowers' credit reputation; customer acquisition by defining the profile of the most profitable customer in the common database; quality improvement of archive information and revealing data insights in archival financial documents, etc. [23].

In education the profiling method is used to make digital profiles of the learning process participants. Digital profiles of the **learning** process participants facilitate solving the problem of insufficient analytical substantiation for taking pedagogical and management decisions [16]. For instance, in secondary education use of digital technology to gather and process information on the participants helps to build students' digital profiles which display data for tracing an individual development pathway of each student and for comparing their performance to the average figures of the class, group or an educational institution. At the same time the profiling method is applied to create a digital profile of teachers as participants of the education process where the profile data provide an opportunity to evaluate their work [24].

In marketing digital profiling methods are used extensively to study consumers and develop advertising offers (products) on the basis of these profiles. The overwhelming majority of data is collected by cookies (online data) placed on various websites by independent data brokers (for example, Acxiom or Eyeota) [25]. The collected data furnished by data brokers are sold to advertisers in order to target digital advertising to new consumers with which a company has no relations yet, and consequently, of which has no data. Thus, advertisers use the obtained information on digital users in order to profile consumers for marketing purposes [26].

In spite of disputability of use of profiling in the ethnic field this method may also be applied for racial profiling practiced by law enforcement authorities. Racing profiling is use of a person's race or ethnicity by law enforcement officials as a key factor when deciding whether to stop (detain), interrogate or arrest such person if the race or ethnicity is mentioned in the description of certain suspects of a crime [27].

The profiling method is used in aviation in order to prevent terrorist attacks and ensure safety in civil aviation. Aviation profiling implies creation of a passenger profile by study of various features characteristic of a suspicious appearance. A passenger profile is the basis for assigning a person to a certain class according to the degree of danger he/she constitutes [28]. For the purpose of transport safety decisions on additional passengers' inspections are taken on the basis of a passenger profile. In this case profiling provides an opportunity to take preventive measures in order to avoid acts of unlawful interference in operations of civil aviation and other transportation infrastructure facilities.

On the basis of diversity of the considered fields of the profiling method modern uses one can make the conclusion that this method may be applied in any field related to people's interaction and analysis of their behaviour including study of financial relations. Therefore, in order to form a methodological approach and define the possible uses of the profiling method in the financial market we applied the analog method, analysis and synthesis. At the first stage we synthesized the available information concerning the essence and use of digital profiling in various fields and industries, then we analyzed the methodological approached applied in these fields determining: the profiling object in each field; its algorithm and stages; criteria and distinctive features of data assessment; the information base necessary for profiling. The third stage of the research is founded on the analog method and reveals the fields in the financial market which by their designation and characteristic features are similar to the industries and fields of profiling application studied before. This led us to the conclusions on the possibilities and uses of profiling in the financial market. At the last research stage, we synthesized the results of the second stage developing the algorithm for elaboration of the methodological approach to profiling in the financial market.

Profiling in Criminology

The profiling object in criminology is the offender profile.

Various tools are used when this method is applied in the abovementioned sphere: conventional and digital ones. They facilitate analysis and assessment of the main components (indicators) of the offender profile.

Three main components are studied when building a criminal profile [7]:

- modus operandi (a way of committing a crime) is a series of actions which characterizes a crime instrument. The way of committing a crime is presented from the functional standpoint of committing a criminal act. So, further one can define the category of a crime;
- social indicators of an individual expressed as emotional-volitional features or psychological constitution which determine the individual's behaviour when the crime is committed;
- pattern in crime represented as a unique combination of behaviour – offender's actions beyond the scope of criminal action functional characteristics and aimed at emotional fulfillment of the person committing a crime.

Additional components of the offender profile assessed by digital profiling are digital footprints and samples. These components show the distinctive features of individual's behavioral signs which are specific for each person. Therein, behaviourial characteristics of an individual are detected regardless of the profiling subject's will [29]. When digital profiling is performed the information, base contains initial information of the crime obtained by analysis of digital footprints and samples, other types of information from chats, blogs, social networks, various forums etc. Individual's interaction with digital environment forms an integral whole in cyberdomain where electronic signals are stored for some time. These signals manifest vestiges of a crime and individual's behavioral signs which serve as indicators constituting the offender profile.

The whole aggregate of crimes and performed actions contains the offender's personal attributes, his/her psychological constitution, social and psychological features of the offender or a criminal group which also create the offender profile.

In criminology profiling has a certain algorithm presented as a sequential actions cycle and consisting of the following stages [30].

1) Defining the profiling purpose — determining the necessary information for a certain case.
2) Data collection and evaluation with the gathered information.
3) Selection of relevant information and subsequent defining of indicators for various areas of exploration.
4) Identifying inconsistencies similarities by means of comparing information indicators.
5) Defining criteria applying comparison methods and building of the offender profile.
6) Analysis of the offender profile obtained by profiling and comparison of this profile to the original purpose.

Table 1 shows characteristics of contents of traditional and digital profiling in criminology [7, p. 391].

Table 1. Characteristics of traditional and digital profiling in criminology

Profiling stage	Traditional profiling	Digital profiling
Data collection	Obtaining information on circumstances of a crime; facts; evidence represented by photos and video records; witnesses' statements	Collecting information on the system structure; electronic data; data obtained by means of promising hypotheses
Working out a solution applying the processed data collected at the previous stage	Data systematization by means of classification schemes and tables	Data transfer to a file journal; data processing and program analysis; categorizing; development of an offender model for identification

Profiling stage	Traditional profiling	Digital profiling
Criminal actions evaluation	Reconstruction of behaviour of the individual who committed criminal actions, and of behaviour of the individual who was the victim of criminal actions	Evaluation of characteristics of the digital device used for criminal actions; assessment of crime methods and instruments; evaluation of interaction of means and methods of crime. Defining behaviourial characteristics of the offender
Offender profiling	Modelling of the initial profile on the basis of collected and processed information. Following clues of the crime. Logical analysis and reconstruction of the crime by obtaining new knowledge about it	Data mining and link analysis. Detecting stable, typical, information and psychological relations by the artificial intelligence method
Investigation	Modelling of the offender profile for correlation and comparison to suspects. Profile updating on the basis of the information obtained at this stage of correlation	Universalization and optimization of the link analysis data. Detailed elaboration of structural elements and their relations defined at previous stages. Use in the investigation of the information obtained in the form of processed behaviourial data. Feedback

Table 1 displaying profiling stages shows that traditional and digital profiling in criminology apply methods of offender's modelling rather similar in their essence. But it should be noted that at the same time the means applied to achieve the goal are different.

The digital profiling method requires a particularly complex intellectual activity in criminology. The main challenges of its use which determine its distinctive features are as follows:

- incomplete compliance and incomplete documenting of certain problematics;
- difficulty of consolidation of data related to human nature and the data inserted by informatics;
- doubtfulness of the data obtained as a result of a psychological investigation and traditional criminalistic profiling.

Criminalistic profiling is distinctive in creation of various versions of behaviour when committing a crime, identifying of the causes of such criminal behaviour and its nature. Various means and knowledge of criminal sciences are used to generate and identify data applying criminalistic profiling.

Profiling in management – human resource management (HR sphere)

In HR management the object of profiling is candidates' profiles and company employees' profiles. Just as in criminology, HR profiling is performed using traditional and digital tools.

In traditional profiling candidates are assessed by means of a direct contact with an individual in order to obtain necessary information for making the candidate profile, in other words, an interview. During an interview human behaviour is assessed and predicted by psychological methods. The information furnished by the candidate (direct answers) is used as the information base to form candidate's profile indicators. The data collected for study of the indicators which form the candidate's profile comprise the psychophysiological state, stress resistance; expertise level needed for the job; person's trustworthiness.

In order to obtain unbiased information from a candidate projective techniques are used to ask questions during the interview, thus, creating his / her profile. The projective technique is a methodology of asking questions in such a way that the question formulation makes a person to answer unconsciously on the basis of his / her personality characteristics and experience which ensures the maximum truthful information.

In order to get unbiassed information and build a full candidate's profile additional techniques of information collection are also applied, including digital profiling. Various digital tools are used for digital profiling (job sites, social networks etc.) where additional information may be gathered beforehand which will form an unbiassed candidate's profile. Thus, various publicly available information resources and databases are used for HR digital profiling. All publicly available information about an individual (photos, posts, reposts, personal information in the profile, number of friends etc.) published and written by a person in social networks is studied. On the basis of all collected data a conclusion is made of the person's view of the world, experience, personal values and beliefs.

Information from search systems (Yandex, Google etc.) where all digital footprints are traced using the individual's personal details (full name, telephone, e-mail) is used as a digital tool in digital profiling of a candidate. Digital footprints give useful information characteristic of a person, for example, attitude to lawsuits with the companies by which he / she has been employed.

The federal site of judicial enforcement officers is also a publicly available source used to build the candidate's profile. It provides information on the candidate's orders of enforcement and outstanding debts, distrained property and unpaid traffic fines on the basis of the region of residence and full name. This characterizes the candidate's attitude to his/her obligations and a probable risk factor in case of use / borrowing of third parties' funds.

In HR profiling user pages in social networks are analyzed. In order to achieve the most reliable, quick and complete result of this analysis HR specialists use customized applications for person's (candidate's) profiling and further assessment. Profiling applications in social networks are mainly automated which saves HR specialist's time. Automated applications used to analyze social media pages are publicly available.

Automated applications for page profiling are as follows: Cambridge, VK LikeChecker, socialdatahub etc. These servers grant access to databases of social network users as quantitative data on direct conversions, selected posts according to specified criteria, quantitative information on reposts, likes and total account activity. Such databases provide an opportunity to evaluate various types of statistics on a certain network user.

The indicators used to analyze a person's profile in social networks may be presented as follows [31]:

- time of attendance (activity) of social networks: number of pages and online time;
- location of the user's electronic device (geolocation);
- tagging of marks at web pages and posts topics;
- personal information provided in social networks (personal information, career, social status, interests etc.);
- publicity of the social profile.

Thus, when analyzing a person's profile in social networks study of all abovementioned indicators allows to assess congruence of the data stated in the curriculum vitae and to build an initial profile of a certain user as a prospective candidate. Further it may serve as a criterion for assessment of the created profile.

The president of ANO Scientific Research Center of Corporate Seciruty, profiler-polygraphologist Anna Kulik presented and described the following stages of human resources profiling [32].

1st stage – making the list of candidate's specifications (defining criteria to assess the candidate's profile).

2nd stage – search for and analysis of candidates (CV) on the basis of the specifications defined at the previous stage.

3rd stage – contact with the candidate to analyze and assess his / her personality (candidate profiling).

When HR profiling of company employees is performed salary indicators, working hours and employee's file (education, length of employment etc.) are studied, as well as estimated figures related to employees' skills and their personal characteristics (KPI (key performance indicators)).

Profiling in marketing

Profile of a potential consumer of goods, works or services planned for advertising is the profiling object in marketing [36].

Marketing profiling, similar to bank profiling is the foundation for development of customized offers of goods and services. In banking it is represented by credit proposals (period, amount etc.), in marketing – by other product or services offers.

Information on consumers for marketing profiling is obtained in various ways used by data brokers. Data brokers (or information brokers) are companies engaged in gathering and sale of information on people represented as their personal information. Data broker companies started developing and collecting actively information for consumer profiling in the age of progress of Internet and digital services which provide public access to huge amounts of information. Currently there is a great number of companies acting as information brokers.

USA legislation in accordance with the Data Privacy Protection Act allows data brokers to use a huge amount of information attributes about a person. In the European Union data brokers comply with law taking advantage of network users' carelessness in executing their user agreements.

The information collected by data brokers comprises information on location (users' addresses), personal property (owned vehicles), personal data from social networks, online shopping history and transaction bank operations using bank cards and search and watch history of web sites.

Data brokers gather data from various publicly available Internet sources and also purchase data from government agencies and organizations furnished by commercial companies which store information on their customers.

Personal information on people (prospective consumers) collected and arranged by data brokers may be conventionally divided into two groups [37].

1) Information obtained by hacking special protection of the sites of retail and maintenance service companies.
2) Data stated by web site visitors when they fill in personal pages and questionaries.

The unified database created and aggregated by the so called data brokers serves as the information base for marketing profiling.

Consumers' profiling by data brokers consists of the following stages [13].

1) Information collection by data brokers on persons (prospective consumers) from various web sites (Internet resources).

2) Synthesizing of the collected information on consumer's visits into anonymized user profiles.
3) Making conclusions on consumers on the basis of heuristics and machine learning and consumer profile identification according to various criteria (gender, age, interests etc.).
4) Gathering the audience as an aggregate of various persons' profiles to sell it to advertisers in order to target digital advertising to new consumers.

Thus, potential consumers' profiling provides an opportunity to generate more personal ideas for people from the audience gathered for a certain commercial offer in the market and allows to arrange communication with a consumer in order to attract attention to the product or service.

Profiling in education

In education the object of the profiling method is a student and teacher profile.

In order to create a student and teacher profile the following basic data are used which currently are gathered in the database of the Electronic Diary for secondary schools [24]:

- student's personal information (student's unique identifier);
- year;
- teacher's personal information (teacher's unique identifier);
- taught subjects / disciplines;
- dates, lesson topics;
- knowledge assessment forms and the result.

Students are profiled by applying the comparative analysis to their performance comparing it to the class and the cohort of students. Such comparison is called a T-criterion comparison. The Student's statistical T-criterion comparison provides a visual display of obtained data in diagrams. The diagrams visualize student's performance in comparison to the class and cohort and they show trends in performance on the basis of the linear regression method. Thus, due to study of the student's performance diagrams conclusions are made on the causes which influence improvement or decline in performance: influence of the student's personal characteristics on knowledge absorption and school performance or a poor education level. It should be noted that performance diagrams allow to define advisability of use of mean values performance triggers for each subject. As a result, the obtained and analyzed data provide an opportunity to develop special recommendations to deal with a student's individual learning trajectory which is the main component of his / her learning profile.

So, the student learning profile created on the basis of the Electronic Diary allows to solve the following problems:

- monitoring of the data indicative of the student's performance, presented in the detailed description of performance by subjects with a possibility to specify target values;
- compiling of students' rating according to their performance in classes and cohort on the basis of statistical performance comparisons presented in the detailed description of performance by subjects by means of the T-criterion method;
- defining the students' performance trend using the regression analysis algorithms.

In order profile a teacher inner and external analysis of the grades assigned by this teacher are conducted. The inner analysis is carried out on the basis of the grades on the subjects with a breakdown by the cohort, average grades and in comparison to performance of classes all over the school. The external analysis is conducted on the basis of the average grades comparison algorithms and a variety of grades given by the teacher taking into consideration various knowledge assessment forms.

Teacher profiling allows to obtain data important for the headmaster who, in his/her turn, has an opportunity to control teachers' performance using the collected data. As a result, an education environment participant's profile provides an opportunity to solve the problem of insufficient analytical substantiation of pedagogical and management decisions.

Profiling in aviation

In aviation (transportation) a passenger profile is the object of the profiling method.

In aviation profiling the following fields of application of this method may be defined: preflight inspection in an airport; questioning of passengers undergoing an inspection; surveillance of the psychological state of passengers etc.

The stages of profiling in transportation are as follows [28].

1) Initial surveillance of a passenger to define his / her characteristics and suspicious behaviour, identify alerting signs. The initial surveillance allows to define beforehand the passenger's type by the flight purpose (business trip, tourism etc.). Thus, initial conclusions about the observed passenger are made at the first stage.
2) Inspection of documents for identity check and defining the reliability and validity of submitted data.
3) Interview with a passenger showing suspicious signs registered at the previous stages in order to define whether it is necessary to conduct additional inspections for suspicious behaviour and security threat.
4) Questioning the passenger showing suspicious signs in order to solve existing doubts and to get answers to the questions the profiling aviation officers have.
5) Characterizing the passenger taking into consideration the information obtained at the previous stages: passenger classification according

to safety categories and threat level. Development of further security measures as regards the passenger taking into consideration the assigned classification. Passengers classification is made in accordance with their transport threat level established by profiling. So, there are low, normal, high and extremely high risk passengers. On the basis of the defined risk level of a certain passenger a decision is taken on additional safety measures to be taken by the security service and law enforcement authorities in order to adopt the final resolution on the passenger's involvement in a planned terrorist attack or an act of unlawful interference.

Racial profiling

In spite of the increasing popularity of this research field a series of methodological and theoretical problems impede it. The main problem is complexity of empiric detecting of racial disbalance in the work of law enforcement authorities related to the continuing search for a reliable "denominator" and insufficiency of simple establishing of racial disproportion for an unambiguous conclusion on existence of racial profiling. As long as in a significant part of research the abovementioned limitations have not been taken into consideration and the conclusions are extremely hasty one should be very careful when using them [38]. For this reason, we eliminated the racing profiling method from a detailed study and abstained from its use in development of the methodology.

Discussion

Analysis showed that in spite of an extensive use the theoretical and methodological basis of the digital profiling method has been studied and described in a piecewise way and is scarcely used in the financial market. Therein, the behavioural finance theory places high emphasis on study of the personality characteristics system and financial behaviour. Therefore, on the basis of lessons learnt and research for use of profiling in various fields we defined the general principles of the profiling algorithm and found similar fields and opportunities of its use in the financial market.

As was already mentioned, the essence of the "digital profiling" method consists in automated collection and electronic processing of data from huge information arrays on the basis of a previously selected set of characteristics of the studied object's profile. As we established, the characteristics studied when creating the profile depend on the type of studied relations. When the financial market is studied financial relations are analyzed, therefore it is necessary to take into consideration their characteristics and distinctive features. At the same time, apart from the specific features, inherent only in a certain type of relations one should take into consideration general features which are basic and define the profile subject's behaviour type. Such features comprise: life and occupational experience, social roles, volitive and moral, intellectual and emotional characteristics [7].

Literature emphasizes that currently scientific theory does not define the components of a profile. Nevertheless, its three most important components are determined as follows:

- means and methods of relations fulfillment which define the role, functions and actions of an individual in such relations (depending on occupational and other specific skills, knowledge and resources in this field etc.);
- social and economic characteristics of the studied object;
- unique behaviour combinations, as a rule, defined by a unique experience of relationship with other individuals and personal attributes as well as by response to changes and procedures.

Consolidation of the existing approaches to profiling in various fields allowed us to determine its main stages:

1) defining the profiling goal (the most important information types, distinctive features and characteristics of the studied object in accordance with the type of relations and environment of their fulfillment);
2) collection and evaluation of the data containing the information necessary for profiling by means of study of the information base;
3) selection of the information pertinent to the studied field and defining specific indicators;
4) determining differences and similarities by correlation of relevant information in comparison to indicators;
5) making the list of the most significant criteria on the basis of which the system of qualitative and quantitative indicators is created – building the "digital profile" model on the ground of the basic elements by means of mental or logical, mathematical or cybernetical modeling, reconstruction;
6) analysis and monitoring of the digital profile in order to reveal and predict the trends and changes as well as to assess it against the initial goal.

On the basis of the profiling stages, this method algorithm is as follows:

1) setting the profiling goal;
2) choosing the profiling object;
3) profiling planning (tools, applied methods etc.);
4) defining the profiling subject (who and why will perform profiling);
5) information collection and processing for profiling on the basis of the predetermined goal;
6) selection, systematization, classification and analysis of the collected data;
7) finalizing of profiling findings, creating profiles and formulating conclusions, developing recommendations and proposals.

Study of various fields of the method application showed that usually the accumulated databases on profiling objects (data on customers, employees, offenders etc.) are used as the information base.

Besides the main information sources are: publicly available information resources and databases represented by search systems and web pages with a huge amount of information concerning page users and digital footprints which remain as a result of interrelation executed through communication channels of an individual (digital user) and digital environment as the integral whole in cyberdomain. The databases created by means of pretesting / questionnaire survey of a certain group of people are extensively used as the information base.

The information selection criteria for profile creation in each field are extremely specific and defined on the basis of the initial goal formulated at the initial stage. Therefore, in order to determine correctly the profiling criteria in a certain field, first of all, the expected results are to be defined. All data collected for profiling may be divided into several levels from the point of view of such result [6].

The first level – the data collected by online services without the customer's consent ("uncontrolled" data used to take decisions on possible interaction ways).

The second level – information on the customer's behaviour in the digital space, metadata (location, content he / she is interested in, keystroke dynamics etc.) which may be the foundation for studying the personality, temperament, inclinations, customer's attitude to certain things.

The third level – secondary data selected on the basis of the algorithmic analysis and comparison to the data on other customers. It provides an opportunity to reveal underlying behavioral factors such as weaknesses, intelligence level, dependences, intentions, obsessional ideas etc. Such information on subconscious mechanisms and automatic responses in customers' behaviour may be used to create informed needs, encourage to take decisions.

Approaching the problem of profiling in the financial market it is necessary to emphasize that the field of finance is in the process of a drastic technology transformation and restructuring as well as transfer to the customer-oriented platform model which implies use of digital algorithmic methods of information processing already applied in some segments [39; 40].

In particular, in the credit market the profiling object is a profile of the bank customer who intends to receive a banking service or who has already received it. In banking profiling is performed by means of data mining. Depending on the type of initial information and the method of data extraction from such information this type of analysis is divided into analytical, visual and text data mining.

The profiling methodology in the commercial sphere comprises algorithms of matching of the customer profile to typical product packages in order to ensure a system-level functioning of procedures of product sales to the customer audience and in order to improve products on the basis of analysis of real and automatically created customer profiles.

A bank customer profile comprises the following data (indicators): customer location, age; education level; marital status, occupation; level of problems which dictates the need to receive a banking service; level of spending funds within a certain period; way of thinking and logic of taking decisions on funds spending; level of knowledge on bank products; level of readiness to purchase the service / bank product.

For digital profiling of a bank customer the following indicators are studied additionally:

- level of awareness and use of digital devices;
- level of readiness to furnish information on oneself (personal information) by means of digital technology (digital trust) [33].

Customers are classified using customer profiles created on the basis of the indicators described above. Such classification is used for segmentation of the customer base and further development of successful proposals of bank products and services.

Profiling in banking is applied to define customer (prospective borrower) insolvency probability. In this case profiling is performed by means of scoring. Scoring is a method of dividing prospective borrowers (bank customers) into groups on the basis of some variables characteristic of them: borrower's personal information and credit history (amounts of previous loans, timeliness of repayment, delays in payment etc.).

The aggregate of all information collected about the borrower provides an opportunity to create his / her profile and make the final estimate of his/her creditworthiness. So, the profile estimate allows to classify the borrower and define the decisions as regards granting him / her a loan.

Creditworthiness of a prospective borrower is determined by means of the data mining system on the basis of retrospective information which allows by means of classification to detect a borrower who has repaid or has not repaid the loan in prior periods. Thus, all bank customers are divided into two groups: the ones who have repaid loans and the ones who have not. Each group provides an opportunity to define the borrower's main signs of potential non repayment. It helps to assess beforehand the collected information on a new customer and to assign him / her to a certain group.

As a consequence, the data mining tools allow to do customer profiling, i.e. classify customers as "good" and "bad" borrowers. Customer classification according to groups of non-repayment risk has a direct effect on solving the problems of defining individual credit terms for a customer (credit limits, interest rate level, loan term etc.).

Currently innovations are introduced in banking scoring in the form of borrower psychographic profiling. The innovation consists in use of new efficient methods of borrower profile creation applying a non-conventional evaluation of bankruptcy probability. This innovative method is offered by VisualDNA which is the leader in the market of data analysis. VisualDNA developed a unique technology of psychographic profiling of financial organizations' customers in order to predict their bankruptcy probability. The technology was founded on the studies in the field of personality development and human behavior psychology.

The main advantage of the VisualDNA technology which offers its own rating of borrowers is no need in credit history information for a person's profiling. The VisualDNA profiling technology implies use of psychographic data obtained by testing. Such data provide an opportunity to influence the quality of scoring models performance maximizing the profit of financial organizations without increase of risk.

The psychographic profiling by means of the VisualDNA technology consists of the following stages [33]:

1) customer testing and data collecting on a prospective borrower;
2) automated processing of data using the VisualDNA program followed by forming of the result;
3) entry of data into the scoring model together with the data on the borrower's credit history;
4) forming of the final profiling result: VisualDNA borrower rating (profile).

It should be noted that the tools of the profiling method in banking are applied to the borrowers – individual persons and to the borrowers – legal entities. The profiling methodology for individual persons and legal entities when evaluating their creditworthiness differs.

When profiling tools are applied to legal entities corporate creditworthiness indicators are used and analyzed. They provide an opportunity to further classify the company and assign it to a certain category.

At the initial stages of legal entities profiling all documents of the prospective corporate borrower are studied to determine the customer's ability and readiness to repay the loan in full within the period established by the bank. In this case corporate legal documents which describe the company operations and certify their legitimacy are studied as well as financial documents which form accounting (financial) reports [34].

All data collected from legal and financial documents of a legal entity are assessed by the creditworthiness criteria represented by corporate liquidity indicators. On the basis of comparison of the obtained values to the specified criteria a legal entity is assigned a certain category for further creation of the company profile and taking the decision on granting or rejecting a loan by the bank.

Usually the following categories (classes) of borrowers – legal entities are defined: prime-quality borrower; limited creditworthiness borrower; insolvent borrower [35]. So, the profiling method of a borrower – legal entity on the basis of the scoring model enables a credit organization to evaluate creditworthiness of its customers and minimize its credit risks by means of taking reasoned decisions on granting loans.

Study of financial behaviour of USA higher education institutions on the basis of the multilevel latent class analysis revealed the opportunity to create and trace profiles of their income and expenditure in a changeable environment. This confirms the possibility of applying digital profiling for study of financial relations participants which are legal entities and entrepreneurs [41]. Therein, researchers of corporate lending risks on the basis of hybrid neural networks and fuzzy models emphasize that it is necessary to use a unified procedure of choosing corresponding indicators in order to reduce the degree of uncertainty and noise in publicly available data on the basis of such methods as credit scoring, neural modeling, fuzzy logic model etc. [42]. This confirms the necessity of developing a unified methodological approach.

In insurance algorithmic profiling is used to generate individual insurance policies, to assess risks and pay premiums on the basis of study of the behaviour of the insured. But according to specialists availability of individual information may have a negative effect on the insurance fundamental principles based on risk aggregation, distribution and interinfluence within the insuring parties' pool as well as cause unjustified discrimination of customers [43]. In scientists' opinion, this concern should not be considered for a single financial market segment but within the whole social medium. So, they make the conclusion that it is necessary to develop and introduce special limitative methods of anti-discriminatory regulation including financial regulation. Therein the issues of protection of rights of non-professional market participants and customers become of primary importance [39; 45].

Analysis of the credit and insurance sectors showed that mainly digital profiling is applied in the activities related to elevated risk. Preconditions depend on the interests of the financial market participants and their need to obtain more diversified and higher quality services by means of digitalization [46]. The conclusion on the necessity to monitor risks is confirmed in various scientific papers [39; 40; 42–44; 46; 47].

In order to reveal the possibilities of use of the digital profiling method in the financial market we applied the analog method which laid the main emphasis on the results of analysis of the profiling method application in other fields.

Currently one of important behaviourial characteristics of the financial market participants is their financial literacy which influences investment activity, and consequently, in the long run defines the demand in the market. Therefore, in this case we can apply the profiling experience from the education sector to the financial market. The financial market participants' – financial services consumers' – profile is the profiling object. The results will serve as a source of information for the World Bank, Central Bank of the Russian Federation, Ministry of Finance of the Russian Federation not just to assess the degree of population's financial literacy but also to monitor the investment behaviour in the financial market. Further this will provide an opportunity to develop an efficient regulatory policy.

Therein the main methods and tools for data collection and indicators forming may be questionnaire survey (testing) when signing up at special sites (for example, fincult.ru) and conducting trainings for improvement of financial literacy. The collected data will be processed by means of correlation, comparison and classification. The information may be registered in an electronic journal.

The profiling method from criminology may be applied to study fraud and crimes in the financial market where the seller (credit / financial organizations) along with the customer will be the research object. In this case profiling will be a source of information for the financial market regulator as well as for law enforcement authorities in order to avoid the risk of theft and loss of funds in the financial market and to improve efficiency of the market regulation.

When market participants are profiled for fraud the information base for data collection will be as follows: applications and evidence from the police database concerning fraud in the financial market as well as defrauders' digital footprints gathered by means of study of cyberdomain for behaviour of defrauders, fraud procedure, cyber locations of fraud and ways of performing operations.

Conclusion

Study of digital profiling issues is important for science, society, business and each individual because it has an ever increasing influence on various fields of economics and finance. Creation of a digital profile in the financial market is a significant issue for all its participants: professionals and non-professionals, individual persons and legal entities as well as for regulators. A variety of financial relations preconditions different versions and possibilities of its use. Experience suggests that it is necessary to take into consideration the risks related to personal, social and national security. Therefore, each market participant has to study to create and control a digital profile at the micro and macro level. A unified methodological approach to digital profiling is necessary to create the digital identity culture. Also, clear and available rules which enable the market participants to control fully digital data and their own digital projection are necessary.

The methodological approach to financial market profiling allows to create the financial market profile on the basis of its participants' profiling. We offer to consider the financial market profile as an aggregate of participants' digital profiles which provides a general characteristic of the market as a whole. Such approach allows to describe "unaccounted" aggregate digital characteristics of the market using unofficial information sources. Application of this approach provides an opportunity to obtain a digital "portrait" of a certain participant, segment or level of the financial market. Therein it is possible and necessary to use experience from other fields and sectors in order to expand the method application in the financial market taking into consideration the distinctive features and trends of its development.

References

1. "Digital profile": Demanded by banks, convenient for customers. NBJ: National Banking Journal. May 20, 2020. URL: http://nbj.ru/publs/aktual-naja-tema/2020/05/20/tsifrovoi-profil-vostrebovan-bankami-udoben-dlja-klientov/ (accessed on 20.11.2020). (In Russ.).
2. Text of the bill on digital profiles of Russians. Federal portal of draft normative legal acts. URL: https://regulation.gov.ru/projects#npa=89871 (accessed on 20.11.2020). (In Russ.).
3. National program "Digital economy of the Russian Federation" dated Dec. 24, 2018. URL: http://government.ru/rugovclassifier/614/events/ (accessed on 24.11.2020). (In Russ.).
4. Pyatina E.A., Ilina T.G., Tyuleneva N.A., Khabibulina A.N. Analysis of digital profile of the financial market: A methodological approach of Russian Central Bank. *SHS Web of Conferences*. 2020;80:01023. DOI: 10.1051/shsconf/20208001023
5. Foygel E.I., Kozuleva A.A. Using profiling in the operational, investigative and expert activities. *Sibirskie ugolovno-protsessual'nye i kriminalisticheskie chteniya = Siberian Criminal Process and Criminalistic Readings*. 2015;(2):223-233. URL: https://cyberleninka.ru/article/n/ispolzovanie-metoda-profaylinga-v-operativnoy-sledstvennoy-i-ekspertnoy-deyatelnosti (accessed on 07.12.2020). (In Russ.).
6. Kondakov A.M., Kostyleva A.A. Digital identity, digital self-identification, digital profile: Problem statement. *Vestnik Rossiiskogo universiteta druzhby narodov. Seriya: Informatizatsiya obrazovaniya = RUDN Journal of Informatization in Education*. 2019;16(3):207-218. (In Russ.). DOI: 10.22363/2312-8631-2019-16-3-207-218
7. Sukhodolov A.P., Kaluzhina M.A., Spasennikov B.A., Kolodin V.S. Digital criminology: The method of digital profiling of an unidentified criminal's behavior. *Vserossiiskii kriminologicheskii zhurnal = Russian Journal of Criminology*. 2019;13(3):385-394. DOI: 10.17150/2500-4255.2019.13(3).385-394
8. Leenes R.E. User-centric identity management as an indispensable tool for privacy protection. *International Journal of Intellectual Property Management*. 2008;2(4):345-371. DOI: 10.1504/IJIPM.2008.021431
9. Luffarelli J., Markou P., Stamatogiannakis A., Gonçalves D. The effect of corporate social performance on the financial performance of business-to-business and business-to-consumer firms. *Corporate Social Responsibility and Environmental Management*. 2019;26(6):1333-1350. DOI: 10.1002/csr.1750

10. Pop C., Georgescu M.-A. Credit enhancements and the Romanian municipal bond market. *Transylvanian Review of Administrative Sciences*. 2016;(48):104-123.
11. Harrison J.A., Budworth M.-H. Unintended consequences of a digital presence: Employment-related implications for job seekers. *Career Development International*. 2015;20(4):294-314. DOI: 10.1108/CDI-06-2014-0080
12. Pybus J. Social networks and cultural workers: Towards an archive for the prosumer. *Journal of Cultural Economy*. 2013;6(2):137-152. DOI: 10.1080/17530350.2012.742850
13. Neumann N., Tucker C.E., Whitfield T. Frontiers: How effective is third-party consumer profiling? Evidence from field studies. *Marketing Science*. 2019;38(6):918-926. DOI: 10.1287/mksc.2019.1188
14. Siso-Calvo B., Arquero-Avilés R. Plataformas digitales y reputación académica: Análisis del área de Biblioteconomía y Documentación en España. *Ibersid*. 2020;14(1):69-77.
15. Guerin C., Aitchison C., Carter S. Digital and distributed: Learning and teaching doctoral writing through social media. *Teaching in Higher Education*. 2020;25(2):238-254. DOI: 10.1080/13562517.2018.1557138
16. Masterson M. An exploration of the potential role of digital technologies for promoting learning in foreign language classrooms: Lessons for a pandemic. *International Journal of Emerging Technologies in Learning*. 2020;15(14):83-96. DOI: 10.3991/ijet.v15i14.13297
17. Sivanesan S. Alex & I: Narrative and network resistance. *Social Identities*. 2019;25(4):559-572. DOI: 10.1080/13504630.2018.1514161
18. Adams N.B., DeVaney T.A. Digital ethnicity – Emerging profiles. In: CELDA 2019: 16th Int. conf. on cognition and exploratory learning in digital age (Cagliari, 7-9 Nov. 2019). International Association for Development of the Information Society; 2019:435-438.
19. Lee M.F. Exploring learners' digital profile among the youth. In: 2016 IEEE conf. on e-learning, e-management and e-services (IC3e) (Langkawi, 10-12 Oct. 2016). New York: IEEE; 2017:91-95. DOI: 10.1109/IC3e.2016.8009046
20. Vlachopoulos D., Pitsiavas D. The digital profile of primary school principals: Achieving effective educational administration through ICT. *International Journal of Educational Organization and Leadership*. 2016;23(3):17-28. DOI: 10.18848/2329-1656/CGP/v23i03/17-28
21. Martynova M.E., Kamshilov S.G. Digital technologies in personnel management of the company. *Obshchestvo, ekonomika, upravlenie = Society, Economy, Management*. 2019;4(4):69-74. URL: https://cyberleninka.ru/article/n/tsifrovye-tehnologii-v-upravlenii-personalom-kompanii (accessed on 01.12.2020). (In Russ.).
22. Yavorskii N.K. Digital technologies in the personnel management system. *Molodoi uchenyi = Young Scientist*. 2020;(19):260-262. URL: https://moluch.ru/archive/309/69896/ (accessed on 02.12.2020). (In Russ.).
23. Rudskaya E.N., Poltavskaya Yu.Yu. Profiling the digital customer: New formats in intellectual data analysis. *Molodoi uchenyi = Young Scientist*. 2015;(21):464-471. URL: https://moluch.ru/archive/101/22843/ (accessed on 02.12.2020). (In Russ.).
24. Samborskaya L.N., Myasnikova L.A. The main methods of constructing the "digital profile" model using the example of Moscow schools. *Interaktivnaya nauka = Interactive Science*. 2017;(3):68-86. URL: https://cyberleninka.ru/article/n/osnovnye-metody-postroeniya-modeli-tsifrovoy-profil-na-primere-shkol-g-moskvy (accessed on 03.12.2020). (In Russ.).
25. De Bruyn A., Otter T. Bayesian customer profiling: Applications to age and political partisanship estimation. *SSRN Electronic Journal*. 2016. DOI: 10.2139/ssrn.2740293.
26. Trusov M., Ma L., Jamal Z. Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting. *Marketing Science*. 2016;35(3):405-426. DOI: 10.1287/mksc.2015.0956
27. Bikeeva E.S. The concept of racial profiling and the problems of its use in law enforcement. *Vestnik Yuzhno-Ural'skogo gosudarstvennogo universiteta. Seriya: Pravo = Bulletin of the South Ural State University. Series "Law"*. 2011;(40):42-43. URL: https://cyberleninka.ru/article/n/ponyatie-rasovogo-profilirovaniya-i-problemy-ego-ispolzovaniya-v-pravoohranitelnoy-deyatelnosti (accessed on 03.12.2020). (In Russ.).
28. Vozjenikova O.S., Kuznetsov D.A. Profiling technology in the field of aviation (transport) security. *Nauchno-metodicheskii elektronnyi zhurnal Kontsept = Scientific and Methodological Electronic Journal "Concept"*. 2014;(12):176-180. URL: http://e-koncept.ru/2014/14368.htm (In Russ.).
29. Colombini C.M., Colella A. Digital scene of crime: Technique of profiling users. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*. 2012;3(3):50-73. URL: http://isyou.info/jowua/papers/jowua-v3n3-4.pdf
30. Butenko V. Relevance of using the profiling method in the investigation of serial rapes. In: Topical issues of jurisprudence. Proc. 5th Int. sci.-pract. conf. Penza: Nauka i prosveshchenie; 2018:50-52. (In Russ.).

31. Galanova E.V. Personality profiling based on the analysis of its social media account. *Innovatsionnaya nauka = Innovation Science*. 2019;(2):58-61. URL: https://cyberleninka.ru/article/n/profilirovanie-lichnosti-na-osnove-analiza-ee-akkaunta-v-sotsialnyh-setyah (accessed on 06.12.2020). (In Russ.).

32. Official website of Anna Kulik, president of Research Center for Corporate Security. URL: https://anna-kulik.ru/category/profajling/ (accessed on 06.12.2020). (In Russ.).

33. Rudskaya E.N., Poltavskaya Yu.Yu. Borrower profiling technologies in banking: Innovations in scoring and minimizing fraud risks. *Molodoi uchenyi = Young Scientist*. 2015;(24):567-574. URL: https://moluch.ru/archive/104/24447/ (In Russ.).

34. Giannopoulos V., Aggelopoulos E. Predicting SME loan delinquencies during recession using accounting data and SME characteristics: The case of Greece. *Intelligent Systems in Accounting, Finance and Management*. 2019;26(2):71-82. DOI: 10.1002/isaf.1456

35. Makaeva A.M., Sharif'yanova Z.F. Credit scoring as a tool for effective assessment of the creditworthiness of a commercial bank borrower. *Innovatsionnaya nauka = Innovation Science*. 2016;(4-1):202-207. (In Russ.).

36. Kim Y., Street W.N., Russell G.J., Menczer F. Customer targeting: A neural network approach guided by genetic algorithms. *Management Science*. 2005;51(2):264-276. DOI: 10.1287/mnsc.1040.0296

37. Murthi B.P.S., Sarkar S. The role of the management sciences in research on personalization. *Management Science*. 2003;49(10):1344-1362. DOI: 10.1287/mnsc.49.10.1344.17313

38. Grigoryeva K.S. Racial profiling: The history and current state of research. *Demograficheskoe obozrenie = Demographic Review*. 2019;6(4):104-127. URL: https://cyberleninka.ru/article/n/rasovoe-profilirovanie-istoriya-i-sovremennoe-sostoyanie-issledovaniy (accessed on 07.12.2020). (In Russ.).

39. Vives X. Digital disruption in banking. *Annual Review of Financial Economics*. 2019;11:243-272. DOI: 10.1146/annurev-financial-100719-120854

40. Romānova I., Kudinska M. Banking and fintech: A challenge or opportunity? In: Grima S. et al, eds. Contemporary issues in finance: Current challenges from across Europe. Bingley: Emerald Group Publ. Ltd.; 2016;98:21-35. (Contemporary Studies in Economic and Financial Analysis Series). DOI: 10.1108/S1569-375920160000098002

41. Barringer S.N. The changing finances of public higher education organizations: Diversity, change, and discontinuity. In: Berman E.P., Paradeise C., eds. The university under pressure. Bingley: Emerald Group Publ. Ltd.; 2016:223-263. (Research in the Sociology of Organizations. Vol. 46). DOI: 10.1108/S0733-558X20160000046008

42. Gorbatkov S., Farkhieva S. Bankruptcy risk assessment in corporate lending based on hybrid neural networks and fuzzy models. *Korporativnye finansy = Journal of Corporate Finance Research*. 2016;13(1):28-39. DOI: 10.17323/j.jcfr.2073-0438.13.1.2019.28-39

43. Cevolini A., Esposito E. From pool to profile: Social consequences of algorithmic prediction in insurance. *Big Data & Society*. 2020;7(2). DOI: 10.1177/2053951720939228

44. Mann M., Matzner T. Challenging algorithmic profiling: The limits of data protection and anti-discrimination in response to emergent discrimination. *Big Data & Society*. 2019;6(2). DOI:10.1177/2053951719895805

45. Kharisma D.B. Urgency of financial technology (Fintech) laws in Indonesia. *International Journal of Law and Management*. 2020. (In print). DOI: 10.1108/IJLMA-08-2020-0233

46. Maramygin M.S., Chernova G.V., Reshetnikova L.G. Digital transformation of the financial services market in Russia: Trends and specificity. *Upravlenets = The Manager*. 2019;10(3):70-82. (In Russ.). DOI: 10.29141/2218-5003-2019-10-3-7

47. Chernyakov M., Chernyakova M. Technological risks of the digital economy. *Korporativnye finansy = Journal of Corporate Finance Research*. 2018;12(4):99-109. DOI: 10.17323/j.jcfr.2073-0438.12.4.2018.99-109

Influence of country-specific determinants on performance of small and medium enterprises of Europe

Byubyukan Kushubakova
Candidate of economic sciences (Ph.D.), Lecturer
ORCID
E-mail: kushubakova@yandex.ru
Department of Economic and Legal Security
Bashkir State University, Ufa, Russia

Sofia Strakhova
Analysis and Reporting Specialist
ORCID
E-mail: sofya.strakhova@yandex.ru
Nutricia Danone, OOO, the Moscow Region, Russia

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 61-89 (2020)
DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.61-89
Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

Influence of country-specific determinants on performance of small and medium enterprises of Europe

Abstract

A lot of obstacles stand in the way of small and medium enterprises formation. One of the first ones is an external financing gap in the majority of Central and Eastern Europe countries. Considering the totality of problems identified by entrepreneurs one may notice that the major part of them is made up of external impact factors.

The purpose of the present study is revealing the influence of country-specific determinants on performance of small and medium enterprises in 24 European countries. The research analyzed 54,512 SME within the period of 2013 to 2017.

The practical value of the research consists in the fact that its results may be useful for: governmental agencies in optimizing the existing small and medium enterprises support programs, emergent entrepreneurs when choosing the country to start up their business and for a better understanding of their environment, management when choosing the ways of entrepreneurship geographical expansion.

The applied importance of this paper consists in defining the most significant country-specific determinants of SME performance.

The regression analysis results show that the majority of small and medium enterprises from the point of view of macroeconomic and political conditions exist "in spite of, not thanks to something". We also identified a negative relation between the government machinery efficiency as such and its efficiency in relation to SME which means that a lot of effort is necessary for improvement in this sphere. Analysis of the difference between developed and emerging countries revealed a slight positive influence of corruption on SME's return on assets in emerging countries. Northern Europe is considered to be the friendliest region for small and medium enterprises while Eastern Europe is the least favourable one.

Key words: SMB, SME, ROA, performance, external determinants, corruption

JEL classification: G32, G41, K00, O30

Introduction

Small and medium enterprises (SME or small and medium business – SMB) are one of the drivers of economic and scientific-and-technological advance and the main job creator in all economic sectors. Through the whole SME life cycle a lot of factors (external and internal ones) influence various aspects of the small business's life. These factors may have a direct or indirect impact.

There is a series of studies dedicated to influence of external factors on various spheres of SME functioning. They range from the studies dedicated to analysis of influence of country-specific determinants on financial leverage [1; 2], working capital [3] to psychological and management studies - external influence on personality indicators of entrepreneurs as factors of small business success [4; 5].

Although the previous studies have made an unquestionable contribution to understanding of the factors which influence SME performance the papers in this field are still in the course of development. The issue of the extent of influence of a variety of country-specific factors on SME performance and development is still pending because a lot of previous research in this field are focused mainly on large enterprises.

The majority of studies use indexes and poll numbers (generally available ones as well as the ones developed and conducted by the author) to assess influence of external factors on the main indicators. In most cases the papers study influence of indirect factors of the external environment. It is caused by an absence of or incomplete summary information available in the field in question. For example, in Russia there is no unified database which records government expenditure on financing of SME development assistance. While the federal budget data is published on a regular basis the information on Russian constituent entities, municipal entities and various types of small and medium enterprises' support (in monetary terms) is not aggregated. This is another obstacle in the way of research in this field.

In general, the existing information on the factors which influence success of SCE activities is fragmented and this theme still needs elaboration due to insufficiency of theoretical basics [6; 7] and data which could be used for research.

Literature Review

Distinctive Features of SME in Developed and Emerging Countries

There are special established criteria in various countries according to which enterprises are classified as micro, small and medium ones. Fundamentally, they are defined on the basis of two criteria: revenue and stuff headcount. This paper deals with European countries. For this reason in order to simplify data processing and classify the companies in the sample we used the criteria established the European Commission for all European countries (instead of individual criteria for each country). Table 1 represents an example of difference in SME classification between the European Commission criteria and the ones of Federal Law No. 209-FZ On Development of Small and Medium-Sized Entrepreneurship in the Russian Federation.

For today the fact that it is necessary to develop and support small enterprises is beyond dispute. Comparison of the small business' role in growth of economic and socially important indicators (GDP, export, employment of population etc.) may serve as evidence. When considering the SMB status indicators [8] one may emphasize that European countries show better results than Russia, but lower than Israel or Japan (Figure 1).

Table 1. SME Classification Criteria[1,2]

	Russia[3]		European countries	
	Revenue, million Euro	Stuff headcount	Revenue, million Euro	Stuff headcount
Medium	10–25	101–250	10–50	50–250
Small	1.5–10	15–100	2–10	10–50
Micro	< 1.5	< 15	< 2	< 10

[1] Federal Law No. 209-FZ On Development of Small and Medium-Sized Entrepreneurship in the Russian Federation.

[2] European Commission. What is an SME? URL: http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en

[3] These limitations are changed at the legislative level each five years.

Figure 1. Indicators of the Status of Small and Medium Business [8]

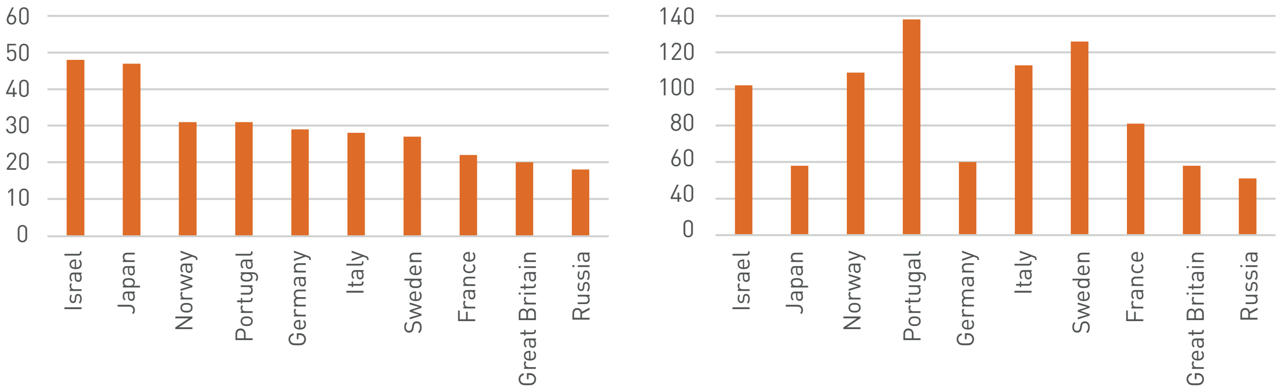
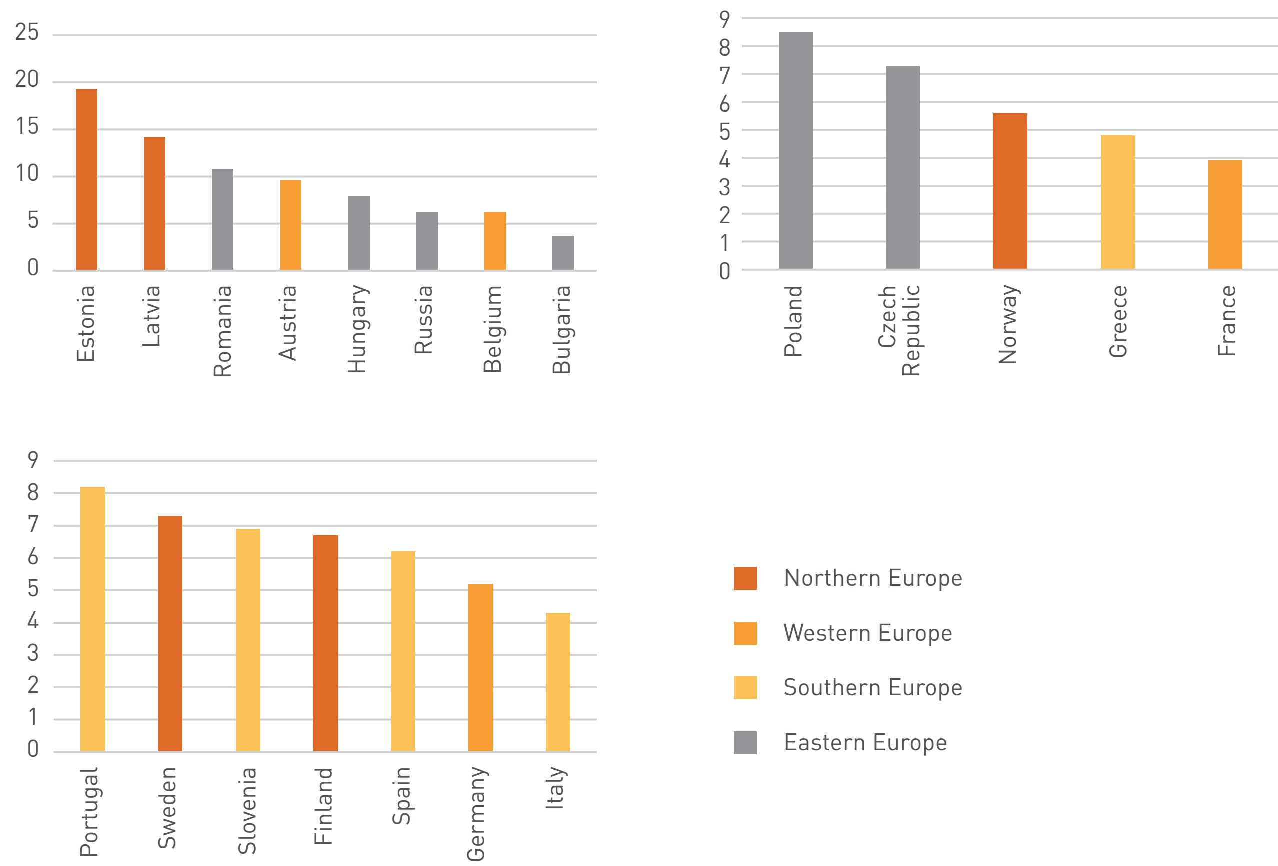


Figure 2. Global Entrepreneurship Monitor of the Population Aged 18–64, % [11]



The data offered by the Global Entrepreneurship Monitor (GEM) based on annual polls does not provide an understanding of the general trend for increase of business activity. However, Eastern Europe is the most advanced region in terms of this indicator (Figure 2). In accordance with GERA report for 2017 it is mainly due to the crisis [9]. Russian analysts agree with it, they say that increasingly more people are forced to go into business because they have lost their jobs.

There are ratings which provide a full assessment of favourability of conditions for business. The annual ones are comprised of Ease of Doing Business (compiled by the World Bank on the basis of annual data) and Best Countries for Business (published by Forbes).

Ease of Doing Business is the rating which highest ranking is indicative of the quality and simplicity of business governing in the country as well as a high level of property rights protection (the regulatory environment is more favourable for incorporation and business development). Since 2001 over 800 scientific works have used this rating data (starting a business, dealing with construction permits, getting electricity, registering property, getting credits, protecting minority investors, paying taxes, trading across borders, enforcing contract, resolving insolvency). The results of the researches show a strong interrelation between economic growth and improvement of the conduct of business rules.

Best Countries for Business is the rating compiled for 12 previous years by the American Financial and Economics Magazine Forbes. This rating is based on 15 factors: property rights, innovation, taxes, technology, corruption, infrastructure, market size, political risk, quality of life, workforce, freedom (trade, monetary and personal). Unlike the rating of the World Bank the methodology of index calculation in this ranking was changed significantly. That is why it is impossible to determine the general trend of ease of doing business for each country in dynamics for the whole time of the rating existence.

On the basis of analysis of these ratings for five years one can indicate the following general trend: the top positions are occupied by Northern European countries, Western Europe follows them, Southern European countries are spread across the sample in a random way and the majority of Eastern European countries are at the bottom of the rating (Table 2).

There are a lot of obstacles in the way of SMB formation and development. One of the first obstacles in the majority of Central and Eastern Europe countries is external financing gap [13]. See detailed information on the external financing gap of SME in various countries in the reports by the European Investment Bank. They also state a review of countries' economic status, evaluation of demand and offer of SMB financing.

Table 2. Forbes rating Best Countries for Business in 2018[4]

Country	Code	Forbes rating position **
Great Britain	GBR	1
Sweden	SWE	2
The Netherlands	NLD	4
Denmark	DNK	7
Ireland	IRL	11
Finland	FIN	13
Germany	DEU	14
Norway	NOR	15
Spain	ESP	18
Belgium	BEL	20
France	FRA	21
Austria	AUT	22
Luxembourg	LUX	23
Portugal	PRT	25
Iceland	ISL	26
Lithuania	LTU	27
Estonia	EST	28
Czech Republic	CZE	29
Italy	ITA	30
Slovenia	SVN	31
Poland	POL	34
Latvia	LVA	36
Slovakia	SK	38
Hungary	HUN	40
Romania	ROU	41
Greece	GRC	42
Bulgaria	BGR	46
Russia	RUS	55
Ukraine	UKR	77

Northern Europe
Western Europe
Southern Europe
Eastern Europe

There are a number of works dealing which this theme which define and assess alternative ways of solving the problem of financing gap. From statistical point of view annual reports by the Organization for Economic Cooperation and Development (OECD) are the most informative ones. In terms of providing data on calculation methodology, determining financing gap and analysis of alternative financing the paper The European Capital Markets Study: Estimating the Financing Gaps of SMEs [15] and Estimating the SME Financing Gap in Europe and Can Marketplace Lending Help Bridge the SME Financing Gap? by A. McCahery [18] are the most comprehensive ones.

Then SMB representatives define the following main problems: search for buyers; difficulties with access to highly-qualified personnel; problems with search for target markets; legislation imperfection – governmental policy; corruption. All these factors influence the extent to which operating expenses and risks impede SMB's access to external financing.

[4] Distribution by regions is made in the paper in accordance with the classification of the United Nations Statistics Division. Source: Forbes Best Countries for Business. URL: https://www.forbes.com/best-countries-for-business/list/#tab:overall (reference date: 23.01.2019).

Summing up the information obtained from the above sources the authors analyze an alternative financing for each individual country. The most frequently mentioned alternative financing methods are business angels, venture funds, various government programs and other ways of government support [19].

Country-Specific Determinants as Factors of Influence on SMB Performance Efficiency

Since 1990s a number of studies has been conducted in order to define the factors which explain SME's performance efficiency. Nevertheless, in spite of a wide range of factors mentioned in literature the scientists failed to agree on a common point of view on this topic [20; 21]. In the literature review on common characteristics of successful small enterprises and their founders [21] the authors came to the conclusion that "there is no such thing as a simple model". Besides, if we return to the list of SMB problems, we can see that it is comprised of external environment factors.

One of the latest and most comprehensive systematizations of external environment factors which define SME development is presented in the paper by D.R.Khairullina [22]. The author divided the factors into two groups depending on the extent of influence on business (direct and indirect one). The direct influence factors are: suppliers, customers, institutional-organizational environment, government support system, competitors, contact audience, support infrastructure. The indirect influence factors are as follows: social and demographic, legal, political, social and cultural, research and development, natural and climatic, international ones.

Under current conditions of economic management, it is reasonable to consider external and internal factors as a whole in order to develop effective management solutions. Speaking of characteristics of business, its internal factors scientists place emphasis on human capital [23; 24], financial standing [25], size and organizational structure of a company [26] and corporate culture [27].

As for characteristics of the entrepreneur himself the studied literature suggests that business success is related to certain psychological and personal qualities, first of all, readiness to risk in complex situations [28; 29], flexibility and ability to align oneself with conditions of uncertainty [30], masculinity and leadership skills [31], ability to make decisions and smooth problems over, tendency towards creativity and innovativeness [28], education, knowledge and experience [20]. The abovementioned research use polls as an information base. If we consider personal qualities of entrepreneurs and their subordinates we can use Hofstede's paper, his six dimensions of personality in accordance with country-specific determinants (power distance (degree of participation in taking decisions), individualism / collectivism, masculinity / femininity, uncertainty acceptance, orientation time horizon (long-term / short-term)). However, some papers disagree with Hofstede's dimensions results [33].

In spite of the studies which emphasize importance of personality determinants there are papers which results show that entrepreneur's personality characteristics are formed and changed depending on experience, improving management skills and business environment [4; 5]. Researches by M. Simpson, J. Padmore, N. Newman and M. Simpson, N. Tuck, S. Bellamy confirm importance of knowledge and experience obtained in various trainings [20; 7].

Influence of business climate determinants on success and failures of business is a matter of common knowledge. Such determinants comprise: social and political systems, legislation, infrastructure factors, the technological development level and trends in this sphere, competitive intensity [21; 34; 35]. The paper by E. G. Rogoff [34] describes in detail how entrepreneurs and business owners perceive the factors which influence SMB performance. As a result 11 factors were revealed which include external ones (beyond the entrepreneur's control): business regulation system at the legislative and executive level, labour market, external financing system, competition, economic environment, technological development level. Applying another approach – the Automatic Network Replenishment (ANR) to detect priority success factors of Turkish SME Karpak and Topcu [36] made the conclusion that external factors (political environment, legislation, legal and regulatory framework for SMB, competitive intensity and maturity of the industry sector) have a greater influence as distinct from internal ones. Study of the factors which influence small and medium business in the British chemical industry showed that the most important factor is the legal framework [37]. Also on the basis of the BEEPS database G.V.Shirokova and K.A.Bogatyreva [38] showed that a negative assessment of tax regulation, judiciary system and political instability increases internationalization of SMB companies indicating obstacles to SMEs' development – a negative assessment of tax rates, corruption and procedures of getting business registration licenses (permits).

The external factors indicative of the level of democracy, public management and supremacy of law are described in the paper by G.L. Munck [39]. The author lists the indicators which represent legal and political factors of external environment dividing them into: rule of law indicators, democratic governance indicators, democratic regime indicators.

In accordance with the conclusions of the report of the Global Entrepreneurship Monitor there is a relation between business activity and economic growth of the country, however, it may differ depending on the country economic development, economics orientation: resources, efficiency and focus on innovation. The type of economics does not just determine the special features of SMB development but also forms a set of factors which influence foundation of new enterprises and business climate. A U-shape relationship was reveled between business activity and the level of economic development. It is explained by the fact that in a country where macroeconomic and political stability prevails strong enterprises develop. At the same time in the countries with a low GDP per capita small business dominates among the forms of entrepreneurship. In line with economic growth and revenue increase the growing demand is satisfied, employment grows, and significance of large companies increases simultaneously with slowdown in the rates of SMB development. Thus, decrease in business activity for the low-income countries may be considered a positive sign [40]. As for the relationship between macroeconomic indicators and SME Audretsch and Mahmood [41] asserted that the threat of business liquidation is greater when the level of unemployment in the industry sector is high. Gupta and Kartick [42] in their paper proved influence of economic and social factors on performance efficiency of the companies engaged in alternative energy forms.

As for research and development indirect factors of influence a research should be mentioned in accordance with which a hostile external environment forces SMB to improve the innovation strategy. Thus, the level of technological and product innovation grows having a positive effect on productive efficiency [43]. Audretsch [44] asserted that technological capability was very important over the long term for competitive ability of new companies. Agarwal and Audretsch [45] also presumed that corporate survivability depended on technology and the life cycle stage of the industry sector.

It is impossible to stay away from the corruption topic. It combines political, social and public-and-cultural implications. Vu, Tran, Nguyen, & Lim [46] assert that corruption is a widespread phenomenon, especially in emerging countries. M.S. Safavian and D.H. Graham [47] conducted a research of SMB in Russia and summed up the following: small enterprises are exposed to the same level of bureaucracy as large ones. They indicate bureaucracy and rental payments as great obstacles in the way of business growth.

Tonoyan, Strohmeyer, Habib and Perlitz [48] showed that SMB's participation in corruptive transactions is partly related to the formal and informal institutional structure of each country and to a greater extent is due to low efficiency of financial and legal institutions. Considering illegal business practices as a widespread business practice entrepreneur get a substantiation in order to find excuses for their own corrupt practices. Moreover, the business environment where family relations, friends and bureaucracy prevail reduces contractor's opportunism to a corrupt transaction, thus paving the way for corruption. However, in the paper by A.Gladysheva, J.Kishilova [49] hypotheses of a positive influence of political relations (membership of an affiliated person / government agent in the board of directors) on access to debt financing and on a negative relationship between political relations and cost of debt have not been confirmed.

J. Hunady [50] basing analysis of corruption in European countries on polls, used indexes (Rule of Law, GE) in his paper to show the government and legal component. As a result, he revealed a negative relationship between the rule of law, government efficiency, public responsibility and corruption level in a country.

However, there are results which, at first view, defy common sense. Thus, in India a positive influence of bribery on export business and corporate innovation was noticed [51].

Analysis of literature on government support showed no unambiguous influence on performance of small and medium business. Angulo-Ruiz [52] determined that benefit from government support depends to a great extent on the market conditions and business environment.

Borbas [53] in his paper tells of the progress of influence of the Small Business Act (SBA) in Central and Eastern Europe which provides for a comprehensive cornerstone of policy in relation to SMB and development of entrepreneurship (estimation of efficiency of 10 programs in accordance with this Act). Actually, a lot of support measures may be offered by to those in power but far from all SMB representatives may use them. The author thinks that Central and Eastern Europe is an "underperforming" region (the same result is stated in the paper by Berko, Agota [54] using Hungary as an example). Although, speaking of Austria, it should be noted that the country economics functioned well in the time of the crisis showing a low unemployment level which did not incite entrepreneurs to risk in case of numerous attractive but unsafe opportunities. In order to stimulate entrepreneurship growth the government made concessions to high-technology startups, and as the year-end results of 2018 show it had an effect. The author considers Poland the most successful country in the sample which cancelled the largest part of red-tapery and simplified the business registration procedure. SBA information on SMB in the Czech Republic is ambiguous because the entrepreneurship and self-employed persons' level is above the average over Europe, however, perception of business climate by SME representatives is rather negative. SBA also evaluates positively business climate in Romania. 20% of economically active population in this country are self-employed persons, 27% intend to go into business but it is emphasized that in Romania there are less opportunities for implementation of business ideas than in European countries on average. Hungary improved twice the entrepreneurship indicators in the period of 2009 to 2014. In the authors' opinion, a new taxation system, support of junior enterprises and providing various indirect government support (for example, assistance in drafting a business plan) facilitated it. The purpose of this paper is to show the main differences between postsocialist and non-socialist European countries. The paper makes the conclusion that the reason for underdevelopment of SMB in Western Europe in comparison to Central Europe is absence of significant support measures and dawdling of the procedures going on in political institutions. In the opinion of L. Borbas [53], the gap between the west and east of Europe will grow if the above problems are dismissed.

However, when we speak of Great Britain's experience, one should mention the paper by Galbraith, McAdam, Woods, McGowan [55] on the necessity to elaborate one of SME support programs concerning taking into consideration the political and innovation component of the business environment.

Bergström [56] pointed out in his paper that subsidy allocation is not always effective because it is based on pollical relations and is performed for political purposes instead of prospects and social influence of the company. Consequently, the companies will, probably, "incur unofficial expenses" in order to win the government support. These phenomena in the sphere of government support may increase deviations in efficient resource allocation among companies and, consequently, may result in a slow growth of income or even decrease of return on assets [57]. Nguyen, Tran, Do also emphasize in their paper absence of a positive relation between the government support and SME profitability as well as a necessity to focus government programs on startup support rather than on noneffective private companies in Vietnam (the researchers use the PCI index in their paper).

There is no common conclusion concerning influence of government support on efficiency of SMB activity. We have examples of positive influence of government support [58] as well as those of negative influence. So, the paper by Bergström [56] shows that government support reduces return on sales.

Study of public and cultural diversity also does not produce a conclusive result. When Majocchi, Valle and D'angelo [59] studied Italian companies for a five-year period they established that multinationality as such had no influence on corporate performance. Gupta and Kartick [42], in their turn, pointed out the importance of national and cultural aspects which explain the difference in corporate financial indicators involved in alternative energy forms in various countries.

Literature offers different interpretations of the corporate performance efficiency: from growth of sales and sales indicator logarithm per an employee [60; 61] to return on assets (the indicator most frequently used in financial literature).

As for influence of corporate internal characteristics on performance efficiency, Whittington [62] asserted that larger companies, as a rule, had different opportunities and abilities for attaining higher figures in comparison to small business due to the scale effect. Some researches also prove a significant influence of the company size on its performance [63–65].

According to the trade-off theory higher-income companies should use more debt to gain on the tax of interest deduction [66] which implies a positive relation between profitability and debt because large companies are more attractive than small enterprises for a fund receiver when he needs external financing. On the contrary, the pecking order theory assumes that if financing is necessary the company investments have a certain hierarchy when funding sources are chosen. First, the accumulated own funds are used, then, third-party resources, and then debts and, finally, issue of new shares. Profitable companies have an opportunity of self financing and a lower need in debt increment [67], so, the pecking order theory presumes a negative relation between the debt and profitability. A negative relation between corporate profitability and debt was also detected in empirical research [68–70].

While on the subject of external influence factors, I. Zdráhal, G. Chmelíková, I. Blažková [71] assert that GDP growth and market competition have a positive impact on corporate profitability.

A. Sadeghi [72] proved that external factors ("success factors"), especially the policy and regulation, technology factor and entrepreneurship determinants are the most important ones in achieving success by small and medium high-tech enterprises.

Political risk is a part of the overall risk of corporate operation. Kobrin [73] defines political risk as a probability of negative consequences caused by political events. More generally, political risk may be defined as any unexpected change in the country's governmental policy which influences the business environment in which companies operate [74]. In 2000 Henisz [75] calculated the political constraint index (PCI) which measured this type of risk and had already been used in numerous empiric papers [59]. In the countries where politicians are more prudent in their decisions the index is higher. The majority of research studied influence of political instability on the investment level in the country, the result was a negative relation between these two indicators. The negative relation is due to the fact that when a political risk is high negative consequences of political events are more probable. This phenomenon is pertinent for large companies because they have different means to influence on and negotiate with political authorities concerning their investments, consequently, they can manage this particular risk. The situation is quite reverse with small and medium enterprises which have a smaller market power when investing in a foreign country in case of business expansion, taking into consideration a limited amount of transferred funds. Moreover, a potential impact of an unfavourable decision of political authorities is greater for SME because unfavourable political events may place them under the threat of liquidation. This is to say that for small enterprises investments in high political risk countries may be reasonable only if return on investment justifies the extra risk. Zahra, Garvis [76] used the subjective measurement of perceived environment risk and found out that companies which strain after international expansion have a higher profitability. Consequently, the higher the political risk which SME face the greater the economic performance. It is confirmed by the paper of Majocchi, Valle, D'angelo [59].

Majocchi, Valle, D'angelo [59] showed that the following indicators were the most important ones in influence on performance: political risk, financial stability of a country and economic growth (the latter had been confirmed by

T.J. Andersen [77] earlier). The general conclusion made by the authors states that for SME choice of the territory where subsidiary companies are founded is decisive because it influences greatly their overall economic performance.

R.W. Click [78] in his research revealed that business cycle and country rating have a positive impact on profitability of foreign direct investment. This effect should be stronger for SME because a decision on setting up a company entails contribution of numerous resources and, as a rule, is related to large markets. Consequently, if a market functions well and the economic state measured by the country rating is positive it is most probable that this positive effect will be manifested in corporate economic performance.

The paper which studied Russian SMB [79] showed a negative influence of corruption on corporate performance. Bureaucracy and significant transaction costs increase small enterprises' vulnerability to administrative pressure. In order to survive in such environment Russian SME should be of a larger size in comparison to SME of developed countries. A. Mitra [51] also made conclusions on bribe consequences and corporate performance in India. Bribes take on the role of corporate income tax and reduce performance.

Thapa [80] established the following key factors defining micro-enterprise performance: management skills, achievement need, independence need, creativity, internal locus of control and management foresight; the company-specific factors, in particular its age, size and starting financial restrictions; environment-related factors.

Hypotheses Generation

As a result of the conducted research the following hypotheses founded on theoretical and empiric bases have been put forward.

H_1: there is a significant positive relation between the innovative development level and SMB performance.

The innovative development is important for companies from the point of view of external and internal influence. In particular it concerns SME. Considering the innovation development level as an internal factor one can mention the papers by Stewart Jr, Roth [28] and Simpson, Tuck, Bellamy [20] which discuss the importance of creativity, entrepreneurial innovation, entrepreneur's education, knowledge and experience as the factors influencing success in corporate performance. The innovation development level may also be considered as an external indirect influence factor which has been proved in the papers by Audretsch [44], Agarwal, Audretsch [45] and Perez-de-lema, Hansen, Madrid-Gujjarro, Silva-Santos [43]).

H_2: there is a significant positive relation between the country regulatory environment and SME performance.

Papers by Karpak, Topcu [36], Lampadarios [37] have proved significance of legislation and legal and regulatory framework for SME operations. In particular we would like to emphasize the legal framework related to borrowers' and creditors' rights protection because the major obstacle in the way of SME global development is insufficiency of external financing. This has been proved in numerous publications and statistical materials.

H_3: there is a significant negative relation between the corruption level in a country and SME performance.

Analysis of academic papers dedicated to this topic found out cases of a positive relation between the corruption component in a country and corporate performance, however, these cases occur mainly in Asian countries ("the East Asian paradox") [51]. This paper considers SME of European countries, for this reason the hypothesis above has been proposed. A negative influence of corruption (in various forms) in this sense has been revealed in the papers by M.S. Safavian, D.H. Graham [47], G.V.Shirokova and T.V.Tsukanova [38], Golikova, Kuznetsov [79].

H_4: there is a significant positive relation between public and cultural determinants characteristic of successful entrepreneurs and SMB performance.

Such determinants comprise: risk propensity [28; 29], flexibility and ability to align oneself with conditions of uncertainty [30], masculinity and leadership skills [31], ability to make decisions and smooth problems over. It is supposed that in the countries where the determinants (according to Hofstede dimensions) are presented by small figures SMB performance is higher.

H_5: there is a significant positive relation between business climate (from the macroeconomic point of view) and SME performance.

In an environment where macroeconomic and political stability prevails strong enterprises develop. Earlier the positive relation between macroenvironment and performance has been detected by Audretsch, Mahmood [41] and Gupta, Kartick [42].

H_6: there is a significant negative relation between the political risk level in a country and SME performance.

When the political risk is high the possibility of detrimental consequences of political events is greater. Thus, we make an assumption that for small enterprises investments in high political risk countries may be reasonable only if return on investment justifies the extra risk. So, the higher the political risk which SME face the greater the economic performance. It is confirmed by the paper of Zahra, Garvis [76], Majocchi, Valle, D'angelo [59].

H_7: there is a significant positive relation between SMB size and its profitability.

This assertion has been discussed above [63–65].

H_8: there is a significant negative relation between financial leverage and SME's return on assets.

The empiric studies by Degryse [68], Mateev, Poutziouris, Ivanov [69], Nunes, Serrasqueiro [70] detected a negative relation between profitability and corporate indebtedness.

Data and Methodology

The sample of small and medium enterprises used in this research has been made on the basis of the Amadeus database (Bureau Van Dijk). The geographical spread of the sample has been defined on the basis of the Forbes rating Best Countries for Business for 2018 which presents clusterization of certain European regions. The framework established by the European Commission and described above is taken into consideration as criteria for defining SMB. Thus, the sample comprises enterprises of 24 countries. The initial sample consisted of 250,000 companies. In general, the research applies 12 samples: the total sample, 4 samples in accordance with regional distribution of Europe by the United Nations Statistics Division, 2 samples covering developed and emerging countries (in accordance with IMF's distribution), 5 samples of innovative companies (total and the one related to regions of Europe) (Figures 3-5).

The Amadeus platform was used in order to obtain financial indicators describing company characteristics. For example, the key performance indicator in this paper is represented by return on assets presented as net profit - total assets.

Other indicators – corporate characteristics were also collected. It reduced the initial sample significantly because a lot of companies have no necessary data. So, the SME sample was diminished up to 54,512 companies. A five-year period of 2013 to 2017 was chosen for the research. The analysis uses the panel data methodology, so the sample accounts for 272,560 unique observations.

Figure 3. Percentage ratio of companies in the total sample

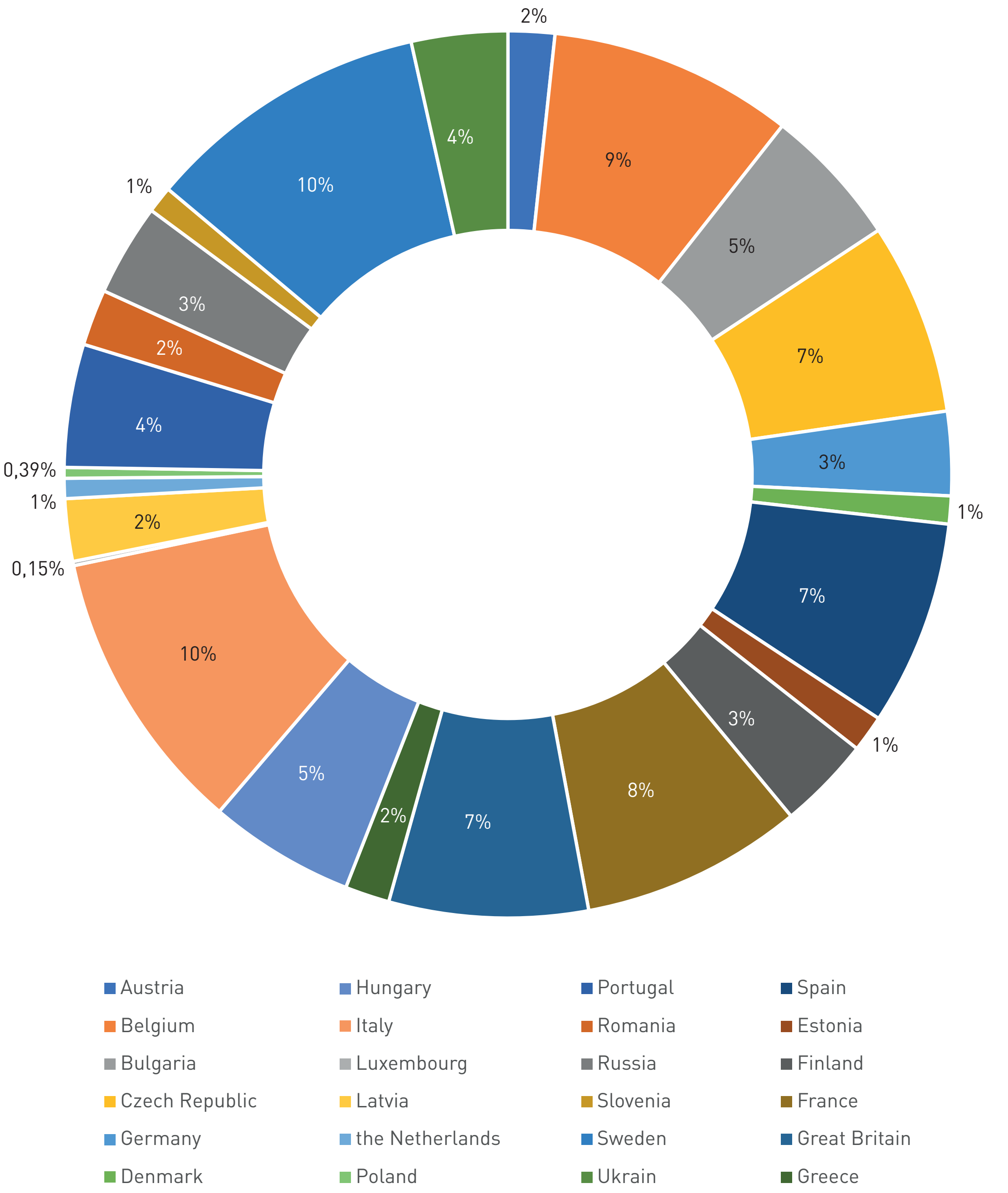
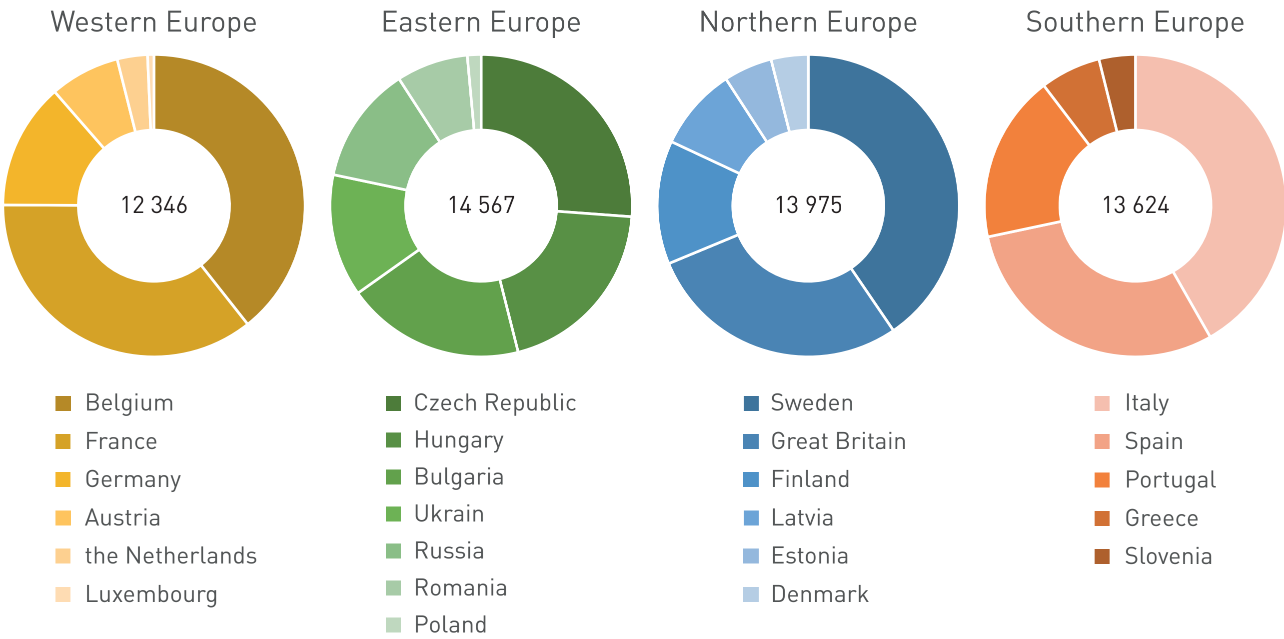
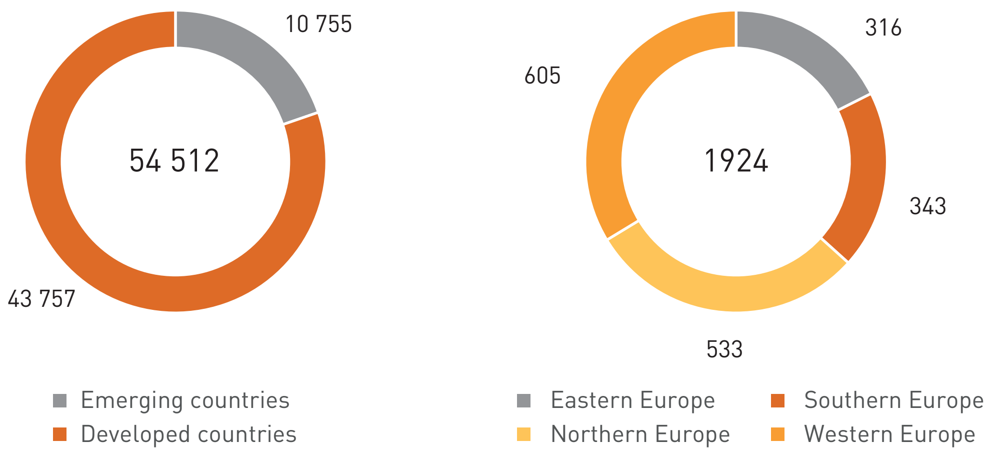


Figure 4. Number of small and medium enterprises in Western Europe (1), Eastern Europe (2), Northern Europe (3), Southern Europe (4)



Source: author's calculations.

Figure 5. Number of: small and medium enterprises of developed and emerging European countries (1), innovative European SME (2)



Source: author's calculateions.

Apart from the indicators on each certain company we have collected country-specific determinants applying the methodology developed by D.R.Khairullina [22]. The factor system she offered is presented in Figure 6. On the basis of this system indexes characterizing the external environment factors have been collected.

The macroeconomic indicators for each country stated in the paper are mainly taken from the publicly available database Worldbank.

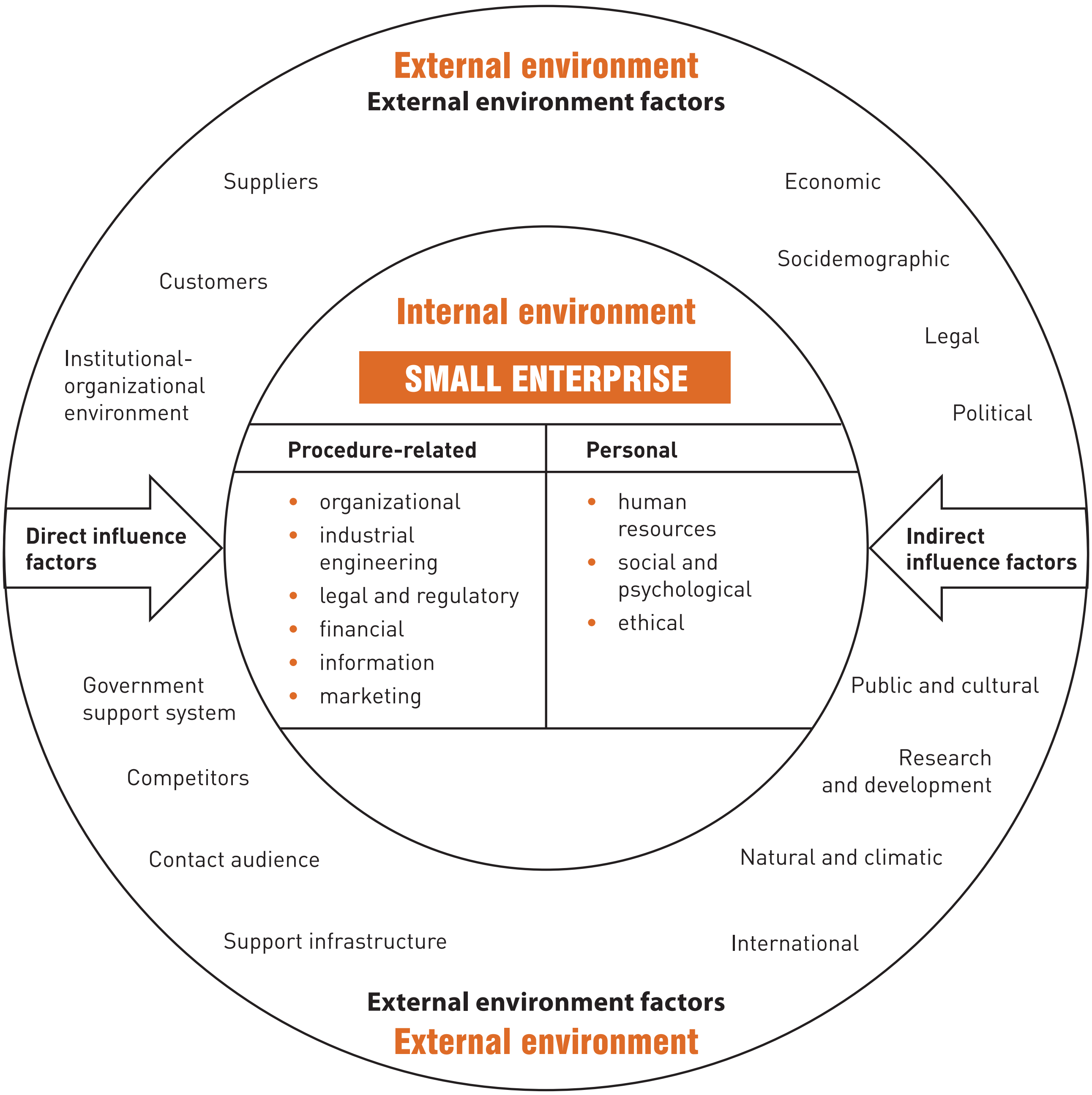
The sample of innovation small and medium enterprises is worth noting individually. SME's definition as innovation enterprises was based on the idea from the paper by Dagmar Vávrová [81] which uses industrial NACE codes of the Bureau Van Dijk database. The paper determines the following range of innovative sectors: drug production (NACE code: 21.); electronics, optics, equipment manufacturing (NACE codes: 26.1 – 26.8); audio-visual devices (NACE codes: 59, 60); ICT sector (NACE codes: 61, 62); information sector (NACE codes: 63); research and development (NACE codes: 72.1, 72.2).

The main variables

The purpose of this research is to evaluate influence of external factors on SMB performance represented as return on assets (ROA). In this relation we can define two groups of variables (Figure 7): company-specific determinants and country-specific determinants. The first group is comprised of: the natural logarithm of the number of employees LnEMP as the company size and the balance variable – a debt to own DTA ratio – financial leverage. The second group consists of the variables – indexes which show different types of external influence on SME performance.

- legal and political factors of external environment – the rule of law indicators (The Heritage Foundation & Wall Street Journal's Index of Economic Freedom WSJI, the corruption perception index CPI, rule of law index ROL, civil liberties index CLI, legal rights index LRI);
- legal and political factors of external environment - democratic governance indicators (country-specific rating of political stability PSI), the governance efficiency index GEI, political constraint index PCI);
- legal and political factors of external environment – democratic regime indexes (the political rights index PRI);
- economic and sociodemographic indexes (business climate index represented as the index of expenses on business startup in a country CBS);
- research and development index – the global innovation index GII;
- public and cultural environment index – cultural diversity CDI.

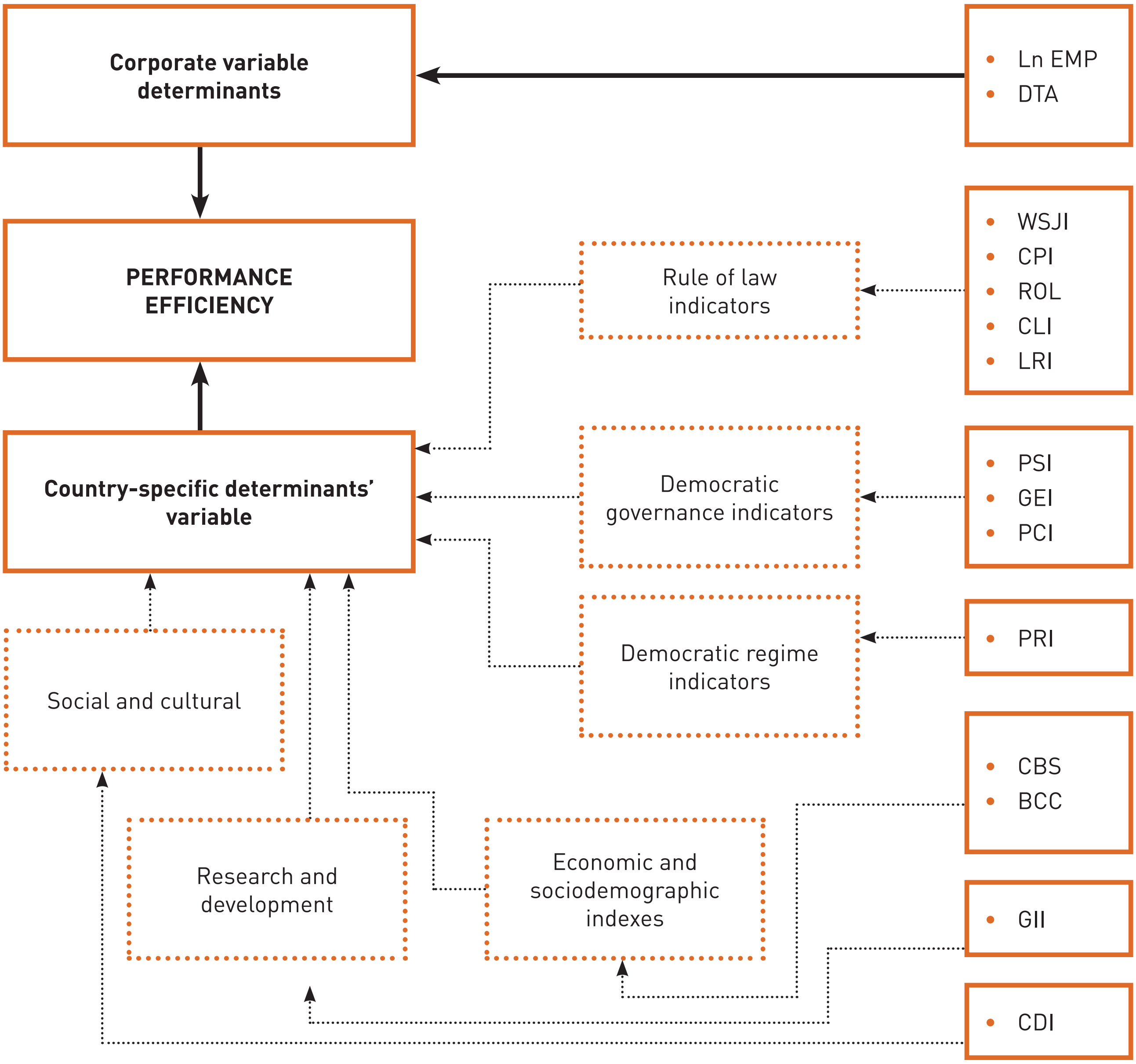
Figure 6. System of the factors defining small business development



Source: [22].

Scoring is used in the rating systems to create indexes.

Figure 7. Graphic representation of the model



Source: the diagram was developed by the author of the paper.

The variables are described in Table 3 in more detail.

Table 3. Expected variables values, units of measure and sources

Variable	Definition	Expected sign	Source	Measurement
Rule of law indexes				
WSJI	Economic freedom index	+	https://www.heritage.org	Index from 0 to 100
CPI	Corruption perception index	+	https://www.transparency.org	Index from 0 to 100
ROL	Rule of law index	+	https://worldjusticeproject.org	Index from 0 to 1
CLI	Civic liberties index	+	https://freedomhouse.org	Index from 0 to 100
LRI	Legal rights index	+	www.worldbank.org	Index from 0 to 10

Variable	Definition	Expected sign	Source	Measurement
Democratic governance index				
PSI	Political stability index	+	https://www.theglobaleconomy.com	Index from 0 –3 to 3
PCI	Political constraint index	–	https://mgmt.wharton.upenn.edu	Index from 0 to 1
GEI	Governance efficiency index	+	www.worldbank.org	Index from 0 to 10
Economic and sociodemographic indicators				
CBS	Business climate	=	www.worldbank.org	Index from 0 to 200
BCC	Business climate (macro)	+	www.worldbank.org www.standardandpoors.com	Dummy variable
Research and development indicator				
GII	Global innovation index	+	https://www.globalinnovationindex.org	Index from 0 to 100
Public and cultural indicator				
CDI	Cultural diversity index	+	https://www.hofstede-insights.com	Sum of 4 measurements from 0 to 100
Company-specific variables				
LnEMP	Number of employees	+	Amadeus Database	Natural logarithm of the number of employees
DTA	Financial leverage	–	Amadeus Database	Total debt / Total assets

Source: offered by the author.

It is reasonable to explain CPI, CDI and CBS indexes.

The corruption perception index, according to the hypothesis suggested before is negatively associated with corporate performance but as long as the value of this index grows along with corruption decrease we expect to see in the results a positive relation of this indicator with ROA.

The cultural diversity index is interpreted differently in various sources and is used in various scientific fields (internal technology, mass media, psychology, finance etc.). This index is based on the results of polls of persons - representatives of 93 countries consolidated into four (six, since recently) dimensions which comprise Hofstede' cultural dimensions typology. In this research in accordance with the studied literature four dimensions have been chosen which correspond to successful entrepreneurship: uncertainty avoidance (UAI as opposed to risk propensity), masculinity (MAS), internal locus of control, long-term orientation (LTO).

The values of the above indicators are added together for each country separately (except for UAI, as long as it is a reverse indicator to the one we need we deducted the UAI value from the maximum possible value -100).

CBS index which represents costs for business startup in a country, like CPI in the hypothesis above has the negative sign, however, the higher the value the more favourable the conditions for business startup are (see the expenses below).

The dummy variable BCC which represents business climate in a country from the macroeconomical point of view belongs to the economic and sociodemographic group of variables. The variable takes on the value one when the condition is observed at which the rate of inflation in the country is below the average for the countries in the sample while the credit rating of the country and GDP growth are above the average across the sample. Thus, the variable is created to represent favourability of macroeconomic conditions for business. The country credit rating was taken from the Standard & Poor's database. In order to transform it into a linear scale the rating value D was imputed as one and subsequently in the same way, in ascending order, all letter designations of the rating were transformed.

Research Methodology and Theoretical Model

This research implies econometric regression analysis of panel data. There are several stages of the analysis: defining the model types (pooled, random-effects or fixed-effects one); elimination of econometric supposition disarrangement (problems of heteroscedasticity, endogeneity, multicollinearity).

In order to choose the best specification three tests have been carried out. When choosing from among the pooled regression model and fixed-effects model the Wald test yielded the results in favour of the latter model. We also conducted the Breusch-Pagan test which showed that in all research models the zero hypothesis was rejected substantiating the choice of the random-effects model. As a result of the Haussmann test the zero hypothesis was discarded in all cases which means that the fixed-effects model specification is necessary. See all test results related to choosing specification in table 4.

Table 4. Samples testing results for defining the model type

Dependent variable model specification		Total sample	Northern Europe	Western Europe	Southern Europe	Eastern Europe
Breusch-Pagan test	χ2	4.2e+05	1.2e+05	1.0e+05	1.1e+05	1.0e+05
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Wald test	F	45.40	68.54	48.45	38.55	35.49
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Haussmann test	χ2	11,178.08	131.25	62.20	480.46	3,955.09
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000

Taking into consideration the test results (using the total and particular samples by European regions) and presence of the time-constant variables important for this research in particular, we took the decision to apply both fixed- and random-effects models.

The main model proposed for research initially appeared as follows:

$$\begin{aligned}\text{Perform}_{it} = {} & \alpha + \beta_1\text{LnEMP}_{it} + \beta_2\text{DTA}_{it} + \beta_3\text{CPI}_{it} + \\ & +\beta_4\text{GII}_{it} + \beta_5\text{WSJI}_{it} + \beta_6\text{ROL}_{it} + \beta_7\text{CLI}_{it} + \beta_8\text{LRI}_{it} + \\ & +\beta_9\text{PSI}_{it} + \beta_{10}\text{GEI}_{it} + \beta_{11}\text{PCI}_{it} + \beta_{12}\text{PRI}_{it} + \beta_{13}\text{CDI}_{it} + , \\ & +\beta_{14}\text{CBS}_{it} + \beta_{15}\text{BCC}_{it} + \varepsilon_{it}\end{aligned}$$

where Perform_{it} – return on assets for each company i within the period of t; α – constant; ε_{it} – standard error for company i within the period of t.

On the basis of tests, in order to reveale the problems of multicollinearity, endogeneity, heteroscedasticity, which influence consistency and efficiency of estimates the models were rearranged.

The test for multicollinearity using the Pearson correlation matrix and the variance inflation factor (VIF) revealed a serious multicollinearity problem and, thus, helped to choose between variables – indexes k from the same group of external factors which makes the indexes (in the context of this paper) interchangeable. We selected variables from each individual sample in the following groups: rule of law indicators; democratic governance indicators; economic and sociodemographic indexes.

In order to eliminate the endogeneity problem between financial leverage and return on assets the DTA indicator in the research is lagged within the period of t-1.

So, the principal model is simplified as follows:

$$\begin{aligned}\text{Perform}_{it} = {} & \alpha + \beta_1\text{LnEMP}_{it} + \beta_2\text{DTA}_{i(t-1)} + \beta_3\text{CPI}_{it} + \\ & +\beta_4\text{GII}_{it} + \beta_5\text{LRI}_{it} + \beta_6\text{ROL}_{it} + \beta_7\text{PSI}_{it} + \beta_8\text{PCI}_{it} + \\ & +\beta_9\text{CDI}_{it} + \beta_{10}\text{CBS}_{it} + \beta_{11}\text{BCC}_{it} + \varepsilon_{it}.\end{aligned}$$

Some models of samples according to European regions are modified due to multicollinearity. So, in the models for Southern and Western Europe the GII indicator will be assessed separately, while in Northern and Eastern Europe the CPI indicator will be evaluated this way. Separate regressions were made for the rest of the variables not included in the models.

The autocorrelation and heteroscedasticity problems result in inefficiency of coefficients assessments while they are still unbiased and consistent.

In order to detect inhomogenuity of observations (heteroscedasticity) we conducted a modified Wald test. The tests results included in Table 5 are indicative of heteroscedasticity in all existing models. The determined problem is corrected by means of White corrections due to which t statistics increase and standard deviations reduce.

The period of research is five years which may be considered a short temporal series. For this reason the autocorrelation problem will have no serious consequences.

We also complied two samples which subdivide the total sample into developed and emerging countries. The models in these samples are tested for choice of specification (see the results in Table 6).

Table 5. Test results for heteroscedasticity

		Total sample	Northern Europe	Western Europe	Southern Europe	Eastern Europe
Wald test	χ2	8.1e+10	2.4e+08	7.1e+09	5.0e+08	7.3e+08
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 6. Results of samples testing in order to define the model type

Dependent variable model specification		Developed countries	Emerging countries
Breusch-Pagan test	χ2	1.1e+05	24775.87
	P-value	0.0000	0.0000
Wald test	F	6.32	5.73
	P-value	0.0000	0.0000
Haussmann test	χ2	1,783.69	415.77
	P-value	0.0000	0.0000

Table 7. Test results for heteroscedasticity

		Developed countries	Emerging countries
Wald test	χ2	1.2e+10	5.5e+08
	P-value	0.0000	0.0000

Now we proceed to developing a market for innovation companies' sample. In order to define the model specification tests were carried out (Table 8).

Table 8. Samples testing results for defining the model type

Dependent variable model specification		Total sample	Northern Europe	Western Europe	Southern Europe	Eastern Europe
Breusch-Pagan test	χ2	5,612.19	1,573.21	1,998.54	1,115.28	956.93
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Wald test	F	7.53	7.08	7.88	7.84	7.13
	P-value	0.0000	0.0000	0.0000	0,0000	0.0000
Haussmann test	χ2	62.67	12,70	13,15	12.94	2.29
	P-value	0.0000	0.2409	0.2152	0.2269	0.9972

Taking into consideration the obtained results and the necessity to accept for consideration the time-constant variables we took the decision to use fixed- and random-effects models.

Taking into consideration the multicollinearity problem the following theoretical models were made:

for developed countries

$$\begin{aligned}\text{Perform}_{it} = \alpha + \beta_1\text{LnEMP}_{it} + \beta_2\text{DTA}_{i(t-1)} + \beta_3\text{CPI}_{it} + \\ +\beta_4\text{GII}_{it} + \beta_5\text{LRI}_{it} + \beta_6\text{ROL}_{it} + \beta_7\text{PSI}_{it} + \beta_8\text{PCI}_{it} + \\ +\beta_9\text{CDI}_{it} + \beta_{10}\text{GEI}_{it} + \beta_{11}\text{CBS}_{it} + \beta_{11}\text{BCC}_{it} + \varepsilon_{it};\end{aligned}$$

for emerging countries

$$\begin{aligned}\text{Perform}_{it} = \alpha + \beta_1\text{LnEMP}_{it} + \beta_2\text{DTA}_{i(t-1)} + \\ +\beta_3\text{CPI}_{it} + \beta_4\text{GII}_{it} + \beta_5\text{LRI}_{it} + \beta_6\text{CLI}_{it} + \beta_7\text{PSI}_{it} + \\ +\beta_8\text{PCI}_{it} + \beta_9\text{CDI}_{it} + \beta_{10}\text{GEI}_{it} + \beta_{11}\text{PRI}_{it} + \\ +\beta_{10}\text{CBS}_{it} + \beta_{11}\text{BCC}_{it} + \varepsilon_{it}.\end{aligned}$$

The heteroscedasticity test confirmed existence of this problem (see the results of the modified Wald test in Table 7). For this reason the Wald corrections were applied to the models.

Thus, we chose fixed- and random-effects models for the total sample and random-effects models for the samples according to European regions.

Here we verify them for multicollinearity. The model appears as follows:

$$\text{Perform}_{it} = \alpha + \beta_1 \text{LnEMP}_{it} + \beta_2 \text{DTA}_{i(t-1)} + \\ +\beta_3 \text{CPI}_{it} + \beta_4 \text{GII}_{it} + \beta_5 \text{LRI}_{it} + \beta_6 \text{ROL}_{it} + \\ +\beta_7 \text{PSI}_{it} + \beta_8 \text{PCI}_{it} + \beta_9 \text{CDI}_{it} + \beta_{10} \text{CBS}_{it} + \\ +\beta_{11} \text{BCC}_{it} + \beta_{12} \text{GEI}_{it} + \varepsilon_{it}.$$

For certain European regions the principal model was rearranged taking into consideration multicollinearity. Separate regressions were made with the variables not included in the models.

The heteroscedasticity analysis showed existence of this problem (Table 9), so the White corrections were applied.

Table 9. Test results for heteroscedasticity

		Total sample	Northern Europe	Western Europe	Southern Europe	Eastern Europe
Wald test	χ2	1.0e+08	7.6e+06	1.2e+08	1.6e+06	4.3e+06
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000

Analysis of Influence of Country-Specific Determinants on European SMB

See results of the regression analysis in Table 10.

As we see in Table 9 hypothesis 1 is confirmed concerning a positive significant relation between the innovative development level and SMB performance which supports the importance of the research and development factor. However, one should pay attention to the coefficient of the GII variable. It is positive and significant at a 1% and 5% level, however, when the indicator increases by 1 point SME's return on assets grows by 0.0505 which cannot be considered a strong influence.

We also confirmed hypothesis 2 on a positive and significant relation of the legal environment factors, in particular: rule of law indicators from the comprehensive point of view (ROL) and from the point of view of borrowers' and creditor's rights (LRI) and SME performance efficiency.

The analysis showed that the corruption component represented as the CPI index is insignificant which refutes hypothesis 3.

The public and cultural factor represented by the determinants which characterize successful entrepreneurs (CDI) revealed a positive and significant relation with SME performance efficiency, thus, confirming hypothesis 4. But again we have to draw attention to the coefficient of the CDI variable which amounted to 0.0167 and is indicative of a relative power (here – weakness) of influence.

Table 10. Regression analysis results of the total sample of European SME

Variables	Total sample (fe)	Total sample (re)
GII	0.0505***	0.0288***
	(0.0166)	(0.0102)
LRI	0.144***	0.270***
	(0.0375)	(0.0173)
ROL	1.454***	−0.809***
	(0.310)	(0.256)
CPI	0.000445	−0.0319***
	(0.00772)	(0.00431)
o.CDI	–	
LnEMP	0.692***	−0.267***
	(0.0770)	(0.0371)
DTA	−17.15***	−13.95***
	(0.278)	(0.154)
CBS	−0.112***	−0.142***
	(0.0157)	(0.00948)
BCC	−0.196***	−0.182***
	(0.0372)	(0.0339)
PCI	−5.631***	−1.185***
	(0.915)	(0.316)
PSI	−0.300**	−0.547***
	(0.120)	(0.0716)
CDI		0.0167***
		(0.00517)
Constant	11.56***	14.75***
	(1.145)	(0.413)
Observations	272,560	272,560
R^2	0.075	
Number of companies	54,512	54,512

Standard errors in parentheses:

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

The results of the relation between SME performance efficiency and macroeconomic business climate were unexpected. This relation is significant at a 1% and 5% level and negative. However, the obtained result complements and confirms hypothesis 6 described below. The relation with the macroeconomic environment will be described in detail when we study regions individually. In view of the aforesaid, hypothesis 5 is rejected from the macroeconomic point of view.

The result on the costs for business startup (CBS) showed that the lower the costs in a country the less SME's return on assets is.

The political factor of external influence is expressed in the model by means of indexes of political constraint (PCI) and political stability (PSI). Therein, PCI may be called an index which is indicative of the power characteristics and PSI is an index presenting manifestation of people's sentiment as a representation of the political component in the countries. A significant negative relation was revealed between the political environment level and SMB performance. This is indicative of the fact that for entrepreneurs investments in high political risk countries may be reasonable only if return on investment justifies the extra risk. So we confirm hypothesis 6.

For the sake of the model completeness we included the variables of corporate determinants in it. Hypotheses 7 and 8 are confirmed for these variables. Analysis results showed a significant positive relation between SMB size and its profitability as well as a significant negative relation between financial leverage and SME's return on assets.

We analyzed separately the results of the regression analysis of SME's return on assets with GEI, PRI indicators. The choice between the random- and fixed-effects models was made on the basis of Breusch-Pagan and Haussmann tests. The results confirm a logically and intuitively realized relation between business success and political rights freedom (PRI). The governance efficiency indicator (GEI) turned out to be the distinctive one showing a significant and negative result. However, the coefficient of the variable amounted to 0.0024. So, the obtained result may be explained by imperfection of the aggregate sample as long as there is no opportunity to take into consideration all SMB representatives in the countries chosen for the research.

Summing up the results obtained from the total sample we notice a positive influence of innovation, legal environment and public and cultural characteristics development on SMB performance. A negative relation was detected between performance efficiency and political environment, business climate (from the point of view of macroeconomic conditions and costs for business startup). The analysis results also showed absence of corruption influence on SMB in European countries all through the sample.

Analysis of Influence of Country-Specific Determinants on SMB of Certain European Regions

See the regression analysis results for countries from certain European regions in Table 11. The choice between the random- and fixed-effects models was made on the basis of Breusch-Pagan and Haussmann tests.

The analysis results confirm hypothesis 1 for all European regions except for Eastern Europe. In Eastern Europe the CII indicator is insignificant. The biggest coefficient of the variable is registered in the Northern Europe model, the smallest coefficient – in the Southern Europe model.

The situation with the legal environment indicator is not so definite as in the total sample. The hypothesis of a positive and significant relation of the rule of law from the comprehensive point of view (ROL) was confirmed only for Southern Europe. In the Western and Eastern regions this indicator is insignificant and in the Northern region it is even negative. The rule of law from the point of view of borrowers' and lenders' rights protection (LRI) showed a negative significant relation with SME performance efficiency in Northern and Eastern Europe. In the Western and Southern region this indicator was insignificant which in general is indicative of invalidity of hypothesis 2. Still the assumption that economically underdeveloped countries, having realized the importance of external financing for SME, introduce measures to improve legal protection of credit relations parties is confirmed. This is manifested in the obtained results.

Table 11. Regression analysis results of samples for European SME

	North Eur	North Eur	West Eur	West Eur	South Eur	South Eur	East Eur	East Eur
Variables	(fe)	(re)	(fe)	(re)	(fe)	(re)	(fe)	(re)
GII	0.370***	0.274***					–0.0359	0.0865***
	(0.0510)	(0.0329)					(0.0321)	(0.0287)
o.LRI	–		–		–		–	
ROL	–6.64***	–6.867***	0.282	–0.0258	8.690***	7.760***	–0.531	–4.390***
	(2.303)	(0.588)	(0.394)	(0.388)	(0.634)	(0.573)	(1.965)	(1.132)

	North Eur	North Eur	West Eur	West Eur	South Eur	South Eur	East Eur	East Eur
o.CDI	–		–		–		–	
LnEMP	0.195	–0.359***	0.624***	–0.652***	0.645***	0.102*	0.943***	–0.431***
	(0.216)	(0.0857)	(0.162)	(0.0745)	(0.109)	(0.0572)	(0.141)	(0.0744)
DTA	–19.01***	–14.00***	–14.53***	–11.44***	–14.65***	–11.97***	–18.19***	–16.41***
	(0.607)	(0.324)	(0.481)	(0.272)	(0.456)	(0.241)	(0.515)	(0.307)
CBS	0.122	0.139	0.0409	–0.0939**	–0.0768***	–0.211***	–0.0013**	–0.0855***
	(0.111)	(0.109)	(0.0815)	(0.0395)	(0.0200)	(0.0173)	(0.2633)	(0.0230)
BCC	0.571***	0.478***	–0.102	–0.106*	–0.380***	–0.508***	–1.435***	–1.670***
	(0.0839)	(0.0793)	(0.0640)	(0.0635)	(0.0491)	(0.0488)	(0.141)	(0.127)
PCI	–11.93*	–10.70***	7.325	–3.474***	–5.990***	–1.387	–12.79***	–2.848***
	(6.898)	(3.325)	(6.060)	(0.563)	(1.181)	(1.070)	(1.578)	(0.830)
PSI	–0.890**	–1.917***	–0.496**	–0.479**	4.900***	3.093***	–0.842***	–1.129***
	(0.427)	(0.348)	(0.207)	(0.196)	(0.252)	(0.173)	(0.205)	(0.154)
LRI		–0.663***		–0.0788		0.0359		–0.129***
		(0.163)		(0.0981)		(0.0497)		(0.0420)
CDI		–0.110***		0.0316		0.200***		0.0197
		(0.0283)		(0.0246)		(0.0137)		(0.0165)
CPI			0.163***	0.105***	0.101***	0.0279***		
			(0.0259)	(0.0179)	(0.00961)	(0.00781)		
Constant	9.045**	20.91***	–0.874	7.099***	0.749	–2.467***	21.42***	19.29***
	(4.590)	(3.256)	(4.827)	(1.356)	(0.825)	(0.735)	(1.546)	(1.085)
Observations	69,875	69,875	61,815	61,815	68,120	68,120	72,835	72,835
R^2	0.067		0.068		0.099		0.094	
Number of companies	13,975	13,975	12,363	12,363	13,624	13,624	14,567	14,567

Standard errors in parentheses:*** p<0.01, ** p<0.05, * p<0.1.

As for influence of the corruption component the hypothesis on a significant negative relation between the corruption level and SMB performance was confirmed for the Western, Southern and Eastern regions. It is worth noting individually that positive values of coefficients are indicated in the presented results and it is indicative of the negative relation in virtue of the definition of the CPI index. The North Europe countries where this indicator is negative were an exception (which should not be approached with a critical eye because the difference between CPI values of the Northern region countries is small and all these CPI indicators are above the average on the general CPI scale), i.e. hypothesis 3 is rejected only for the northern countries.

The results obtained for the public and cultural determinants indicator may be called contradicting. The hypothesis on a significant positive relation of this indicator and SME performance is discarded for Western and Eastern Europe (the CDI indicator is insignificant). For Southern Europe the hypothesis was confirmed while for Northern Europe it was rejected with an unexpected result of a negative significant relation between the entrepreneurial determinants characteristic of population and SME performance efficiency.

The results concerning business climate from the macroeconomic point of view were mixed. Hypothesis 5 of a positive significant relation of indicators (ROA and BCC) was confirmed only for Northern Europe. In the Western region the hypothesis was discarded due to insignificance of the indicator. In the Southern and Eastern regions the hypothesis was also discarded, however, a significant negative relation between indicators was detected. While on the subject of founding an enterprise in a country we can emphasize a positive relation between costs on business startup and SME's return on assets in Eastern and Southern Europe (when the costs grow return on assets increases). In the Northern and Western regions costs on business startup are not significant. The obtained results are indicative of the fact that often (in this paper it concerns the sample of SME for Southern and Eastern Europe) SMB exists "in spite of, not thanks to".

Hypothesis 6 which asserts that there is a significant negative relation between the political risk level in a country and SME performance efficiency is admitted for the Northern and Eastern regions. In Western Europe the hypothesis was confirmed only concerning the political stability when it is represented as "a manifestation of people's sentiment" and was discarded concerning "power determinants" (the PCI variable is insignificant). The situation is reverse with the Southern region (the PCI indicator is significant while the PSI indicator – insignificant).

The hypotheses related to company determinants were confirmed similarly to the general sample results. A significant positive relation between SMB size and profitability is pointed out in three regions out of four. In Northern Europe this indicator is insignificant. A significant negative relation between financial leverage and SME's return on assets was revealed in all European regions.

Thus, let us sum up the results for each region separately.

Northern Europe

The level of innovative and technological development (the strongest influence among all studied regions) and macroeconomic environment have a positive influence on SME performance in Northern Europe. Taking into consideration insignificance of costs for business startup for SME of this region and a positive influence of macroeconomic environment we can speak of a favourable business climate. It should be noted that Northern Europe is the only region with a positive influence of business climate among all analyzed regions. The negative influence on SME's return on assets was detected with legal and political environment. The result of corruption analysis which showed a positive relation with SME performance was quite surprising but, as noted above, all values of the corruption indicator among Northern European countries indicate its extremely low level (except for Latvia, however, where this indicator is above the average).

Western Europe

In this region innovative development has a positive impact on SME's return on assets. Corruption and political environment have an adverse effect on SME performance. Other considered external factors (in particular: costs of business startup and macroeconomic environment, legal environment, public and cultural differences and political environment as an aggregate of government agencies' characteristics) were insignificant.

Southern Europe

Innovative development, legal environment, manifestation of people's sentiments in politics and the public and cultural factor have a positive effect on small and medium enterprises of the Southern region. At the same time costs, macroeconomic environment, political environment (as a power characteristic feature) and corruption have a negative impact on SME of Southern Europe. As for costs of business startup it should be noted that the research results show the following relation: the more the costs the higher the SME's return on assets in the region.

Eastern Europe

Innovations and technology development, legal environment and the public and cultural factor have no influence of SME of this region. Business climate, political environment and corruption, in their turn, have a negative impact on SME's performance in the region. Costs of business startup, similar to the Southern region, have a positive relation with SMB return on assets in the region.

Analysis of Influence of Country-Specific Determinants on Small and Medium Enterprises of Developed and Emerging European Countries

See the analysis results in Table 12. Similar to the collected results presented earlier here the hypotheses related to corporate determinants (size of small and medium enterprises is related significantly and positively to return on assets of such enterprises while financial leverage has a significant and negative relation with this indicator) are confirmed.

The innovative development level is positive and significant for SMB of developed countries. For SME of emerging countries the GII indicator is insignificant which manifests absence of influence of the technology innovative development level on return on assets in these countries. Hypothesis 1 is confirmed for developed countries and rejected for emerging countries.

Influence of legal environment of developed countries is positive, but it is significant only at a 10% level. This indicator is considered in the research for emerging countries separately and it is insignificant. Thus, hypothesis 2 is confirmed for developed countries and is rejected for emerging countries. However, from the point of view of lenders' and borrowers' rights protection hypothesis 2 is confirmed in both cases. The indicator of a democratic regime (political rights index (PRI)) and civil liberties index are positive and significant in both samples.

A positive coefficient of the CPI predicated variable for developed countries is indicative of a negative relation between the corruption level and SMB profitability, which is not the case with emerging countries. This phenomenon may be substantiated by a poor performance of financial and legal institutions as well as by the formal and informal institutional structure of each country (confirmed earlier by Tonoyan, Strohmeyer, Habib, Perlitz, (2010)). Thus, hypothesis 3 is confirmed for developed countries and rejected for emerging countries.

Table 12. Regression analysis results of samples for SME of developed and emerging countries

	Developed countries	Developed countries	Emerging countries	Emerging countries
GII	0.141***	0.0698***	–0.0162	0.00549
	(0.0208)	(0.0126)	(0.0575)	(0.0496)
ROL	0.565*	–1.028***		
	(0.321)	(0.251)		
LRI	0.398***	0.271***	0.427***	–0.170***
	(0.0699)	(0.0245)	(0.0766)	(0.0454)
CLI			0.322***	–0.0987***
			(0.0680)	(0.0332)
PRI			0.203***	0.141***
			(0.0421)	(0.0378)
CPI	0.0233***	–0.0272***	–0.0653**	0.0410**
	(0.00825)	(0.00515)	(0.0326)	(0.0197)
CDI		0.00545		0.102***
		(0.00553)		(0.0245)
CBS	–0.0325**	–0.109***	–0.439***	–0.199***
	(0.0156)	(0.0103)	(0.0916)	(0.0511)
BCC	0.129***	–0.00547	–0.327	–1.503***
	(0.0367)	(0.0331)	(0.205)	(0.184)
PCI	10.12***	0.559	–4.603**	0.162
	(1.002)	(0.381)	(1.902)	(1.205)
PSI	0.574***	0.0281	–1.038***	–1.437***
	(0.136)	(0.0862)	(0.245)	(0.192)

	Developed countries	Developed countries	Emerging countries	Emerging countries
LnEMP	0.424***	–0.238***	1.022***	–0.392***
	(0.0823)	(0.0385)	(0.166)	(0.0925)
DTA	–16.03***	–12.43***	–19.63***	–17.78***
	(0.307)	(0.162)	(0.566)	(0.347)
GEI	–0.0623***	–0.00804***	–0.122***	–0.0529***
	(0.00855)	(0.00298)	(0.0219)	(0.0167)
o.CDI	–		–	
Constant	0.885	11.12***	5.822	18.54***
	(1.372)	(0.540)	(3.755)	(1.970)
Observations	218,785	218,785	53,775	53,775
R^2	0.066		0.107	
Number of companies	43,757	43,757	10,755	10,755

Standard errors in parentheses:
*** p<0.01, ** p<0.05, * p<0.1.

The public and cultural factor turned out to be positive and it is significant for SME of emerging countries. For developed countries this indicator is insignificant.

Costs of business startup are of great significance for SME of emerging countries, however, in developed countries a negative (in its essence the relation is positive) significant relation between this indicator and SMB profitability was identified. Macroeconomic business climate is significant and positive for SME of developed countries (which disproves of hypothesis 5) and it is insignificant of entrepreneurs from emerging countries.

Analysis of influence of political stability in the countries confirmed the assumption that small business in emerging countries exists "in spite of". So, in developed countries the PCI and PSI indicators are related positively to SME profitability which is opposite to the results for SME of emerging countries (hypothesis 6).

The result concerning influence of the government machinery efficiency and SMB profitability was controversial. A negative significant relation of indicators in both samples was obtained.

Analysis of Influence of Country-Specific Determinants on Innovative Small and Medium Enterprises of European Countries

Table 13 states results of the regression analysis of the total sample of innovative SME and Table 14 – results of the regression analysis of innovative SME of European regions.

The results of the regression analysis of the total sample of innovative small and medium enterprises manifest efficiency of the policy of innovative SMEs' support implemented by the government which is manifested through a positive significant influence of the governance efficiency on SME's return on assets. However, it should be noted that this indicator is significant only at a 10% level.

Table 13. Results of the regression analysis of the total sample of European innovative SME

Variables	Total sample (fe)	Total sample (re)
LnEMP	0.360	–0.402**
	(0.285)	(0.174)
DTA	–13.89***	–12.46***
	(0.732)	(0.548)
CPI	0.0337	–0.0392*
	(0.0398)	(0.0228)
GII	0.0258	–0.00139
	(0.0849)	(0.0540)
ROL	–0.475	–1.538
	(1.652)	(1.290)

Variables	Total sample (fe)	Total sample (re)
LRI	–0.262	0.180*
	(0.171)	(0.0925)
PSI	–0.595	–0.919**
	(0.621)	(0.408)
GEI	0.0807*	–0.0111
	(0.0440)	(0.0195)
PCI	–0.282	2.898*
	(4.507)	(1.647)
o.CDI	–	
CBS	–0.204**	–0.231***
	(0.0906)	(0.0514)
BCC	0.155	0.187
	(0.191)	(0.174)
CDI		0.0861***
		(0.0290)

Variables	Total sample (fe)	Total sample (re)
Constant	5.924	15.25***
	(5.752)	(2.217)
Observations	8,920	8,920
R^2	0.051	
Number of companies	1,784	1,784

Standard errors in parentheses:

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

One of the hypotheses related to corporate determinants, namely, a negative significant relation between financial leverage and innovative SME performance was confirmed.

The public and cultural factor is defined as a significant one in influence on performance efficiency of European innovative SME.

As a result of the research also a significant positive influence of costs (in its essence) of business startup on SME performance was found out.

Considering the results of Table 13 one can note that in all samples financial leverage has a negative significant influence on SME's return on assets, thus confirming one of the hypotheses on corporate determinants.

Table 14. Results of the regression analysis of the total sample of innovative SME of certain European regions

Variables	North Eur (re)	West Eur (re)	South Eur (re)	East Eur (re)
LnEMP	0.100	–0.532	0.761	–0.184
	(0.509)	(0.354)	(0.463)	(0.382)
DTA	–12.77***	–11.54***	–14.45***	–10.33***
	(1.645)	(1.261)	(1.391)	(1.314)
GII		0.179		
		(0.127)		
ROL	1.09***	–1.031	4.536	2.458
	(4.394)	(1.803)	(3.957)	(8.008)
LRI	–1.363	–0.697	–0.00765	–0.553**
	(1.079)	(0.536)	(0.393)	(0.235)
PSI	–2.010	–1.705**	0.401	–0.979
	(2.017)	(0.826)	(1.265)	(0.920)

Variables	North Eur (re)	West Eur (re)	South Eur (re)	East Eur (re)
GEI		0.0346		
		(0.0287)		
PCI	13.70	3.797	–2.377	–2.681
	(23.78)	(2.679)	(6.906)	(3.847)
CBS	0.0552	0.0340	–0.231	–0.154
	(0.454)	(0.143)	(0.155)	(0.1000)
BCC	0.625	–0.0393	–0.781**	–1.500**
	(0.434)	(0.297)	(0.320)	(0.679)
CDI	0.151		0.293***	0.102
	(0.173)		(0.107)	(0.0803)
CPI			0.0668	0.0135
			(0.0457)	(0.0852)
Constant	21.20	4.730	–4.756	14.90***
	(22.57)	(8.717)	(4.419)	(4.961)
Observations	2,655	3,025	1,715	1,580
Number of companies	533	605	343	316

Standard errors in parentheses:

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

Northern region

The only significant indicator in the general model of the region is rule of law. Separately performed regressions for the indicators not included in the total sample allow to make the conclusion that the innovative development level has a positive impact on SME performance in the sample. This is not the case with government machinery efficiency and corruption. The obtained results are indicative of the necessity to go on improving the work of government authorities on SME support programs and of a positive influence of corruption on innovative SME performance.

Western region

A negative significant relation between political stability from the point of view of manifestation of people's sentiment (PSI) and performance efficiency of innovative SME (hypothesis 6 is confirmed) is revealed in the principal sample model. The regressions verified separately with corruption indicators and the public and cultural factor showed an insignificant result.

Southern region

Analysis of the principal model confirms hypothesis 4 on a positive influence of the public and cultural factor on success of innovative SME and also rejects hypothesis 5 because a negative relation between macroeconomic environment and return on assets of the SME from the sample was revealed. A separate analysis of regressions with the variables not included in the general model showed absence of influence of the country innovative development level and a positive influence of government machinery efficiency.

Eastern region

The principal model of this region showed a significant negative relation of return on assets of SME from the sample with rule of law from the point of view of credit relations and macroeconomic environment. The influence of government authorities efficiency and country innovative development considered separately is insignificant.

Conclusion

In this paper we present analysis of influence of country-specific determinants on corporate performance. The subject of research is SMB from 24 European countries.

According to the review of available literature and various mass media sources we detected dependencies between certain external environment factors and corporate performance which formed the basis for the eight hypotheses suggested in the research (six of them consider influence of external factors).

The research samples were compiled on the basis of the Forbes rating Best Countries for Business, geographical division of Europe into regions made by the United Nations Statistics Division and the criteria established by the European Commission for defining SMB. 54,512 small and medium enterprises were analyzed in the paper. The total number of observations amounted to 272,560 unique values. The Amadeus database (Bureau Van Dijk) was used to collect data.

The empiric part of the research is represented by the regression analysis of panel data applying fixed-effects models as the main ones and random-effects models due to presence of time-constant variables. The used time period is 2013–2017. The regressions comprised the following variables – corporate determinants often used in papers: return on assets (ROA), company size (number of employees) (LnEMP), financial leverage (DTA). The distinctive feature of the research is use of indexes as a manifestation of external influence factors – country-specific determinants.

On the basis of the results of the regression analysis we considered the suggested hypotheses on influence of the innovative development level, corruption, legal environment, political factors, business climate and public and cultural determinants on performance of small and medium enterprises. The results for all 24 European countries in the sample are indicative of a positive influence of development of innovation, legal environment and public and cultural determinants on SMB performance. Political environment and business climate have a negative impact on SME performance. Corruption was insignificant for SMB in Europe.

Considering regional analysis results we can emphasize their similarity to the conclusions of the Forbes rating Best Countries for Business concerning the Northern region of Europe as the most favourable area for SMB startup and operation and concerning the Eastern region of Europe as the least favourable in this respect. The Western region showed to a greater extent SME nonsusceptibility to the indirect factors considered in the conducted research. There is no straightforward assessment of the Southern region because its countries are located in a random way.

The results as regards indicators of business climate, political environment and governance efficiency are indicative of the reality where SMB exists "in spite of, not thanks to", except for the countries of the Northern region where a negative influence is registered only for the governance efficiency indicator. However, the indicator of credit relations protection manifests a positive trend in the national policy of the countries where SME's return on assets is lower.

From the point of view of developed and emerging countries interesting results were obtained. So, innovation and legal environment turned out to be insignificant for emerging countries and significant – for developed ones. A weak significant positive relation of corruption and SME's return on assets of emerging countries in the sample was revealed as a result of the research. Costs of business startup have a positive effect on SME of developed and emerging countries. Therein macroeconomic climate and political environment have a positive impact on SME's return on assets in developed countries while in emerging countries this influence is negative.

According to the research results the innovative SMB of Europe was susceptible to costs of business startup (a positive relation) and government authorities efficiency (a positive relation). The results are indicative of a positive influence of public and cultural characteristics on performance of these SME. Additional calculations also showed a positive influence of the democratic regime, economic freedom and civil liberties on return on assets of innovative small and medium enterprises.

When studying the research results on regional distinctive features of external factors' influence on innovative SME a negative relation with business climate of enterprises in the Southern and Eastern regions should be noted. The level of country innovative development is significant only for innovative SME of the Northern region. Government efficiency has a positive impact on SME of the Southern region and a negative impact on SME of the Northern region. According to the research results, the corruption component has a positive effect on innovative companies of the Northern region and remains insignificant in other regions. The public and cultural factor is significant only for the Southern region and has a positive effect on return on assets of innovative SME of this region.

In spite of the fact that the goals of this paper have been achieved there is still a series of fields which need further research. Thus, the issue of influence of direct external factors on performance of small and medium enterprises is still unresolved. Due to insufficiency of data in publicly available sources this topic is left unaddressed and earlier papers confirm it.

References

1. De Jong, Abe, Nguyen, Thuy Thu, Kabir, Rezaul. "Capital Structure Around the World: The Roles of Firm- and Country-Specific Determinants" Journal of Banking and Finance, vol. 32, no. 9, (2008).

2. Jõeveer, Karin. “Firm, country and macroeconomic determinants of capital structure: Evidence from transition economies”. Journal of Comparative Economics, Elsevier, vol. 41 no.1 (2013) 294-308.
3. Koralun-Bereźnicka J. “On the Relative Importance of Corporate Working Capital Determinants : Findings from the EU Countries”. Contemporary Economics, 8(4) (2014): 415–434.
4. Covin J. G., Slevin D. P. “Strategic management of small firms in hostile and benign environments.” Strategic Management Journal, 10(1) (1989): 75–87.
5. Rauch A., Frese M. “A contingency approach to small scale business success: A longitudinal study on the effects of environmental hostility and uncertainty on the relationship of planning and success.” Frontiers of Entrepreneurship Research (1998): 190–200.
6. Dobbs, M., & Hamilton R. “Small business growth: Recent evidence and new directions”. International Journal of Entrepreneurial Behaviour & Research, 13(5) (2007): 296–322.
7. Simpson M., Padmore J., Newman N. “Towards a new model of success and performance in SMEs.” International Journal of Entrepreneurial Behavior & Research, 18(3), (2012): 264–285.
8. Sinitsyna E.D., “*Sravnitel'nyi analiz effektivnosti nalogovykh i byudzhetnykh mer podderzhki malogo predprinimatel'stva v Rossii*” Vestnik VolGU. 9, no. 15 (2017): 138-145. (In Russ.).
9. Global Entrepreneurship Monitor. Global Report 2016/17. Global Entrepreneurship Research Association (GERA), 2017
10. Global Entrepreneurship Monitor Adult Population Survey. URL: https://www.gemconsortium.org/data/sets (дата обращения: 20.01.2019)
11. Podtserob M. « *S 2014 goda uroven' predprinimatel'skoi aktivnosti vyros v Rossii na tret' – GEM* ». 2017 URL: https://www.vedomosti.ru/management/articles/2017/02/07/676449-uroven-predprinimatelskoi-aktivnosti (дата оборащения: 13.03.2019) (In Russ.).
12. World Bank «Ease of Doing Business». URL: http://www.doingbusiness.org/en/rankings (дата обращения: 23.01.2019)
13. Konings J., Rizov M., Vandenbusschedet H. “Investment and financial constraints in transition economies: micro evidence from Poland, the Czech Republic, Bulgaria and Romania”. Economics Letters, 78, no. 2, (2003): 253–258.
14. Forbes «Best Countries for Business». URL:https://www.forbes.com/best-countries-for-business/list/#tab:overall (дата обращения: 23.01.2019)
15. Mc Cahery J., Lopez de Silanes F., Schoenmaker D., Stanisic D. “The European Capital Markets Study: Estimating the Financing Gaps of SMEs”, (2015)
16. Financing SMEs and Entrepreneurs 2018: An OECD Scoreboard, OECD Publishing, Paris. URL: http://dx.doi.org/10.1787/fin_sme_ent-2018-en
17. (дата обращения: 23.01.2019).
18. OECD Studies on SME and Entrepreneurship, OECD Publishing, Paris. URL: http://dx.doi.org/10/1787/978926423907-en (дата обращения: 20.01.2019).
19. McCahery J. A. «Estimating the SME Financing Gap in Europe», 2018
20. Rupeika-Apoga R. «Financing in SMEs: Case of the Baltic States». Procedia - Social and Behavioral Sciences. vol. 150, no.15, (2014): 116-125.
21. Simpson M., Tuck N., Bellamy S. “Small business success factors: The role of education and training.” Education and Training, 46(8/9), (2004): 481–491
22. Watson K., Hogarth-Scott S., Wilson N. “Small business start-ups: Success factors and support implications.” International Journal of Entrepreneurial Behavior & Research, 4(3) (1998): 217–238.
23. Khairullina D.R. “*Faktory, opredelyayushchie razvitie malogo biznesa.*” *Upravlenie ekonomicheskimi sistemami: elektronnyi nauchnyi zhurnal*. 97, no.3 (2017): 4. (In Russ.).
24. Cooper A. C., Gimeno-Gascon F. J., Woo C. Y. “Initial human and financial capital as predictors of new venture performance.” Journal of Business Venturing, 9(5) (1994): 371–395.
25. Russel D. “*Model' dlya analiza raboty soveta direktorov: rol' vnutrennikh i vneshnikh funktsii nezavisimykh direktorov*”. Journal of Corporate Finance Research / Korporativnye Finansy 2, no.2, (2010): 110-124. (In Russ.).
26. Theriou G., Chatzoudes D., Matlay H. “Exploring the entrepreneurship–performance relationship: Evidence from Greek SMEs.” Journal of Small Business and Enterprise Development, vol. 22 issue: 2, (2015): 352-375.
27. Meijaard, J., Brand, MJ. & Mosselman, M., “Organizational structure and performance in dutch small firms” Small Business Economics. 25, 1, (2005): 83-96
28. Choueke R., Armstrong R. “Culture: A missing perspective on small-and medium-sized enterprise development?” International Journal of Entrepreneurial Behavior & Research, 6(4), (2000): 227–238

29. Stewart W. H., Roth P. L. Risk propensity differences between entrepreneurs and managers: A meta-analytic review. Journal of Applied Psychology, 86(1), (2001): 145–153.

30. Shirokova G.V., Bogatyreva K.A. "*Vzaimosvyaz' predprinimatel'skoi orientatsii i rezul'tatov deyatel'nosti firmy: rezul'taty issledovaniya rossiiskikh firm malogo i srednego biznesa*" // Vestn. S.-Peterb. un-ta. 8, no. 1. (2014): 3–27. (In Russ.).

31. Mueller S. L., Thomas A. S. "Culture and entrepreneurial potential: A nine country study of locus of control and innovativeness." Journal of Business Venturing,16(1), (2001): 51–75

32. Benzing C., Chu H. M., Kara O. "Entrepreneurs in Turkey: A factor analysis of motivations, success factors, and problems." Journal of Small Business Management, 47(1), (2009): 58–91.

33. Country comparison. Hofstede Insights. URL: https://www.hofstede-insights.com/country-comparison/russia/ (дата обращения: 13.03.19)

34. NG, Siew Imm, LIM, Xin Jean. Are Hofstede's and Schwartz's values frameworks equally predictive across contexts? [online]. vol.21, no.1, (2019): 33-47.

35. Rogoff E. G., Lee M. S., Suh D. C. "Who done it?" attributions by entrepreneurs and experts of the factors that cause and impede small business success." Journal of Small Business Management, 42(4), (2004): 364–376.

36. Halabi C. E., Lussier R. N. "A model for predicting small firm performance: Increasing the probability of entrepreneurial success in Chile." Journal of Small Business and Enterprise Development, 21(1), (2014): 4–25

37. Karpak B., Topcu I. "Small medium manufacturing enterprises in Turkey: An analytic network process framework for prioritizing factors affecting success." International Journal of Production Economics, 125(1), (2010): 60–70.

38. Lampadarios E. "Critical success factors for SMEs: An empirical study in the UK chemical distribution industry." International Journal of Business and Management, 11(7), (2016): 67–82.

39. Shirokova G.V., Tsukanova T.V. "*Vliyanie natsional'noi institutsional'noi sredy na stepen' internatsionalizatsii firm malogo i srednego biznesa iz stran s perekhodnymi ekonomikami*" // Vestn. S.-Peterb. un-ta. 8, no. 1. (2012): 26–51. (In Russ.).

40. Gerardo L. Munck, 2003. Measures of Democracy, Governance and Rule of Law: An Overview of Cross-National Data Sets. URL: http://siteresources.worldbank.org/EXTWBIGOVANTCOR/Resources/Measuresofdemocracy.pdf (дата обращения: 27.02.19)

41. Vasilenok V.L.., Aleksashkina E.I. "*Razvitie predprinimatel'stva i faktory, ego opredelyayushchie*". Science journal NRU ITMO. Seriya «Ekonomika i ekologicheskii menedzhme» 12, no.1 (2013): 8-9. (In Russ.).

42. Audretsch D.B., Mahmood T. "New-firm survival: New results using a hazard function", Review of Economics and Statistics vol. 77, (1995): 97-103

43. Gupta, Kartick. "Do economic and societal factors influence the financial performance of alternative energy firms?". Energy Economics, Elsevier, vol. 65, (2017): 172-182.

44. Perez-de-lema D.G., Hansen P., Madrid-Gujjarro A., Silva-Santos J.L.(2018) "Influence of the business environment in the dynamics of innovation and in the performance of SMEs". International Journal of Innovation Management. URL: https://www.worldscientific.com/doi/abs/10.1142/S1363919619500440?journalCode=ijim (дата обращения: 17.03.2019)

45. Audretsch D.B. "New Firm Survival and the Technological Regime", Review of Economics and Statistics, 68, (1991): 520-526.

46. Agarwal R., Audretsch D.B. "Does Entry Size Matter? The Impact of the Life Cycle and Technology on Firm Survival" Journal of Industrial Economics, 49, (2001): 21-43.

47. Vu H., Tran T. Q., Nguyen T., Lim S. "Corruption, types of corruption and firm financial performance: New evidence from a transitional economy". Journal of Business Ethics, (2016): 1-12.

48. Safavian, Mehnaz S., Graham, Douglas H. "Corruption and Microenterprises in Russia". World Development, Elsevier, vol. 29(7) (2000): 1215-1224.

49. Tonoyan V., Strohmeyer R., Habib M., Perlitz M. "Corruption and entrepreneurship: how formal and informal institutions shape small firm behavior in transition and mature market economies", Entrepreneurship theory and practice 34 (5) (2010): 803-832.

50. Gladysheva A., Kishilova J. "*Vliyanie politicheskikh svyazei i gosudarstvennoi sobstvennosti na deyatel'nost' firm v Rossii*", Journal of Corporate Finance Research /Korporativnye Finansy. 12, no.1 (2018): 20-43. (In Russ.).

51. Hunady J. "Individual and institutional determinants of corruption in the EU countries: the problem of its tolerance." Economia Politica: Journal of Analytical and Institutional Economics, Springer; Fondazione Edison, vol. 34 no.1, (2017): 139-157

52. Sharma, Chandan & Mitra, Arup."Corruption, governance and firm performance: Evidence from Indian enterprises". Journal of Policy Modeling, Elsevier, vol. 37(5) (2015): 835-851.

53. Angulo-Ruiz F., Pergelova A. “The impact of government financial support on the performance of new firms: the role of competitive advantage as an intermediate outcome” Entrepreneurship & Regional Development, 26(9–10), (2014): 663–705.

54. Borbas L. “Supporting SMEs in Central-Eastern Europe.” Volume of Management, Enterprise and Benchmarking in the 21ST Century, (2014): 87 – 106

55. Berko L., Agota G. “Policy for Support of Small and Medium-size Enterprises in Hungary: The Case of the Central Region, Post-Communist Economies”. Post-Communist Economies, vol. 15 no. 2 (2003): 243 – 257.

56. Galbraith B., McAdam R., Woods J., McGowan T. “Putting policy into practice: an exploratory study of SME innovation support in a peripheral UK region”, Entrepreneurship & Regional Development (2017): 1-20

57. Bergström F. “Capital subsidies and the performance of firms.” Small business economics 14(3), (2000): 183–193.

58. Zhang H., Li L., Zhou D., Zhou, P. “Political connections, government subsidies and firm financial performance: Evidence from renewable energy manufacturing in China.” ' Renewable Energy' , 63(2) (2014): 330–336.

59. Hansen H., Rand J., Tarp, F. “Enterprise growth and survival in Vietnam: does government support matter?” The Journal of Development Studies, 45(7), (2009): 1048–1069.

60. Majocchi A., Valle L. D., D’angelo A. “Internationalisation, culture distance and country characteristics: a Bayesian analysis of SMEs financial performance” Journal of Business Economics and Management, 16(2) (2013): 307–324.

61. Delener N., Farooq O., Bakhadirov M. “Is Innovation a Determinant for SME Performance? Cross-Country Analysis of the Economies of Former USSR Countries.” Entrepreneurship in Transition Economies. Springer International Publishing (2017): 97–111.

62. Kwamena Minta Nyarku & Stephen Oduro. “Examining the Effect of Corruption and Bureaucracy on SMEs Growth in the Kumasi Metropolis of Ghana”. Universities, Entrepreneurship and Enterprise Development in Africa, German African University Partnership Platform for the Development of Entrepreneurs and Small/Medium Enterprises. (2017) URL: https://pub.h-brs.de/frontdoor/deliver/index/docId/3425/file/GAUP_Conference_Proceedings_2017_154.pdf

63. http://dx.doi.org/10.7819/rbgn.v0i0.3956. (дата обращения: 27.03.19)

64. Whittington G. “The profitability and size of United Kingdom companies, 1960-1974.” The Journal of Indus- trial Economics., 25(4) (1980): 334-352.

65. Hall M., Weiss L. “Firm size and profitability.” Review of economics and statistics, 49, (1967): 319 – 331

66. Ramasamy B., Ong D., Yeung M. C. H. “Firm size, ownership and performance in the Malaysian palm oil industry.” Asian Academy of Management Journal of Accounting and Finance., 1, (2005): 81 - 104

67. Gebreeyesus, M. (2009) Innovation and microenterprises growth in Ethiopia. UNU-MERIT working papers, http: www.merit.unu.edu/publications/wppdf/2009/wp2009-053.pdf. (дата обращения: 23.01.2019)

68. Modigliani F., Miller M. “Corporate income taxes and the cost of capital: A correction.” American Economic Review 53, (1963): 433–443.

69. Myers S., Majluf N., “Corporate financing and investment decisions when firms have information that investors do not have.” Journal of Financial Economics 13(2), (1984): 187-221

70. Degryse H., Goeij P., Kappert P. “The impact of firm and industry characteristics on small firms’ capital structure.” Small Business Economics 38(4) (2012):431-447

71. Mateev M., Poutziouris P., Ivanov K. “On the determinants of SME capital structure in Central and Eastern Europe: A dynamic panel analysis.” Research in International Business and Finance 27(1) (2013): 28-51

72. Serrasqueiro Z., Nunes P. “The capital structure of Portuguese SMEs: Empirical evidence using Dynamic Panel Data.” Transformation in Business & Economics 10(1), (2011): 62-80.

73. Zdráhal I., Chmelíková G., Blažková I. “Sector-Wide and Country-Specific Drivers of Firm Performance in the Visegrad Group Dairy Industry”, AGRIS on-line Papers in Economics and Informatics, vol. 10, no. 4 (2018): 89-100.

74. Sadeghi A. “Success factors of high-tech SMEs in Iran: A fuzzy MCDM approach.” The Journal of High Technology Management Research, 29(1), (2018): 71–87.

75. Kobrin S. J. “Political risk: a review and reconsideration.” Journal of International Business Studies 10(1) (1979): 67–80.

76. Butler K. C., Domingo Castelo J. “A note on political risk and the required return on foreign direct investment.” Journal of International Business 29(3) (1998): 599–607.

77. Henisz W. J. “The institutional environment for economic growth.” Economics and Politics 12(1) (2000): 1–31.

78. Zahra, S. A., & Garvis, D. M. (2000). International corporate entrepreneurship and firm performance: The moderating effect of international environmental hostility. Journal of Business Venturing, 15(5), 469-492.

79. Andersen T. J. "Multinational risk and performance outcomes: effects of knowledge intensity and industry context." International Business Review 21(2), (2012): 239–252.

80. Click R. W. "Financial and political risks in US direct foreign investment." Journal of International Business Studies 36(5) (2005): 559–575

81. Golikova V., Kuznetsov B. "Suboptimal Size: Factors Preventing the Growth of Russian Small and Medium-Sized Enterprises". Foresight and STI Governance, National Research University Higher School of Economics, vol. 11(3) (2017): 83-93.

82. Thapa A. "Determinants of microenterprise performance in Nepal." Small Business Economics, vol. 45, issue 3, (2015): 581-594.

83. Dagmar Vávrová. «Approaches to the classification of high-tech companies from the negative and positive point of view». Perspectives of Business and Entrepreneurship Development in Digital Age. 16 (2017): 125 - 136

What Impact does Artificial Intelligence have on Corporate Governance?

Irina Ivashkovskaya
Doctor of Economics, Professor Head of Corporate Finance Center (HSE) Head of School of Finance
National Research University Higher School of Economics,
ORCID
E-mail: iivashkovskaya@hse.ru

Ilya Ivaninskiy
PhD student, Department of Finance
National Research University Higher School of Economics
ORCID
E-mail: iivaninskiy@hse.ru

Journal of Corporate Finance Research, Vol. 14, No. 4, pp. 90-101 (2020)
DOI: https://doi.org/10.17323/j.jcfr.2073-0438.14.4.2020.90-101
Received 15 October 2020 | **Peer-reviewed** 23 October 2020 | **Accepted** 24 October 2020

What Impact does Artificial Intelligence have on Corporate Governance?

Abstract

In recent years, the topic of 'digital transformation' has become a primary focus in the areas of business and research. Among digital technologies, the area attracting the most investment is artificial intelligence (AI). Research shows that AI can benefit corporate governance in a variety of ways.

In this article, we identify two academic streams on the topic and evaluate the existing literature. The first stream analyses AI-driven improvements in governance mechanisms such as boards of directors (BoD). The second stream explores the digital-driven organisational changes and broad governance adaptations necessary for AI improvements. We evaluate the evidence for AI implementation in improving and evolving traditional aspects of corporate governance.

The examined authors argue that digital technologies transform the nature of a firm, making it less based on traditional sources of authority. There is consensus that this environment calls for fundamental reconsideration of corporate governance and for the revision of regulatory models, moving towards decentralisation. Specific areas examined in these contexts include jobs automation, agency conflict, auditing processes, the selection of BoD members, compliance functions, data analytics, and capital allocation.

The examined research indicates that AI improves corporate governance and lowers agency cost by automating decision making using real-time big data analysis. However, while researchers propose multiple novel approaches to governance, practical implementation of those approaches or an empirical analysis of the results of such experiments is yet to occur.

Despite the consensus among researchers on the positive impact of AI for governance and implementations as making AI a part of BoD, open questions and skepticism persist. This is indicative of the immaturity of AI as a technology in terms of development and implementation, and as such there is ample scope for future research. We propose multiple areas within this article where opportunities exist for further insight within this burgeoning field.

JEL classification: G32, G34

Key words: corporate governance, artificial intelligence, digital transformation

Introduction

In recent years, the topic of 'digital transformation' has become a primary focus in the areas of business and research. Technologies such as blockchain and the 'internet of things' are transforming the way firms operate, creating what has been termed the fourth industrial revolution' [1]; [2]. Among digital technologies, the area attracting the most investment is artificial intelligence (AI) [3]. AI has been defined as "a technology that applies systems to machines so that machines can think like humans" [4]. The existing literature on this topic covers three types of AI (from basic to advanced): 1) Robotic process automation - the automation of basic human tasks such as creation of reports, etc. [5]; 2) Machine learning – the automation of decision-making, often without human intervention [6]; 3) AI approximating human behavior - so called artificial general intelligence or "strong" AI [7]; [8]. It is worth noting that the third type of AI is currently only at the theoretical stage. Companies have been applying robotic process automation for a long time [9], but AI in the machine learning area only became possible and relatively wide-spread with recent advances of technologies such as deep learning, image recognition, and cheaper computing [10]; [11]. Research shows that AI has the potential to transform corporate governance in a fundamental way. In this article, we identify two literature streams on the topic. The first analyses AI-driven improvements of governance mechanisms such as boards of directors (BoD). The second stream explores the organisational changes and broad governance adaptations necessary to adapt to AI and other improvements in digital technology.

The first literature stream examines the logic of jobs automation and its implementation. While robots are not yet expected to replace people in offices, there are opportunities and a several potential benefits from process automation that would benefit multiple stakeholders involved in corporate governance (shareholders, BoD, auditors, etc.) [12]. It is worth noting that at the foundation of any type of AI lies big data analysis, which by itself is already beneficial from a corporate governance perspective [13]; [14]. However, machine learning promises to make the biggest difference to corporate governance tools. Issa et al. show that employing AI features increases the accuracy of external auditing [15]. Multiple authors have demonstrated that it may allow the shareholders, the BoD, and auditors to move from systems of periodically reviewing data samples towards a systems of continuous analysis of all the data available about a firm in real time [16]; [17]. Other potential benefits of AI go beyond information processing. For example, Erel et al. demonstrate that machine-learning outperforms humans when selecting BoD members [18], and Cunningham and Stein argue that it helps with anomalies detection [19]. Wang et al. argue that machine learning helps identify risk factors and prevent corporate misbehaviour [20]. Bae argues that a more accurate prediction of financial distress can assist with the better decision making of CFO and boardroom and benefit investors [21]. An adjacent literature stream covers "algorithmic governance", which explores full decision-making automation [22]. However, to the best of our knowledge, this stream is yet to cover the corporate governance. There are of course AI skeptics. For example, Dignam argues that AI may aggravate such problems as discrimination, create problem such as liability attribution, and that it should be treated with caution [23]. Williams et al. go so far as to argue that algorithms may discriminate on the basis of "the data they lack", i.e. discrimination resulting from the omission of certain parameters fed into models, which makes it even harder to detect [24].

Some researchers exploring the topic of organisational change have argued that digital technologies transform the nature of a firm, making it less based on traditional sources of corporate authority [25]. Parker and Van Alstyne highlight the importance of platform-based business models such as Uber [26], while Fenwick and Vermeulen highlight that digital technologies change "who, what, when, and how people 'trust'" [27]. These researchers agree that this environment calls for fundamental reconsideration of corporate governance, making it much more decentralised, to reflect the changing nature of the business. There have also been calls to revise regulatory models accordingly. Luna et al. argue for the benefits of agile governance [28], while Ansell and Gash explore the topic of collaborative governance [29].

The rest of this article is structured as follows: in section 2, we briefly review AI technology and the types currently in use; in sections 3 and 4, we review the literature according to the two categories of impact of AI on corporate governance mentioned above; in section 5, we provide conclusions and discuss some of the most promising areas for future research.

Artificial Intelligence

Given the relative novelty of the technology, there is not yet a single universally accepted definition for artificial intelligence. Farrow defines AI in a relatively broad way as "computer science aiming to perform tasks that replicate human or animal intelligence and behaviour" [30]. Eliasy and Przychodzen define it a more technical way as an "algorithm that is capable of learning and thinking. Learning is defined as the ability to update the coefficients and parameters of an algorithm…" [31]. Multiple authors draw a line between 'weak' and 'strong' AI [32]; [23] [10]. Where 'weak' AI is defined as focused on narrow tasks while 'strong' AI is "functionally equivalent to a human's intellectual capabilities" [10]. As mentioned in the introduction, 'strong' or 'general' AI does not exist in practice [33]; [23] [10] and hence, we do not devote a separate section to it.

Despite the diversity of definitions, the one feature that finds its way to all the definitions of AI is the processing of data. This feature is so important that some researchers even call current AI models "overly dependent on big data" [34]. In this section of the article we first talk about big data as a foundation of any type of AI; we then talk about the types of AI mentioned above and conclude with a brief overview of so-called "explainable AI" which is a separate stream of literature.

Big data as a foundation of AI

As mentioned above, big data is the foundation of any type of AI. While there are multiple definitions of what big data is, a consensual definition is "the information asset characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value" [35]. The technology by now can be considered as a rather mature one. There are numerous proprietary as well as open source solutions available for corporations to store, analyze and use big data in decision making. There are multiple studies demonstrating that the use of big data and advanced analytics are beneficial for many aspects of a firm's life across multiple industries and geographies [36]. Zhu shows that managers have less of an opportunity to trade on their private information for firms for which larger sets of alternative data are available, which is beneficial from the corporate governance perspective [37]. Multiple authors highlight the importance and benefits of big data analysis for auditing and accounting, which are very important corporate governance tools [38]; [39]. Cao, Chychyla and Stewart show how big data applications can improve the effectiveness of a financial statements audit [40], while Yoon et al. argue for the use of big data as complementary audit evidence [41]. Finally, Krahel and Titera call for a revision of accounting standards to include not only data representation, but also data creation and analysis [14].

Despite the benefits of big data usage, there are important limitations. Arguably the most important limitation involves the preservation of data confidentiality, especially where data is shared among multiple organisations. Van den Broek and van Veenstra show that organisations collaborating on the topic of big data tend to create a form of hierarchical governance arrangements when personal data and commercially sensitive data are used, although this hampers innovation [42]. Several authors bring an extra angle to the discussion by showing that less than 1% of world data is currently analysed, meaning that while there are already large volumes of data available for us, there is much more yet to come, and we can expect many more applications [43].

Robotic Process Automation as the most basic form of AI

As discussed in the introduction, the largest portion of research on AI follows the logic of jobs automation. Hence, it comes as no surprise that the most basic type of AI application is the application of algorithms to automate routine human tasks, such as report creation (known as 'Robotic Process Automation'). As Mendling et al. point out "The so-called robots are software programs that interact with systems such as enterprise resource planning and customer relationship management systems [44]. The robots can gather data from systems and update them by imitating manual screen-based manipulations". This application is relatively basic. Crosman even calls it "the lowest-IQ form of AI" [45]. Hence, only a few authors acknowledge it as AI [45]; [46]. Yet, this type of AI has been a reliable source of value creation for many firms across variety of industries. Fersht and Slaby argue that robotic process automation is a threat to traditional low-cost outsourcing [5]. Acemoğlu and Restrepo show that robotic process automation helps to replace low-skill jobs, which creates a threat of increased unemployment [47]. Moffit et al. demonstrate the importance of robotics for auditing purposes [48]. Lacity et al. show the successes of studies of robotics implementation in the context of a utilities company [49]. Aguirre and Rodriguez demonstrate that robots help improve the productivity of both front and back-office functions, although other authors point out that robots do not necessarily decrease the duration of operations [50].

Machine learning — currently the most advanced form of AI

Machine learning in its various forms is currently the most advanced type of AI that exists in practice. Brynjolfsson and Mcafee state that "the most important general-purpose technology of our era is artificial intelligence, particularly machine learning (ML)" [51]. As Kibria et al. point out, the terms 'machine learning' and 'AI' are often used interchangeably [52]. Eliasy and Przychodzen define such learning as "the ability to update coefficients and parameters of an algorithm to enable it to recognise the pattern between input and output data" [31]. The difference from the previously described AI applications, then, is the ability of the model to "update itself", as opposed to following pre-defined values. Mullainathan and Spiess highlight that the "…fundamental insight behind [the machine learning] breakthroughs is as much statistical as computational" [53]. Machine learning has multiple applications, e.g. Lightbourne has shown that it can significantly lower the cost of financial advice, making it more accessible for the general public [54], and is now applied by the largest investment firms [55].

Within the universe of machine learning models, there is an important type known as 'deep learning'. "Deep learning, a new frontier in AI focusing on computational models (deep neural networks) for information representation, has the capacity to automatically extract features from unstructured or semi-structured data like images, speech, text, video, etc." [15]. As Jarrahi nicely summarises, deep learning allows machines "to learn from raw data itself and expand by integrating larger data sets" [11]. While deep learning is currently at the cutting edge of machine learning, it raises important ethical problems, the most obvious being the lack of ability to explain exactly what is happening within the model, which gives rise to the stream of literature on 'explainable AI' (see the section after the next one).

Explainable Artificial Intelligence

The subject of AI in general raises several ethical concerns [56]. As mentioned before, deep machine learning in particular creates an important question in terms of outcomes' explainability. As Arrieta et al. put it, "when decisions derived from such systems ultimately affect humans' lives (as in e.g. medicine, law or defense), there is an emerging need for understanding how such decisions are furnished by AI methods" [6]. This is so because the algorithm itself not only picks the sizes of the coefficients, but also the set of parameters that define the outcome. This feature gave rise to a stream of research dedicated to the questions of the 'explainability' of AI [57]; [58]; [32]. The authors contributing to the stream explore the ways to ensure that decisions made using AI do not suffer from biases and do not discriminate, e.g. against certain groups of people. The importance of this topic was confirmed by cases whereby an Amazon recruiting algorithm discriminates against female work candidates. This case became public and Amazon had to discontinue the algorithm [23].

Impact of AI on traditional corporate governance

While robots are not yet walking the corridors of offices and AI sitting on a board of directors remains a relatively new and rare phenomenon, there are several real and potential use cases of AI for corporate governance discussed in literature [59]; [60]. These use cases mostly follow the logic of jobs automation, which implies that a significant portion of jobs may soon be automated. Frey and Osborne predict that automation may replace 47% of today's jobs [61]. The general conclusion within this literature stream is that AI improves corporate governance and lowers the agency cost [27] by automating decision making using real-time big data analysis [62]. We see two buckets in the existing literature on the topic of corporate governance: first, a discussion on the role of AI for providing reliable information for shareholders and BoD primarily through improved audit, which is an important governance mechanism [63]; and second, the automation of certain BoD and management functions, including selecting BoD members. An adjacent literature stream covers "algorithmic governance" exploring benefits and issues of full decision-making automation through complex algorithms [22].

AI for providing reliable information for shareholders and BoD

At the core of the principal-agent conflict lies information asymmetry between the shareholders and the management of a firm [64]. Management may manipulate the data demonstrated to the shareholders seeking its own private interests [12]. One mechanism applied to establish the required level of trust in the financial data is the hiring of external audit firms, which verify the accuracy of the financial statements [65]; [66]. This situation is suboptimal from several points of view. First, it makes BoD and shareholders wait for a quarterly report to appear to get a glimpse of their firm's operations [12]. Second, it focuses audit firms on a relatively routine process of manual raw data verification instead of focusing on more relevant services, such as assurance of information systems, etc. [67]; [68]; [69]. Moreover, Beisland et al.; Hope et al.; Francis and Wang show that audit quality remains an important concern for all stakeholders involved in the process [65]; [66]; [70]. Manita et al. point out some problems with current external audit processes that prevent audit from being a useful tool for the improvement of decision making. A major challenge is that it provides analysis of historical data and not of the forward looking information, which produces absolutely standardized results. These results do not satisfy the needs of all the potential decision makers [12]. Research shows that AI applications can potentially solve, or at least mitigate this situation.

As discussed above, big data is the foundation of any type of AI, and using data from various sources discussed above is beneficial from the corporate governance point of view. At the very minimum, these additional data sources should be used as a complementary evidence [41]. Manita et al. argue that even within a firm, data is increasingly generated automatically and stored in secure systems that allow very limited opportunities for manipulation [12]. Providing this data to shareholders would dramatically reduce information asymmetry and hence improve the governance of the firm. However, despite being generally beneficial, big data proliferation leads to a situation when information asymmetry changes its nature. Now governing bodies such as BoD need not only to get as much data as possible and ensure that the management-provided data is reliable - they also have to navigate the increasingly-complicated data landscape, adding an extra layer of challenge [71].

Several researchers (see e.g. [48] for detailed review) show that robotic process automation, as the most basic form of AI, is beneficial for audit firms that automate a bulk of tasks, while also increasing the output accuracy and focusing on more value-adding jobs [15]. However, the changes discussed above would require a significant adaptation of audit firms' business models and focus. Manita et al. argue that digitisation of audit firms may allow firms to check not only the historical, but also current information, which further limits the opportunities of management to manipulate information [12]. Krahel and Tiera argue that audit firms should spend time on data analysis rather on data collection [14]. Kim et al. show instruments for the analysis of big data, including identifying and eliminating redundant data [72].

While providing shareholders with more accurate and timely data is already an important step toward improving the corporate governance, machine learning application opportunities discussed in literature extend even further. Several authors argue that machine processing creates opportunity for audit firms to switch from reviewing sample documents to reviewing full data sets, thus creating so called continuous auditing, and enabling BoD and shareholders to access the data in real time, and not having to wait for the regular reports [16]; [73]; [40].

As we see, application of big data and AI has real benefits from the corporate governance point of view. But for these benefits to fully materialise, industry participants and regulators will need to adapt. Several researchers call for revision of accounting standards to include not only data representation, but also data creation and analysis [14]. It is important to note that large audit firms readily embrace the AI opportunities by investing in technologies such as IBM Watson, etc. [74].

While the promise of reduced principal-agent conflict seems clear, the actual consequences are yet to be researched empirically. Questions remain to be satisfactorily answered, including for example, do firms applying AI experience more or less conflict in the organisation, or do those firms have better corporate governance.

AI for minimising agency costs by decisions' automation

One of the root causes of the principal-agent conflict is a passive investor base, resulting from the dispersed ownership status of firms [75]. This root cause leads to two important consequences: 1) shareholders hire directors (and most notably independent directors) to represent their interests in the BoD; 2) BoD establishes rules and procedures to ensure that management does not abuse its power [18]; [76]. Research shows that AI and advanced big data analytics can bring significant improvements to both the aforementioned situations, and hence improve corporate governance and mitigate the principal-agent conflict. However, since both situations are relatively advanced in terms of development, we only see machine learning applications as appropriate tools to address them.

The process of selecting BoD members is a complicated one, involving not only selection, but also election of the directors. The selection of BoD members is among the most common causes for conflict at shareholder meetings [77]. Erel et al. show that machine learning outperforms humans in selecting BoD members [18]. The authors construct several machine learning algorithms to select the directors for a large set of firms and predict which directors would perform better in a firm. The support of shareholders on the next director election is used as a proxy variable for analysing directors' performance and show that the directors selected using AI algorithms perform better. The authors analyse which characteristics of directors are overrated in human analysis. As they put it, "the algorithm is saying exactly what institutional shareholders have been saying for a long time: that directors who are not old friends of management and come from different backgrounds are more likely to monitor management". However, the authors also note that algorithms should be used as an aid, not as a replacement for a human judgement. Despite the proposed advantages, to the best of our knowledge, this process is yet to be applied in practice.

Following a similar research pattern, Hernandez-Perdomo et al. propose a machine-learning solution for the assessment of a firm's corporate governance, picking the best performing firms as measured by RoA [78].

In theory, there is no reason why a firm would limit itself only to machine-learning-based directors selection. There are at least two instances, when a firm "hired" AI as a BoD member. In one case it was a Hong Kong-based investment fund [60] and an earlier case, it was Finnish software company Tieto [27]. However, since the evidence remains rather anecdotal, the success of these measures remains to be researched. More concretely, it is not clear whether this improves a firm's performance or even if shareholders appreciate such an initiative.

However, the potential benefits of AI expand beyond the BoD. Several researchers argue that automated data processing can potentially improve decision making and prevent management from abusing its power. At the very minimum, AI can improve the quality of internal reporting, including raising the quality of audit as discussed above [13], and can aid in anomalies detection [19].

However, the benefits go farther than that. Wang et al. argue that machine learning helps identify risk factors and prevent corporate misbehavior [20]. By using the random forest algorithm (a popular machine learning tool) in the context of the Chinese construction industry, Wang et al. detect 11 parameters related to corporate governance linked to corporate illegal activities. This instrument, authors argue, may be beneficial for investors as well as regulators to take proactive measures against such firms. Hajek and Henriques follow a similar pattern and suggest several machine learning methods for corporate fraud detection [79]. Pai et al. develop a model that helps detect potential corporate fraud, assisting auditors and ultimately, investors [80].

Kiron and Unruh expand the logic of using the predictive abilities of AI and argue that in the age of AI the BoD can improve their work by continuously monitoring firms' management by way of creating an AI-based monitoring system that identifies events that trigger alerts to the board throughout the year [81].

AI applications expand beyond monitoring activities by the BoD to improvement and automation of certain managerial decisions. Bae argues that AI may be a useful tool for the prediction of financial distress [21]. The authors construct an algorithm that allows them to predict the firms that are likely to face financial distress. This tool, they argue, can assist with better decision making by the CFO and boardroom, and ultimately benefit investors.

Libert et al. argue that AI has multiple uses in a boardroom, e.g. for tracking and suggesting optimal capital allocation in R&D by comparing the actions of a firm to its competitors; for scanning the market for new competitors by reviewing the press releases; and for analysing the internal communications to assess the corporate morale to improve the operational decision-making [71]. Authors propose three steps to take a full advantage of AI in corporate governance that are similar to the steps taken in the medical industry that has many successful AI use cases: 1) build what authors call the “corporate genome”, i.e. the dataset that encompasses the information on many firms, linking it to corporate performance; 2) quantify an individual company to assess its competitiveness and trajectory; 3) use AI to recommend a course of action to improve the organisation’s performance.

Despite the positive attitude, there are of course AI skeptics. Dignam argues that AI may aggravate problems such as discrimination, creates problems of liability attribution, and should be treated with caution [23]. The author proceeds to argue that the current perception of AI is too heavily biased by science fiction, and the general public may not fully understand the realities, including the nature of the firms dominating the corporate and technical space. Yet, Kleinberg et al. and Sunstein argue that algorithms, if applied properly, may help minimise discrimination resulting from the application of human judgement [82]; [83]. Lightbourne brings another angle to the discussion by raising the question of whether AI algorithms will fulfill its fiduciary duties in a similar way a human would [54].

Montes and Goertzel share similar concerns and point out that “AI is currently dominated by an oligopoly of centralised mega-corporations who focus on the interests of their stakeholders” [84]. They further argue that this situation is negative for smaller businesses with less capital and may be harmful for humanity overall in the longer run.

Algorithmic governance as a next stage of governance automation

Research on the topic of AI applications for decision making expands beyond the corporate governance use cases discussed above. As noted earlier, a very important feature of big data is the lack of opportunity for a human to analyse it in a comprehensive way. Hence, society will have to rely on algorithms to work with ever-increasing amounts of data. What is important is that people do not always have a full understanding of the inner works of the algorithms that impact their lives. As shown in several works [85]; [86]; [87], this may be beneficial or problematic for society at large. Researchers working in the field of algorithmic governance aim to ensure that society benefits from the emerging opportunities [22]. As Katzenbach puts it, “algorithmic governance is a form of social ordering that relies on coordination between actors, is based on rules and incorporates particularly complex computer based epistemic procedures” [88]. To the best of our knowledge, this field is yet to explicitly cover the topic of corporate governance. However, going forward, this promises to be an important topic.

Organisational change driven by AI and other digital technologies

Researchers working in the area of organisational change argue that digital technologies transform the nature of a firm. Fenwick and Vermeulen highlight that digital technologies change “who, what, when, and how people ‘trust’” [27]. These changes in turn require changes in corporate governance requirements, mechanisms and regulations.

Several authors argue that one of the key changes in the nature of the business driven by the emerging technologies is the rising importance of platform business models [25]; [26]; [89]; [90]; [91]; [92]. While there are multiple theories as to what exactly constitutes a platform business model and what features it has, arguably a good general definition is a firm that enables direct interactions between two or more distinct sides, where each side is affiliated with the platform; those sides retain control over the key terms of the interaction, as opposed to the intermediary taking control of those terms [90]. Parker and Van Alstyne show platform-organised technology firms (the most well-known are Apple, Amazon, Google, and Facebook) rank among the largest in terms of market capitalisation globally [26]. The authors explore the microeconomic features of such firms. Authors show that these firms face important trade-offs such as the degree of openness they apply, i.e. how long a firm retains rights to the innovations before opening it for other developers to build on. Using the Cobb–Douglas function, authors show that opening the code earlier and creating profits via royalties may be more profitable than keeping the code closed.

Fenwick, McCahery, and Vermeulen argue that there is no doubt that the platform model is replacing traditional economic theories based on organisations, firms, and markets [25]. These authors argue that the traditional corporate governance mechanisms are designed for the ‘old’ type of hierarchical organisations whose sole purpose is benefiting shareholders as opposed to a broader set of stakeholders involved in platform business models. Authors highlight that a narrow focus on shareholders’ benefits is suboptimal in the long run, as it creates an environment in which conservative decision-making is prioritised. Authors conclude that traditional governance is not optimal for the new type of platform organisation. They outline three strategies that make platform-based firms successful: 1) leveraging current and near-future digital technologies to create more ‘community-driven’ forms of organisation; 2) building an ‘open and accessible platform culture’; and 3) facilitating the creation, curation, and consumption of meaningful ‘content’. To make these strategies work, authors point out, much more open communications and governance are required.

Fenwick and Vermeulen show that there are two ways of implementing the new emerging technologies to the ‘old’ world of corporations [27]. The more basic one is the ‘retrofitting’ of a technology, i.e. using AI or blockchain to achieve cost savings of a traditional firm. Authors show that while this approach is relatively straightforward and clearly has its advantages, it definitely does not allow us to realise the full potential of the emerging technologies. Fenwick and Vermeulen argue that data-driven decision making, made possible by AI, may not fit the traditional model of corporate governance based on 'people and accountability'. It requires what the authors call "community-driven corporate governance", which would allow a broader group of people to make decisions without a central authority.

The discussion around the need for a change in governance expands beyond the field of corporate governance. Multiple researchers show that the current environment calls for a fundamental reconsideration of governance, making it more decentralised, and to revise regulatory models accordingly. This field is called collaborative governance. Ansell and Gash provide a comprehensive review [29]. Authors show that collaborative governance is a concept, and an alternative to adversarial and managerial modes of policymaking and implementation. It brings "public and private stakeholders together in collective forums with public agencies to engage in consensus-oriented decision making." Ansell and Gash identify parameters influencing the success of collaborative governance implementation. Examples of such parameters are a "prior history of conflict or cooperation, the incentives for stakeholders to participate, power and resources imbalances", etc. Additionally, the authors show factors crucial within the collaborative process: face-to-face dialogue, trust building, etc. Authors conclude that collaboration is most successful when "forums focus on 'small wins' that deepen trust, commitment, and shared understanding". However, the governance examples discussed by the authors do not include the field of corporate governance, which would be a very promising study.

Luna et al. bring another angle to the discussion of adjustments of corporate governance [28]. Authors look for opportunities to implement agile methodology in the corporate governance setting. Agile software development is a proven way to improve the process of software development and authors argue that the principles of the agile manifesto, such as "individuals and interactions over processes and tools" may be beneficial for corporate governance [93]. Authors conduct this research in the context of information and communication technology governance, which is a subset of corporate governance focusing on information technology (IT) and its performance systems and risk management. The authors conduct a comprehensive review of concepts of the principles of the 'Manifesto for Agile Software Development' [93] and the 'Critical Success Factors of Projects of implementation and improvement of Governance in ICT'. After identifying these principles, the authors conduct a survey of professionals in the field to show that both sets of principles are highly beneficial for each other and hence may be applied as a joined "agile governance" mode. While the conclusion is no doubt a very important one, the study is limited to ICT governance and not corporate governance in general, which would be a very important extension of the research.

As we have seen, emerging digital technologies pose fundamental questions of the basic principles of firms operations, making firms more open and decentralised. This creates the need for a review of traditional corporate governance mechanisms designed for traditional hierarchical business structures. While researchers propose multiple novel approaches to governance, to the best of our knowledge, there are yet to be practical implementations of those approaches or an empirical analysis of the results of such experiments, which creates an opportunity for future research.

Conclusion

As we have seen, AI in its various forms poses a great promise for improvement of corporate governance as we know it. Big data, as a foundation of any AI application is by itself already beneficial, as it may mitigate the instances of the typical principal-agent conflict. Process automation through the use of robotics may improve the quality of data available for shareholders, and hence empower them to make better decisions and decrease the disproportionate power of management. Machine learning techniques may automate or at least improve a significant part of the decision-making process, including the selection of BoD members, as well as helping to detect corporate misconduct. Importantly, AI creates an opportunity to transition from sporadic monitoring from the BoD and shareholders to continuous monitoring of management. At the same time, management would also benefit from AI through better information processing, and hence would be able to act in the best interest of the shareholders. Automation, of course, should be taken seriously and without rush, as more complex forms of AI create a spectrum of challenges involving the ability of people to understand how the decisions are made (hence, the explainable AI trend).

We have also seen that AI together with other emerging digital technologies changes the nature of business and firms. Firms are becoming more decentralised and inclusive of the interests of stakeholders beyond shareholders and management. This fundamental change creates a need for a broader "corporate governance overhaul". New proposed approaches to governance are more inclusive, and community- and consensus-based.

Despite the relative consensus among researchers on the positive impact of AI for governance and implementations as making AI a part of BoD, there are still multiple open questions. Do AI-exploring firms have better corporate governance and weaker levels of principal-agent conflict? Do shareholders appreciate it, i.e., does investment in AI make the shareholders friendlier or more hostile towards a firm's management? Do firms exploring alternative corporate governance benefit from it? What type of AI application is the best from the corporate governance point of view? What is the best way to proceed with AI implementation? These questions remain to be researched going forward and provide ample material for practical and academic evaluation.

References

1. Schwab K. The fourth industrial revolution. New York: Currency Books; 2017. 192 p.
2. Grove H., Clouse M., Schaffner L.G., Digitalization impacts on corporate governance. *Journal of Governance and Regulation*. 2018;7(4):51-63. DOI: 10.22495/jgr_v7_i4_p6
3. How to unlock innovation with deep tech. BCG. 2020. URL: https://www.bcg.com/featured-insights/how-to/invest-in-deep-tech-startups (accessed on 29.07 2020).
4. Go E.J., Moon J., Kim J. Analysis of the current and future of the Artificial Intelligence in financial industry with Big Data techniques . *Global Business and Finance Review*. 2020;25(1):102-117. DOI: 10.17549/gbfr.2020.25.1.102
5. Fersht P., Slaby J.R. Robotic automation emerges as a threat to traditional low-cost outsourcing. HfS Research Ltd. 2012. URL: https://www.horsesforsources.com/wp-content/uploads/2016/06/RS-1210_Robotic-automation-emerges-as-a-threat-060516.pdf
6. Arrieta A.B., Díaz-Rodríguez N., Del Ser J., Bennetot A., Tabik S., Barbado A., García S., Gil-López S., Molina D., Benjamins R., Chatila R., Herrera F. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*. 2020;58:82-115. DOI: 10.1016/j.inffus.2019.12.012
7. Franklin S. A foundational architecture for artificial general intelligence. In: Goertzel B., Wang P., eds. Advances in artificial general intelligence: Concepts, architectures and algorithms. Amsterdam: IOS Press; 2007;157:36-54. (Frontiers in Artificial Intelligence and Applications Series).
8. Goertzel B. The AGI revolution: An inside view of the rise of Artificial General Intelligence. Los Angeles, CA: Humanity+ Press; 2016. 612 p.
9. Yu L., Wang S., Lai K.K. An intelligent-agent-based fuzzy group decision making model for financial multicriteria decision support: The case of credit scoring. *European Journal of Operational Research*. 2009;195(3):942-959. DOI: 10.1016/j.ejor.2007.11.025
10. Feijóo C., Kwon Y., Bauer J.M., Bohlin E., Howell B., Jain R., Potgieter P., Vu K., Whalley J., Xia J. Harnessing artificial intelligence (AI) to increase wellbeing for all: The case for a new technology diplomacy. *Telecommunications Policy*. 2020;44(6):101998. DOI: 10.1016/j.telpol.2020.101988
11. Jarrahi M.H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*. 2018;61(4):577-586. DOI: 10.1016/j.bushor.2018.03.007
12. Manita R., Elommal N., Baudier P., Hikkerova L. The digital transformation of external audit and its impact on corporate governance. *Technological Forecasting and Social Change*. 2020;150:119751. DOI: 10.1016/j.techfore.2019.119751
13. Lombardi D.R., Bloch R., Vasarhelyi M.A. The current state and future of the audit profession. *Current Issues in Auditing*. 2015;9(1):10-16. DOI: 10.2308/ciia-50988
14. Krahel J.P., Titera W.R. Consequences of Big Data and formalization on accounting and auditing standards. *Accounting Horizons*. 2015;29(2):409-422. DOI: 10.2308/acch-51065
15. Issa H., Sun T., Vasarhelyi M.A. Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of Emerging Technologies in Accounting*. 2016;13(2):1-20. DOI: 10.2308/jeta-10511
16. Chan D.Y., Vasarhelyi M.A. Innovation and practice of continuous auditing. *International Journal of Accounting Information Systems*. 2011;12(2):152-160. DOI: 10.1016/j.accinf.2011.01.001
17. Zhang J., Yang X., Appelbaum D.A. Toward effective Big Data analysis in continuous auditing. *Accounting Horizons*. 2015;29(2):469-476. DOI: 10.2308/acch-51070
18. Erel I., Stern L.H., Tan C., Weisbach M.S. Selecting directors using machine learning. NBER Working Paper. 2018;(24435). URL: https://www.nber.org/papers/w24435.pdf
19. Cunningham L.M., Stein S.E. Using visualization software in the audit of revenue transactions to identify anomalies. *Issues in Accounting Education*. 2018;33(4):33-46. DOI: 10.2308/iace-52146
20. Wang R., Asghari V., Hsu S.-C., Lee C.-J., Chen J.-H. Detecting corporate misconduct through random forest in China's construction industry. *Journal of Cleaner Production*. 2020;268:122266. DOI: 10.1016/j.jclepro.2020.122266
21. Bae J.K. Predicting financial distress of the South Korean manufacturing industries. *Expert Systems with Applications*. 2012;39(10):9159-9165. DOI: 10.1016/j.eswa.2012.02.058
22. Danaher J., Hogan M.J., Noone C., Kennedy R., Behan A., De Paor A., Felzmann H., Haklay M., Khoo S.-M., Morison J., Murphy M.H. et al. Algorithmic governance: Developing a research agenda through the power of collective intelligence. *Big Data & Society*. 2017;4(2). DOI: 10.1177/2053951717726554
23. Dignam A. Artificial intelligence, tech corporate governance and the public interest regulatory response. *Cambridge Journal of Regions, Economy and Society*. 2020;13(1):37-54. DOI: 10.1093/cjres/rsaa002

24. Williams B.A., Brooks C.F., Shmargad Y. How algorithms discriminate based on data they lack: Challenges, solutions, and policy implications. *Journal of Information Policy*. 2018;8:78-115. DOI: 10.5325/jinfopoli.8.2018.0078

25. Fenwick M., McCahery J.A., Vermeulen E.P. The end of 'corporate' governance: Hello 'platform' governance. *European Business Organization Law Review*. 2019;20(1):171-199. DOI: 10.1007/s40804-019-00137-z

26. Parker G.G., Van Alstyne M.W., Choudary S.P. Platform revolution: How networked markets are transforming the economy and how to make them work for you. New York, London: W.W. Norton & Co.; 2016. 352 p.

27. Fenwick M., Vermeulen E.P. Technology and corporate governance: Blockchain, crypto, and artificial intelligence. *Texas Journal of Business Law*. 2019;48(1):1-15.

28. Luna A.J., Costa C.P., Moura H.P., Novaes M.A., do Nascimento C.A. Agile governance in information and communication technologies: Shifting paradigms. *Journal of Information Systems and Technology Management*. 2010;7(2):311-334. DOI: 10.4301/S1807-17752010000200004

29. Ansell C., Gash A. Collaborative governance in theory and practice. *Journal of Public Administration Research and Theory*. 2008;18(4):543-571. DOI: 10.1093/jopart/mum032

30. Farrow E. To augment human capacity – Artificial intelligence evolution through causal layered analysis. *Futures*. 2019;108:61-71. DOI: 10.1016/j.futures.2019.02.022

31. Eliasy A., Przychodzen J. The role of AI in capital structure to enhance corporate funding strategies. *Array*. 2020;6:100017. DOI: 10.1016/j.array.2020.100017

32. Gasser U., Almeida V.A. A layered model for AI governance. *IEEE Internet Computing*. 2017;21(6):58-62. DOI: 10.1109/MIC.2017.4180835

33. Domingos P. The master algorithm: How the quest for the ultimate learning machine will remake our world. New York: Basic Books; 2015. 354 p.

34. Lu H., Li Y., Chen M., Kim H., Serikawa S. Brain intelligence: Go beyond artificial intelligence. Mobile Networks and Applications. 2018;23(2):368-375. DOI: 10.1007/s11036-017-0932-8

35. De Mauro A., Greco M., Grimaldi M. A formal definition of Big Data based on its essential features. *Library Review*. 2016;65(3):122-135. DOI: 10.1108/LR-06-2015-0061

36. Chen M., Mao S., Liu Y. Big data: A survey. *Mobile Networks and Applications*. 2014;19(2):171-209. DOI 10.1007/s11036-013-0489-0

37. Zhu C. Big data as a governance mechanism. *The Review of Financial Studies*. 2019;32(5):2021-2061. DOI: 10.1093/rfs/hhy081

38. Al-Htaybat K., von Alberti-Alhtaybat L. Big Data and corporate reporting: Impacts and paradoxes. *Accounting, Auditing & Accountability Journal*. 2017;30(4):850-873. DOI: 10.1108/AAAJ-07-2015-2139

39. Ashbaugh H., Warfield T.D. Audits as a corporate governance mechanism: Evidence from the German market. *Journal of International Accounting Research*. 2003;2(1):1-21. DOI: 10.2308/jiar.2003.2.1.1

40. Cao M., Chychyla R., Stewart T. Big Data analytics in financial statement audits. *Accounting Horizons*. 2015;29(2):423-429. DOI: 10.2308/acch-51068

41. Yoon K., Hoogduin L., Zhang L. Big Data as complementary audit evidence. *Accounting Horizons*. 2015;29(2):431-438. DOI: 10.2308/acch-51076

42. Van den Broek T., van Veenstra A.F. Governance of big data collaborations: How to balance regulatory compliance and disruptive innovation. *Technological Forecasting and Social Change*. 2018;129:330-338. DOI: 10.1016/j.techfore.2017.09.040

43. Burn-Murdoch J. Study: Less than 1% of the world's data is analysed, over 80% is unprotected. The Guardian. Dec. 12, 2012. URL: https://www.theguardian.com/news/datablog/2012/dec/19/big-data-study-digital-universe-global-volume

44. Mendling J., Decker G., Hull R., Reijers H.A., Weber I. How do machine learning, robotic process automation, and blockchains affect the human factor in business process management? *Communications of the Association for Information Systems*. 2018;43(1):297-320. DOI: 10.17705/1CAIS.04319

45. Crosman P. How Artificial Intelligence is reshaping jobs in banking. *American Banker*. 2018;183(88):1. URL: http://files.parsintl.com/eprints/S060220.pdf

46. Van der Aalst W.M.P., Bichler M., Heinzl A. Robotic process automation. *Business & Information Systems Engineering*. 2018;60(4):269-272. DOI: 10.1007/s12599-018-0542-4

47. Acemoğlu D., Restrepo P. Robots and jobs: Evidence from US labor markets. NBER Working Paper. 2017;(23285). URL: https://www.nber.org/papers/w23285.pdf

48. Moffitt K.C., Rozario A.M., Vasarhelyi M.A. Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting*. 2018;15(1):1-10. DOI: 10.2308/jeta-10589

49. Lacity M., Willcocks L.P., Craig A. Robotic process automation: Mature capabilities in the energy sector. The Outsourcing Unit Working Research Paper. 2015;(15/06). URL: http://eprints.lse.ac.uk/64520/1/OUWRPS_15_06_published.pdf

50. Aguirre S., Rodriguez A. Automation of a business process using robotic process automation (RPA): A case study. In: Applied computer sciences in engineering: Workshop on engineering applications 2017. Cham: Springer-Verlag; 2017:65-71. DOI: 10.1007/978-3-319-66963-2_7

51. Brynjolfsson E., Mcafee A.N. The business of artificial intelligence. Harvard Business Review. July 21, 2017. URL:https://starlab-alliance.com/wp-content/uploads/2017/09/The-Business-of-Artificial-Intelligence.pdf

52. Kibria M.G., Nguyen K., Villardi G.P., Zhao O., Ishizu K., Kojima F. Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. *IEEE Access*. 2018;6:32328-32338. DOI: 10.1109/ACCESS.2018.2837692

53. Mullainathan S., Spiess J. Machine learning: An applied econometric approach. *Journal of Economic Perspectives*. 2017;31(2):87-106. DOI: 10.1257/jep.31.2.87

54. Lightbourne J. Algorithms & fiduciaries: Existing and proposed regulatory approaches to artificially intelligent financial planners. *Duke Law Journal*. 2017;67(3/4):651-679.

55. Tokic D. BlackRock Robo-Advisor 4.0: When artificial intelligence replaces human discretion. *Strategic Change*. 2018;27(4):285-290. DOI: 10.1002/jsc.2201

56. Butcher J., Beridze I. What is the state of artificial intelligence governance globally? *The RUSI Journal*. 2019;164(5-6):88-96. DOI: 10.1080/03071847.2019.1694260

57. Miller T. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*. 2019;267:1-38. DOI: 10.1016/j.artint.2018.07.007

58. Murdoch W.J., Singh C., Kumbier K., Abbasi-Asl R., Yu B. Interpretable machine learning: Definitions, methods, and applications. *Proceedings of the National Academy of Sciences*. 2019;116(44):201900654. DOI: 10.1073/pnas.1900654116

59. Willcocks L.P., Lacity M., Craig A. The IT function and robotic process automation. The Outsourcing Unit Working Research Paper. 2015;(15/05). URL: https://eprints.lse.ac.uk/64519/1/OUWRPS_15_05_published.pdf

60. Mosco G.D. AI and boards of directors: Preliminary notes from the perspective of Italian corporate law. *SSRN Electronic Journal*. 2020. DOI: 10.2139/ssrn.3531924

61. Frey C.B., Osborne M.A. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*. 2017;114:254-280. DOI: 10.1016/j.techfore.2016.08.019

62. Moll J., Yigitbasioglu O. The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review*. 2019;51(6):100833. DOI: 10.1016/j.bar.2019.04.002

63. Carcello J.V., Hermanson D.R., Ye Z. Corporate governance research in accounting and auditing: Insights, practice implications, and future research directions. *Auditing: A Journal of Practice & Theory*. 2011;30(3):1-31. DOI: 10.2308/ajpt-10112

64. Jensen M.C., Meckling W.H. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*. 1976;3(4):305-360. DOI: 10.1016/0304-405X(76)90026-X

65. Beisland L.A., Mersland R., Strøm R.Ø. Audit quality and corporate governance: Evidence from the microfinance industry. *International Journal of Auditing*. 2015;19(3):218-237. DOI: 10.1111/ijau.12041

66. Hope O.-K., Kang T., Thomas W., Yoo Y.K. Culture and auditor choice: A test of the secrecy hypothesis. *Journal of Accounting and Public Policy*. 2008;27(5):357-373. DOI: 10.1016/j.jaccpubpol.2008.07.003

67. Wallace W.A. The economic role of the audit in free and regulated markets: A look back and a look forward. *Research in Accounting Regulation*. 2004;17:267-298. DOI: 10.1016/S1052-0457(04)17012-4

68. Jeacle I. "And the BAFTA goes to […]": The assurance role of the auditor in the film awards ceremony. *Accounting, Auditing & Accountability Journal*. 2014;27(5):778-808. DOI: 10.1108/AAAJ-03-2013-1252

69. Andon P., Free C., Sivabalan P. The legitimacy of new assurance providers: Making the cap fit. *Accounting, Organizations and Society*. 2014;39(2):75-96. DOI: 10.1016/j.aos.2014.01.005

70. Francis J.R., Wang D. The joint effect of investor protection and Big 4 audits on earnings quality around the world. *Contemporary Accounting Research*. 2008;25(1):157-191. DOI: 10.1506/car.25.1.6

71. Libert B., Beck M., Bonchek M. AI in the boardroom: The next realm of corporate governance. MIT Sloan Management Review. Oct. 19, 2017. URL: https://static1.squarespace.com/static/576007632b8ddee314f02a2f/t/5c67b50c4e17b62748153034/1550300434251/MITSMR+-+AI+in+the+boardroom%2C+the+next+realm+of+corporate+governance.pdf

72. Kim D., Song S., Choi B.-Y. Data deduplication for data optimization for storage and network systems. Cham: Springer International Publishing; 2016. 262 p.

73. Kitchin R. Big Data, new epistemologies and paradigm shifts. *Big Data & Society*. 2014;1(1). DOI: 10.1177/2053951714528481

74. Kokina J., Davenport T.H. The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*. 2017;14(1):115-122. DOI: 10.2308/jeta-51730

75. Roe M.J. A political theory of American corporate finance. *Columbia Law Review*. 1991;91(1):10-67. DOI: 10.2307/1122856

76. Warther V.A. Board effectiveness and board dissent: A model of the board's relationship to management and shareholders. *Journal of Corporate Finance*. 1998;4(1):53-70. DOI: 10.1016/S0929-1199(97)00009-6

77. Buchanan B., Netter J.M., Yang T. Are shareholder proposals an important corporate governance device? Evidence from US and UK shareholder proposals. *SSRN Electronic Journal*. 2010. DOI: 10.2139/ssrn.1572016

78. Hernandez-Perdomo E., Guney Y., Rocco C.M. A reliability model for assessing corporate governance using machine learning techniques. *Reliability Engineering & System Safety*. 2019;185:220-231. DOI: 10.1016/j.ress.2018.12.027

79. Hajek P., Henriques R. Mining corporate annual reports for intelligent detection of financial statement fraud – A comparative study of machine learning methods. *Knowledge-Based Systems*. 2017;128:139-152. DOI: 10.1016/j.knosys.2017.05.001

80. Pai P.-F., Hsu M.-F., Wang M. A support vector machine-based model for detecting top management fraud. *Knowledge-Based Systems*. 2011;24(2):314-321. DOI: 10.1016/j.knosys.2010.10.003

81. Kiron D., Unruh G. Corporate 'purpose' is no substitute for good governance. MIT Sloan Management Review. Apr. 10. 2018. URL: https://sloanreview.mit.edu/article/corporate-purpose-is-no-substitute-for-good-governance/ (accessed on 29.07.2020).

82. Kleinberg J., Ludwig J., Mullainathan S., Sunstein C.R. Discrimination in the age of algorithms. *Journal of Legal Analysis*. 2018;10:113-174. DOI: 10.1093/jla/laz001

83. Sunstein C.R. Algorithms, correcting biases. *Social Research: An International Quarterly*. 2019;86(2):499-511. URL: http://eliassi.org/sunstein_2019_algs_correcting_biases.pdf

84. Montes G.A., Goertzel B. Distributed, decentralized, and democratized artificial intelligence. *Technological Forecasting and Social Change*. 2019;141:354-358. DOI: 10.1016/j.techfore.2018.11.010

85. Danaher J. The threat of algocracy: Reality, resistance and accommodation. *Philosophy & Technology*. 2016;29(3):245-268. DOI: 10.1007/s13347-015-0211-1

86. Pasquale F. The black box society: The secret algorithms that control money and information. Cambridge, London: Harvard University Press; 2015. 320 p.

87. Zarsky T. The trouble with algorithmic decisions: An analytic road map to examine efficiency and fairness in automated and opaque decision making. *Science, Technology, & Human Values*. 2016;41(1):118-132. DOI: 10.1177/0162243915605575

88. Katzenbach C., Ulbricht L. Algorithmic governance. *Internet Policy Review*. 2019;8(4):1-8. DOI: 10.14763/2019.4.1424

89. Evans D.S., Hagiu A., Schmalensee R. Invisible engines: How software platforms drive innovation and transform industries. Cambridge, MA: The MIT Press; 2008. 408 p.

90. Hagiu A., Wright J. Multi-sided platforms. *International Journal of Industrial Organization*. 2015;43:162-174. DOI: 10.1016/j.ijindorg.2015.03.003

91. Altman E.J., Tushman M.L. Platforms, open/user innovation, and ecosystems: A strategic leadership perspective. In: Entrepreneurship, innovation, and platforms: Advances in Strategic Management. 2007;37:177-207. DOI: 10.1108/S0742-332220170000037007

92. Leoni G., Parker L.D. Governance and control of sharing economy platforms: Hosting on Airbnb. *The British Accounting Review*. 2019;51(6):100814. DOI: 10.1016/j.bar.2018.12.001

93. Beck K., Beedle M., Van Bennekum A., Cockburn A., Cunningham W., Fowler M., Grenning J., Highsmith J., Hunt A., Jeffries R., Kern J. et al. Manifesto for agile software development. 2001. URL: https://moodle2019-20.ua.es/moodle/pluginfile.php/2213/mod_resource/content/2/agile-manifesto.pdf (accessed on 16.08.2020).