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Applying Complementary Credit Scores to Calculate Aggregate Ranking

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Abstract

Researchers have been improving credit scoring models for decades, as an increase in the predictive ability of scoring even by a small amount can allow financial institutions to avoid significant losses. Many researchers believe that ensembles of classifiers or aggregated scorings are the most effective. However, ensembles outperform base classifiers by thousandths of a percent on unbalanced samples.

This article proposes an aggregated scoring model. In contrast to previous models, its base classifiers are focused on identifying different types of borrowers. We illustrate the effectiveness of such scoring aggregation on real unbalanced data.

As the effectiveness indicator we use the performance measure of the area under the ROC curve. The DeLong, DeLong and Clarke-Pearson test is used to measure the statistical difference between two or more areas. In addition, we apply a logistic model of defaults (logistic regression) to the data of company financial statements. This model is usually used to identify default borrowers. To obtain a scoring aimed at non-default borrowers, we employ a modified Kemeny median, which was initially developed to rank companies with credit ratings. Both scores are aggregated by logistic regression.

Our data Russian banks that existed or defaulted between July 1, 2010, and July 1, 2015. This sample of banks is highly unbalanced, with a concentration of defaults of about 5%. The aggregation was carried out for banks with several ratings. We show that aggregated classifiers based on different types of information significantly improve the discriminatory power of scoring even on an unbalanced sample. Moreover, the absolute value of this improvement surpasses all the values previously obtained from unbalanced samples.

The aggregated scoring and the approach to its construction can be applied by financial institutions to credit risk assessment and as an auxiliary tool in the decision-making process thanks to the relatively high interpretability of the scores.

Keywords: forward stepwise selection, logistic regression, Kemeny median, credit scoring, statistical learning

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Introduction

Scoring models have been developing for decades. Researchers have proposed and compared different approaches to data preparation for model construction and approaches to selecting factors which influence credit quality and their generation. They have also studied the best approaches to assessing credit score capability/accuracy and the credit score methods themselves. This was done to improve scoring accuracy, insofar as a gain or loss of a percentage point in accuracy can lead to multimillion profits or losses for banks and other financial institutions [1].

Over the past ten years, scholars have believed that the best practice is to use machine learning models [2] and so-called "ensembles" [3] to construct credit scores. The basic idea of an ensemble lies in the aggregation of modelled base classifiers (scores) with the help of a model/algorithm. There exist different classifications of ensembles [3–5]; however, their division into bagging, boosting, and stacking ensembles is the most common. Bagging is the combination of several independent scorings (base classifiers, weak learners) constructed in a parallel way on the basis of independent random samples. Random forests are a well-known example of bagging. Boosting is the aggregation of several successively constructed base scorings. Stacking is the combination of different base classifiers (for example, logistic regression and a decision tree) that are trained simultaneously. They are combined in the ensemble model (strong learner), which includes different voting rules, statistical models and machine learning methods. The ensemble paradigm makes ensembles relevant: several aggregated classifiers usually show greater discriminatory power/accuracy than a single classifier [5]. Nevertheless, some researchers have shown that ensemble models sometimes fail to surpass machine learning methods in regard to certain criteria [4; 6]. Also, their practical applicability is usually limited: in most cases, they are "black boxes" which are difficult to interpret because machine learning methods and other ensembles are often used as the base classifiers. Therefore, some researchers [7] have attempted to simplify the interpretability of ensemble models, including machine learning methods.

In this paper, we focus on using complementary weak learners to calculate aggregate rankings. We chose the logistic model of defaults and a modified Kemeny median [8] as two weak classifiers of this type due to their relatively high interpretability. We consider them to be complementary for our purposes for the following reasons:

The logistic model (regression) is usually trained for defining default borrowers using corporate financial statements. In other words, the first weak learner is focused on default borrowers.

The modified Kemeny median has been proposed as a tool for credit rating aggregation. Usually, companies which have a better-than-average creditworthiness want to have credit ratings in particular because they are ready to disclose to a rating agency more information than just financial statements. So, this ranking is potentially aimed at non-default companies.

We propose to use logistic regression as the strong learner. It should be noted that logistic regressions, including ridge and lasso, were used as ensemble models in [1; 9] and proved to be superior to other methods considered in these papers.

Our study is based on a sample of banks during the period between July 1, 2010, and July 1, 2015. This sample is characterized by a low default concentration of 5.76%. Financial performance indicators, identifiers of external or government support, and ratings of credit rating agencies were used to create rankings. It was shown that the aggregation of two base classifiers focused on the identification of different types of borrowers results in an improvement of the predictive power of aggregated credit scoring in comparison to base classifiers.

The interpretability of weak and strong learners makes it possible to use aggregate rankings not only as an additional parameter for decision making in financial institutions but also to evaluate default probability in risk management [10; 11]. The proposed weak learners constitute the scientific novelty of this paper: they were trained using potentially complementary information (ratings and financial statements). We know of only one similar study [12] that trained weak learners using market indicators and financial statements. However, the ensemble did not outperform the base classifier in discriminatory power [12].

Literature Review

The number of papers devoted to credit scoring methods has grown exponentially over the past 30 years [3]. In the last five years, researchers have continued their attempts to improve credit scoring for legal entities [13–15]and even more so for financial institutions involved in lending to SMEs. The importance of credit scoring has increased recently because of the financial crisis and increased capital requirements for banks. There are, however, only few studies that develop credit coring models for SME lending. The objective of this study is to introduce a novel, more accurate credit risk estimation approach for SMEs business lending. Based on traditional statistical methods and recent artificial intelligence (AI). However, the majority of papers make use of databases of natural persons [16]. The reason is that such databases are in open access and available for parsing. These samples have been used to compare well-known approaches to credit scoring calculation [17] the volume of databases that financial companies manage is so great that it has become necessary to address this problem, and the solution to this can be found in Big Data techniques applied to massive financial datasets for segmenting risk groups. In this paper, the presence of large datasets is approached through the development of some Monte Carlo experiments using known techniques and algorithms. In addition, a linear mixed model (LMM) and propose new ones [18]. Different ensembles [18; 19] and logistic regressions [20] have been identified as the best scoring methods. In addition, papers dedicated to the comparison of well-known methods often consider neural networks [21] and decision trees [22] to be the best.

Such a diversity of best methods is partially explained by the wide range of simultaneously applied classification quality criteria. Many authors [4; 9] agree that it is better to use several model performance measures at once. Nevertheless, other researchers [23; 24] continue to apply only conventional methods calculated on the basis of an error matrix.

In this paper, we propose looking at credit scoring aggregation from a slightly different perspective. Usually, only one type of data is used to create base scorings: financial statements or characteristics of natural persons [25]normally taking between 50% and 80% of the total project time. It is in this stage that data in a relational database are transformed for applying a data mining technique. This stage is a complex task that demands from database designers a strong interaction with experts having a broad knowledge about the application domain. Frameworks aiming to systemize this stage have significant limitations when applied to Credit Behavioral Scoring solutions. This paper proposes a framework based on the Model Driven Development approach to systemize the mentioned stage. This work has three main contributions: 1 or company market indicators [13]and even more so for financial institutions involved in lending to SMEs. The importance of credit scoring has increased recently because of the financial crisis and increased capital requirements for banks. There are, however, only few studies that develop credit coring models for SME lending. The objective of this study is to introduce a novel, more accurate credit risk estimation approach for SMEs business lending. Based on traditional statistical methods and recent artificial intelligence (AI. Indicator categories from financial statements complement each other, and machine learning methods can be applied to assess the nonlinear relations between them. However, the creditworthiness of a company may be characterized by factors that are recorded only partially or not at all in statements. These ratings may potentially complement the indicators of corporate financial statements: companies disclose more information to credit rating agencies (CRAs) than one can find in the public domain [26]. In addition, companies with a better creditworthiness, all other things being equal, tend to resort to CRAs: such companies are developing and need external ratings to expand into new markets, for example. Thus, one may conjecture that the collective opinion of credit rating agencies may complement information from financial statements.

In this paper, we will use classical logistic regression as the base classifier and as the aggregated model. This practice was applied in the sample is class imbalanced [9; 27]. Class imbalance may affect the accuracy of default predictions, as classifiers tend to be biased towards the majority class (good borrowers, which showed the advantage of this approach over base classifiers.

In order to calculate base classifiers, a preliminary preparation of data is carried out. One of the stages of preliminary preparation is parameter selection by means of forward feature selection. Nevertheless, it is necessary to describe the data sample before we explain the methodology in detail. This is due to the fact that the choice of methods depends on the data.

Data

The main data pool comprises publicly available information on 958 banks for the period between July 1, 2010, and July 1, 2015, which represents approximately 80% of all banks operating in the Russian Federation during this period. 134 of these banks had two or more ratings calculated by seven credit rating agencies: AK&M, Expert RA (EXP), National Rating Agency (NRA), RusRating (RUS), Fitch Ratings, Moody's Analytics, and Standard & Poor's. This data pool was formally divided into three parts: data on banks up to July 2014, data on banks after July 2014, and data on banks with two and more credit ratings.

Data on banks up to and including July 2014 comprises 70% of the observations of the main pool or 13,570 observations. The default concentration is 4.6%. In terms of default/non-default observations, this sample is highly unbalanced. It comprises indicators from bank report forms 101 and 102 and statutory requirements information (form 135) posted on the website of the Bank of Russia[1] and information on support from the Russian government or foreign banks. This sample was used to train the logistic model of defaults.

Data on banks after July 2014 consists of 4,261 observations with a default concentration of 9.25%. The list of indicators was the same as in the sample described above. This sample was used to test the logistic model of defaults.

Data on banks with two and more credit ratings is part of the two samples described above. This sample consists of observations on 134 banks. The sample size is 1,700 observations, 17 of which are defaults. This sample is also unbalanced and has a default concentration of 2.72%. In addition to the indicators described above, it includes CRA ratings. For the purposes of creating scoring ratings, categories were assigned numerical values, where 0 was attributed to the higher rating category of each credit rating agency (CRA). Then, the numerical value of each lower category was increased by 1. As the last two columns of Table 1 show, the number of assigned rating categories varied greatly from agency to agency.

[1] URL: https://www.cbr.ru/credit/

Table 1. Descriptive statistics of 7 CRA ratings

Variable	Number of observations	Average	Mode	Standard deviation	Min.	Max.
AK&M	209	1.92345	2	0.67502	1	4
EXP	652	1.63497	2	0.87912	0	6
FCH	609	4.92939	0	3.78709	0	14
MDS	1108	6.22563	9	3.12457	0	15
NRA	627	3.70973	3	1.73995	0	13
RUS	246	4.23577	6	2.57644	0	10
SNP	511	5.04305	6	2.8694	0	21

Source: author's calculations.

If we consider previous papers that, in one way or another, studied CRA ratings using Russian data (for example, [28]), we see that the general distribution of agency ratings has changed little. The most frequent ratings are low ratings in the investment grade or best ratings in the speculative grade. The data on ratings is taken from the RUData system[2]. Consensus and aggregate rankings are calculated using this sample.

The low default concentration and small size of the sample of banks with several ratings is insufficient for dividing it into training and test samples to create a logistic model. This is why samples of banks with one or no ratings are used in this study.

Methodology

This chapter consists of several parts. "Logistic Regression" describes the preliminary preparation of data for making a scoring using the logistic model of defaults, the logistic model itself, and ways of validating it. "Modified Kemeny Median" has a similar structure. "Aggregation" describes the mechanism for aggregating the two rankings obtained from the logistic model and the modified Kemeny median. "Model Power Indicator" describes the tool applied to verify the efficiency (power) of obtained rankings.

Logistic Regression

Linear prediction of the logistic model of defaults or the "continuous" rating of the defaults prediction model is used as the first baseline ranking (classifier) [29]. Due to its simplicity, transparency, interpretability and a relatively high discriminatory power, this scoring model continues to be the industry standard [3; 28].

Data preparation. In this paper, observations with missing data were not used for building the logistic regression. Such an approach is frequently used for calculating credit scorings [23; 24], insofar as it does not generate a bias of estimators due to an inappropriately chosen way of imputation of missing values [30]. The forward stepwise selection method was used for features selection for the logistic model. This approach adds a relevant variable to the defined significant variables. If this variable is significant and significantly improves the model, it is also included. In spite of its simplicity, this approach is still widely used to select parameters [16]. Multicollinearity was controlled by means of a correlation matrix. It was controlled both at the intermediate stage of model building and at the final stage.

Logistic regression. In credit scoring problems, the logistic model may be formulated as follows: bank i has rating y_i, which is equal to 0 if there is no bank default and 1 if there is bank default. This rating depends on the latent variable y_i^*, which represents the bank credit quality:

$$y_i = \begin{cases} 1 \ \mathit{if} \geqslant 0 \ (\mathit{default}) \\ 0 \ \mathit{otherwise} (\mathit{no\ default}) \end{cases}, \quad (1)$$

1 *if* $y_i^* \geqslant 0$ (default).
0 *otherwise* (no default)

In turn, y_i^* linearly depends on X – factors that may predict the bank creditworthiness. They may be continuous and categorical quantities that represent relevant financial, macroeconomic and other indicators. In this case, the probability of a bank being default or non-default is as follows, respectively:

$$P(y_i = 1) = P(y_i^* \geq 0) = P(X_i'\beta + \varepsilon \geq 0); \quad (2)$$
$$P(y_i = 0) = 1 - F(X_i'\beta),$$

where X_i' is the transposed matrix of factors describing the bank's creditworthiness, ε is an unobservable random component with logistic distribution, and F is a logistic

[2] URL: https://rudata.info/

distribution function. The linear predictions are calculated as follows:

$$R_i^{contin} = \sum_{j=1}^{n} X_i^{'}\beta.$$

In this paper, R^{contin} is used as one of the base scorings focused on default borrowers.

Validation. The complete sample of banks is used to build the logistic model, regardless of whether they have a rating or not. This sample is divided into training and test subsamples. This is done on an out-of-time basis and it's no coincidence. Such a validation method is used in credit scoring studies [31; 32].

Modified Kemeny Median

Data preparation. Unlike the previous method, observations with missing data for certain variables were used for building a modified Kemeny median (consensus ranking). To create a consensus ranking, we used the ratings of seven rating agencies operating in Russia from July 2010 to July 2015.

Modified Kemeny median. Another base classifier is represented by the Kemeny median [8], whose application results in the so-called "consensus ranking". This method is based on the interpretation of credit rating as a relative ranking of objects in accordance with a CRA's opinion on the credit quality of each object. On the basis of the ratings specific nature as expert information, we modified the concept of Kemeni distance between rankings. This made it possible to find a unique solution that least contradicts the opinions of rating agencies with an acceptable accuracy within an acceptable time:

$$R^{cons} = argmin \sum_{k=1}^{m} \varphi_k \left[\tilde{d}\left(R, R_k\right) + \lambda \delta^2 \left(R, R_k\right) \right], \qquad (3)$$

where R^{cons} is the resulting (aggregated) rating, m is the number of aggregated ratings, R_k is the kth rating, $d\left(R', R''\right)$ is the rank measure of distance between ratings R' and R'' (number of contradictory rankings for all pairs of companies), λ is the regularization parameter (relative significance of the secondary criterion), $\delta^2\left(R', R''\right)$ is the additional (secondary) criterion (shows the extent of contradiction significance),

and $\varphi_k > 0, \sum_{k=1}^{m} \varphi_k = 1$

are weights representing the degree of confidence in the ratings of a given agency.

R^{cons} is a non-strict bank ranking. Each combination of ratings is assigned its own numerical value, and so the granularity degree of R^{cons} depends on the number of such combinations, and the order of each combination in R^{cons} depends on its inconsistency with other ratings.

Validation. It is impossible to apply common validation measures such as cross-validation types to this method. The reason is that the modified Kemeny median is a result of a non-parametric approach that cannot be used for another sample directly without mapping.

The Kemeny median was originally a voting method that was subsequently used as an aggregator of credit ratings for banks. The collective opinion of credit rating agencies may complement information from financial statements: companies disclose to credit rating agencies information which may be absent from publicly available data. Thus, it is expected that the combination of the logistic model of defaults built on publicly available data and the ranking obtained from CRA ratings will surpass these base classifiers.

Aggregation

Logistic regression is applied as a strong classifier in this paper. The binary default/non-default variable y_i, arranged in the same way as in function (1), still serves as the interpretable factor. However, to create an aggregated scoring, y_i is predicted using the following two factors:

$$P\left(y_i = 1\right) = F\left(\gamma_0 + \gamma_1 R_i^{contin} + \gamma_2 R_i^{cons} + \varepsilon \geq 0\right), \qquad (4)$$

where γ_j is a coefficient obtained from assessing the logistic regression with the help of the maximum likelihood method and F is the logistic distribution function. The aggregated scoring itself is calculated as follows:

$$R_i^{agregated} = \gamma_0 + \gamma_1 R_i^{contin} + \gamma_2 R_i^{cons}. \qquad (5)$$

Model Power Indicator

We use the indicator of the area under the ROC curve (hereafter, AUCROC) as a measure of the discriminatory power of all scorings. This indicator is appropriate for unbalanced samples – in particular, because it takes different errors into account [1, p. 2]. In addition, this indicator does not underrate or overrate its values due to erroneous classification or default distribution [7, p. 38]. The resulting indicator values should be interpreted as follows: the closer the AUCROC value to 1, the greater the discriminatory power of the credit indicator. This indicator is described in more detail in [33].

The statistical significance of differences between the AUCROC of base classifiers and the aggregated model is defined by means of the DeLong, DeLong and Clarke-Pearson test [34] at a 10% significance level.

Results

This section deals with the discriminatory powers of credit scorings made with the help of base classifiers and through the aggregation of scorings.

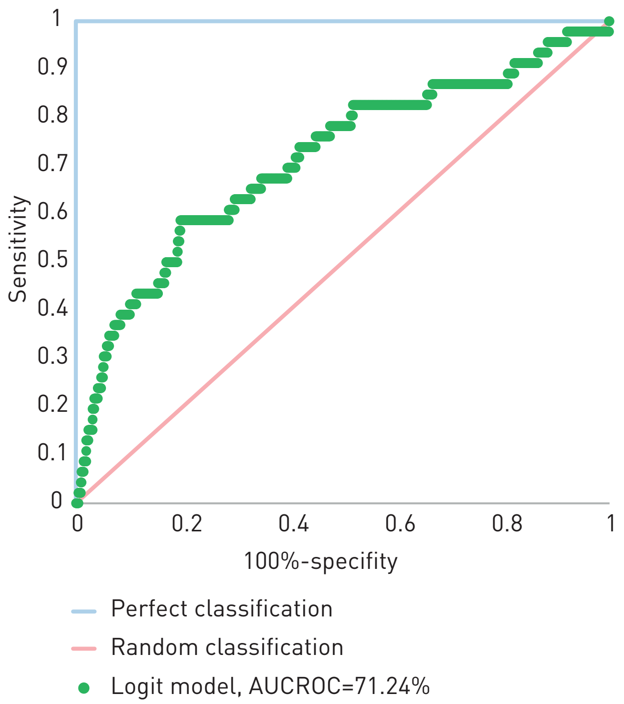
Logistic Model of Defaults

The model was trained on a sample of Russian banks from the period July 1, 2010 – July 1, 2014. The following factors were selected:

1) Ratio of the deposits of a legal entity to its bank assets.
2) Regulatory requirement of "the biggest possible credit risks" H7.
3) Regulatory requirement of long-term liquidity H4.
4) Amount of granted short-term credits.

The AUCROC of the obtained logistic model is equal to 68.26%. In the test sample, the AUCROC is 70.03%. The AUCROC consistency in these two non-overlapping samples indicates that the model has not been retrained. In the sample of banks with two and more ratings, the AUCROC is equal to 71.4% (Figure 1). The quicker growth of ROC diagram at the origin means that the default model defines default banks better.

Figure 1. ROC and AUCROC of the logistic model on a sample of banks with two or more ratings

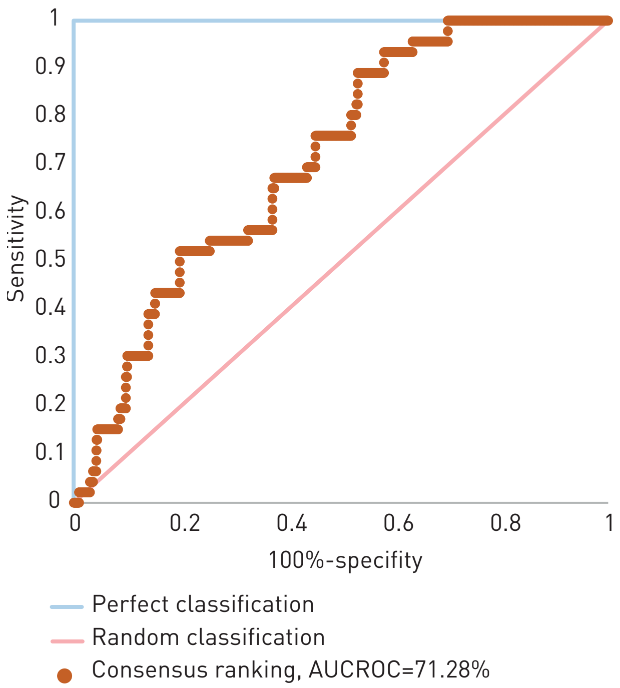


According to the quality criterion of scoring models from [35], this model shows a good discriminatory power from a practical standpoint. This is confirmed by the results of [9; 21], which built logistic regressions using unbalanced samples. In such a case, the AUCROC of the logistic model usually lies in the range 60–74%.

Consensus Ranking

The consensus ranking was calculated on the basis of a sample consisting of banks with two or more ratings. The consensus AUCROC is equal to 71.28% (Figure 2). This ranking defines trustworthy borrowers better, as the right part of the ROC diagram is almost horizontal. The reason for this is that this aggregated rating is based on information about banks which basically have a rating. This is a positive signal for the market: the bank is not afraid of its creditworthiness assessment and can afford it in practice.

Figure 2. ROC and AUCROC of the consensus ranking on a sample of banks with two or more ratings



This ranking also has high discriminatory power from a practical standpoint and is as good as statistical models and machine learning methods in a low-default environment [36; 37]. The consensus ranking is statistically indiscernible at a 10% significance level with a logistic model of defaults according to the DeLong, DeLong and Clarke-Pearson test (p-value = 99.3%).

Aggregate Ranking

The aggregated ranking was built from the two previous rankings. Logistic regression was the aggregated model. We obtained a scoring with the AUCROC equal to 76.16% (Figure 3).

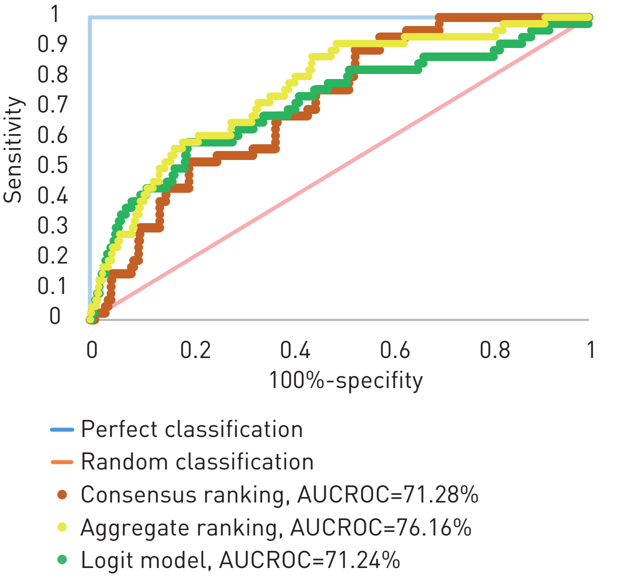
Statistically, the ranking surpasses the two base scorings at a 10% significance level[3], showing the relevance of aggregating several baseline rankings and ensembling. In addition, one should note that aggregated scoring includes the best characteristics of both baseline rankings. It defines default and non-default borrowers with similar precision. Moreover, previously proposed versions of aggregate classifiers showed a growth in the AUCROC not exceeding 3% [38; 39] on unbalanced samples.

[3] $H_0 : AUCROC^{contin} = AUCROC^{aggregated}, p-value = 1.79\%$.

$H_0 : AUCROC^{cons} = AUCROC^{aggregated}, p-value = 9.22\%$.

$H_0 : AUCROC^{contin} = AUCROC^{cons} = AUCROC^{aggregated}, p-value = 0\%$.

Figure 3. ROC and AUCROC of the aggregated model and two base classifiers on a sample of banks with two or more ratings



Conclusion

Financial institutions need to identify both default and non-default contractors or customers in order to enable their management to take informed decisions when solving risk management problems. In this paper, we propose the aggregation of credit scorings made with methods focused on different types of borrowers: the logistic model of defaults and the modified Kemeny median. Logistic regression is used as the strong learner.

Our data sample consists of Russian banks from the period July 2010 – July 2015, including credit ratings. From a practical standpoint, the discriminatory power of baseline rankings is high and typical for credit scorings in a low-default environment. However, their aggregation using logistic regression resulted in a significant growth in the discriminatory power of scoring. Moreover, this increment surpassed the increments of ensembles or aggregated rankings on unbalanced samples described in earlier literature. As long as the applied classifiers demonstrate a relatively high interpretability, such a model can be also used by financial institutions for risk management.

In further research, feature engineering techniques (for example, principle component analysis) may be applied as explanatory factors, provided the obtained index is interpretable. It is also possible to expand the set of base scorings by adding market scorings and some other interpretable scorings obtained, for example, from discriminant analysis, decision trees, etc.

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Testing Market Reaction on Stock Market Delisting in Russia

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Abstract

This paper expands the available information on the effects of delisting in Russia, and represents a rare empirical analysis of the impact of external events on securities prices in this major global market. We seek to evaluate how stock prices of competing companies fluctuate around the dates of stock market delisting announcements and completion.

We analyse stock prices as correlated with company delisting events from 2004 to 2019 on 552 companies on the Russian MOEX Exchange. The event study methodology is used to evaluate the abnormal returns of rival companies close to relevant delisting dates. These data were checked for statistical significance using the standardised Patell residual test.

The results indicate a significant competitive effect on stock prices both on the dates of delisting announcement and on completion, with more significant returns close to announcement dates. These effects were found to influence the prospects not just of individual groups of companies, but of all market participants.

We may conclude from our results that delisting is not an event limited in effect to only one company, but impacts the industry as a whole, temporarily changing its value. As such, it will interest both shareholders and managers of public companies, and any participants of industries in which delisting occurs.

Keywords: delisting, delisting intra-industry effects, competitive effects, information effects, delisting abnormal returns

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Introduction

Companies issue their shares on the stock market in order to attract major new investments. To implement a successful IPO and stock listing, managers must consider many factors, both external and internal. In this regard, many researchers and economists study stock markets around the world as well as companies' movements towards stock markets [1]. However, most articles do not focus on the factors and variables not provided for by general asset pricing models. Very few studies have been published based on an empirical analysis of the impact of external events on securities prices.

Studying the range of factors that can affect the value of securities is especially important for both corporations and ordinary investors [2]. Corporations are interested in studying this topic for the successful circulation of their shares on the stock exchange, while potential investors are interested in a reasonable investment of their assets. Several articles published by major Russian financial resources [3; 4; 5] raise concerns for investors who may face an unexpected delisting of companies in Russia. This indicates the importance and relevance of this topic for investors, in order to expand available information on the effects of delisting in Russia. In addition to the fundamental internal indicators of the company, which underlie most pricing models, an external circumstance – in other words, an event mainly originating in other corporations – may affect the value of assets [6]. These events include IPOs and delisting from the market.

In Russia, according to the website of the Moscow Exchange, 20 companies were delisted from the stock exchange in 2019, while an average of 26 companies per year were delisted from the stock exchange from 2010 to 2019, which is 7.4% of the total amount of listed companies. This suggests that delisting is an ongoing problem for stock market players and is not becoming less valuable. Moreover, according to Bloomberg, companies spent 26 billion dollars on buying stock from their shareholders for a 9-month period in 2020. This amount exceeds the comparable period of 2019 by 25 times [7].

In general, listing as a phenomenon has received much more attention in the literature than the reverse process – delisting. This is especially true of literature based on the Russian market. Of course, many articles have focused on delisting research, but the effects of delisting on other companies in the industry have not been investigated. Most of the existing studies consider the abnormal return of a specific company before and after delisting, without spreading the effect on the industry [8]. A limited number of works investigate events more widely, believing that delisting is not an event of one firm but to some degree affects the entire industry.

Considering the possible consequences of some events for the industry, in most cases, researchers note informational effects [9; 10]. In the case of delisting, they have a negative effect on the stock prices of other companies. The expected stock exclusion of one company from the quotation list may signal adverse market conditions, in other words, that the demand for company capital in this sector is low, and investors are pessimistic [11]. On this basis, there is a likelihood that other firms may also delist, and the value of shares in this market will fall. It is possible to observe such effects both at the time of announcement of the delisting decision of a company, and after the completion of this event.

This paper aims to expand the existing concept of delisting by examining the competitive effects that can strengthen (or weaken) the industry when announcing and (or) completing the stock exclusion of publicly traded competitors. To be more precise, this work primarily seeks the answer to the following question: do investors and managers of competing firms face changing stock prices in response to delisting in the industry? To answer this question, we use the event study method.

The main objectives of this study are to find out whether delisting has a significant impact on competitive firms in the industry, and if the result is positive, to determine which set of effects caused it. We base our study on two theories that perceive opposite effects of delisting. Delisting can affect an industry in two possible ways. On the one hand, the exclusion of the company's shares from the stock exchange quotation list can lead to a negative effect, scaring off existing and potential investors from the industry. On the other hand, a reduction in the number of companies in an industry can have a positive effect on stock prices. That is, due to weakening competition in the industry, firms can increase their market share and obtain growth in the value of assets.

The other novel contribution of this study is that it provides empirical evidence from the Russian market, which is poorly studied, but has an interest for investors because of its size. We suppose that the results of the study will also be interesting for company managers. Firstly, they will get more information that will help them manage their capital, considering the possible risks and market mechanisms described in the work. At the same time, company managers will be able to adjust their market behaviours in response to the delisting announcement to mitigate possible price fluctuations.

This paper is structured as follows. We start with a literature review that connects our study with existing literature on the delisting phenomenon and its impact on the competitive environment. Then, we present the main hypotheses of our study. The next section describes the research methodology and explains the data collection process. The following section reports and discusses the empirical results of the study. In the final section, conclusions are presented.

Literature Review

Main reasons for companies to delist

The main goal of most companies in the modern world is to increase the wealth of shareholders [12]. Thus, investors enter the stock market and choose companies that care about increasing their wealth. Therefore, there is a need to study the factors that make it possible to achieve success on the stock exchange. This study considers delisting as a tool for influencing stock quotes, and therefore the welfare of investors.

Delisting is scarcely covered in the scientific literature [13]. Delisting is viewed as the phenomenon opposite to the decision to become a public company [14]. It is the process of excluding company shares from the stock market quotation list [15; 16].

The study of the reasons leading to delisting is a particularly relevant topic since this event affects not only the economy of the company itself but can also harm investors who own shares. In addition, the frequency of this event can damage the reputation of the exchange on which it occurred, which is why some traders are afraid to engage with it [17]. Considering the possible global implications, it is necessary to better study the nature of delisting.

Delisting is divided into two types: voluntary and involuntary [15]. According to Macey et al. [17], involuntary delisting appears due to non-compliance with regulatory requirements, or due to the bankruptcy or liquidation of a company. In such cases, companies are forced to delist. On the other hand, voluntary delisting is a consequence of managerial choice.

Involuntary or forced delisting of shares is the most unpleasant option for both the issuer and its investors. In this case, the stock exchange excludes financial instruments from its list due to the issuer's inconsistency with listing parameters. Involuntary delisting may have the following reasons: bankruptcy of the issuing company, liquidation or reorganisation of the issuing company, suspension of the issue of securities due to violations of the issuing rules, the issuer's inaccurate financial statements, the decrease in the value of the net assets of the mutual fund below the minimum, expiration of the listing agreement, and non-payment by the issuer of the listing services.

The difference between voluntary and involuntary delisting is that in case of involuntary delisting, it is the management of the issuing company who decides to leave the exchange. The most common reasons for voluntary delisting include the following: financial problems of the company, the choice of a different strategy for attracting investments, the desire to become a private company, and company consolidation. For example, in 2018, Russian operator Megafon delisted both from the London and Moscow stock exchanges, following a new strategy to pursue new opportunities away from its core telecoms business with the aim of becoming a leader in Russia's digital ecosystem. As the new CEO, Gevork Vermishyan, has stated, the new strategy would require "broader partnerships with state-owned corporations, transactions with higher risks and investments with lower returns". The operator warned it would also need to use its free cash to make investments, likely eliminating the payment of dividends [18]. So, the status of a public company was no longer a priority of Megafon management.

The regulation framework for delisting in Russia is formed by laws 39-FZ "On the securities market" and 208-FZ "On joint stock companies". The Moscow Exchange imposes additional restrictions on the issuer, which are reflected in the 'Listing Rules' document.

The delisting procedure in Russia is as follows: the issuer or the exchange sends an application to the 'Listing Department', after which the application is considered within a month and an expert opinion is given. If the delisting is approved, the main shareholders notify the other investors about it and publish the offer to buy back the shares. Sometimes, share buybacks may begin before the delisting is publicly announced.

According to findings by Pour and Lasfer [19] voluntarily delisting is most likely to occur about four years after the IPO date. In addition, leverage on the IPO date is much higher for willingly delisted companies than for control groups (non-delisted companies). Companies voluntarily go private when their leverage is relatively high because they have a low growth opportunity and profitability; in addition, they are incapable of raising equity and might wish to cut the costs associated with being listed. These firms are less likely to achieve the goals like rebalance of the account or raise funding to finance the growth opportunities. As a result, the motivation to voluntary delisting is a lack of financial opportunities, which occurs in case of costs of listing exceed the benefits of it.

A firm may decide to remove its shares from public access for several reasons. The main ones include mergers and acquisitions. In this case, delisting is rather nominal in nature since the company usually excludes its shares for a while in order to rename them [17]. In other words, the company reissues shares after a while with a different name. Another reason for voluntary delisting is the decision of firms to become private or to reorganise a corporation into a closed joint-stock company, as an alternative way to profit [20; 21]. Often, such a decision is made by the company in order to reduce the costs required for circulation on the exchange. Some studies on this topic have concluded that the decision to become a private company is made if the company is underestimated by the market [22]. Managers of firms see no reason to incur listing losses because they expect a higher market valuation of the company.

A number of similar studies have a different conclusion: the decision to stop the public circulation of shares in favour of privatisation is made by small firms for which the first does not pay back the costs of maintaining the listing [22]. Another option is possible, and the costs that the exchange requires, compared to other expenses, are more significant for small companies, in contrast to large companies. As a result, the firm decides that a private status is more profitable [23; 24].

Pour and Lasfer [19] revealed that firms with higher intangible assets, but relatively lower market value of equity are more likely to be voluntarily delisted. The main reason for delisting is high leverage. In other words, shares of firms with relatively high debt do not pay for themselves in the stock market or no longer need additional capital to finance their investments.

Research by Bharath and Dittmar [20] suggests that firms have a higher probability of delisting if they have lower stock liquidity. This paper also shows that the lack of visibility, together with the uncertainty of stock prices, stock returns and analysts' forecasts, leads to low interest of investors in a company, which is positively associated with the probability of delisting.

Firms delist when the net expected benefits of listing are negative. In this trade-off framework, regulatory changes increase compliance costs, and the implementation of the SOX Act in 2002 in the USA is often cited as a major driver of delisting.

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Firms also delist when unfavourable regulatory changes increase compliance costs [25] or decrease benefits for investors. The implementation of the Sarbanes-Oxley Act (SOX) in the USA is an illustration of such changes and is often named as one of the major drivers of delisting for the foreign companies from US market [26; 27]. Sudden change of regulation also drives cross-delisting. Many Russian issuers voluntarily delisted in 2015–2019 from foreign exchanges while remaining at Moscow Exchange because of the unfavourable regulation that downgraded the attractiveness of international exchanges. For example, in 2018 MTS withdrew its depository receipts from NYSE after the new agreement on offshore taxation had been imposed [28].

In addition to the reasons considered, there is another assumption that might explain the decision on privacy: the problem of agent-principal [29]. Some public operations cause conflicts in the management of the company, and privacy can be a solution to the problem, i.e., a compromise [30]. Thus, delisting can bring benefits to shareholders, increasing their well-being. In summary, the phenomenon of voluntary delisting is due to two groups of factors – a compromise between costs and benefits, and agency costs. Liao [31] studied the delisting behaviour of firms from emerging markets, including Russia, and concluded that the likelihood of delisting on these markets is inversely related with the level of corporate governance and investors protection: the better are the institutions that protect shareholders, the higher is the probability that the companies stay publicly listed. The firms from countries with weaker corporate governance may tend to delist in order to soften their agency problems.

Involuntary delisting usually occurs at the legislative level due to violation of strict exchange rules or fraud. Any exchange has a strict set of rules that every public company must follow. Typically, the minimum requirements for extending a listing of a company's shares include the agreed minimum number of shareholders, a certain number of shares, a certain average monthly trading size, and a minimum market capitalisation of the company. Involuntary delisting also can be caused by the economic insolvency of the company, that is, bankruptcy. However, it is worth noting that in any case, the final decision on the exclusion of shares from the quotation list is made by the exchange. Thus, inappropriate behavior for the exchange may cause the delisting of the company's shares from the market in question.

The impact of delisting on the industry

A small number of articles were published on the effects of delisting on the stock prices of competing firms. Most of the literature studies isolated asset pricing, or the causes of certain market events, such as IPOs, delisting, bankruptcy, and so on [13]. Two goals dominate in such works: to determine the most significant factor that increases the likelihood of an event, and to analyse the impact of this event on the company [19; 21; 32].

Other studies focus on assessing the effects of an event such as delisting, on the industry in which it occurred. The main idea is that the event is not limited to the company in which it occurred but is able to influence competitors. Thus, there are two main effects on stock prices of companies: information and competitive effects [33]. If the influence exerted by information that some company has disclosed on the market is similar for the announcing company and for the industry, then it is called the information effect, or infection effect. In this paper, it is assumed that delisting can exert an information effect causing negative consequences and underestimation of competing companies in the market.

The second type of effect operates on the industry differently. If the disclosed information has a contrary effect on competitors in comparison with the announcing company, this effect is called a competitive effect [34]. This study suggests that it is positive. When shares are removed from the exchange lists, the concentration of companies in the industry decreases, thereby opening new opportunities for competitors [35]. The hypothesis is that this phenomenon leads to higher stock prices of competing firms. However, there is no unequivocal opinion on what effect dominates the market.

Studies aimed at determining the prevailing effect include the work of Lang and Stulz [11]. The article focuses on the study of intra-industry effects in response to a company bankruptcy announcement. As a result, the authors distinguish the information effect as dominant. The reason is that the bankruptcy announcement reveals negative financial information that may apply to the entire industry, which reduces market expectations about the profitability of other firms. They also concluded that high leverage enhances the negative information effect for firms but does not affect the competitive effect. Thus, with an increase in the Herfindahl-Hirschman index, the competitive effect increases when the information effect does not change. Shumway [16] came up with similar results, which documents the backlash for companies delisting due to bankruptcy and other negative reasons.

Laux et al. [36] investigated the price changes of competing companies in response to announcements of a change in dividend policy and obtained opposite results. In this case, the information effect has an impact on the industry if the announcer has a high degree of market power, with high competition within the industry. However, the overall reaction of companies within the industry is close to zero. This shows that competitive effects offset information effects and vice versa. Thus, unlike the above authors, Laux et al. [36] believe that the effect may vary within the industry and depends on the individual performance of firms. The key differences are the relative effect on the firm if the income of this firm is determined by industry-wide factors. In other words, if a firm uses common resources and has similar production processes and a similar labour market to other firms, then a review of the dividends of an industry competitor will entail a review of the dividend policy in that company. However, if a company does not have extensive market power and a growth rate higher than that of the declaring company, then the event will not affect it and vice versa.

Other authors also support this conclusion about balancing informational and competitive effects. Slovin et al. [37] believe that the event does not have a significant impact, and it all depends on the specificity of individual industries and the saturation of companies in it.

Cai et al. [38] studied the information environment and its effect on stock prices of delisting firms. The results showed the importance of the information effect for both voluntary and forced delisting. Sanger and Peterson [8] came to a similar conclusion.

Park et al. [15] also studied the information effect, with a focus on involuntary delisting. However, it cannot be fully compared with the works of Lang and Stulz [11] and Shumway [16] because the informational effects within companies are investigated, and not their intra-industry impact. The authors evaluate the existence of trade in classified information until the company is excluded from the quotation list. The assumption is since large shareholders take part in the management of the company, they can use their information advantage and participate in information trading. In addition to cases of bankruptcy, the authors add to the sample firms those excluded due to failure to provide an audit opinion, write-off of all capital or suspension of a banking operation. As a result, the stock prices of such companies sharply decline one year before the official announcement of delisting due to the information effect. In parallel, Park et al. [15] called the increase in liquidity the main reason for the delisting of a company's shares. Such findings are consistent with the conclusions by Liu et al. [39], who also call liquidity the main reason for the exclusion of shares.

Andrukovich [40] obtained similar results for his investigation of the causes of delisting and stock returns on the US stock market. He notes that both with pre-announced delisting and with delisting without prior notice, stock prices are rapidly falling. The main reason for the price reduction is the company's liquidity. Beaver et al. [41] found that the firm receives their main income from delisting in the first month after the event.

Separately, it is worth noting that Beaver et al. [41] pay much attention to the description of the methodology of such studies. Considerable attention was paid to the method of collecting data from the CRSP and the errors that most researchers make when working with information about delisting. The authors note that, firstly, the net income from delisting is incorrectly estimated, since this value depends on the day of the month on which the delisting occurred. They indicate that approximately half of the delisting occurs outside the date range provided by the CRSP, and two thirds of companies are excluded due to zero post-event earnings.

However, none of the above researchers described the data collection process. Only Park et al. [15] indicate that they collected data manually, presumably from the personal websites of companies. The effectiveness of the data collected by other authors remains in question.

In addition, a small number of authors shared the final sample by the size of the delisting. The exclusion of a company with a small number of shares in the market may have a weaker effect on the industry than a company with a large turnover. However, this is difficult work, since by excluding small volumes from the database, the results may be contaminated, and the studies may lose their accuracy and quality of assessment.

Another detail relates to the study area. Only the data of Beaver et al. [41], as well as Andrukovich [40] from the above articles are based on markets where there is a circulation of shares after delisting, outside the main exchange. In other words, after removing shares from quotes, shareholders can still obtain some profit from them, which cannot be said about the rest of the research. This point could also affect the purity of the results.

Hypotheses development

This paper is aimed at studying the competitiveness of firms in various sectors of the market, based on indicators of their share prices. Few works have examined the delisting effect on the market, and as a result there is not a large amount of literature that could predetermine the results of this study. However, referring to existing similar works, it is worth saying that they do not agree in conclusions and cannot accurately name the dominant effect. The main question of this study is as follows: does delisting affect competitors in the same industry? The main hypothesis is that competitors' stock prices respond to delisting in the industry where these firms are located. Thus, it is formulated as follows:

Announcement / completion of delisting by a company leads to an increase in stock prices of publicly traded competing firms in the industry.

Since the purpose of the study is not only to discover the company's reaction to changes in the industry, but also to determine the specific direction of the reaction, i.e., whether it relates to competitive or information sensitivity, the main hypothesis is divided as follows:

Hypothesis 1a: Announcement / completion of delisting results in higher share prices for publicly traded competitors in the industry.

Hypothesis 1b: Announcement / completion of delisting results in lower share prices for publicly traded competitors in the industry.

The most obvious way to test the hypothesis is to evaluate the stock returns of industry competitors around the dates of the announcement and the completion of delisting [34]. Abnormal returns will be calculated, that is, returns that differ from the normal returns of a particular company in the industry, then their average value will be evaluated before and after the announcement / completion of the delisting. If the exclusion of shares from quotation lists leads to a positive price effect on other firms in the industry, that is, abnormal returns are greater than zero, then the competitive effect is dominant. The predominant effect will be tested for significance with a residual Patell test. Both the competitive and information effects have some influences on firms, but the former prevails over the latter [35; 42]. Thus, this statement helps us determine which effect is likely to cause a significant impact on company prices.

In general, the presented hypothesis reflects the conclusions that were drawn in existing studies. We expand them for statistical analysis of industry effects. The lack of an unambiguous opinion about the nature of delisting, its impact on competing companies, prompt us to carefully study these points in order to come to our own definite conclusions. Accurate and effective methods are needed to achieve the set goals, and they will be described in the next section.

Methodology and data

The empirical analysis of this study is based on the event study methodology. The choice of this method is justified by its application in all sources described in the literature review. The event study method suggests a way to assess the contribution of an event to a firm's value by analysing its financial characteristics.

The effectiveness of event study methodology is supported by numerous studies. MacKinlay [43] discusses advantages and limitations of this methodology, including examining the issue of contamination of the results. MacKinlay recommends using daily stock returns for clearer results and non-parametric tests. We considered these issues when conducting this study.

Another reason for mistrust in the event study methodology is possible errors because of an inaccurate event date. However, in our case, the delisting date is documented, so the probability of such errors is close to zero.

In addition to the above, researchers [42; 44; 45] proved the robustness of the methodology, which is supported by the use of special nonparametric tests that take into account cross-sectional variance, as well as the compilation of the results into cumulative average abnormal returns (CAAR). CAAR is the sum of abnormal returns divided by their number. This is how we determine the overall average impact of delisting on competitors' stock prices, but we will discuss this in more detail below.

We obtained the values of dependent variables, such as abnormal returns for competing firms by using this approach. The expected returns for each firm are obtained by applying the least squares regression model using actual stock returns for daily stock market index returns.

Abnormal performance indicators

The study uses the aggregate abnormal returns of directly and indirectly competing firms in response to the announcement and completion of delisting in an industry. Like the excluded firms, each competing firm has its own OKVED code1. Separation of companies by industry is necessary to adjust the valuation and consider potential correlations of income. The event study methodology is used to assess their deviation of returns. Returns are estimated both on the date of the announcement of delisting by the company and on the date of its completion [46].

The abnormal return ($AR_{i,t}$) of firm *i* at the time of event *t* is calculated as the difference between the actual return and the expected return ($ER_{i,t}$)if there is no event:

$$AR_{i,t} = R_{i,t} - ER_{i,t}, \quad (1)$$

where is the actual return, and is the expected return of firm *i* at the time *t* of the event.

The expected return is unconditional for the event but depends on a specific information set. It is estimated using the usual least squares regression with the actual profitability of the companies. The evaluation period is 180 days from 220 to 40 days before the date of announcement / completion of delisting, which is defined as $t = 0$. In addition, the parameters are individual for each competing company. Thus, the following market equation is evaluated:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + e_{i,t}, \quad (2)$$

where is the actual return of firm *i* at the time *t*; is the stock market index return, and are special assessment parameters for each company. The index of Moscow Exchange (IMOEX) is taken as the market index. The use of the Moscow Exchange Index complies with the recommendations of the event study methodology [44].

[1] OKVED – All-Russian classification of types of economic activity includes all classified types of economic activity in the country and relates each company with specific sector of economy as SIC in the USA does.

The event window covers 10 days before and after the event. Hsu et al. [34] came to similar conclusions and determined that up to 20 days before / after the event, the firm's return does not differ from the expected one, but within 10 days this value becomes significant.

The expected return is estimated using the least squares model, that is, by evaluating the parameters and the daily return of the IMOEX market index:

$$ER_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt}\,, \quad (3)$$

where is the expected return, which we substitute in equation (1) and find the abnormal return of competing firms.

This model is a one-factor capital asset pricing model (CAPM). The CAPM model is one of the most common ways to calculate the expected profitability of companies, especially in the event study methodology. Fernandez [47] confirmed the feasibility of using the model especially for short-term runs. Some authors have questioned the use of CAPM in favor of more advanced versions of the model such as consumption based CAPM (CCAPM). However, Chen [48] proved otherwise by confirming the performance of a standard CAPM versus a CCAPM. In addition, the use of CAPM is also justified for estimating the expected return on stocks in emerging markets [49].

The event study methodology proposes to calculate the cumulative abnormal returns (*CAR*) for all results. This is how we determine the overall impact of delisting on competitors stock prices. This value simply sums up the abnormal return of a competing company for a certain period before and after the event announcement / completion:

$$CAR_{iT_1}^{T_2} = \sum_{t=T_1}^{T_2} AR_{it}\,. \quad (4)$$

However, the use of this variable cannot objectively show the results; therefore, the use of cumulative average abnormal returns is recommended. It is based on average abnormal returns (*AAR*). *AAR* is the average of each company's abnormal returns in the event window close to the event announcement / completion date:

$$AAR_0 = \frac{1}{N}\sum_{i=1}^{N} AR_{i0}\,, \quad (5)$$

$$CAAR_{T_1}^{T_2} = \sum_{i=1}^{N} CAR_{it=T_1}^{T_2}\,, \quad (6)$$

where N is the number of firms.

Researchers often criticise *CAAR* because this tool is short-term and should not be used in studies of long periods [51]. A performance indicator that can reflect stock price reactions in the long run is better. However, this study focuses on a short-term analysis of stock prices, so it looks reasonable to use *CAAR*.

After that, the results must be checked using statistical tests.

Statistical significance tests

It is necessary to check the null hypothesis that the average abnormal yield at time t is zero. In the study, there is a risk of cross-sectional correlation, so the usual Student criterion cannot be applied. Thus, the standardised residual test developed by Pattel [52] is applied.

Cross-correlation in abnormal returns

The dependence of variables in the cross section is an important problem that can affect the correctness of the result, and the null hypothesis would be rejected more often than it is required by the data [53; 54; 55].

The main reason for the correlation is the same macroeconomic and industry factors affecting all stock prices. As a result, the dynamics of price changes may coincide. However, a similar problem is attributed mainly to studies that are based on a long observation period. The reason is the large horizon of events that can affect data. Thus, cross-correlation is almost not related to short-term studies [56]. However, if delisting occurred close to the considered moment of assessment, then cross-dependence takes place.

Since the assumption of independent data is rejected, the use of the standard Student criterion is impossible. Brown and Warner [57] proposed another criterion, adjusted for the standard deviation of residues, and standardised by the *t*-criterion:

$$t = \frac{AAR_0}{S(AAR_0)}, \quad (7)$$

where AAR_0 is defined in (5) and $S\left(AAR_0\right)$ is an estimate of the standard deviation of the average abnormal return $\sigma\left(AAR_0\right)$. Let T be the evaluation period, measured in weeks, then $S\left(AR_i\right)$ is calculated as follows:

$$S\left(AR_i\right) = \sqrt{\frac{\sum_{t=1}^{T}\left(AR_{it} - \frac{\sum_t AR_{it}}{T}\right)^2}{T-2}}\,. \quad (8)$$

Patell [52] developed a standardised residual test for use in event analysis. The null hypothesis is that the average abnormal yield is zero. For testing, the standard deviation of abnormal returns must be corrected for the standard error. The latter must be adjusted by the prediction error obtained from the time series of abnormal returns in estimated window.

$$SAR_{it} = \frac{AR_{it}}{S\left(AR_{it}\right)}, \quad (9)$$

where $S\left(AR_i\right)$ is the forecast error, adjusted by the standard deviation, which is calculated as follows:

$$S^2\left(AR_{it}\right) = S^2\left(AR_i\right) * \left(1 + \frac{1}{M_i} + \frac{\left(R_{mt} - \bar{R}_m\right)^2}{\sum_{t=T_0}^{T_1}\left(R_{mt} - \bar{R}_m\right)^2}\right), \quad (10)$$

where $\overline{R}_m$ is the average market return, SAR_{it} has a student distribution with $M_i$minus2 degrees of freedom.

M_i is the number of missed returns.

The statistical test to verify *CAAR* against the null hypothesis that its value is zero is:

$$z_{Patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{\sum_{t=T_1}^{T_2} SAR_{it}}{S(CSAR_i)}. \qquad (11)$$

Here *CSAR* is the sum of series of abnormal returns. A standardised residual test is more accurate for cross-correlated data. Boehmer et al. [53] reported that this method can perfectly test the null hypothesis in all cases except when the event causes an increase in variance.

Data collection and sampling

The main part of the dataset was collected from several sources. The official Moscow Exchange contains stock delisting information of companies, their announcement and completion dates and the corresponding company names. In addition, the information on all listed stocks was taken from this website. However, the Moscow exchange website does not allow obtaining historical stock quotes necessary for calculating returns; therefore, the online resource 'www.investing.com' was used.

Also, the Moscow Exchange does not indicate the company's industry, so we addressed the list-org resource. This database provides OKVED codes (indicators for economic activities that mark the industry) for each company.

Thus, the database is formed from the following variables: dates of delisting announcement / completion, stock quotes of industry competitors, OKVED codes that reflect the industry and, accordingly, its competitors.

The data sampling was implemented as follows. First, we collected data on companies whose shares were delisted from the stock exchange from 2004 to 2019. This paper uses information about operations performed on the Russian MOEX exchange. The Moscow exchange website contains information on 552 companies that completed delisting within the study period.

After obtaining the initial database, we identified industries in which each company operated. The list-org resource that provides OKVED codes for each registered company was used for this purpose.

To obtain high-quality results, the available data must be filtered. To begin with, we deleted the companies with missing values. As a result, the sample was reduced by 12 positions.

The next step was to delete small operations, i.e., those with transaction amounts not exceeding 8,000,000 rubles. Such delisting is knocked out of the general distribution, which may cause inaccurate results. Another reason for removing these values is that a little delisting will not affect competing firms and only pollute the estimate [34].

In addition, it makes sense to exclude the delisting of companies in the financial sector from the sample. The structure of the banking industry is different from the rest; therefore, the reaction of their stock prices will not follow the general rule and would interfere with the study [37]. Thus, 80 companies associated with the financial sector were removed from the observations.

Finally, we controlled the dates of delisting announcements and completing at their closeness to other events that could happen and affect share prices. Luckily, this step did not require excluding events from the sample.

The total research sample, after applying all filters, has 376 delisting observations. Table 1 demonstrates the effect of each filter on the available data.

Table 1. Sample selection for completed delisting from 2004 to 2019 on MOEX stock exchange

	Number of observations
Total delisting companies	552
Missing values	12
Deal value less than 8 mln ₽	84
Companies in financial industry	80
Total sample	376

Careful processing of observations is an extremely important part of the study and necessary for their effective use, obtaining high-quality results and getting rid of extraneous noise. Filtering criteria are not too strict; however, they help in keeping the main sample size to avoid unwanted contamination of the results [57].

After receiving the final sample with all completion and announcement dates and OKVED codes, the dataset needs a list of competing firms for each industry. The MOEX website provides data on the names of companies whose shares are listed on the Russian stock exchange. A company is considered a direct competitor of an excluded company if all the numbers of the OKVED code are the same. Otherwise, competition is considered indirect. Thus, after deleting all the missing values, the dataset consists of 351 rival companies.

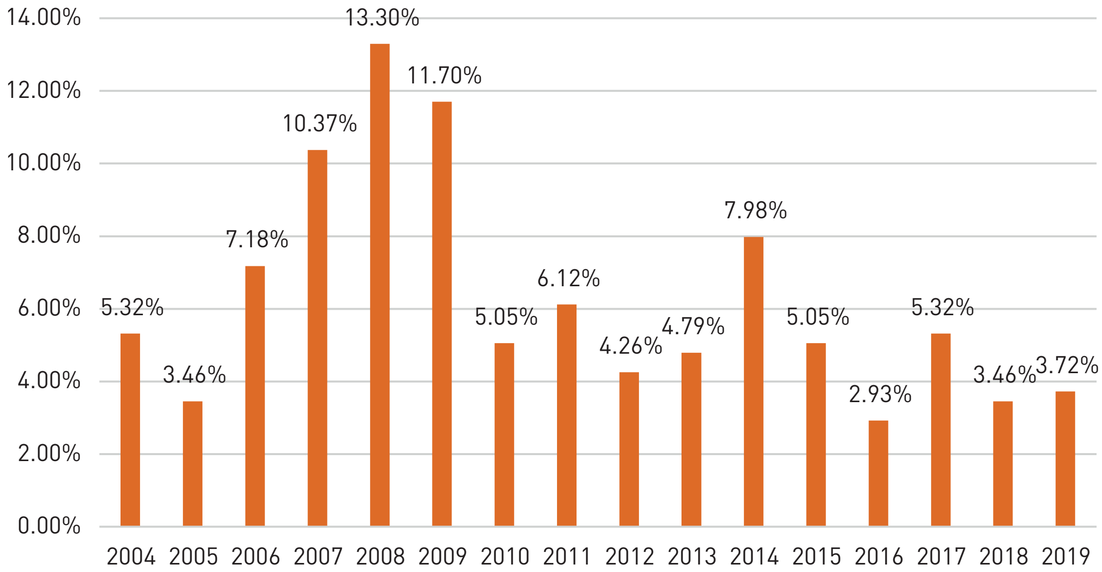
In order to get daily returns for competing firms, we used the www.investing.com database. In addition, information on the IMOEX market index was obtained from this source. After deleting the missing values, the companies whose shares were delisted from the Moscow stock exchange were compared with industry competitors using four-digit OKVED codes. Thus, 376 delisting events from 2004 to 2019 affected competitors in each of their respective industries. Competitors are companies that are listed on the Moscow Stock Exchange before and after the date of delisting announcement / completion and whose OKVED codes coincide with ones of delisted companies. The final sample of competing companies was 6080 observations, in other words, each delisting event affected 16 competitors in the industry, in average.

Descriptive Statistics

This paper primarily uses the list of companies whose shares were removed from the Moscow stock exchange to analyse the price response of competing companies to delisting in the industry from 2004 to 2019. As noted above, the main sample contains 376 observations.

Figure 1 illustrates the delisting distribution during the study period. The graph shows the percentage of delisting from 2004 to 2019 relative to the total delisting during this period. The largest number of stock market exceptions occurred in the period 2007–2009, which is a consequence of the global financial crisis. In addition, a major delisting event was noted in 2014 that is also connected to the crisis in Russia.

Figure 1. Distribution of delisting events by year



Source: authors' own calculations; Moscow Exchange.

Table 2. Descriptive statistics of rival firms

Industry code	Numder of delisted companies	Medium number of rivals	Total rivals
35.11	60	58	3480
35.12	33	28	924
61.1	28	7	196
35.16	22	28	616
70.10	14	5	70
24.45	14	6	84
20.15	12	6	72
51.52	9	5	45
49.50	8	5	40
30.30.3	8	5	40
24.20	8	5	40
64.20	6	5	30
72.19	5	2	10
Others	160	186	433
Total	387	351	6080

Source: authors' calculations; list-org database.

The second sample consists of 351 competing firms. According to Table 2, the largest number of firms is concentrated in the industry with OKVED codes of 35.1* and 61.1*. Firms in the industry 35.1* are engaged in the production and transmission of electricity. Code 61.1* defines companies operating in the field of telecommunications. In Russia, a huge number of companies engaged in these industries, so it is not surprising that they occupy the first lines of the table. The least concentrated sectors are 64.2* and 72.1*. 64.2* characterises the activities of holding companies, and the OKVED code 72.1* includes research companies in the field of natural and technical sciences. Speaking of industries not included in this table, the smallest ones included clay mining, diamond mining and salt mining.

Table 2 also illustrates how many industry competitors are present in the sample for each industry. The concentration of competing firms generally coincides with the concentration of delisting by industry. In general, the study is based on 376 cases of delisting, which are evaluated based on 6080 competing firms in 89 industries described by OKVED codes. The number of competing companies varies over time, but its average value per event is 4 firms, and the median is 3.

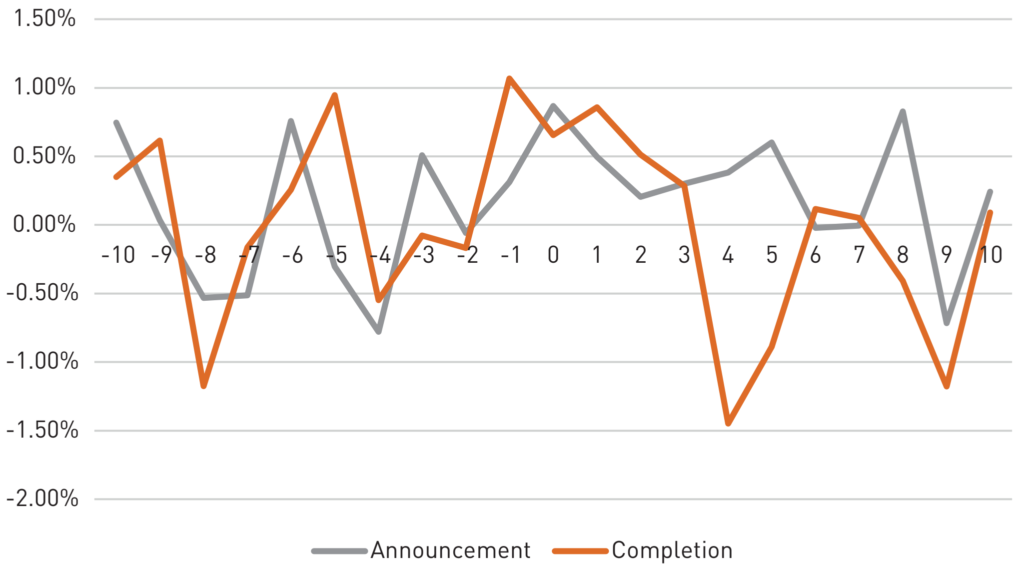
Research results analysis and discussion

After obtaining information about the available sample, it is necessary to proceed to testing existing hypotheses. The intermediate stages of the calculations and the results obtained will be provided one by one in each of the following subsections.

The price reaction assessment within the general delisting sample

This study mainly concentrates two event analyses: close to the delisting announcement dates and near the exclusion completion dates from the Russian stock market. Two sets of abnormal returns were obtained. Figure 2 illustrates the dynamics of the resulting values across the 21-days event window.

Figure 2. Average abnormal returns of rival companies around the announcement / completion dates of delisting



Source: authors' own calculations.

The cumulative average abnormal returns vary strongly throughout the evaluation period. In general, there is a positive price reaction from rival firms on the announcement and the completion dates. It is assumed that informational effects in the delisting case lead to negative effects, and competitive effects, on the contrary, lead to positive ones, so the results obtained indicate the dominance of the latter in all industries. These results contradict those obtained by Lang and Stulz [11], and Laux et al. [36]. The reason for this contradiction may be explained by the different market structure, and more severe competitive environment among public companies within the prevailing industries in the Russian market. However, our results support those by McGilvery et al. [35] that reflect the changes in the market structure.

It is interesting to note that both price reactions close to the dates of the announcement and completion of delisting are characterised by sharp changes, alternating ups and downs. However, abnormal returns linger on positive values around zero. But the CAAR falls again on the fourth day after delisting around the completion date, while the return close to the announcement date remains positive. This may indicate a more significant price response to delisting around its announcement date.

Thus, in Figure 2, it is observed that competitive effects are stronger in all industries than information effects in the delisting case in the industry. This conclusion is confirmed by the CAAR values in Table 3, reflecting different evaluation windows.

The table below illustrates the average positive abnormal returns in different periods of assessment. However, there are several exceptions in the form of negative values: in the event windows [–10; 5] and [–10; 3] in the case of delisting announcement and in the windows [–10; 10], [–3; 10] and [–1; 10] in case of completion of the event. Negative abnormal returns signal a prevailing informational effect. However, according to the standardised residual test, these values are insignificant, so it cannot be argued that the results indicate the presence of an informational effect.

It is interesting to note that in the case of the delisting announcement, negative abnormal returns prevail before the event (in other words, before zero), while in the case of the delisting completion, they prevail after the event. That is, positive price changes begin from the announcement date and end in completion date.

Table 3. Cumulative average abnormal returns around the announcement and completion dates

Event window	Announcement		Completion	
	CAAR, %	Patell Z	CAAR, %	Patell Z
[–10; 10]	0.92	2.743941	–0.04	–0.36835
[–5; 5]	0.57	2.360821	0.06	0.414582
[–3; 3]	0.43	3.936387	0.45	2.590517
[–1; 1]	0.56	2.820624	0.86	2.492173
[–10; 5]	–0.84	0.062014	0.04	0.311122
[–10; 3]	–0.27	1.376843	0.24	3.013184
[–10; 1]	0.43	1.783105	0.22	2.295232
[–5; 3]	0.22	2.696167	0.39	4.138445
[–5; 1]	0.15	0.83912	0.39	3.140381
[–3; 1]	0.43	3.381732	0.47	2.679012
[–3; 5]	0.50	0.265965	0.03	0.168528
[–3; 10]	0.56	2.36279	–0.07	–0.54659
[–5; 10]	0.02	2.13961	–0.04	–0.35455
[–1; 3]	0.52	1.927559	0.68	4.635993
[–1; 5]	0.18	2.000704	0.08	0.330221
[–1; 10]	0.27	2.157483	–0.07	–0.44161

Source: authors' own calculations.

Also, most of the CAAR values close to the delisting announcement dates are statistically significant at the 1%, 5% or 10% level with a few exceptions in the windows [–10; 5], [–10; 3], [–5; 1] and [–3; 5]. The results on the delisting completion dates are mostly insignificant. Basically, the reaction is significant from –10 days before the delisting completion to +3 days after completion. In other words, rival firms do not show a price reaction after the official completion of the event. However, these results confirm our hypothesis about the dominance of a competitive effect, especially on the announcement dates.

Nevertheless, the conclusions of the analysis are quite interesting. Companies experience a positive effect after the announcement of delisting information of a major competitor. Initial industry prospects are instantly reflected in investor sentiment, which increases profit in the industry. However, the conclusion that the delisting completion dates are less significant for company returns is unexpected. Perhaps because information about the event has long been known at the estimated time, it does not have a visible effect.

Nevertheless, the prevalence of the competitive effect is confirmed for both dates. These findings partially coincide with Andrukovich [40] – the reaction is the same for the companies who had announced delisting and those who did not previously notify the market.

Conclusion

This paper is devoted to a delisting study and its consequences for stock prices of industry competitors from 2004 to 2019. The hypothesis of the research is checked using the event study methodology, which analyses the abnormal stock returns of competing firms close to the delisting announcement and completion dates, after which the resulting indicators were evaluated in various event windows. As the next step, cumulative abnormal returns were necessarily checked for statistical significance using the standardised Patell residual test, which considers possible cross-correlation within the samples.

The results of event analysis show that competitors' stock prices begin to rise significantly after the date of announcement of information on delisting in the industry. As for the completion date of the process of exclusion from the stock market quotation lists, the abnormal returns also show positive but less significant values only until the completion date. Thus, the positive reactions of competitors are more pronounced at the time of announcement of the information. This means that new development prospects are immediately revealed for the industry due to weakening competition, and this is not unnoticed by investors; hence, their shares grow in value. These results indicate that competitive effects dominate over informational ones both close to the delisting announcement and completion dates.

As a limitation of the study, the real competitive situation within the industries was not studied. It could be done on the base of Herfindahl–Hirschman index as it is recommended by several studies of involuntary delisting intra-industry effects [9].

It is also worth pointing out that the event study methodology cannot guarantee that the event window is clean. In other words, if the delisting at some point in time bordered on some other major event – the company's IPO, crisis, or other event that could affect the company's share price – the methodology used is not able to separate the effect of the delisting from another event. Thus, the resulting abnormal reruns and the corresponding results may contain injections. But the use of the cumulative average abnormal return CAAR smooths out the errors of other events that can affect prices at a particular moment in time. Since CAAR is considered for the entire sample period, individual influences become insignificant. We also checked the occurrence of such events in our sample

However, there is still a chance of cross-correlation of the data, as some delisting occurred at a close point in time. However, to solve this problem, Patell's standardised residual test was applied, designed specifically to test data with this problem. Thus, every effort has been made to obtain the most correct results.

In general, we can conclude that delisting is not an event limited in effect to only one company. It really has an impact on the industry in which it occurs, temporarily changing its value. The result obtained is important for company managers, shareholders and potential investors. Based on the study, managers will be able to better adjust company policy, knowing for sure what to expect from delisting in the industry. Shareholders will be aware of the rise in prices during the exclusion of industry competitors from the market, which will allow them to manage better their existing securities. At the same time, delisting in the industry becomes a factor increasing the prospects of the industry, which is an important marker for all market participants.

It will be interesting to evaluate other factors in future studies that are theoretically capable of influencing the reaction to the announcement and completion of delisting. These include the degree of monopolisation in the industry, profitability, book value and other indicators of financial and accounting statements. It would also be interesting to evaluate which factors are responsible for the development of information and competitive effects and how they change over time. However, much longer periods of research are needed for such an analysis.

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Can the Fraud Triangle Detect Financial Statement Fraud? An Empirical Study of Manufacturing Companies in Indonesia

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Abstract

This study examines the effect of the following factors on financial statement fraud: (1) external pressure, (2) personal financial need, (3) financial targets, (4) the nature of industry, (5) ineffective monitoring, and (6) rationalization. The population in this study consisted of companies listed on the Indonesia Stock Exchange (IDX) over the period 2016-2018. The analysis was conducted with the help of the logistic regression method.

The results of this study indicate that external pressure, financial targets and the nature of industry have an effect on financial statement fraud, while personal financial need, ineffective monitoring and rationalization have no effect on financial statement fraud. Thus, this study contributes to the understanding that not all aspects of the fraud triangle can detect fraud.

Keywords: financial statement, fraud, fraud triangle

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Introduction

According to the Association of Certified Fraud Examiners (ACFE), fraud is a deliberate act against the law that has a specific purpose (manipulating or giving wrong financial statements to other parties), is carried out by people outside or within the organisation to get benefits, and causes direct or indirect losses to other parties.

ACFE classifies fraud into 3 types – corruption, misappropriation of assets and financial statement fraud [1]. In 2016, ACFE conducted a survey on fraud in Indonesia by distributing questionnaires to CFE certificate holders as well as practitioners experienced in fraud investigations. The results showed that the highest percentage of fraud in Indonesia in 2016 was due to corruption (77%), followed by the misappropriation of assets (19%) and financial statement fraud (4%). However, in 2018, ACFE conducted another study on 220 cases in the Asia Pacific environment and found that financial statement fraud occurred more rarely than other frauds (a percentage of less than 15%) yet caused the greatest total loss – about US$ 700,000. In comparison, corruption caused a total loss of about US$ 500,000 and the misappropriation of assets a loss of about US$ 180,000 [2].

Any company that is proven to have committed fraud loses the trust of investors and third parties such as banks. This has an impact on company performance. Chen et al. [3] showed that a company lost loans after getting penalized for corporate fraud, receiving less loans than companies that did not commit fraud. In addition, its loan interest increased to a higher level than the interest of companies that did not commit fraud. This indicates that fraud has a significant effect on the level of confidence of stakeholders.

The aspects of pressure, opportunity and rationalization that encourage people to commit fraud include external pressure, personal financial need, financial targets, the nature of industry, ineffective monitoring, and rationalization [4]. Based on previous studies that have not obtained consistent results and there still many cases of financial statement fraud occur, this study will examine the aspects that have an effect on financial statement fraud based on the fraud triangle.

A number of studies have used the fraud triangle, including Parlindungan et al. [5], Fitri et al. [6], and Aghghaleh et al. [7]. Fitri et al. [6] examines the motivation for fraud in Indonesia and concludes that it can be explained by the high pressure to maintain financial stability, the leverage and efforts to achieve financial targets, the small number of independent committees, the amount of receivables from affiliates and the frequent changes in auditors. Fitri et al. [6] used the fraud triangle to explain this motivation and the M-score from the Beneish Model to classify companies that commit fraud based on earnings manipulation. Similarly, Parlindungan et al. [5] concluded that financial factors based on the fraud triangle are effective for indicating and predicting financial statement fraud in Indonesia.

Aghghaleh et al. [7] used the fraud triangle, particularly the aspects of pressure and opportunity, to examine the factors that influence corporate fraud in Malaysia. Aghghaleh et al. [7] concluded that greater trade receivables and leverage and smaller control exercised by the audit committee and the board of directors, make a company more likely to commit fraud. The difference between this study and Aghghaleh et al. [7] is that we use the F-score to classify companies that commit fraud, while the latter employs data on companies that violate the Malaysian Security Commission.

In addition to taking a financial approach, Li [8] identifies the possibility of fraud on the basis of psychological aspects by using CEO voice markers of cognitive dissonance or the so-called HMV method developed by Hobson, Mayew, and Venkatachalam [9]. The cognitive dissonance studied by HMV is related to the aspect of attitude or rationalization in the fraud triangle.

The present study focuses on the use of financial data, as it can be directly accessed by the public, allowing the latter to identify factors that encourage fraudulent financial statements. The difference between this study and Fitri et al. [6] is that we use the F-score to classify companies that have been identified as committing fraud and those that have not.

Literature Review

Agency Theory

This theory was proposed by Jensen and Meckling [10], who define it as the relationship between the owners and the agents who manage the owners' resources. This relationship has the potential to cause conflicts between owners and agents due to a conflict of interests.

According to Eisenhardt [11], agency theory uses 3 assumptions about human nature: a. Humans are generally selfish; b. Humans have limited thinking power about future perceptions; c. Humans always avoid risks. These three characteristics result in doubts about the correctness of submitted information, which frequently does not reflect what is happening in the company or is "asymmetric information". Asymmetric information refers to differences in the information available to the agent and the owner, with the agent disposing of more information about the company. Asymmetric information and conflicts of interest result in the agent providing untrue information to the owner, especially if this information is related to the agent's performance, which may include earnings management, resulting in a type of fraudulent financial statement. There are 3 types of agency costs: (1) Costs for supervising the agent, (2) Bonding cost, (3) Residual loss.

Fraud

According to ACFE, fraud is a deliberate act against the law that is carried out by people outside or within the organisation with the specific purpose of getting benefits and that causes direct or indirect losses to other parties. ACFE defines financial statement fraud as a deliberate misstatement of a company's financial situation through manipulated reports or omissions in financial statements in order to deceive users. According to ACFE, fraud can be grouped into several categories:

a) Misappropriation of Company Assets
Fraudulently taking or using company assets for individual interests.

b) Financial Statement Fraud
Fraudulently hiding financial information or manipulating and/or changing financial statements with the aim of tricking the readers of financial statements for personal or group interests.

c) Corruption
Fraudulently abusing authority and power for individual interests.

Fraud also occurs due to corporate culture factors such as bullying and the greed of top management [11]. Fraud can be minimized by improving the work ethos, encouraging proper behaviour and organising well-tailored internal control [12].

Financial Statement Fraud

According to ACFE, there are 2 *modi operandi* (operating methods) used by the perpetrators of financial statement fraud [11]:

a) Presenting higher income or more assets with the intention of tricking stakeholders or financial statement users into believing in the company's performance.

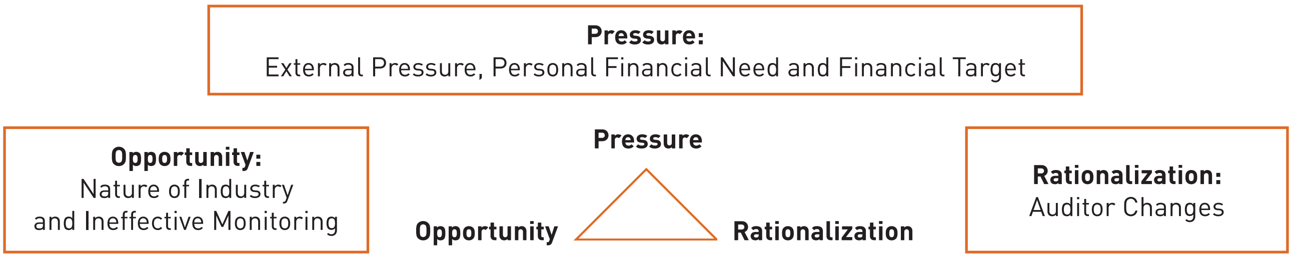
b) Manipulating information by presenting assets as being less than they really are to reduce the amount of tax payments or obligations to the government.

Financial statement fraud can be identified by using the F-score that was developed by Dechow et al. [13]. The F-score model is the sum of two variables: accrual quality and financial performance [14]. Companies with an F-score > 1 have the potential to commit financial statement fraud, while companies with an F-score < 1 have no potential to commit financial statement fraud.

Fraud Triangle

The fraud triangle theory is a method of explaining the causes of fraud proposed by Cressey [15]. According to Statement on Auditing Standards No. 99 [16], several conditions serve as incentives for committing fraud: external pressure, personal financial needs and financial targets. Based on their research results, Maka et al. [17] conclude that models that can significantly indicate financial statement fraud are interest earned, the Altman Z-score and the ratio of debt to equity. The fraud triangle explains the 3 factors involved in a fraud situation (Figure 1).

Figure 1. Fraud triangle



1. Pressure

Free [18] states that fraud occurs when there are (1) an incentive for committing fraud, (2) an opportunity to commit fraud, such as weakness in internal control, and (3) the attitude or ability of individuals to commit fraud.

Romney and Steinbart [19] define pressure as the encouragement or motivation for someone to commit fraud. The pressure can take the form of financial pressure, such as when the actor needs money to assure his lifestyle, and non-financial pressure, such as when a manager is required to show good performance to be superior to others and get the opportunity to obtain a higher position, which indirectly can encourage him to commit fraud.

According to SAS 99 [16], there are several types of pressure for committing fraud:

a) External Pressure

External pressure refers to any external pressure experienced by the company. External pressures on a company include the striving to receive additional funds from external parties in order to be competitive and to show the best financial and profit ratio performance. In addition, companies must also be able to show that they can repay loans, which can also encourage managers to commit fraud. In addition, excess debt levels can also put external pressure on companies to commit financial statement fraud.

b) Personal Financial Need

Personal financial need relates to the condition of company executives who play a strong financial role in the company. Personal financial need also affects the company's financial performance [4].

In this study, personal financial need is measured by the percentage of share ownership by insiders (OSHIP), as share ownership by company executives can affect the company's financial condition. Share ownership by insiders can be used as a control in financial reporting: if the share ownership by insiders is high, then fraud in manipulating financial statements will be reduced.

c) Financial Targets

Financial target refers to any financial target that must be achieved by the company over a given period. This can include pressure put on managers to improve their performance in achieving company targets. Such pressure can lead people to commit fraud to achieve company targets. The higher the ROA value for which the company strives, the more likely it is to commit financial statement fraud.

2. **Opportunity**

Opportunity refers to any opportunity that allows fraud to occur. An opportunity occurs when an actor believes that his fraudulent activity will not be detected or when a colleague of his has previously committed fraud and not received any sanctions, so that the actor believes that he has nothing to fear. Inadequate control systems in the company, weak management supervision and unclear procedures can also create opportunities for fraud.

According to SAS 99 [16], several conditions create opportunities for fraud:

a) Nature of industry

The nature of industry refers to the ideal state of a company or organisation in the industry, including the state of the company's receivables. A company with good performance will minimize the amount of receivables and maximize the revenue of its cash flow. High receivables on sales show that accounts receivable are assets that have a higher risk of manipulation, so they are vulnerable to financial statement fraud occurring through accounts receivable. In this study, the nature of industry is calculated by using the ratio of total accounts receivable.

b) Ineffective monitoring

Ineffective monitoring refers to weak monitoring that creates opportunities for fraud. Ineffective monitoring occurs when there are individuals or small groups that dominate management without compensation control, ineffective supervision of the board of commissioners and audit committee over the process of reporting financial statements, internal decision making and so on.

c) Rationalization

Rationalization refers to a mode of behaviour, trait or ethical value that enables acts of fraud or to a suppressive environment that encourages fraud. Rationalization is one of the important elements of fraud that leads the actor to find justifications for his actions. There are several conditions encouraging rationalization for committing fraud, including auditor change and audit opinion.

Formulation of Hypotheses

1. **Effect of Pressure on Financial Statement Fraud**

This study uses the leverage ratio, personal financial need and financial targets to measure pressure. One of the external pressures on the company is the striving to receive additional funds from external parties in order to be competitive and to show the best financial and profit ratio performance. In addition, a company must also show that it can repay loans, which can also encourage managers to commit fraud.

This study uses the leverage ratio as a proxy for external pressure. Tiffani [4] and Aghghaleh et al. [7] have found that external pressure has an effect on financial statement fraud. In view of the above, the proposed hypothesis is that external pressure has an effect on financial statement fraud because managers may commit fraud in financial statements by presenting financial ratios with good profits to get loans from external parties.

H1: external pressure has an effect on financial statement fraud.

2. **Effect of Financial Need on Financial Statement Fraud**

In addition to external pressure, this study also considers internal pressure. Internal pressure focuses on internal motivation such as employee motivation [20]; problems originated from individual problems [21] where the research uses managerial ownership that shows the financial needs of the company's internal parties. Personal financial need refers to the condition of company executives who play a strong financial role in the company. Personal financial need also affects the company's financial performance [4].

In view of the above, the proposed hypothesis is that personal financial need has an effect on financial statement fraud because share ownership by insiders can lead to fraud in the company. The greater the insider ownership, the smaller the tendency to commit fraud.

H2: Personal financial need has an effect on financial statement.

3. **Effect of Financial Targets on Financial Statement Fraud**

Financial targets refer to situations when managers are required to achieve company targets. This pressure can make managers commit fraud to bring the company's finances in conformity with set targets. In this study, financial targets are calculated using ROA. ROA is a broad measure of the company's operational performance that shows how efficiently assets are being used.

In view of the above, the proposed hypothesis is that financial targets have an effect on financial statement fraud because managers are required to show financial stability and to display good performance by achieving company financial targets that are different from reality [22] so as to get rewards, leading them to commit fraud.

H3: financial targets have an effect on financial statement fraud.

4. **Effect of the Nature of Industry on Financial Statement Fraud**

The opportunity aspect is associated with the nature of industry. The nature of industry refers to the condition of the company in the industry, including accounts receivable, which are handled differently by each company manager. There are certain accounts in financial statements for which the balance is predictably made – for example, obsolete inventories and bad debts. This condition can give managers the opportunity to manipulate financial statements about the account.

This study uses the accounts receivable ratio as a proxy for the nature of industry. The measurement of the allowance for bad debts is subjective which is the focus of managers to commit fraud [23]. Mariati and Indrayani [24] conclude that an increase in accounts receivable indicates that the company's cash turnover is not good, which can affect the company's financial stability and encourage it to commit fraud. Our study is based on a sample of manufacturing companies. One of the important aspects of a manufacturing company is the management of working capital, namely the management of cash, accounts receivable and inventory. Manufacturing companies require larger working capital than service companies. Large working capital can be obtained through good management of accounts receivable [25].

In view of the above, the proposed hypothesis is that the nature of industry has an effect on financial statement fraud because a company that wants to look good reduces the amount of receivables and increases the amount of cash flow. With a reduced amount of accounts receivable and bad debts are made with suspicion, it is very likely that fraud will occur.

H4: the nature of industry has an effect on financial statement fraud.

5. Impact of Ineffective Monitoring on Financial Statement Fraud

Ineffective monitoring refers to a lack of supervision that creates an opportunity for managers to commit fraud. It can happen due to a lack of members on the company's board of commissioners, increasing the probability of fraud due to insufficient supervision [6]. The effectiveness of monitoring is measured as the proportion of independent boards to the total number of boards. The greater the number of independent boards, the more effectively the monitoring prevents fraud. Supervision carried out by an independent board is one aspect of good governance practice. The board of directors is an important mechanism in good governance because it has the highest authority in making decisions in the company [26].

In view of the above, the proposed hypothesis is that effective monitoring has an impact on financial statement fraud, because, when a small group dominates management and inside supervision is lacking, fraud may occur.

H5: ineffective monitoring has an effect on financial statement fraud.

6. Effect of Rationalization on Financial Statement Fraud

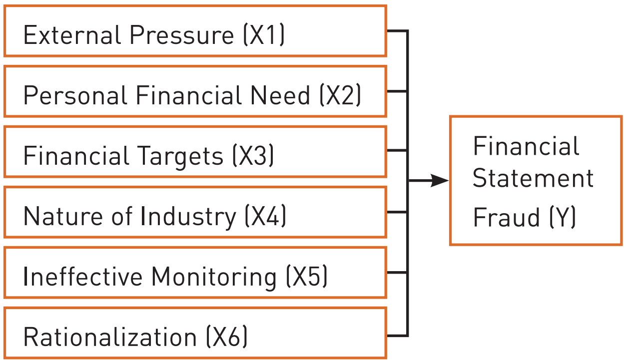
Rationalization refers to the justification of the perpetrator of fraud for his actions. Rationalization is measured by the level of auditor changes. When the auditor changes, rationalization tends to increase. A change of auditor within a company can represent an attempt to remove traces of fraud, especially if the new auditor is unable to disclose the fraud [6].

In view of the above, the proposed hypothesis is that rationalization has an effect on financial statement fraud because a change of auditor suggests that the company is committing fraud and trying to justify it.

H6: rationalization has an effect on financial statement fraud

The research design is presented in Figure 2.

Figure 2. Research Design



Research Methodology

The population used in this study consisted of manufacturing companies listed on the Indonesia Stock Exchange over the period 2016-2018. The sample was taken according to the set criteria. After sampling, there were 24 companies that met these criteria, and so all of the 72 companies were taken as the sample. Perusahaan manufacture yang menjadi sample merupakan perusahaan yang mngelola bahan mentah menjadi barang jadi yang bergerak di tiga sector yaitu sector basic industry and chemicals, miscellaneous industry and consumer goods.

Variable

This study uses dependent and independent variables. The dependent variable is the potential for financial statement fraud, and the independent variable is the fraud triangle (Table 1).

Table 1. Operating Definitions of Variables

Variable	Measurement
Financial statement fraud Financial performance is measured by changes in cash sales accounts, accounts receivable, inventory accounts and income accounts before taxes and interest. A company with an F-score value > 1 has the potential to commit financial statement fraud, while a company with an F-score value < 1 has no potential to commit fraud [27]	$Fscore = accrualquality + financialperformance$ $RSSTaccrual = \frac{(\Delta WC + \Delta NCO + \Delta FIN)}{AverageTotalAsset}$ $WC = currentassets - currentliabilities$ $NCO = (assets - currentassets - investment \,\&\, advance) - (liabilities - currentliabilities - longtermdebt)$ $FIN = investment - liabilities$ $ATS = (beginningassets + endassets)/2$ $financialperformance = changeinreceivable + changeininventories + changeincashsales + changeinearnings$ $changeinreceivable = \frac{\Delta receivable}{averageassets}$ $changeinreceivable = \frac{\Delta receivable}{averageasset}$ $changeininventories = \frac{\Delta inventories}{averageinventories}$ $changeincashsales = \frac{\Delta sales}{sales(t)} - \frac{\Delta receivable}{receivable(t)}$ $changeinearnings = \frac{earning(t)}{averageasset(t)} - \frac{earning(t-1)}{averageasset(t-1)}$
External Pressure In this study, external pressure is calculated using the leverage ratio (debt to asset ratio), because one source of external pressure on companies is their ability to meet loan requirements and repay debts	$leverage = \frac{totaldebt}{totalasset}$
Financial Need In this study, financial need is calculated using managerial ownership (OSHIP), because, when company executives play a strong financial role in the company, the financial need of the executives will also have an effect on company performance	$OSHIP = \frac{Total\ Shared\ Ownership\ of\ Insiders}{Total\ Common\ Shares\ Outstanding}$ $OSHIP = \frac{TotalSharedOwnershipofInsider}{TotalCommonShares}$

Variable	Measurement
Financial Targets The ROA formulation is used to calculate the financial targets, because one of the management performance measures is the effectiveness and efficiency of a company in using assets to generate profits, while ROA is a profitability ratio that measures company performance [14]	$ROA = \frac{earning\ after\ interest\ and\ tax}{total\ assets}$
Change in Accounts Receivable In this study, the nature of industry is calculated using the ratio of total accounts receivable, because certain accounts in financial statements are determined on the basis of estimates – for example, bad debts and obsolete inventories. These conditions can create opportunities for managers to commit fraud	$RECEIVABLE = \frac{receivable(t)}{sales(t)} - \frac{receivable(t-1)}{sales(t-1)}$
Ineffective Monitoring In this study, ineffective monitoring is calculated using BDOUT, which measures the percent of the number of independent commissioners on the board of commissioners, as weak supervision can create opportunities to commit fraud	$BDOUT = \frac{total\ independent\ boards}{total\ boards}$
Rationalization In this study, rationalization is calculated by auditor changes or AUDCHANGE. AUDCHANGE is used because auditor changes may represent an attempt to eliminate traces of fraud found by previous auditors. If the auditor is unable to disclose the fraud that occurred, it will continue to increase, because the manager considers it to be permissible insofar the auditor is unable to disclose it	This measurement uses a dummy variable that is equal to 1 if an auditor change occurred and 0 if no auditor change occurred

Data Analysis

This study used logistic regression. The results of the calculation of the risk of financial statement fraud (F-score) were classified into high and low-risk groups. In addition to logistic regression, the data were processed using OLAP (Online Analitycal Processing) cubes, which are used for databases in multidimensional structures, providing fast answers to complex queries and analysis with the aim of looking more specifically at the companies under the study.

Data Analysis and Discussion

Data Analysis

Descriptive analysis yielded the following means: 0.36 for external pressure, 0.03 for personal financial need, 0.06 for financial target, 0.00 for nature of industry, 0.33 for ineffective monitoring, 0.46 for rationalization and 0.047 for financial statement fraud. The complete descriptive statistics results are shown in Table 2.

Table 2. Descriptive Statistics

Identification	N	Min	Max	Mean	Median	Std. Deviation
External pressure	72	0.13	0.81	0.3675	0.3572	0.16771
Personal financial need	72	0.00	0.38	0.0333	0.0000	0.09489
Financial targets	72	0.00	0.47	0.0957	0.0649	0.09464
Nature of industry	72	–0.25	0.27	–0.0017	0.0010	0.06180
Ineffective monitoring	72	0	0.57	0.3594	0.3333	0.14289
Rationalization	72	0	1	0.46	0.0000	0.502
Financial statement fraud	72	–0.56	1.65	0.0743	0.0472	0.29680

Source: Research Data.

The risk category for financial statement fraud is based on the median value of the processed data, which divides companies into two categories: companies with an F-score < 0.0472 were categorized as low risk and those with an F-score ≥ 0.0472 were categorized as high risk. As shown in Table 3, there are significant differences between high- and low-risk companies.

Table 3. Differential Test for High-risk and Low-risk Companies

	Lavene Test Equality of Variances		t-test for equality means		
	F	Sig.	t	df	Sig. (2-tailed)
Equality variances assumed	0.008	0.930	4.893	70	0.000

Source: Research Data.

The differences in mean and standard deviation between the companies with high-risk and low-risk category are shown in Table 4.

Table 4. Differences in mean and standard deviation between companies in high-risk and low-risk categories

Identification	Mean		Std. Deviation	
	High-risk	Low-risk	High-risk	Low-risk
External pressure	0.3128	0.422	0.11789	0.192
Personal financial need	0.0352	0.032	0.10490	0.085
Financial targets	0.1180	0.073	0.09434	0.090
Nature of industry	–0.0184	0.014	0.05320	0.065
Ineffective monitoring	0.3667	0.35	0.15450	0.132
Rationalization	0.4167	0.5	0.50000	0.5
Financial statement fraud	0.223	–0.0739	0.172	0.32

Source: Research Data.

As Table 4 shows, a significant difference between companies with high and low fraud risk is that companies with high fraud risk have high debt ratios, low financial targets, and receivables that increase every year.

The Omnibus test was conducted with a total of 6 independent variables, resulting in a significance value lower than 0.05 (0.003, to be exact). This shows that there is a significant and simultaneous effect of the independent variables on the dependent variable. The results of the Omnibus test are shown in Table 5.

Table 5. Omnibus Tests of Model Coefficients

Identification		Chi-square	df	Sig.
Step 1	Step	19.822	6	0.003
	Block			
	Model			

Source: Research Data.

The Nagelkerke R Square value is the R-squared value in linear regression. The independent variables were able to explain 32 percent of the dependent variable as seen from the Nagelkerke R Square value of 0.32. The remaining 68 percent can be explained by factors other than the independent variables in the logistic regression results equation. The results of the Nagelkerke R Square and Hosmer-Lomeshow tests are shown in Table 6.

Table 6. Nagelkerke R Square and Hosmer-Lomeshow Tests

Information	Value
Nagelkerke R Square	0.321
Chi-square	9.417
Sig.	0.308

Source: Research Data.

The Hosmer value in Table 6 is 0.308, which is higher than $\alpha = 0.05$, meaning that the logistic regression model is able to explain the data and that there is no difference between the model and its observation value. This shows that the logistic regression equation can be used to explain the relationship between the independent variables and the dependent variable.

Table 7. Significance Test

Information	Sig.	Hypothesis
External Pressure	0.028	H1: Proven
Personal Financial Need	0.932	H2: Not proven
Target Pressure	0.024	H3: Proven
Nature of Industry	0.054	H4: Proven
Opportunity	0.472	H5: Not proven
Rationalization	0.289	H6: Not proven

Source: Research Data.

Table 7 shows that external pressure and target pressure have a significant effect. The nature of industry has a quasi-significant effect, while personal financial need, opportunity and rationalization have no significant effect.

Discussion

External pressure is measured by the ratio of total liabilities to total assets. The results of the hypothesis test in Table 7 show that external pressure has a significance value of 0.028. External pressure has an effect on fraud, because, to obtain a loan from an external party in order to remain competitive, a company must have an excellent financial and profit ratio. In addition, the company must be able to show that it can repay the loan, which can encourage managers to commit fraud.

Target pressure – in this case, the financial target – has a significant effect, as it requires managers to achieve company targets. This pressure can make managers commit fraud to bring company finances into accordance with the set targets. In this study, the financial target was calculated using ROA, which is a broad measure of the company's operational performance that shows how efficiently assets are being used.

Personal financial need has a significance value of 0.932. The significance value is 0.932 > 0.05, which means that personal financial need has no significant effect. The non-significant effect can be explained in the study by the fact that the average share ownership by insiders is only 3.3% and so cannot affect fraud due to its low percentage. This low percentage does not have any effect on management control over the company, so that the company does not have the opportunity to commit fraud.

The nature of industry has a significance value of 0.000 (the calculated value of 0.05 is at the limit of significance). The effect of the nature of industry on the risk of financial fraud is that the condition of accounts receivables responded differently by each company manager. An increase in accounts receivable encourages companies to commit fraud. Accounts receivable management is one aspect of working capital management in addition to cash and inventory. A larger collection period or increased credit sales result in an increase in receivables, which disrupts the company's cash flow. Non-current cash flows can affect profitability, which companies can try to overcome by committing fraud [24].

Opportunity, which is proxied by effective monitoring, has a significance value of 0.472, meaning that ineffective monitoring does not have a significant effect on the risk of financial statement fraud. Members of an independent board of commissioners may take their positions due to the formal requirements of the IDX, which specifies that independent commissioners must account for at least 30% of the total board of commissioners, while majority shareholders continue to play an important role so that the performance of the board does not increase or even declines.

The number of independent members on boards of commissioners does not affect company fraud, which was also shown by Salleh and Othman [28]. Fraud is much more affected by the number of meetings of the board of commissioners. The more frequently meetings are held, the more effective the board of commissioners is in monitoring, improving its chances of uncovering fraud [28].

Rationalization has a significance value of only 0.289 and so does not have a significant effect. Changes of auditor cannot be used to detect fraud, as companies may change auditors not to conceal fraud but to comply with Article 11 of the Government Regulation of the Republic of Indonesia No. 20 of 2015 concerning public accountant practices, which limits the provision of audit services to 5 consecutive fiscal years.

A change of auditor does not indicate that a company has committed financial statement fraud. The Financial Services Authority (OJK) has also regulated auditor changes in Regulation No. 13 / POJK.03 / 2017, where parties providing financial service activities are required to limit the use of audit services from the same public accountant for a maximum of three years.

A number of regulations have been enacted to improve corporate governance, which also reduces the possibility of fraud. Auditor change regulations, strengthening the audit committee is considered only as an effort to increase the image of the company [29]. This regulation has not been fully implemented and its implementation effectiveness has not been optimal [30].

In view of the above, the fraud triangle theory cannot fully explain fraudulent financial statements. In the pressure aspect, external pressure and target pressure determine fraud. Likewise, in the opportunity aspect, only the nature of industry has an effect on fraudulent financial statements. As to the rationalization aspect, it does not show any impact at all on the occurrence of fraud. Based on these results, the indicators of every aspect need to be re-examined. Free [18] concluded that financial statement fraud is closely related to behavioural aspects. This is in line with the results of Trompeter [31], which states that inter-disciplinary research needs to be applied to study the problem of financial statement fraud.

Conclusion

The results of this study shall be useful to auditors, investors and stakeholders to understand the factors influencing the risk of financial statement fraud in Indonesia, especially factors relating to external pressure, target pressure, and the nature of industry. This study supports the conclusions of Yolanda [32] that it is necessary to emphasize the potential risk of fraud in audit reporting.

Further research can use different samples or increase the duration of research to improve the sample, using M-score or Z-score models or even adding new variables for detecting fraud in companies.

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The Determinants of Debt Load for Companies in Emerging Markets

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Abstract

Corporate capital structure is one of the key elements of long-term development, which determines the company value. Consequently, defining the factors that influence the debt load level of a company and, hence, its capital structure is also of great importance.

In this paper we have collected a sample of data of 753 Russian companies and 292 Brazilian companies for 2020 to evaluate the influence of various factors on their debt-load level. The data was downloaded from Bloomberg database and the basis of the analysis focuses on evaluation of conventional academic theories on capital structure, and a regression analysis based on variables extracted from a set of original hypotheses.

Among our results, our analysis illustrates that individual sets of determinants differ significantly in explanatory power, and operate unequally when contrasting Russian companies and Brazilian ones. Additionally, it was established that when companies define their debt load, they do not limit themselves to a single theory of capital structure. We conclude, inter alia, that it is impossible to identify with confidence which of the examined theories companies are most likely to follow in their actions, because observed interrelations between relevant variables and debt load have indications of various academic theories.

Keywords: capital structure, debt financing, debt load, theories of capital structure, profitability, growth opportunities, company size, tangibility, level of company liquidity, rate of return (or discount rate), corporate economic efficiency

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Introduction

In the current circumstances of ever-rising competition, a company's long-term development is inextricably entwined with its efficiency in all economic sectors. Defining the debt load level (and capital structure in general) represented by bond-secured loans and credit funds is one of the key strategic points of this development. Where the debt-load is at an appropriate level, a company minimizes its risk of financial imbalance, which, in turn, enables its market value to rise. Conversely, the incorrect definition of a debt-load level may bring about the loss of a company's competitive advantages, decrease its market value, and/or initiate agency conflicts between company shareholders and managers.

The sustainable long-run development of a company is closely linked with the definition of its capital structure, including the level of its debt financing applying various instruments. Raising debt is a very important development factor because it allows the use of proceeds for investment in the phase of expansion of production capacity. However, an increase in debt load may result in negative consequences and contribute to company bankruptcy.

In recent decades, emerging markets have been growing faster, due to development of industrial production, which has required, among other things, serious financial investments. Nevertheless, industry-based growth is gradually slowing[1]. This means that in an ever-changing environment, companies in these markets need competent debt-load management and an ability to define its determinants in order to maintain their previous growth rates.

The main criteria for selection of companies for this research comprise corporate shares or bonds in circulation in national stock exchanges, as well as companies' affiliations with developed markets. The two samples used consist of 753 Russian and 292 Brazilian companies from the year 2020.

This research may assist shareholders and managers of companies in defining the policy of debt financing in companies (subject to business geography). This research may also be of interest to financial organizations and consulting agencies which render services related to debt-load management.

Explanations of Debt Load Determinants

In the current environment of constantly-growing competition, economic uncertainty, and (particularly in Russia) possible sanction pressures, companies try to obtain as many competitive advantages as possible in order to maintain business growth. The ability to create and use these advantages is directly associated with the opportunity to invest in the development of key business areas. Such investments may be related to modernization of production processes, a study of new technologies and R&D applications, expansion due to horizontal and vertical mergers and acquisitions, etc. Significant cash infusions are necessary to implement such projects. As an example we can see that capital investments of the Mining and Metallurgical Company Norilsk Nickel in 2020 amounted to RUB 123.3 billion[1], while capital investments of PAO Novatek increased to RUB 204.6 billion (the largest amount in the past five years)[2].

Similarly, capital investments of the mining and metallurgical company Norilsk Nickel in 2020 amounted to RUB 123.3 billion[2] while capital investments of PAO Novatek equalled RUB 204.6 billion (the largest amount in the recent five years)[3].

Various instruments are applied to finance the increasing demands of the company, such as financing employing equity capital or raising debt (loan) capital. We may observe that the smaller the cost of raising any debt capital for a company, the bigger its resulting advantage over competitors due to its ability to raise large amounts of financing at a lower cost, to have a reserve for its products' price reduction with lower funding costs, and to have more competitive advantages.

Debt capital is the cheapest of the above-mentioned capital sources. It consists of bond-secured loans or bank loans. However, in case of a serious growth of corporate debt load this type of capital will be more and more expensive and the company's inability to service its debt may result in bankruptcy. Debt load is directly related to corporate capital structure. Therefore, it is important when analysing debt load to take into consideration corporate capital structure in general, i.e., the equity to debt ratio, when defining corporate debt load.

The essential difference between the above types of capital consists of cash flows used to pay for them. While payments for debt capital are defined beforehand, payments for equity capital are made with whatever funds remain after repayment of obligations to all other stakeholders. Besides, in the case of company liquidation, debt investors will be the first ones to be paid. Precisely due to these factors, debt financing is usually less costly than financing using equity capital. However, in the case of debt finacning investors cannot influence company management, while equity capital owners usually have such rights.

It should be noted that these types of financing are represented by external sources. As a corollary to this, we should note the potential zero-debt phenomenon that arises when companies, in general, do not strive to raise external sources and use cash flows generated by their current assets for financing.

[1] Kommersant. Dead-End Development Route. URL: https://www.kommersant.ru/doc/3533278 (application date: 25.02.2021).

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Since debt financing and the definition of debt load determinants is of relevance to our analysis, it is necessary to indicate the main sources of corporate debt capital formation. First of all, it is necessary to define long-term and short-term funding sources. Long term funding sources comprise obligations with a due date later than one calendar year since the date of the latest corporate report. Consequently, short term funding sources include obligations with an earlier due date which is shorter than one calendar year since the date of the latest corporate reports.

A bank loan is the most common and widely used method of raising debt capital. Loans are used to finance investment development projects as well as to maintain a company's current operations. The main advantages of this instrument are its relative simplicity (standard products imply standard documentation and a well-established procedure generally precedes loan preparation) and its availability at all stages of the company life cycle.

A second common instrument for such purposes is capital-raising bonds. This instrument is less widely used because it requires more detailed accompanying documentation, it is usually public, and it imposes certain obligations related to information disclosure in order to obtain credit ratings. Of relevance to this instrument, first it should be noted that the advantage of this instrument is the opportunity to raise funds for a significantly longer period in comparison to a bank loan. Second, it should be noted that under otherwise equal conditions, for the issuer, such funding is less costly than a loan because in the case of bonds the company cooperates directly with debt investors and does not have to pay additional interest to a bank (bank margin) as in the case of a loan. Additionally, an issue with high credit ratings presents an opportunity to issue bonds not just in local but also in foreign currency. This enables a diversification of the related debt portfolio from the point of view of currency as well as from the point of view of investors.

There are also other instruments: for example, the leasing of an asset for a certain period for certain regular payments, and hybrid financing forms which combine debt and equity capital features (preference shares, mezzanine loans etc.).

All the above examples of debt financing instruments show that when companies define their debt load, they may apply various methods of raising capital combining these instruments in different proportions. Ultimately, the definition of the debt load should be based on a strategy of furthering the development of the company and take into consideration its current size and the stage of its life cycle.

Theoretical Framework

Debt load is directly related to the notion of capital structure. As such, in this section of the paper, we will outline and evaluate a list of the most commonly applied academic and practically-relevant theories on capital structure. The majority of current studies are based upon the *theory of capital structure* by Franco Modigliani and Merton Miller (1958) [1]. In their seminal paper from 1958, the authors showed that a company's value would be the same irrespective of its capital structure. In their study, the authors used the assumptions of the perfect capital market, an absence of transaction and agency costs, and a risk-free and consistent debt interest rate, among other variables. Subsequently, several other theories arose in areas of related research, considering additional components of capital structure whilst removing some limitations of the traditional trade-off theory. These include the theory of the firm, the pecking order theory, and the new market timing theory.

Under the *trade-off theory of capital structure* (authors A. Kraus and R. Litzenberger [2]), the claim is made that even though debt financing allows corporations to use the tax shield (thus increasing the company value) one ought to take into consideration the costs of bankruptcy (financial imbalance costs). Bankruptcy costs increase with rising debt and reduce the company value. Thus, the company has to strike a compromise between costs of bankruptcy and benefits of the tax shield and seek an optimal balance between debt and equity resulting in company value maximization. These assumptions have been confirmed on repeated occasions [3–6].

In articulating the *theory of the firm*, a range of problems related to agency costs was considered, with particular significance arising from the influence of papers authored by M. Jensen and W. Meckling [7], Demsetz, [8] Holmstrom and Tirole [9], and Rajan and Zingales [10]. This theory states that conflicts of interest between owners, managers and company creditors may influence corporate financial decisions. The first type of conflict (between owners/managers) is based on the premise that management may pursue interests that are different from the owners' interests, which is assumed to be the maximization of company value. The second type of conflict (with creditors) is related to creditors' unwillingness to provide funds for high-risk projects unsecured by corresponding pledges - while management or owners may face challenges in maximising company value utilising high-risk projects. This premise originates from the assumption that if a company is financed with a bank loan of a small amount, then the bank controls that company. Conversely then, when the company owes the bank a large amount of funds, the company starts to control the bank. In either event, the company incurs expenses related to solving such conflicts. The increase of the debt load may result in more clear manifestations of the second type of conflict (with creditors). As a consequence, this will cause a rise in agency costs for the company.

The *pecking order theory*, as postulated by Myers and Maljuf [11], Myers [12], Frank and Goyal [13] Jindřichovská, Körner [14] and Sheikh, et al. [15] assumes that when making decisions related to choice of funding sources a company will follow a certain hierarchical order of these sources. Undistributed profits (i.e. internal funds) which pose less risk are the foremost resort. If, however, a company needs external funding sources, first of all, least risky debt instruments (e.g. credits, bonds) are used, and subsequently more risky combined instruments (mezzanine, convertible debt) may be applied. Only at the last stage will corporate equity capital (i.e. the issuing of shares) be used to avoid loss of investment opportunities. Thus, the debt load level in this theory is indicative of the company's real need for external funding.

If management follows this theory, it strives to minimize expenditures for capital due to information asymmetry when raising external funding. Asymmetry consists in the fact that, as a rule, managers in the company have more information concerning current performance of the company, its possible growth prospects, and risks which a company may probably face. Besides this, often all information may be unavailable to other agents such as investors and creditors, i.e. to holders of equity and debt financing of the company. In the event this theory is observed in practice, in order to recompense such asymmetry and offset the risks it may entail, external users of information (i.e. investors and creditors) expect to have a bigger rate of return on their investments.

Thus, the pecking order theory assumes that if corporate operations are financed from the company's internal sources, information asymmetry is manifested to the least extent. However, in the case of external financing, this risk grows significantly and it is necessary to mitigate it by means of a higher rate of return for creditors and investors.

The *market timing theory* (McDonald [16], Elliott et al. [17] and Ahmadimousaabad et al. [18]) assumes that companies take a decision on procurement of funding, taking into consideration the current market value of shares. Taking into account the signaling effect, companies prefer to issue shares when they are overvalued and redeem them when they are undervalued.

This paper will empirically test the trade-off theory of capital structure in the two capital markets. In this vein, the studied hypotheses are formulated and measured in terms of contrast and comparison.

Traditional Determinants of Debt Load

A group of decisive factors which determine corporate debt load can be traced to a number of existing studies. These determinants comprise profitability, growth opportunities, firm size, and tangibility. A series of papers dedicated to the study of the influence of these factors on corporate debt load is considered below.

Profitability is one of the most frequently studied factors which directly influences the corporate capital structure and affects its debt load. This parameter indicates whether a company is able to gain profit from its operations after payment of all expenses and the income tax. Depending on the theory of capital structure applied, the relevant views on the influence of this factor on debt load may differ.

The trade-off theory of capital structure implies that the higher the company's profitability indicators, the larger amounts of debt it acquires. It is related to the fact that the company tries to maximize the benefit from the use of the tax shield because as profits grow, the taxes on the tax shield also increase. Additionally, the risk of potential bankruptcy is mitigated along with profits growth. This results in a decrease in the probability of and expenses from potential bankruptcy. A positive relation between these factors was confirmed in papers referenced at numbers [19–21] attached. Nevertheless, there is a significant number of papers that show the opposite effect, for example, the paper by La Rocca et. al referenced at [22], who use an example capital structure of 10,242 small and medium-sized Italian enterprises from 1996 to 2005. The authors identified a negative relation between profit and the debt amount of companies. The same conclusion has been made in other papers dedicated to the study of corporate capital structure in different economies [23; 24].

We suggest that the negative dependence is rather a characteristic of another theory of capital structure – the pecking order theory. As stated above, according to this theory the most preferred funding source of a company are its internal sources, i.e., undistributed profits. This implies that more profitable companies first use their own undistributed profits. This means that owing to a decrease of financing from borrowed funds, corporate debt load will reduce. Apart from the papers mentioned above, the paper by Asen et al. [25] also supports this interpretation, where the authors use as an example Nigerian companies from various economic sectors in the period of 1999 to 2018 and show that profitability indicators for such companies have negative dependence with a long-term and short-term debt.

As such, our Hypothesis No. 1 is: *Profitability exerts a significant negative influence on corporate debt load in emerging markets.*

The *growth opportunities* of a company are also related directly to its attempts to raise additional funding by means of debt obligations. As in the case of profitability, the influence of this factor on the use of debt is differently evaluated by different theories. The trade-off theory assumes a negative relation between debt and growth opportunities. This is due to the fact that companies with high growth potential usually incur greater expenses to procure debt capital [26]. Additionally, the use of internal funds is preferable from the point of view of avoidance of the agency problem and maintenance of financial flexibility for potential future investment decisions.

Other papers [e.g 27; 28] also identified this negative relation. For example, paper [30], using 2,329 Portuguese companies as an example, showed that the higher the company's growth potential was, the more its debt decreased in capital structure. A mixed relationship was found in [29], where the authors explored a sample of Czech SMEs.

However, according to the pecking order theory, dependence between the debt amount and growth opportunities shows positive dynamics. First of all, this is related to the fact that finance investments for quick-growth companies with a high potential often lack resources. For this reason, they are forced to use debt financing to use their investment opportunities. This positive dependence was shown in papers [15; 28; and 30].

Hypothesis No. 2: *Growth opportunities have a significant positive influence on corporate debt load in emerging markets.*

One important determinant of debt load is the *company size*. A study of this factor also gave controversial results. In this context, the perspective of actual influence of the company size on corporate debt depends on the theory under which it is analysed. According to the trade-off theory, dependence of these two indicators will be positive. This is explained by the fact that the bigger the company, the less it is exposed to bankruptcy and financial imbalance risks. Here the saying "too big to fail" is appropriate. Apart from that, the bigger the company, the more stable its cash flows. This is due to the diversification of these flows as the company business grows [32]. Large companies in general have easier access to financing because a wider choice of debt financing instruments is available to them than for small companies, and larger companies have a lower relative cost of financing due to reducing the risk of financial uncertainty. This point of view is confirmed by papers [21; 31; and 33].

Nevertheless, there are a lot of papers that show an inverse relationship between the company size and its debt load. This assumption of the pecking order theory states that as the company grows, it accumulates profit which then becomes a source of internal financing. Thus, as the company grows, it may rely more on undistributed profit as an investment resource. So, the company requires less external financing raised through debt instruments. A negative relation between debt load and the company size is indicated in papers [10; 34].

Hypothesis No. 3: *The company size exerts a significant negative influence on corporate debt load in emerging markets.*

Tangibility is another factor studied in the trade-off theory and pecking order theory. Usually, the proportion of tangible assets in the company total assets is captured by this factor. Generally, both theories of capital structure are based on the fact that the bigger the proportion of tangible assets, the higher the companies' debt load. This dependence is explained by the fact that in order to provide debt funding, banks often require collateral. Tangible assets of the corporation can serve as appropriate collateral [35]. Consequently, the bigger the share of tangible assets, the larger guarantee a company can offer, and the larger is the credit amount the company is able to obtain at the price it can afford. A large proportion of tangible assets also reduces the risk of financial difficulties as long as these assets may be sold to reimburse for creditors' and, probably, shareholders' losses (even in the extreme case of bankruptcy). A positive dependence of the debt amount and proportion of tangible assets was documented in papers [31; 36; 37].

Nevertheless, there are also many papers documenting negative dependence between the debt level and the proportion of corporate tangible assets. This stems from the fact that in the case of a large share of tangible assets in the structure, companies often rely more on seclf-financing using internal sources, and consequently the need for debt usage is lower. Negative relation was detected in papers [24; 30; 38].

Hypothesis No. 4: *Tangibility has a significant negative influence on corporate debt load in emerging markets.*

Other Determinants of Debt Load

The above-mentioned determinants of corporate debt load are most common in the studies dedicated to this topic. Nevertheless, there are other, less common, also important factors defining corporate debt load. Company liquidity is one of them. Apart from that, in this research, we offer to verify the influence of such factors as the required return (or discount rate) of a company (WACC) and corporate economic efficiency. Further, we consider these factors in detail.

The initial theory of capital structure by Modigliani and Miller (1958) implies that capital structure does not influence the company value. That is to say, the debt load level should not depend on the funds the company uses to maximize its value: either borrowed funds or its own funds. In its turn, that means that the required return of the company (which is usually expressed as the discount rate WACC) which takes into consideration corporate capital structure should not influence corporate debt load. This paper offers to study this relation in more detail and uses the company's WACC as one of the determinants which define the debt load level of the company. According to the trade-off theory change of the rate should have a significant impact on corporate debt load because it is based on creating the optimal ratio of debt to equity capital. Therefore, in accordance with the pecking order theory, this dependence should be insignificant because the company is guided by the hierarchy of funding sources rather than the optimal structure.

Hypothesis No. 5: *The company discount rate exerts an insignificant influence on corporate debt load in emerging markets.*

Company *liquidity* is another studied factor. Usually, the current ratio is the indicator of company liquidity. Liquidity is measured as a ratio of current assets to current liabilities capturing the company's ability to cover its short-term liabilities. Consequently, the higher this indicator, the greater the company's ability to address its liabilities and other current investments. Thus, the higher this indicator, the lower the need for external debt financing. It follows from this that dependence between the liquidity level and corporate debt level is negative. This interrelation was identified and discussed in papers [26; 39] and it confirms assumptions of the pecking order theory.

Nevertheless, some research indicates a positive dependence between liquidity and debt level. So, in paper [24] the authors studied Chinese companies in the period of 2006 to 2015 and found out that the higher their liquidity level the greater the debt load. The author attributes it to the fact that with a higher liquidity level the company may afford to raise larger amounts of short-term debt because the higher this indicator the less risky this loan is both for the company and its creditor. This result confirms the trade-off theory.

Hypothesis No. 6: *Liquidity has a significant negative influence on corporate debt load in emerging markets.*

Another factor that may be also determining the debt load of the company is its *economic efficiency*. In this paper, economic efficiency is measured as an excess of the corporate return on assets (ROA) over its weighted average capital cost of capital or the appropriate discount rate WACC.

If the return on assets exceeds the cost of capital for the company, it is economically efficient. This indicates that the company uses its assets with the yield sufficient to cover procurement of the required capital. Consequently, if the return on assets does not cover the capital cost the company is not economically efficient even if it has the net profit.

According to the trade-off theory, economic efficiency will have a positive impact on debt load because the more efficiently the company uses its assets the larger debt it can afford to raise. Correspondingly, its debt load should increase as economic efficiency grows.

On the other hand, in conformity with the pecking order theory, the more efficiently the company manages its assets, the more it can rely on its internal resources when financing new projects. This means that the share of debt financing, as well as the level of debt load, will decrease as the efficiency of use of the company's own assets grows.

Hypothesis No.7: *Economic efficiency has a significant negative influence on corporate debt load in emerging markets.*

This section describes the main theories and empirical studies explaining corporate debt load. Apart from that, we have defined, described and explained the most decisive determinants which influence the corporate debt level. Further, these determinants are considered as factors that influence corporate debt load in emerging markets. The overview of factors relating to debt load is presented in Table 1 below.

Table 1. Influence of factors on debt load in accordance with dominant theories

	Trade-off theory	Pecking order theory
Profitability	Positive	Negative
Tangibility	Positive	Positive
Company size	Positive	Negative
Growth opportunities	Negative	Positive
Discount rate	Significant influence	Insignificant influence
Liquidity	Positive	Negative
Economic efficiency	Positive	Negative

Analysis

The Theoretical Framework for the Study

The main method of study of the influence of determinants on corporate debt load is regression analysis, which reveals the possible relations between different variables used in the model. There are two types of variables in this method. The first one is the dependent variable designated as Y. The second type are explicative variables, usually designated as X (or XI where I is a sequential number of the explicative variable if there are more than one variable). Regression analysis may define dependence between the variables and the contribution of each explanatory variables (regressor) to a change of the dependent variable.

Corporate debt level will be the dependent variable and the factors considered in the previous section will be used as explicative variables. Then it is necessary, first, to decide which indicators will be applied to define the level of corporate debt load.

The most common and well-known indicators which assess corporate debt load are the ones based on the book value, including the debt to equity ratio. It shows the ratio of debt financing to internal financing of the company. A high value of this indicator shows that the company to a serious extent funds its operations employing debt financing which is a signal of possible financial imbalance risks. Nevertheless, this indicator may vary according to the industry sector. For example, if the industry sector in which the company is operating implies large capital expenditures for the conduct of business, this indicator, on average, will be higher than in the sectors which require smaller capital expenditures.

Another important factor is the ratio of total debt to total capital (debt + equity capital) of the company (debt to capital ratio). This indicator manifests which part of corporate total capital (in percentage terms) is financed through debt. As in the previous case, the bigger this indicator the greater the financial imbalance risk of the company.

The frequently used ratio of total debt to company assets (debt to assets ratio) shows which part of corporate aggregate assets is funded through debt financing. This is the interpretation of debt load that we as the dependent variable Y, which designates corporate debt load when building the model:

$$\mathrm{LEV} = \frac{\mathrm{STDebt} + \mathrm{LTDebt}}{\mathrm{TotalAssets}},$$

Where LEV represents the corporate debt load (leverage); STDebt stands for corporate short-term debt; and LTDebt represents corporate long-term debt which comprises bank loans and bonds. A list of all variables, their designations and calculation methods are presented in Table 2.

Table 2. The main variables and their calculation

Variable	Calculation method	Source
Dependent variables		
Debt load (LEV)	$LEV = \frac{TotalDebt}{TotalAssets}$	[40; 41]
Independent variables		
Profitability (PROFIT)	$PROFIT = \frac{EBIT}{TotalAssets}$	[24; 42]
Tangibility (TANG)	$TANG = \frac{FixedAssets}{TotalAssets}$	[30; 41; 43]
Company size (SIZE)	$SIZE = \ln(TotalAssets)$	[40; 41; 44]
Growth opportunities (GROWTH)	$GROWTH = \frac{Revenue_t}{Revenue_{t-1}}$	[31]
Discount rate (WACC)	$WACC =$ Discount rate of the company	This has not been used as a determinant in prior research
Liquidity (LIQ)	$LIQ = \frac{CurrentAssets}{CurrentLiabilities}$	[26]
Economic efficiency (EFF)	$EFF = ROA - WACC$	This has not been used as a determinant in prior research

EBIT means earnings before interest on liabilities and income tax, Total Assets means corporate total assets, Fixed Assets means corporate fixed assets (tangible assets), Revenue stands for company proceeds, CurrentAssets means corporate current assets (short-term), and CurrentLiabilities means corporate short-term liabilities.

Where determinants of defining debt load are concerned, the regression model of this research is formally stated as follows:

$$LEV_{it} = \beta_0 + \beta_1 (PROFIT)_{it} + \beta_2 (TANG)_{it} + \\ + \beta_3 (SIZE)_{it} + \beta_4 (GROWTH)_{it} + \beta_5 (WACC)_{it} + \\ + \beta_6 (LIQ)_{it} + \beta_7 (EFF)_{it} + \varepsilon_{it}.$$

In this model, *i* denotes a company from the sample, and *t* denotes a corresponding time period.

Research Hypotheses

The following hypotheses were generated based on the literature review to study debt load determinants. These hypotheses are tested in the present research to verify the compliance with the trade-off theory of capital structure for companies from the Russian and Brazilian markets. The list of tested hypotheses is presented here including relevant determinants on both markets.

Hypothesis No. 1: *Profitability exerts a significant negative influence on corporate debt load in emerging markets.*

Hypothesis No. 2: *Growth opportunities have a significant positive influence on corporate debt load in emerging markets.*

Hypothesis No. 3: *The company size exerts a significant negative influence on corporate debt load in emerging markets.*

Hypothesis No. 4: *Tangibility has a significant negative influence on corporate debt load in emerging markets.*

Hypothesis No. 5: *The company discount rate exerts an insignificant influence on corporate debt load in emerging markets.*

Hypothesis No. 6: *Liquidity has a significant negative influence on corporate debt load in emerging markets.*

Hypothesis No. 7: *Economic efficiency has a significant negative influence on corporate debt load in emerging markets.*

Depending on the confirmed relation between each individual factor and debt-load, we can then establish which theory of capital structure is the most prevalent on emerging markets.

Applied Data

The main decision criterion to make the list of companies selected during the research was trading their shares or bonds in the Russian or Brazilian stock exchange for Russian and Brazilian companies, respectively. The last calendar year was taken as the research period.

The Bloomberg database was used to collect financial indicators to calculate debt load determinants. Due to incomplete financial data for some companies, we experienced problems with the collection of indicators. For this reason, where possible, we used annual reports of companies to add the indicators absent from the Bloomberg database. After sorting the initial data, we eliminated financial sector companies from the sample, removed duplicated data, and eliminated companies with significant gaps in financial information. The final sample comprised 753 Russian and 292 Brazilian companies.

Empirical Analysis of the Research Results

Results of Econometric Analysis (Russia)

In the following part, we describe the results of the econometric model presented in the previous section. The calculations were performed with the use of STATA and MS Excel. See below for the results of our analysis of the sample of Russian companies.

First of all, we obtained descriptive statistics of all variables indicated in the previous section for Russian companies. See the data in Table 3.

Table 3. Descriptive statistics of variables

Variable	Number of observations	Average	Median	Standard deviation	Minimum	Maximum
LEV	753	0.2599	0.1728	0.3442	0	3.2329
PROFIT	753	0.0572	0.0490	0.1968	–3.1388	1.6224
TANG	753	0.4095	0.3723	0.2633	0	0.9900
SIZE	753	18.1821	17.9568	2.3120	10.9032	26.3908
GROWTH	743	1.0465	1.0046	0.4915	0.0700	10.8000
WACC	694	11.4210	12.0150	3.1840	3.1600	25.7300
LIQ	753	2.9444	1.4267	6.7463	0.0003	97.3025
EFF	753	–9.1178	–8.5700	18.4079	–217.8000	93.6300

Table 4. Correlation matrix of variables

	LEV	PROFIT	TANG	SIZE	GROWTH	WACC	LIQ	EFF
LEV	1							
PROFIT	0.0099	1						
TANG	0.1008*	0.0054	1					
SIZE	0.4106*	0.1154*	0.1801*	1				
GROWTH	0.0464	0.1329*	0.0916	0.1568*	1			
WACC	–0.8544*	0.0362	0.0264	–0.3250*	–0.0186	1		
LIQ	–0.4158*	0.0947	–0.2779*	–0.1622*	–0.0364	0.5087*	1	
EFF	–0.018	0.4776*	–0.0616	–0.0036	0.1299*	0.0244	0.1067*	1

*a 1% significance level.

The following conclusions may be made based on the above data. First of all it should be noted that, on average, the debt-load of Russian companies amounts to approximately 26% (although the sample comprises companies without debt load). The average profitability of companies was just 6% - but at the same time, the capital intensity of Russian companies is rather high because the share of fixed assets in total assets on average exceeds 40%. The size indicator shows that the sample contains rather large companies as well as significantly smaller ones. The indicator of growth opportunities illustrates that the sample comprises companies at different development stages. The liquidity indicator shows that on average Russian companies have a good current ratio, which allows them to cover their current liabilities. At the same time, the economic efficiency indicator demonstrates clearly that, on average, Russian companies show no efficiency.

Subsequently, we have studied the probability distribution of the variables included in the models based on the graph method. See the results in Appendix 1. Then, a correlation matrix was made for the used variables (Table 4).

Analysis shows a significant dependence between debt load and the majority of the determinants mentioned above. A positive relationship is observed between the company size and tangibility, while a negative relationship was revealed for the variables, which define the discount rate of the company and its liquidity. According to the results, we can also state that there is no significant correlation between debt load and profitability. A significant correlation was revealed between efficiency and growth opportunities in this sample. The correlation is considered to be significant if the correlation coefficient between variables exceeds 0.7 (and this is the case only with the discount rate variable). It makes sense from the empirical point of view, because the higher the corporate required profitability, the higher interest the company pays for new debt and thus the new debt becomes less attractive for the company.

Then, we built a regression model based on the equation presented in the next section. The corporate debt load (LEV) is used as the dependent variable. In this model, we replaced the EFF variable, which stands for efficiency with the DEFF dummy variable, which takes on the value of 1 if the company is efficient (ROA>WACC) and correspondingly takes on the value of 0 if, on the contrary, the company is not efficient (ROA<WACC). See the results of the model in Table 5.

Table 5. Results of model evaluation

	LEV
PROFIT	–0.0268
TANG	0.0938***
SIZE	0.0154***
GROWTH	–0.0304*
WACC	–0.0548***
LIQ	–0.0007
DEFF	0.0401
CONS	0.5588***
Adj R-squared	0.4663

*** a 1% significance; ** a 5% significance; * a 10% significance.

The average R-square in the model takes on an acceptable value of 0.4663, i.e., the defined independent variables in the model explain a little less than 50% of changes of the dependent variable. According to Fisher's criterion, at a 0.01 significance level, the zero hypotheses of statistical insignificance of regression is rejected. This means that the equation in general is statistically significant. Several points concerning this model should be explained. First of all, the profitability indicator is not significant at any level. Besides, at a 1% significance level, the variables designating tangibility, size, discount rate and the constant turned out to be important. The positive significant relation between tangibility (the share of fixed assets in corporate assets to be more exact), and corporate debt load confirm both theories of capital structure because it shows that the more opportunities a company has to offer a pledge to secure a debt, the higher that company's debt load. A positive significant relationship between the company size and debt load confirms the trade-off theory of capital structure and indicates that it is expressed in smaller risks of bankruptcy and financial imbalance and in more stable cash flows. A negative significant relationship between the discount rate of a company and its debt load shows that in this case, companies act more following the trade-off theory of capital structure because capital structure influences their debt load.

At the same time, the growth opportunities variable turned out to be significant only at a 10% level, while other variables were statistically insignificant. Thus, in this model the following hypotheses were not confirmed for Russian companies:

Hypothesis No. 1: *Profitability exerts a significant negative influence on corporate debt load in the Russian market* ***(insignificant influence).***

Hypothesis No. 3: *The company size exerts a significant negative influence on corporate debt load in the Russian market* ***(significant positive influence – the trade-off theory).***

Hypothesis No. 4: *Tangibility has a significant negative influence on corporate debt load in in the Russian market* ***(significant positive influence – the trade-off theory).***

Hypothesis No. 5: *The company discount rate exerts an insignificant influence on corporate debt load in the Russian market* ***(significant negative influence – the trade-off theory).***

Hypothesis No. 6: *Liquidity has a significant negative influence on corporate debt load in the Russian market* ***(insignificant influence).***

Hypothesis No. 7: *Economic efficiency has a significant negative influence on corporate debt load in the Russian market **(insignificant influence).***

Hypothesis No. 2 was confirmed partially:*growth opportunities have a significant positive influence on corporate debt load in the Russian market **(significant at a 10% level, negative influence – the trade-off theory).***

Results of econometric analysis (Brazil)

Further, we show the results of the analysis of the sample comprising Brazilian companies. The sample of Brazilian companies was studied in the same way as that of Russian companies. First, we obtained descriptive statistics of all variables. See the data in Table 6.

Table 6. Descriptive statistics of variables

Variable	Number of observations	Average	Median	Standard deviation	Minimum	Maximum
LEV	292	0.3577	0.2997	0.4071	0.0000	4.7325
PROFIT	292	0.0371	0.0601	0.1444	–1.0339	0.3108
TANG	292	0.2631	0.2272	0.2112	0.0000	0.9993
SIZE	292	20.1761	20.2347	1.9317	15.0144	25.9709
GROWTH	288	1.1079	1.0300	0.3702	0.2500	3.5000
WACC	292	13.5186	13.8900	2.1992	3.6300	20.1300
LIQ	291	2.4173	1.6661	4.6423	0.0005	66.4670
EFF	292	–13.4457	–11.1400	14.0992	–82.0600	13.9900

The following conclusions may be made based on the obtained data.

The average debt load of Brazilian companies, on average, amounts to 36% which is 10% more than that of Russian companies. Average profitability amounts to approximately 4% which is a little less than the profitability of Russian companies (6%). Besides, Brazilian companies, unlike Russian ones, show a significantly lower capital intensity – the share of fixed assets in the total assets, on average, amounts to approximately 26%. The size indicator indicates that the sample comprises both large and small companies. The indicator of growth opportunities shows that the sample encompasses companies of various development stages. The liquidity indicator illustrates that Brazilian companies have a good current ratio on average. At the same time, the economic efficiency indicator, in the same way as with Russian companies, shows that on average Brazilian companies are less effective.

Subsequently, the probability distribution of the variables was studied applying the graph method (Appendix 2), and a correlation matrix was made for the used variables (Table 7).

Table 7. Correlation matrix of variables

	LEV	PROFIT	TANG	SIZE	GROWTH	WACC	LIQ	EFF
LEV	1							
PROFIT	–0.0877	1						
TANG	0.2061*	0.0443	1					
SIZE	0.2482*	0.1327	–0.017	1				
GROWTH	–0.0127	0.1701*	0.0076	0.0738	1			
WACC	–0.4495*	–0.054	–0.1912*	–0.0101	0.1028	1		
LIQ	–0.3587*	0.1610*	–0.2026*	–0.0096	0.1051	0.4146*	1	
EFF	–0.1359	0.3880*	0.0319	–0.2164*	0.0345	–0.0304	0.1163	1

* a 1% significance level.

Analysis shows that there is a significant dependence between debt load and the same determinants which have been used for Russian companies. A positive relationship is observed between the company size and tangibility while a negative correlation was detected for the variables which define the discount rate of the company and its liquidity. As in the Russian companies' sample, no significant correlation was revealed between debt load and profitability, efficiency and growth opportunities. No significant correlation is observed between the variables (the correlation ratio exceeds 0.7).

We subsequently built a regression model. The corporate debt load (LEV) is used as the dependent variable. In this model, as in the Russian companies' sample, we replaced the EFF variable which stands for efficiency with the DEFF dummy variable. See the results of the model in Table 8.

Table 8. Results of model evaluation

	LEV
PROFIT	–0.0268**
TANG	0.0938*
SIZE	0.0154
GROWTH	–0.0304
WACC	–0.0548***
LIQ	–0.0007**
DEFF	0.0401
CONS	0.5588***
Adj R-squared	0.1581

*** a 1% significance; ** a 5% significance; * a 10% significance.

The average R-square in the model amounts to 0.1581, which is significantly lower than in the Russian samples. The zero hypothesis of statistical insignificance of this regression is rejected at the 0.01 significance level according to Fisher's criterion. This means that the equation is statistically significant in general. Several points of this model need to be clarified. First of all, in this sample, the profitability indicator turned out to be significant at a 5% level with a negative relation, thus confirming the pecking order theory because the company prefers to rely on its own sources. Additionally, the liquidity indicator was significant at a 5% level with a negative relation, which also confirms the pecking order theory. Only the tangibility variable was at a 10% significance level.

At the same time, at a 1% significance level, only the discount rate variable and the constant were of importance. A significant negative relationship between the corporate discount rate and its debt load shows that in this case, companies act more according to the trade-off theory of capital structure because capital structure influences their debt load.

Besides, other variables turned out to be statistically insignificant. Thus, in this model, the following hypotheses have been confirmed for Brazilian companies.

Hypothesis No. 2: *Growth opportunities have a significant positive influence on corporate debt load in the market* ***(insignificant influence).***

Hypothesis No. 3: *The company size exerts a significant negative influence on corporate debt load in the market* ***(insignificant influence).***

Hypothesis No. 5: *The company discount rate exerts an insignificant influence on corporate debt load in the market* ***(significant negative influence – the trade-off theory).***

Hypothesis No. 7: *Economic efficiency has a significant negative influence on corporate debt load in the market* ***(insignificant influence).***

The following hypotheses were confirmed partially:

Hypothesis No. 1: *Profitability exerts a significant negative influence on corporate debt load in the market* ***(a 5% significance, negative influence – the pecking order theory).***

Hypothesis No. 4: *Tangibility has a significant negative influence on corporate debt load in the market* ***(a 10% significance, positive influence – the trade-off theory).***

Hypothesis No. 6: *Liquidity has a significant negative influence on corporate debt load in the market* ***(a 5% significance, negative influence – the pecking order theory).***

Conclusion

In this paper we have analyzed determinants of the debt load level for a sample of Russian and Brazilian companies in 2020. The sample consists of 753 Russian companies and 292 Brazilian companies. We identified that the same set of determinants differs significantly in explanatory power and suits Russian companies much better than Brazilian ones. Moreover, it was established that on the basis of this set of determinants, it is impossible to identify with confidence which of the two theories companies are most likely to follow in their actions, because the observed interrelations between the examined factors and debt load have indications of the trade-off theory as well as the pecking order theory.

It should be also noted that the WACC variable, specifying the cost of capital turned out to be significant for both samples. This confirms the dependence of debt load on capital structure for companies in both Russia and Brazil. At the same time, the result that economic efficiency has no significant impact on corporate debt load is representative. It may signal to the management that this aspect should be taken into consideration when defining the optimal level of corporate debt load.

In general, and in conclusion, we may also postulate that the issue of economic efficiency and the link thereof to corporate debt is of interest for further study from the point of view of corporate capital structure in markets other than the ones studied presently. Further, we may propose that the operations of certain companies in 2020 in different economic, social, business and cultural contexts widely varies and complicates the strict application of conventional academic theories articulated thus far.

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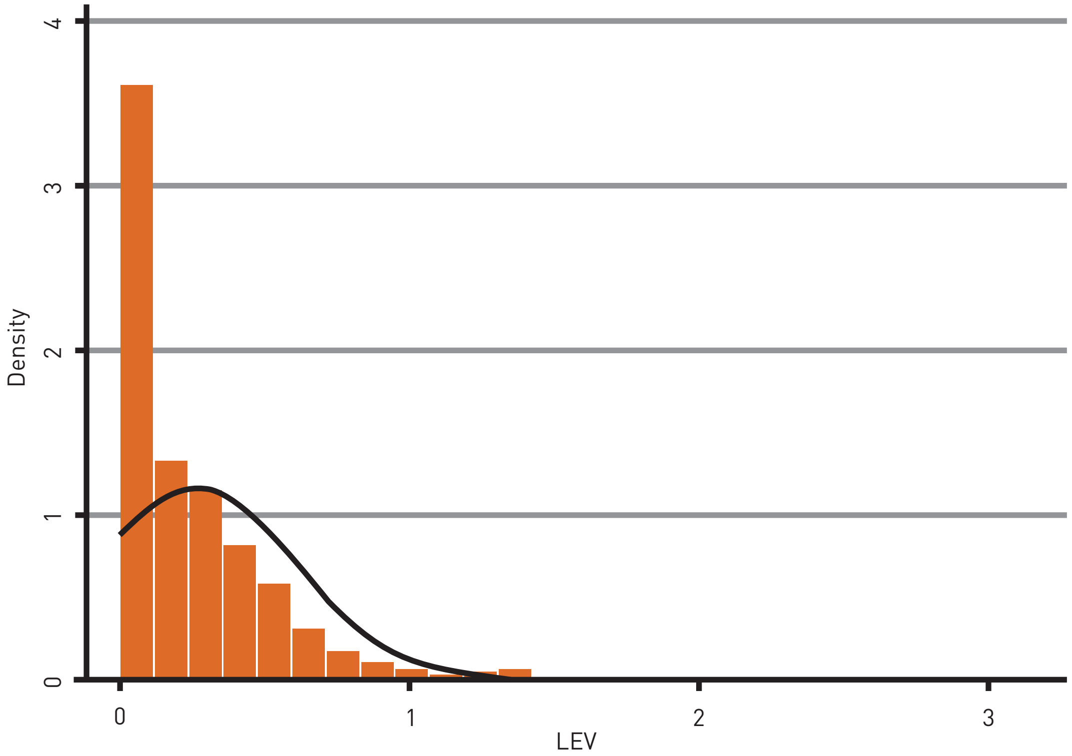
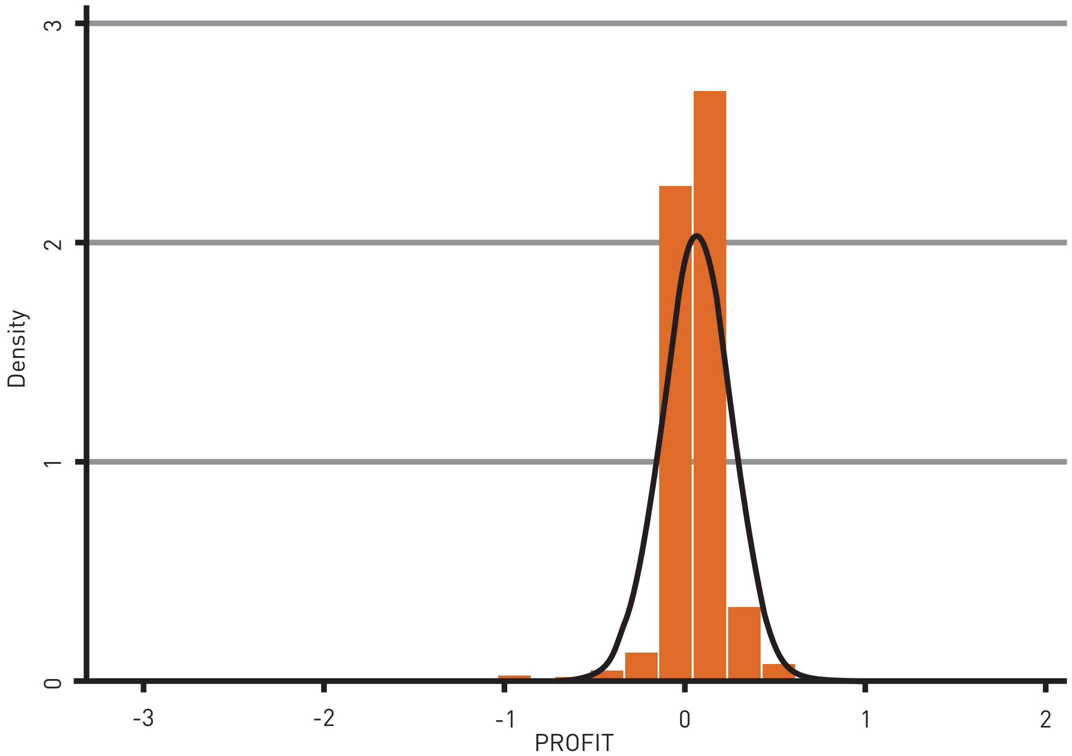
Appendix 1 (Russia)

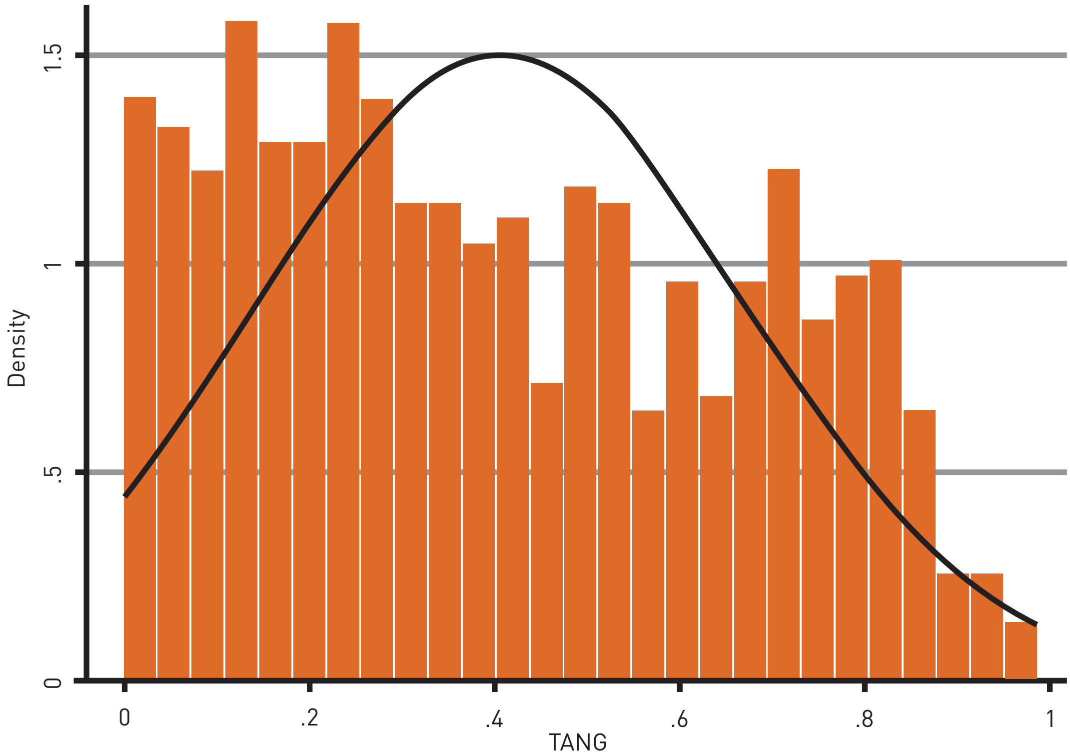
LEV probability distribution



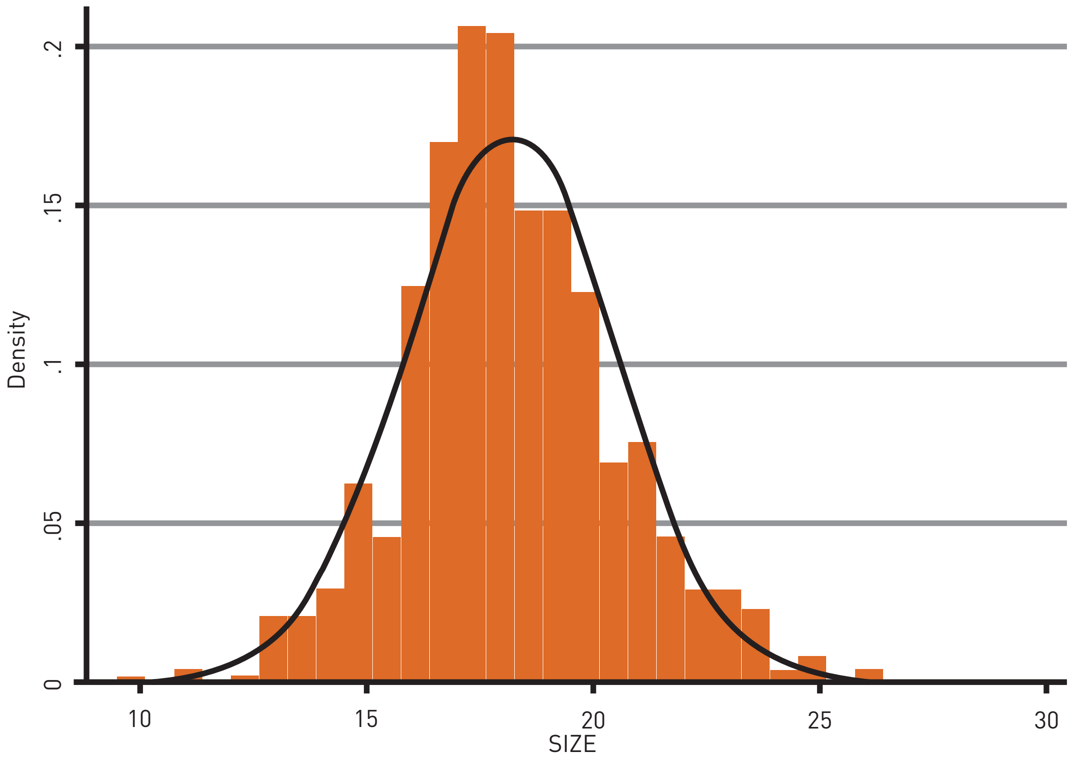
PROFIT probability distribution



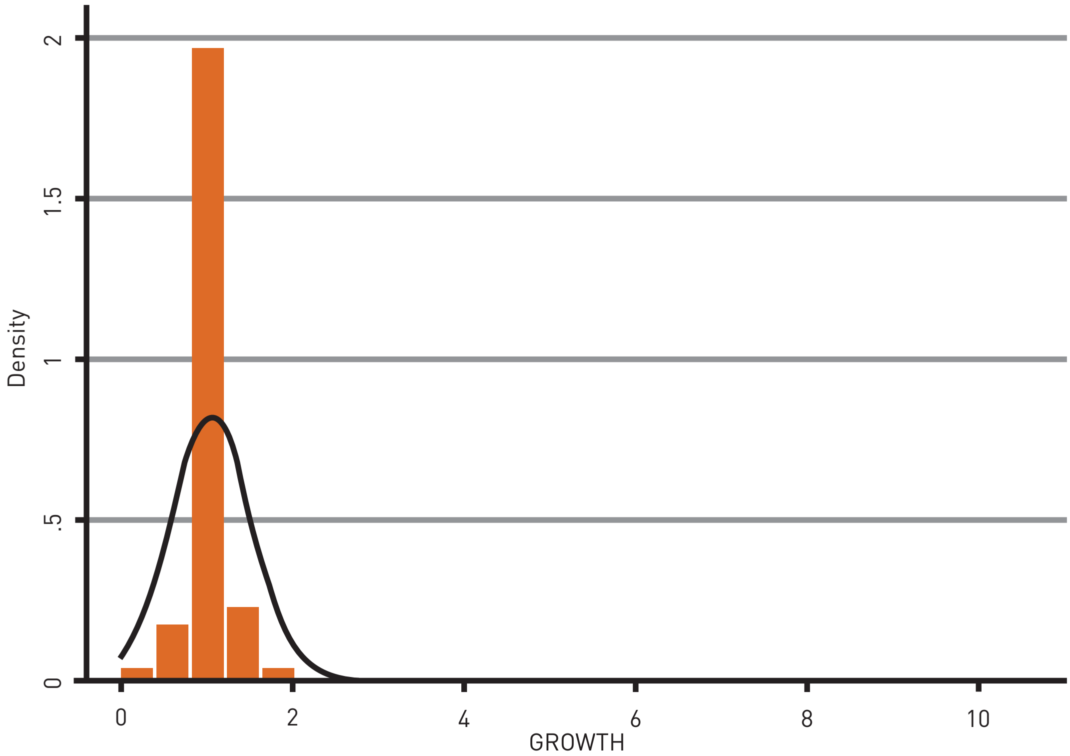
TANG probability distribution



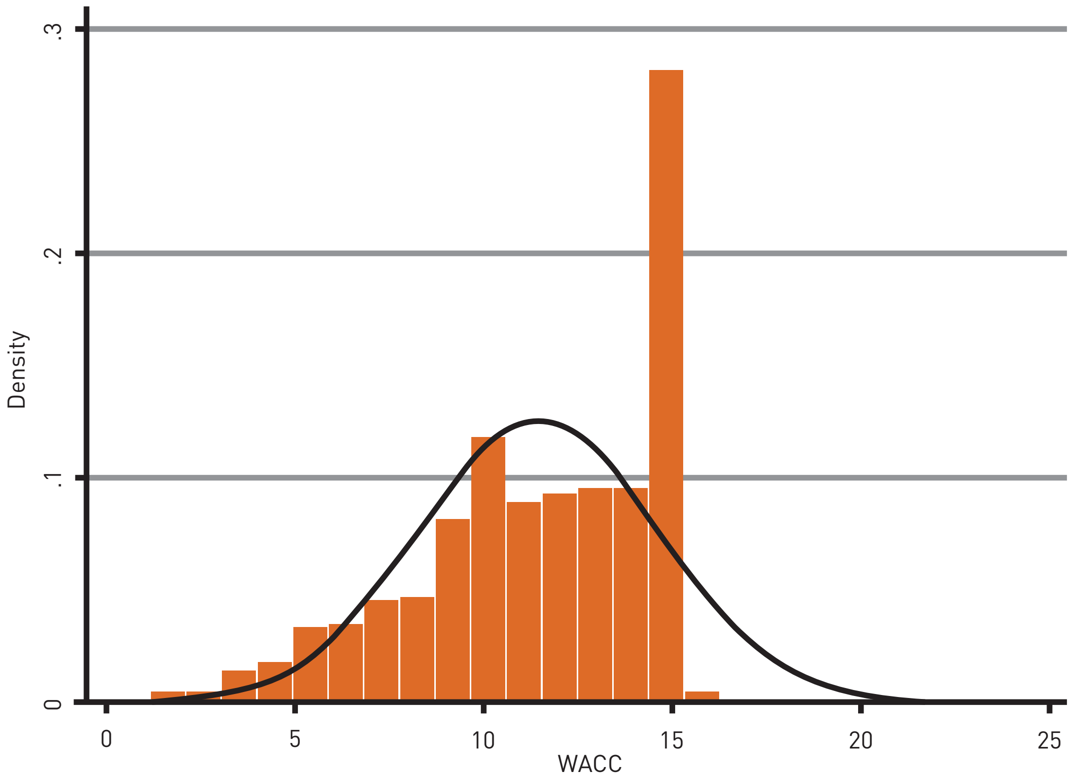
SIZE probability distribution



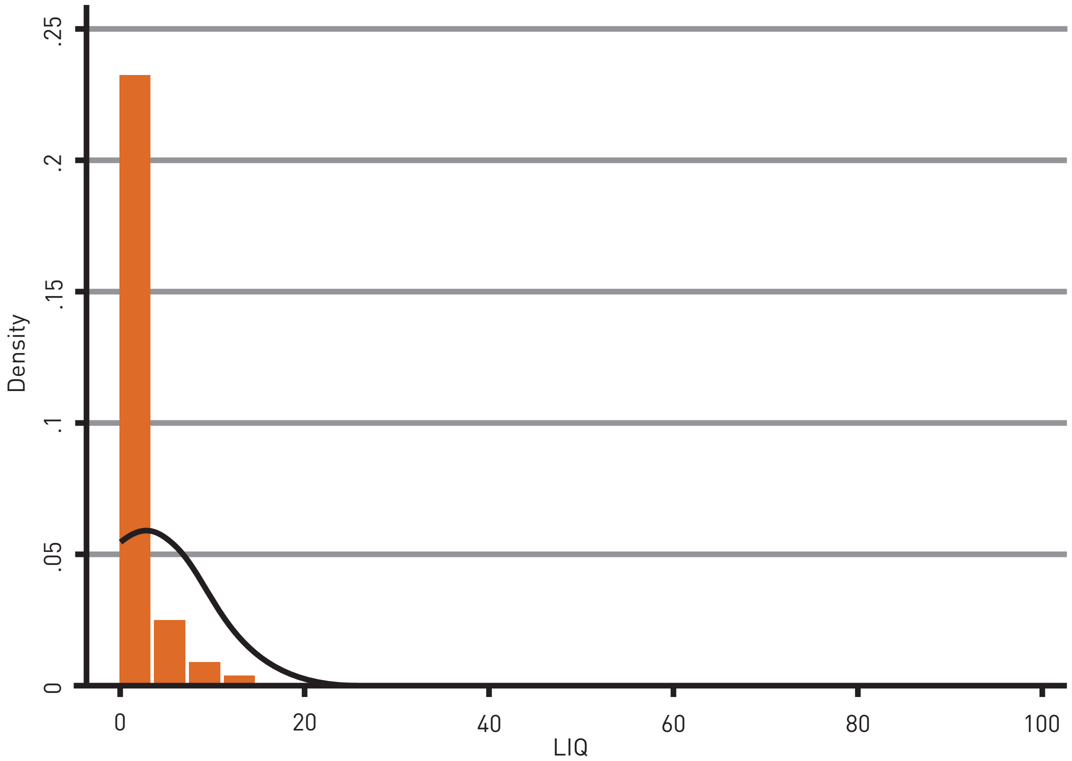
GROWTH probability distribution



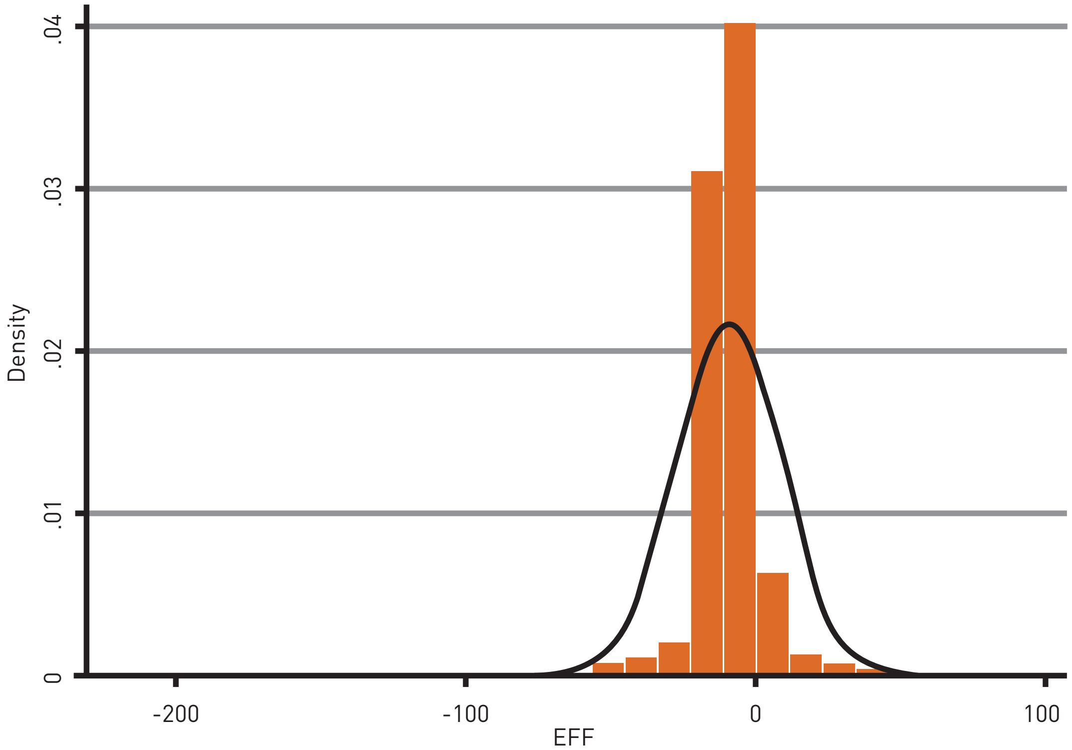
WACC probability distribution



LIQ probability distribution

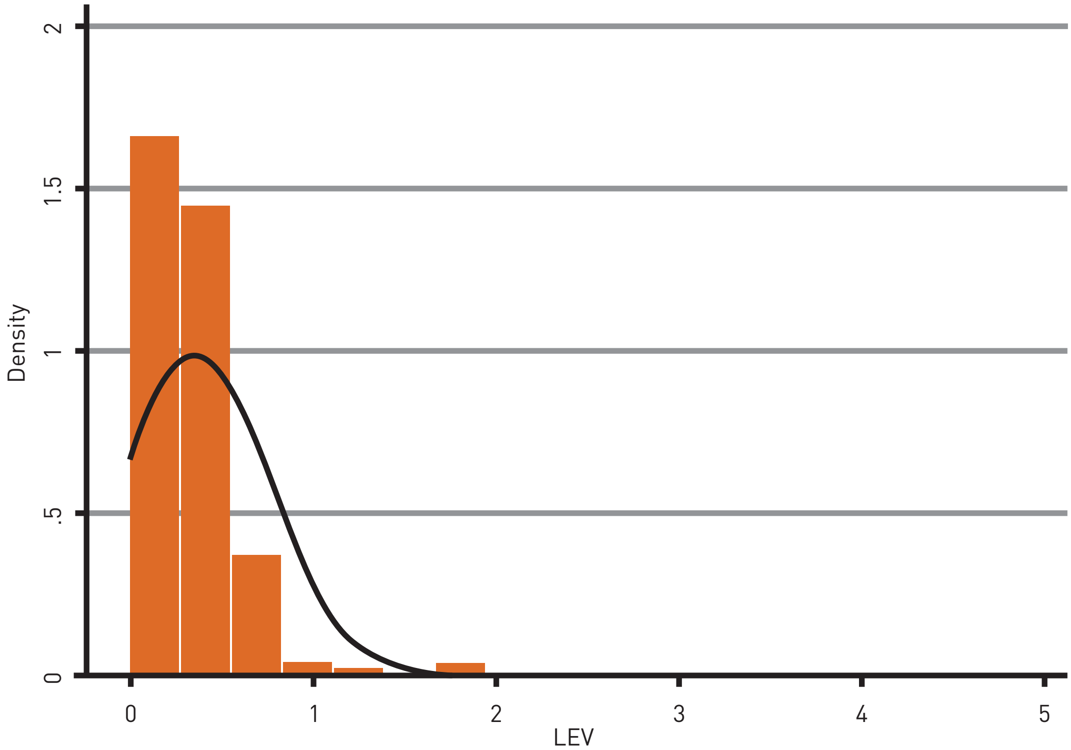


EFF probability distribution



Appendix 2 (Brazil)

LEV probability distribution



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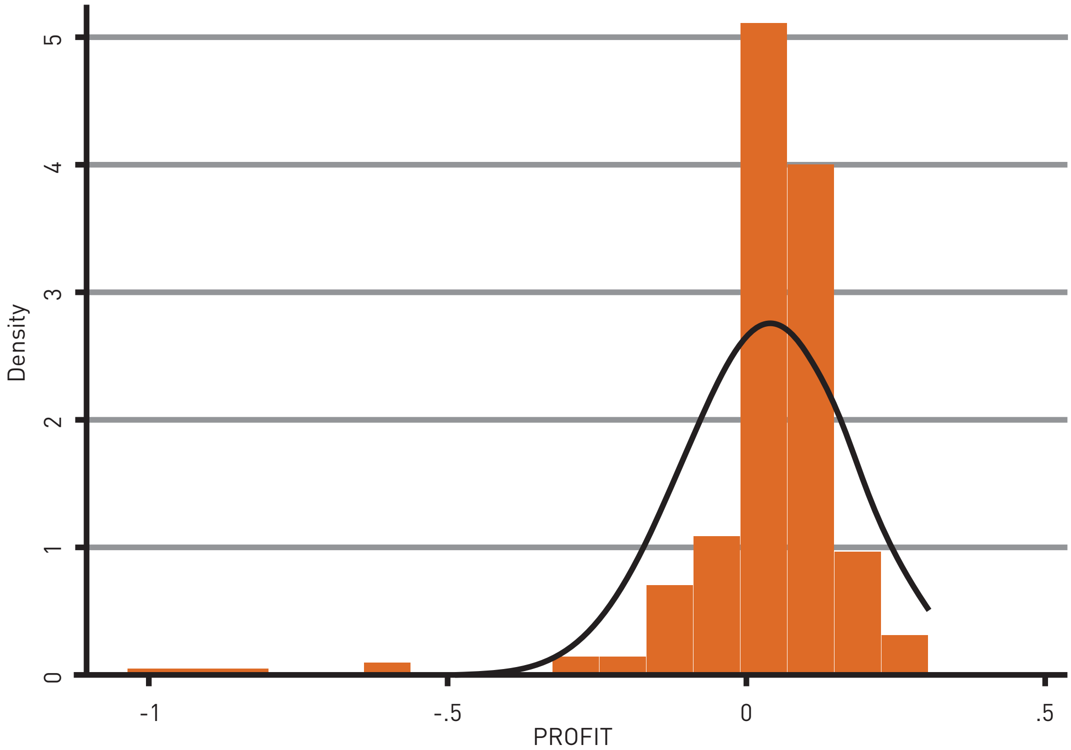

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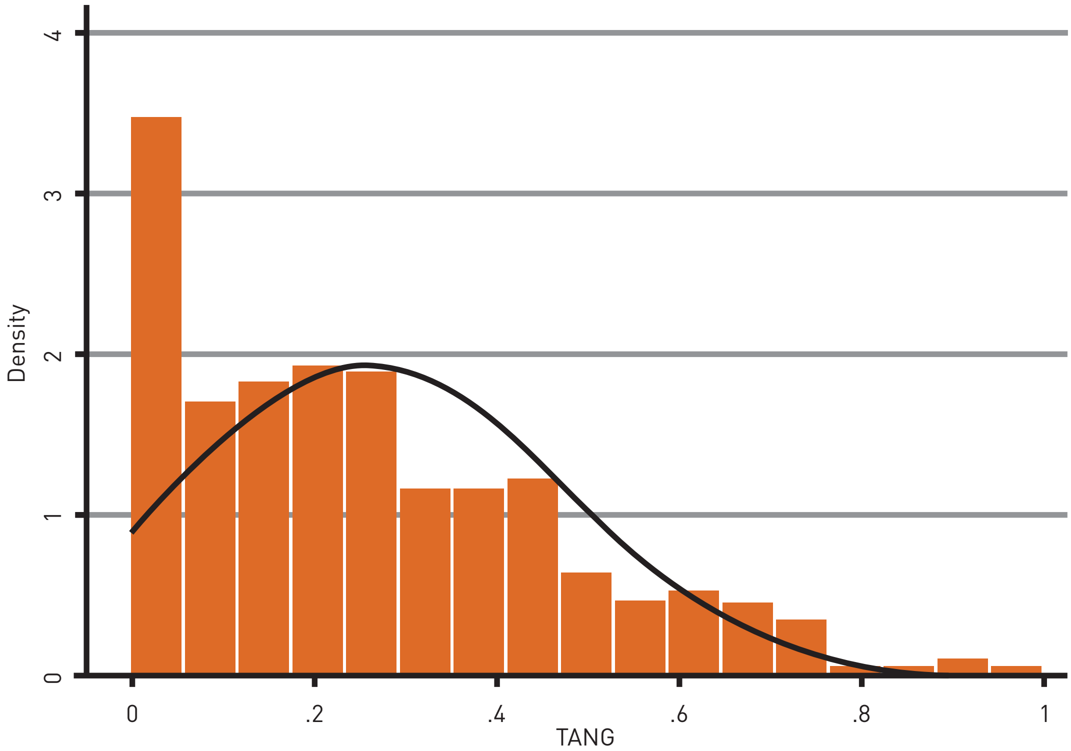

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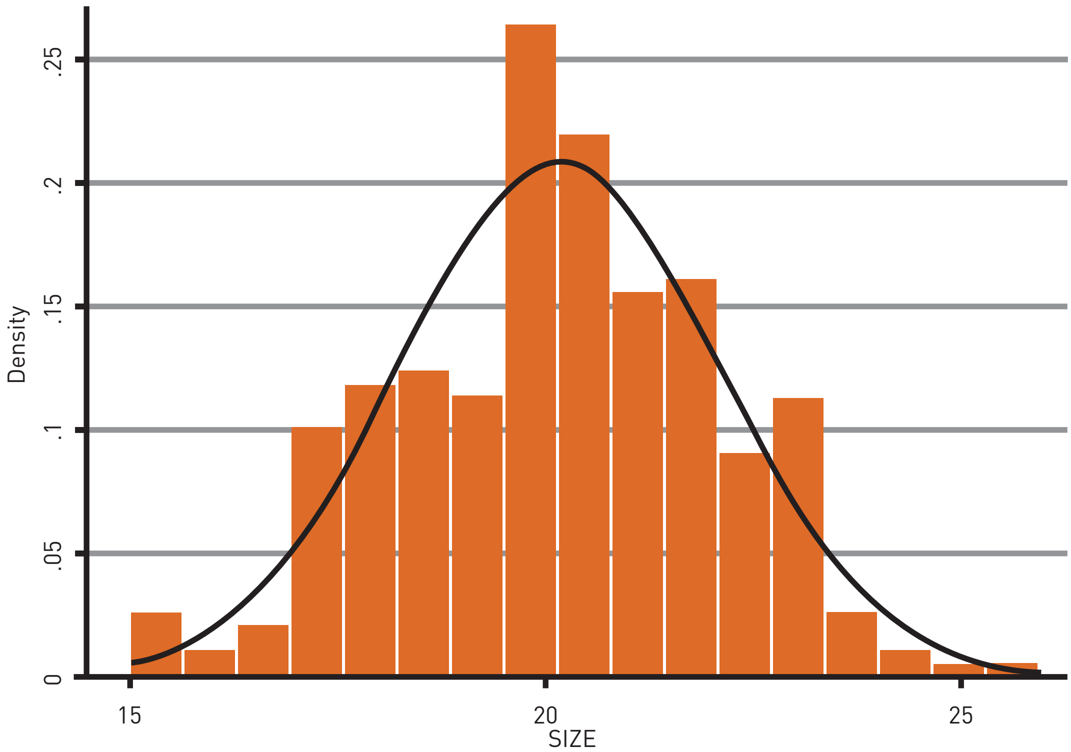

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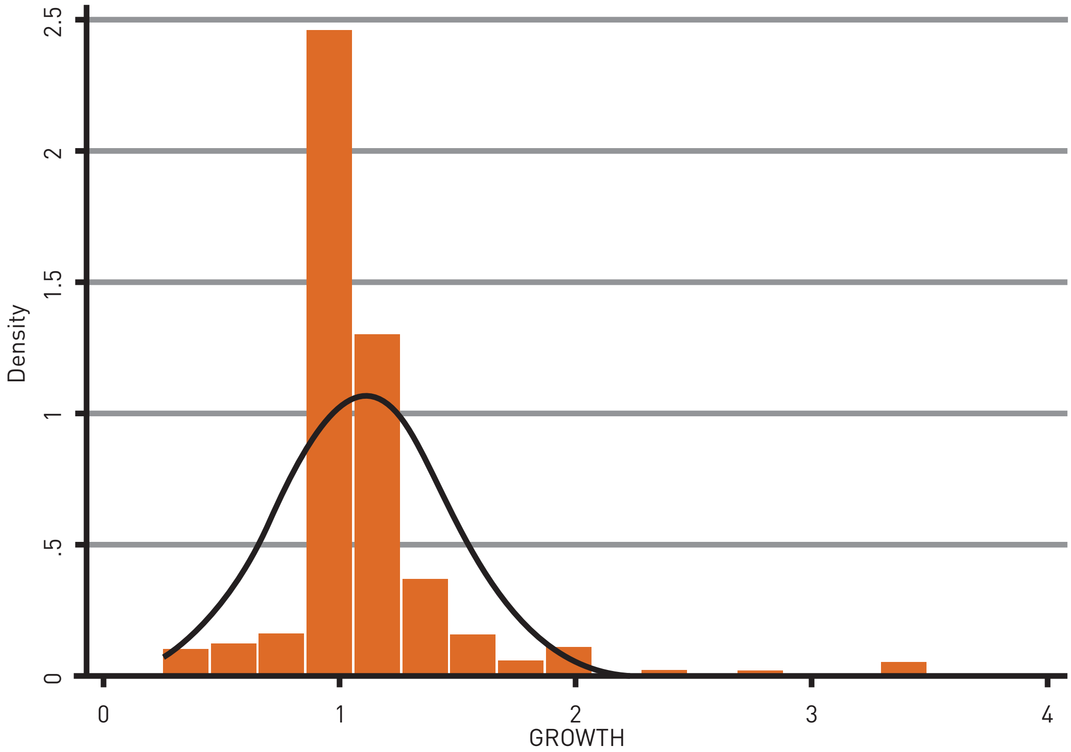

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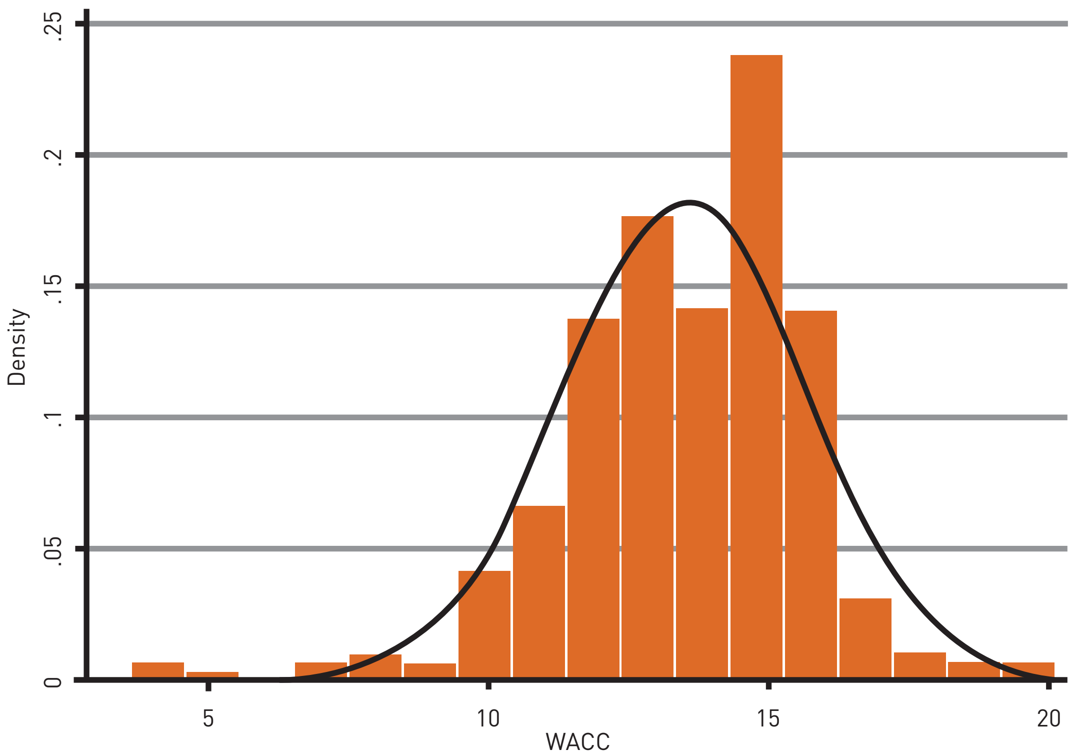

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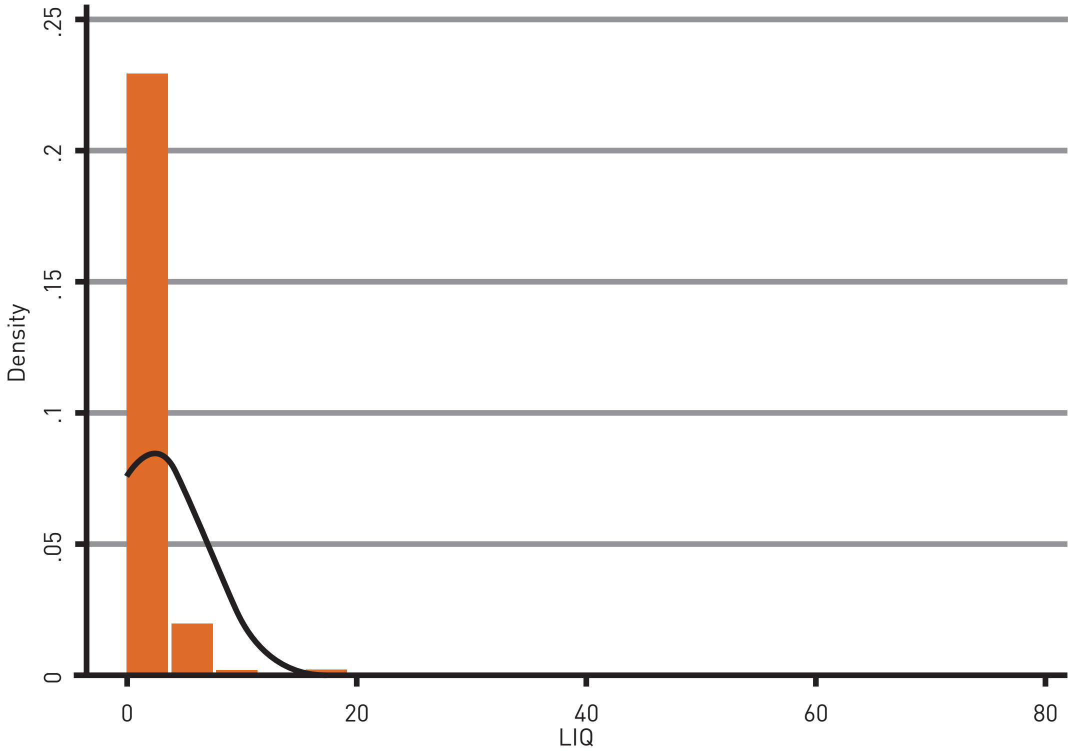

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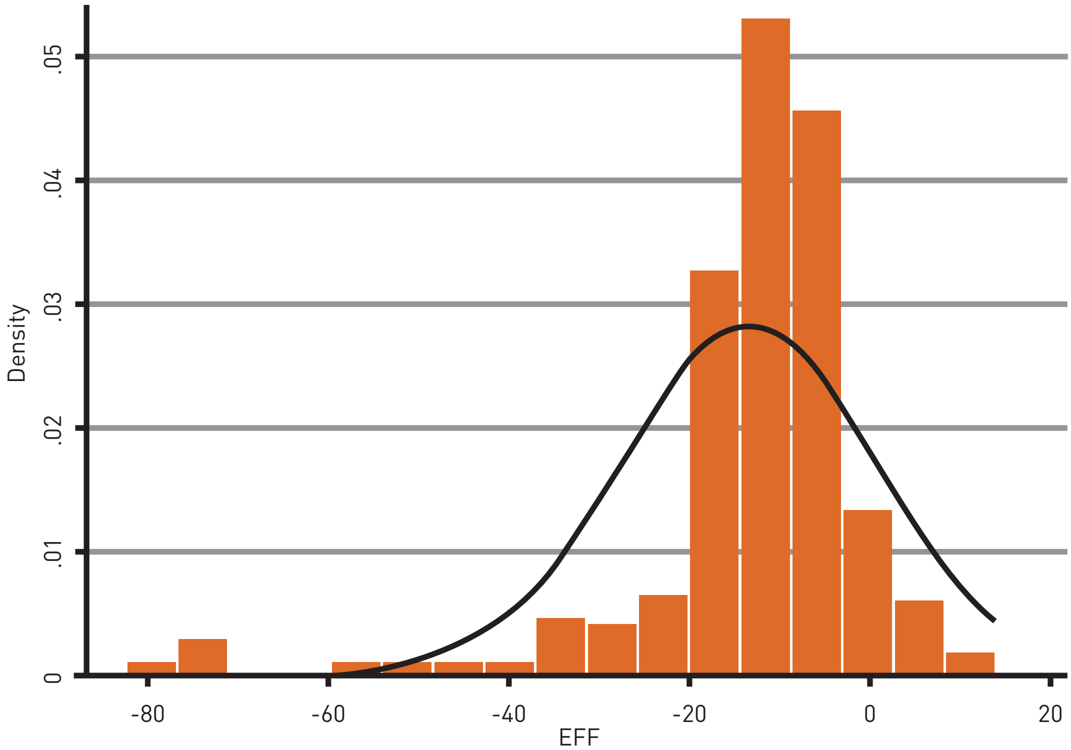

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Cash Management in Russian Metallurgical and Oil and Gas Companies

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Abstract

The problem of money management has remained relevant over the past years. The aim of the study is to assess the impact of debt and cash flow on the amount of cash on companies with and without financial constraints. The main hypothesis of the study is that the impact of debt and cash flow on the level of cash depends on financial constraints which were taken as two proxy variables – dividend payment and bond rating. To substantiate the hypothesis put forward, a regression model of the influence of debt and cash flow on the level of cash is built in the work.

For the analysis, large Russian companies in the metallurgical and oil and gas industries were sorted in accordance with financial constraints. Based on the results of the constructed regression model, the following conclusions can be drawn. Borrowed funds of companies negatively affect the amount of cash on the balance sheet, regardless of the presence and type of financial constraints. Cash flow is not statistically significant for companies without financial constraints.

This study has some limitations. The research results can be useful for corporate CFOs in order to optimize cash balances.

Keywords: cash, cash-management, cash flow, debt, financing, financial constraints

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Introduction

All over the world companies focus increasingly on cash management. It is especially relevant for companies with financial constraints (insofar as such companies cannot get cash through debt financing) because their policy for balance maintenance may be changed significantly.

This paper studies financial constraints in cash management of Russian metallurgical and oil and gas companies. Companies from these industry sectors are leaders in bond issuing in the Russian market. They have a high debt level, therefore, probably financial constraints will have a stronger influence on them. The research purpose is to evaluate influence of debt and cash flow on the amount of balance.

The present paper is of practical importance for the companies concerned with enhancement of efficiency of their cash management. Conclusions and recommendations offered in the paper may be applied in construction of corporate cash flow management systems in order to optimize cash balance. Comprehensive analysis performed in the paper using a sample of Russian metallurgical and oil and gas companies allows us to make conclusions on the extent of influence of debt and cash flow on the amount of cash in the companies with financial constraints and without them. The paper considers two types of financial constraints: dividend payment and bond rating.

At the beginning of the paper, we review the studies dedicated to the range of problems related to dependence of corporate balance on the debt level and amount of cash flows (the trade-off theory and pecking order theory, study of financial constraints), put forward hypotheses on influence of debt and cash flow on the cash amount in companies with financial constraints and without them. Then, on the basis of the sample of Russian metallurgical and oil and gas companies we assess influence of debt and cash flow on the amount of balance.

Cash Management: Review of Studies

Maintaining of the necessary cash balance (cash equivalents are considered in the present paper as cash) and investing of surplus cash are the main objectives of cash management. The amount of cash depends on the following factors: company characteristics, banks' attitude, availability of capital markets and other factors of financial management. However, a complex character of the factors and difficulty in cash management limit capability of many companies for efficient cash management. Instead, as a rule companies define a target cash balance [1].

The trade-off theory and pecking order theory explain the amount of cash balance. So, according to the **trade-off theory** companies adjust their cash up to the optimum amount at which the marginal revenue from possession of cash equals marginal costs. In line with the theory by Keynes [2] the amount of corporate cash depends on the amount of transaction costs, precautionary and speculative motives.

In spite of advantages of cash "surplus" it has a range of drawbacks. The rate of return of cash or liquid securities is low due to a liquidity premium. The cash allocated among shareholders is double taxed: at the corporate and individual level [3]. As per Jensen [4] cash may also increase agency costs. Companies with larger cash amounts do not need access to the capital market for financing, so their managers are out of the market control. If there is no such control managers may pursue their own ends instead of those of shareholders, as a result, corporate performance will be reduced.

Early studies of cash balance by Baumol [5], Tobin [6], Miller and Orr [7] were focused on calculation of its optimum amount, later studies – on empiric rather than theoretical problems. Thus, John [8] studies the relation between financial constraints and cash of corporations. The author provides proof that the cost of financial constraints is related positively to the intent to own cash using various proxies for the basic variable. Beltz and Murray [9] study the trade-off theory in relation to cash and their results confirm the forecasts according to the trade-off theory. Kim et al. [3] and Opler et al. [10] conducted two fundamental studies of the factors which prompted companies to own cash. Kim et al. [3] study the optimum amount of investment into corporate cash according to the trade-off theory. They consider that cash holdings are an increasing function of the external financing cost, cash flow dispersion and future investment opportunities. And vice versa, cash decreases along with increase of opportunity costs. Opler et al. [10] examine two different points of view on possession of cash: the trade-off theory and pecking order theory. They provide empiric proof that both views explain the policy of cash ownership. They think that the amount of cash is an increasing function of growth opportunities, cash flow dispersion and non-cash working capital and a decreasing function of the company size and bond rating (Park [11]).

Unlike the trade-off theory of cash balance maintenance the **pecking order theory** contemplates that there is no optimum balance. According to Myers and Majluf [12] information asymmetry between corporate managers and external investors increases the external financing cost. Relatively less informed investors are reluctant to pay the full cost of securities issued by the company and try to decrease it. Therefore, companies have to sell their securities at a discount, thus, incrementing the external financing. In case of external financing debt is of higher priority than equity capital due to a higher cost of equity capital. The pecking order of financing is as follows: first, companies use internal sources, then - debt, shares are the last financing source in the pecking order. According to this theory the debt level is defined by decisions related to financing and investment implying that there is no optimum capital structure. As with financial leverage cash balance is a result of corporate decisions related to investment and financing. Companies apply their cash flows to finance their investment opportunities or projects, pay off debts in due time and then accumulate unused cash flows as cash balance, when possible. If cash flow does not cover the abovementioned expenses companies apply accumulated cash in order to avoid external financing. If cash flow from operations and cash are insufficient to cover all expenses additional financing is necessary. Cash inflows and outflows define the amount of accumulated cash. It is indicative of absence of the optimum cash balance.

Although the pecking order theory explains corporate cash balance no empiric studies had been carried out before Opler et al. [10]. They verified correspondence of the trade-off theory as well as the pecking order theory on the basis of behavior of target cash balance applying the model of Shyam-Sunder and Myers [13]. The results confirm that both theories explain change of cash balance to a considerable degree. The distinction between the trade-off theory and the pecking order theory concerning the policy of cash balance is not clear. Opler et al. [10] presume that this distinction becomes indefinite because the cost of external financing acquires more importance in the pecking order theory (Musnadi et al. [14]).

Study of influence of **financial constraints** on cash balance is of relevance. Against the background of the perfect capital market a company has an instant access to the external capital market when there is a positive net present value (NPV). External means may be replaced with internal financing sources. In light of this, cash balance is of no significance because it entails a range of expenses (Kim et al. [3]; Opler et al. [10]). However, in the actual world the capital market is imperfect which means that companies may have different opportunities of accessing the capital market. Difference in accessibility may be due to the fact that each company has a different cost of external financing represented by transaction costs. A company with high transaction costs has a limited access to the capital market and pursues the financial policy aimed at saving cash balance. Motivation to hold savings grows when companies have a volatile cash flow and ample investment opportunities. On the other hand, companies without financial constraints do not gain much from maintaining cash balance because they can have access and raise funds in the capital market when necessary. Bates et al. [15] and Hall have proven empirically that companies with financial constraints have more cash than those without such constraints.

Several studies consider influence of financial constraints. Almeida et al. [16] examine the interrelation between financial constraints and availability of cash with a particular focus on structural changes of cash flow depending on the amount of cash. The amount of cash balance increases along with growth of cash flow in companies with financial constraints. Cash of companies without financial constraints influences their cash flows. Acharya et al. [17] study the interrelation between debt and money holdings applying the financial constraints concept. They assume that monetary and debt policies are developed simultaneously supposing that they are related to each other. They create the model which takes into consideration this endogenous relationship and find out that companies with financial constraints show a positive relation between debt and cash holdings while companies without financial constraints show a negative relation. Companies with financial constraints save more funds in case of increase of leverage. Companies without financial constraints reduce the debt level for the purpose of maintaining cash balance.

We will use a modified version of Almeida et al. [16] for empiric analysis. We will divide companies into two groups according to financial constraints they face (Table 1). Companies with financial constraints are less likely to pay dividends (Fazzari et al. [18]; Sarkar, Zhang [19]). Almeida et al. [16] use top (or the lowest) 30 deciles of dividend payments as the critical value of financially unconstrained (financially constrained) companies. If a company pays dividends it is considered to have no financial constraints. Otherwise, it is presumed that the company is financially constrained. The bond rating is descriptive of the company's creditworthiness evaluated by the capital market. A company without a public bond rating within the studied period is considered to be the one with financial constraints. If bonds of a company have a rating within such period the company has no financial constraints (Table 1).

Table 1. Measuring financial constraints

Item	Financial constraint	Notes
Dividend payment	Financially constrained	Dividends not paid
	Financially unconstrained	Dividends paid
Bond rating	Financially constrained	No bond rating
	Financially unconstrained	Bond rating

Source: compiled by the author.

Computational and Analytical Base

Verified Hypotheses

In order to conduct regression analysis of influence of debt and cash flow on cash balance it is necessary to introduce hypotheses which confirm or disprove of such influence. First, we shall consider the **interrelation between cash and debt**.

As far as is known, cash is related negatively to debt. Maintenance of cash balance and debt settlement are equivalent from the point of view of provision of cash holdings (Opler et al. [10]). Cash may be used to finance new investments and it replaces a part of debt (cash – negative debt). Besides, John [8] uses the leverage ratio as a proxy in case of issue of a new debt. He supposes that companies with a high leverage may get access to the capital market and raise funds; consequently, they are unmotivated to hold cash. This enhances the negative interrelation between debt and cash. In accordance with the trade-off theory the interrelation between debt and cash is negative. Along with growth of the financial indebtedness ratio the probability of bankruptcy increases while the cost of financial problems also increments (D'Mello et al. [20]).

According to the pecking order theory there is also a negative interrelation between debt and cash. When the financing requirement is high and even exceeds cash flow companies use undistributed profit, funds. If undistributed profit is not sufficient to cover the financing requirement companies raise additional debt funding. As long as the amount of cash decreases the debt may increment. However, when cash flow is sufficient to cover the investment needs, first, companies pay off debts and accumulate cash. As a rule, debt is related to cash flow negatively.

Now we are going to consider financial constraints. Acharya et al. [17] think that financial constraints have an impact on the interrelation between debt and cash. A company with a limited access to the capital market prefers to accumulate cash instead of repaying debts. However, companies without financial constraints pay off debts before accumulating cash. The interrelation between debt and cash holdings varies depending on financial constraints.

According to Acharya et al. [17] the value of the leverage ratio influences cash balance. For metallurgical and oil and gas companies with a limited access to the capital market debt is related directly to cash holdings. A high debt ratio of such companies may enhance motivation to maintain cash balance or to prepare for a possible default or to avoid financial difficulties. Cash may replace debt for oil and gas and metallurgical companies without financial difficulties. Along with increase of the debt level such companies are motivated to reduce debt instead of maintaining cash balance.

The present research assumes that the relation between debt and cash depends on financial constraints.

Hypothesis 1: *the relation between debt and cash differs depending on financial constraints*.

Hypothesis 1a: *debt is related positively to cash for companies with financial constraints*.

Hypothesis 1b: *debt is related negatively to cash for companies without financial constraints*.

Now, let us examine the **interrelation between cash and cash flow**. Cash flow is considered to be a source of investment financing. Cash flow may replace cash in financing and, thus, it will be related negatively to cash balance. However, a reverse situation is possible. According to the pecking order theory companies with a larger cash flow may have more funds as a result of operating activity. If cash flow from operations exceeds investment needs companies pay off debt and then accumulate cash. As a rule, cash balance increments along with cash flow.

Similarly to the interrelation of debt and cash the relation between cash flow and cash balance may become more transparent if the financial constraints concept is applied. Almeida et al. [16] emphasize this role of financial constraints in the interrelation between cash flow and cash balance. They presume that a company facing difficulties with access to the capital market is motivated to hold cash balance from its cash flow. The accumulated funds assist the company in avoiding high expenses related to external financing. However, this relation is insignificant for companies without financial constraints. A similar grounding may be applied to oil and gas and metallurgical companies. The companies which are unable to get financing in the capital market usually maintain cash balance and use it to finance investments and other expenses. But for companies without financial constraints the relation is negative because cash and cash flows may be interchangeable for the purpose of financing. There is a negative interrelation between cash flow and cash balance.

Thus, the present research puts forward the hypothesis that this relation depends on the extent of financial constraints.

Hypothesis 2: *the relation between cash flow and cash balance changes depending on financial constraints*.

Hypothesis 2a: *cash flow is related positively to cash balance for companies with financial constraints*.

Hypothesis 2B: *cash flow is related negatively to cash balance for companies without financial constraints.*

Methodology

The advanced hypotheses allowed to develop the model of influence of debt and cash flow on cash balance.

According to the pecking order theory if cash flow from operations and cash holdings cannot cover cash outflows represented by investments and debt repayment the company issues additional debt. It is suggested that the existing amount of internal cash flows has a negative impact on borrowed funds which is indicative of an internal interrelation between debt and cash. Foreign studies confirm this endogenous relationship. Opler et al. [10] assert that corporate monetary policy is determined on the basis of lending policy. This endogenous relationship is left out of their model. D'Mello et al. [20] study the endogenous relationship between debt and cash holdings. Thus, this research will comprise the endogenous relationship between debt and cash. The analyzed data from Korea also showed a negative correlation between variables with consideration to data endogeneity (Park [11]).

The ordinary least squares method of linear regression (OLS) does not apply because it gives biased estimators, i.e. there may be an error in the results. Instead, we use in this paper a two-stage least-squares regression model (2SLS) which provides avoidance of endogeneity by means of sequential application of parameters.

The first stage of the 2SLS model is the search for permissible instrumental variables which will not correlate to the variables of the regression. For this purpose two assumptions for the permissible instrumental variables should be fulfilled. Second, they are not associated with an unbiassed error. Analysis of literature sources yielded a set of instrumental variables for debt and company size. Some researchers assert that many companies finance their growth opportunities using debt (Upneja, Dalbor [21]; Tang, Jang [22]). As the company size grows it may have a higher debt level.

Thus, the obtained regression model of analysis of influence of debt and cash flow on cash balance is as follows:

$$CASH_{i,t} = \beta_0 + \beta_1 DEBT_{i,t} + \beta_2 CASHFLOW_{i,t} + \\ +\beta_3 PPE_{i,t} + \beta_4 NWC_{i,t} + \beta_5 STD_{i,t} + \beta_6 CE_{i,t} + \\ +\beta_7 Age_{i,t} + +\beta_8 LnSIZE_{i,t} + \varepsilon_{i,t} \quad , \quad (1)$$

where $CASH_{i,t}$ is cash and cash equivalents of *i* company divided by assets in the *t* year; $DEBTi_{i,t}$ is debt of *i* company divided by assets in the *t* year; $CASHFLOW_{i,t}$ is cash flow of *i* company (earnings after interest and taxes before amortization of property, plant and equipment and intangible assets) divided by assets in the *t* year; $PPE_{i,t}$ is property, plant and equipment of *i* company divided by assets in the *t* year; $NWC_{i,t}$ is net working capital (i.e. Current Assets – Current Liabilities – Cash) of *i* company for the previous 12 quarters; $CE_{i,t}$ is capital expenditures of *i* company divided by assets in the *t* year; $Age_{i,t}$ is age of *i* company (in months); $LnSIZE_{i,t}$ is the size of *i* company in the *t* year (total assets logarithm); $\varepsilon_{i,t}$ – error.

Cash balance (*CASH*) is a dependent variable; the leverage ratio (*DEBT*) and cash flow (*CASHFLOW*) are two independent variables. The rest five variables in this model are control variables.

In order to test reliability we present the results of the **OLS regression**. To compare companies with financial constraints to companies without financial constraints we calculated a regression of four pairs of subgroups in this paper (two regression models × two measurements of financial constraints).

It is necessary to check the problem of endogeneity and instrument reliability before using proxy variables. The Sargan test is applied to verify instrument reliability. The null hypothesis for the Sargan test states that the instrument variable does not correlate with an error. The null hypothesis for verification of variables is not rejected, therefore, we may consider that instrumental variables are correct.

In order to verify existence of the endogeneity problem in the model with a new instrumental variable it is necessary to conduct the Durbin-Wu-Hausman test (DWH). The DWH test compares consistent estimators of OLS to 2SLS estimators. If the null hypothesis is rejected it means that the results of our regression will have inconsistent estimators. However, according to our data the hypothesis cannot be rejected, therefore in this research we will use instrumental variables.

Data Description

At the next stage, after developing the model we created a sample of Russian metallurgical and oil and gas companies which we used to evaluate influence of debt and cash flow on cash balance. Companies from these industry sectors are leaders of the Russian market in issue of bonds. They have a high debt level and therefore, probably, financial constraints will exert a greater impact. We chose for the research the period from 2008 to 2018 – 11 years (2019 and 2020 of pandemic have not been added to the calculation because of a greater volatility of values).

The data used in the present research has been obtained from Bureau van Dijk, RUSLANA. After uploading the information was processed and verified for outlying data and financial information for the whole chosen period. So, after data processing we chose 197 metallurgical companies and 135 oil and gas companies.

Empiric Part: Regression Analysis

We start analysis of the results with the aggregated sample of Russian metallurgical and oil and gas companies irrespective of financial constraints. There is codirectional dynamics of cash balance and cash flow in the period from the first quarter of 2008 to the fourth quarter of 2018. The larger free cash flows of companies the more funds they hold for potential internal financing. These results are compliant with the pecking order theory.

See the descriptive information of the sample for the metallurgical industry in Table 2, for the oil and gas industry – in Table 3.

Table 2. Descriptive statistics of metallurgical industry variables

Indicator	Mean	Standard deviation	Minimum	Maximum
Cash balance (*CASH*)	0.122	0.118	0.000	0.400
Debt (*DEBT*)	0.978	0.520	0.248	1.804
Cash flow (*CASHFLOW*)	0.075	0.089	–0.026	0.274
Property, plant and equipment (*PPE*)	0.781	0.157	0.457	0.998
Net working capital (*NWC*)	0.098	0.060	0.002	0.209
Standard deviation of cash flow (*STD*)	0.845	0.169	0.704	1.043
Capital expenditures (*Capex*)	0.530	0.365	–0.077	0.964
Company age (*Age*)	17.609	22.892	5.000	264.000
Company size (*LnSIZE*)	14.047	0.481	13.157	14.589

Source: authors' calculation applying RUSLANA.

In the metallurgical industry (Table 2) the mean ratio of cash to total assets amounts to 12.2%. Debt exceeds 97.8%. It means that metallurgical companies depend strongly on debt financing. Property, plant and equipment account for a high percentage of assets (over 70%). Cash flow in the total assets amounts to approximately 7.5%. Cash flow volatility calculated as a ratio of standard deviation of cash flows to their mean value for three years amounts to 84.5%. Such volatility is indicative of serious fluctuations of cash flows.

Table 3. Descriptive statistics of variables in oil and gas companies

Indicator	Mean	Standard deviation	Minimum	Maximum
Cash balance (*CASH*)	0.074	0.188	0.000	0.729
Debt (*DEBT*)	0.912	0.451	0.000	2.000
Cash flow (*CASHFLOW*)	0.062	0.131	–0.133	0.238
Property, plant and equipment (*PPE*)	0.550	0.342	0.000	0.951
Net working capital (*NWC*)	0.383	0.196	0.119	0.855
Standard deviation of cash flow (*STD*)	0.380	0.149	0.223	0.522
Capital expenditures (*Capex*)	0.626	0.358	–0.594	0.511
Company age (*Age*)	17.269	11.378	5.000	103.000
Company size (*LnSIZE*)	17.498	0.448	16.999	18.500

Source: authors' calculation applying RUSLANA.

Table 4. Comparison of key variables of companies with and without financial constraints

Indicator	Dividends		Bonds	
	with constraints	without constraints	with constraints	without constraints
Cash balance (*CASH*)	0.093	0.079	0.090	0.089
Debt (*DEBT*)	0.635	0.667	0.677	0.595
Cash flow (*CASHFLOW*)	0.029	0.033	0.030	0.030
Number of observations	196	101	165	137

Source: authors' calculation applying RUSLANA.

In the oil and gas industry (Table 3) the average amount of cash on the books of oil and gas companies is approximately 7% which is less than in metallurgical companies. Debt of oil and gas companies is a little less but it is still rather high – 91.2%, which is indicative of a large amount of borrowed funds.

Now, we are going to verify data for the multicollinearity problem because if it exists our estimators will be inefficient. We built Pearson correlation matrices of variables for metallurgical and oil and gas companies. So, we may make the conclusion that debt to equity ratio, property, plant and equipment; capital expenditures, the company age and company size correlate negatively to cash holdings. Cash flow, net working capital and cash flow volatility correlate positively to cash holdings. However, correlation in both industries is not strong, therefore there are no assumptions that the data is multicollinear.

Further we are going to compare variables in the groups with financial constraints and without them (Table 4).

As a rule, companies with financial constraints have more cash than companies without constraints. Further statistical testing is necessary to verify this hypothesis in terms of money. It remains to be seen whether companies with financial constraints have a greater debt than companies without financial constraints. First, we consider dividend payment as a financial constraint. The companies without financial constraints (do not pay dividends) show a bigger debt to equity ratio as compared to the companies with financial constraints. In the periods of reducing the debt load of Russian metallurgical and oil and gas companies cash outflows used to repay previous loans and credits decrease while high indicators of operations' profitability allow companies to increase the dividends they pay. There is also a trend in many studied companies to improve their investment attractiveness by increasing shareholders' dividends even despite reducing of net cash flow (in 2011–2013 and 2017–2018).

Now we pass on to another proxy variable – bond rating. Companies with bond rating as well as companies without bond rating prefer to maintain the same amount of cash at the end of the year which indicates that this financial constraint has no influence on the value of cash savings.

Table 5 is illustrative of comparison of cash between companies with financial constraints and without them. The table shows no statistically significant difference between groups of companies with financial constraints and without them.

The models of the OLS and 2SLS regressions were used for analysis of the collected data. See the results of the OLS and 2SLS regressions for companies with financial constraints in Table 6.

Table 5. Comparison of cash to total assets between groups of companies with and without financial constraints

Indicator	Dividends	Bonds
Companies with financial constraints	0.093 (196)	0.089 (165)
Company without financial constraints	0.079 (101)	0.090 (137)
Difference in cash	0.014	0.001
t statistics	1.53	–1.797

Note: * p < 0.1; ** p < 0.05; *** p < 0.01; the number of observations is enclosed in parentheses.

Source: authors' calculation applying RUSLANA.

Table 6. Impact of debt on the amount of cash in a company with financial constraints (OLS and 2SLS)

Indicator	Dividend payment (no payment)				Bond rating (no bond rating)			
	OLS		2SLS		OLS		2SLS	
	Ratio	T	Ratio	T	Ratio	T	Ratio	T
Debt (*DEBT*)	–0.268	–1.962***	–0.822	–6.69***	–0.239	–8.56***	–0.781	-8.01***
Cash flow (*CASHFLOW*)	0.311	3.08***	0.199	2.49***	0.333	3.63***	0.164	2.18***
Property, plant and equipment (*PPE*)	–0.250	–9.92***	–0.113	–2.87***	–0.227	–8.81***	–0.075	-2.04***
Net working capital (*NWC*)	–0.105	–4.55***	–0.296	–5.34***	–0.097	–4.69***	–0.238	–5.92***
Standard deviation of cash flow (*STD*)	0.722	5.20***	0.758	5.86***	0.893	10.20***	0.763	8.32***
Capital expenditures (*CE*)	–0.067	–1.37	–0.482	–3.86***	–0.121	–2.27***	–0.472	–4.22***
Company age (*Age*)	0.000	4.23***	0.000	3.58***	0.000	6.21***	0.000	5.87***
Constant (*CONSTANT*)	0.364	11.82***	0.607	10.39***	0.334	9.71***	0.579	11.79***
N	196		196		165		165	
F	19.90		28.87		102.91		49.50	
R^2	0.505		0.178		0.570		0.144	

Source: authors' calculation applying RUSLANA.

From the first line of Table 6 we see that debt is negatively related to cash. Irrespective of the chosen model (OLS and 2SLS) the variable is significant at a 1% level. It means that the less debt is raised by a company the larger is the amount of its cash (irrespective of the way of measuring of financial constraints: the fact of dividend payment or existing bond rating). So, if debt is decreased by 1% the value of free cash flows will be reduced by 0.8% more. Therefore hypothesis 1 (influence of debt may be different due to financial constraints) and hypothesis 1a (debt has a positive impact on the cash amount in companies with financial constraints) are rejected. The second line of Table 6 shows that cash flow is related positively to cash holding in the OLS and 2SLS models. The influence is significant and positive, i.e. with a larger cash flow a company may hold bigger amounts at its bank accounts irrespective of the type of its financial constraints. When there is a financial constraint of raising borrowed funds increase of corporate cash flows raises the probability and also strengthens companies' desire to hold a large amount in their accounts. The results are in line with the conclusions made in the paper by Almeida et al. [16]. Hypothesis 2a of a positive influence of cash flows cannot be rejected.

Let us see how debt influences the amount of cash in a company without financial constraints (Table 7).

Table 7. Impact of debt on the amount of cash in a company without financial constraints (results of OLS and 2SLS models)

Indicator	Dividend payment (no payment)				Bond rating (no bond rating)			
	OLS		2SLS		OLS		2SLS	
	Ratio	T	Ratio	T	Ratio	T	Ratio	T
Debt (*DEBT*)	–0.301	–6.71***	–0.522	–6.29***	–0.430	–10.4***	–0.961	11.88***
Cash flow (*CASHFLOW*)	0.086	0.62	–0.127	–0.87	–0.461	–1.53	0.297	0.78
Property, plant and equipment (*PPE*)	–0.125	–7.05***	–0.083	–3.75	–0.174	–10.37***	–0.161	–7.68***
Net working capital (*NWC*)	–0.148	–4.73***	–0.208	–5.28***	–0.303	–3.05***	–0.544	–6.14***
Standard deviation of cash flow (*STD*)	1.077	11.97***	0.993	14.78***	0.317	1.08	1.806	3.49***
Capital expenditures (*CE*)	–0.200	–1.13	–0.143	–1.15	0.004	0.06	–0.160	–1.76*
Company age (*Age*)	0.000	7.55***	0.000	6.95***	0.000	5.72***	0.000	5.98***
Constant (*CONSTANT*)	0.283	7.20***	0.394	8.96***	0.392	11.53***	0.620	15.56***
N	101		101		137		137	
F	55.45		80.38		17.40		22.66	
R^2	0.682		0.625		0.559		0.059	

Source: authors' calculation applying RUSLANA.

Companies without financial constraints show the result similar to the one of companies with financial constraints. The debt level of the company has a negative impact on cash balance. The result is statistically significant and indicates that companies without financial constraints may replace easily the internal financing with the external one. Besides, in case of increase of debt by 1% in companies with bond rating cash will decrease by 0.96%. It may be due to the fact that the price of raising a bank loan or issue of a bond-secured loan is lower than issue of shares, hence, it is more available for companies. Thus, the conclusion, according to which companies with less financial constraints related to debt use less cash, accords with the conclusions by Acharya et al. [17]). Hypothesis 1b (on a negative impact of debt on cash) is not rejected and hypothesis 1 (the relation between debt and cash differs depending on financial constraints) is accepted partially.

As opposed to the forecast of the researchers whose publications have been mentioned in this paper cash flow is statistically insignificant for companies without financial constraints. This result was obtained both for companies not paying dividends and for those which have financial bond rating. Companies with a better access to the capital market are not motivated to save funds from cash flow (Almeida et al. [16]). Cash flow cannot replace cash balance for financing of the company. Hypothesis 2b is rejected and hypothesis 2 (the interrelation between cash flow and cash balance changes depending on financial constraints) may be rejected only partially.

Control variables show that the greater volatility of cash flow the larger the amount a company holds in its accounts. This result applies to both: companies with financial constraints and companies without them. When the variation of cash grows companies try to hold more cash because due to a serious volatility they need more cash to cover a possible deficiency of cash flows or a provisional demand for liquidity (Kim et al. [3]). Non-cash working capital is related negatively to cash confirming that it may be replaced with cash (Opler et al. [10]).

Conclusion

The purpose of the research was to evaluate influence of debt and cash flow on the amount of cash in companies. This paper shows the role of financial constraints related to maintenance of cash balance of large metallurgical and oil and gas companies which have not been taken into consideration before. We have analyzed the interrelation between debt, cash flow and cash balance of a company in case of different financial constraints. Academic literature explains dependence of the described variables using existing financial theories, such as the trade-off theory and pecking order theory. However, study of the interrelation between debt and cash flows led to ambiguous conclusions. This paper adds to understanding of the interrelation between variables on the basis of the financial constraints concept. For the conducted analysis the companies were chosen on the basis of financial constraints applying two proxy variables: dividend payment and bond rating. Taking into consideration the endogenous relationship between debt and cash balance the 2SLS regression has been used in the paper.

The paper established that debt had a negative impact on the amount of cash in large Russian metallurgical and oil and gas companies irrespective of existence of financial constraints and their type. However, there is a slight difference in the extent of debt influence.

As a rule, companies with financial constraints with larger cash flows have larger cash balance (difficulties in accessing the capital market makes companies hold the unused cash flow in the form of cash). Companies without financial constraints show no systematic consistent pattern between cash flows and cash balance. The results accord with Almeida et al. [16].

This paper may offer recommendations to metallurgical and oil and gas companies with financial constraints in the sphere of financial policy.

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How Patents Influence Market Value of Industrial Enterprises' Assets?

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Abstract

Scientists and engineers are continuously patenting innovative ideas such as inventions, industrial designs, and utility models. It is therefore relevant to pose the question of the influence of intellectual property in the field of innovative technologies on the market value of the assets of industrial enterprises.

We analyse the dependence of the results of intellectual activity in the field of advanced technologies on the capitalization of innovative industrial production after the adoption of the developed technologies.

We consider patent landscapes, analyse research publications, and study the dependence of financial indicators on the results of intellectual activity at enterprises producing computers, optics and electronic equipment.

Our research methodology is based on the statistical analysis of the dependence of the financial results of industrial enterprises on the actual application of the results of intellectual activity to the technological process.

We define the object of analysis by citing research articles and surveys from the WoS database. The patent landscape is assessed using data from commercial information systems such as Orbit Intelligence (Questel) and Amadeus (Bureau van Dijk, Moody's Analytics) that make it possible to visually show the links between patent activity and technological trends in the computer and electronic technology industries.

The research results shall be useful for assessing the effectiveness of employing patents in manufacturing and the prospects of improving production technologies for the formation of corporate innovative technological policy.

We conclude that the use of information on patent trends is an effective tool for increasing the competitiveness of enterprises producing electronic equipment. The priority financing of innovative technologies ensures the sustainable development of the manufacturing industry and have a positive impact on the profitability of enterprise assets.

Keywords: intellectual property, results of intellectual activity, corporate finance, returns on assets, innovative technologies, patent landscape, computer and electronic equipment manufacturing

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Introduction

Over the past decade (2010–2019), intellectual property rights such as patents, utility models, industrial designs and trademarks have significantly grown in volume.[1] Why has this occurred? Why have researchers been willing to incur expenses for protecting intellectual innovations? In actual fact, they do so to cast the legal foundations for competitive advantages in different areas of business. Researchers are interested in the trends and development prospects of advanced technology markets and production relations in a wide variety of industrial sectors. There are 6,472 academic papers and surveys relating to intellectual property in the Web of Science Core Collection database for 2016–2021 (as of August 2021). Approximately 1,220 of them (19%) deal with legal aspects, 709 (11%) with management, and 732 (11%) with economics. One way or another, several rapidly developing groups of technologies are considered to be the most advanced and cutting-edge in the world. Science as a productive power spurs the development of big data, robotic technologies, additive manufacturing, the Internet of things (IoT), artificial intelligence, blockchain and other advanced technologies [1–5assessing patent risks has attracted fast-growing attention from both researchers and practitioners in studies of technological innovation. Following the existing literature on risks and intellectual property (IP]. Patent protection issues are thus relevant for both inventors and businessmen.

Data and Methods

VOSviewer software, a free programme which creates illustrative network interface maps of scientific literature, was applied to analyse publications. VOSviewer can be used to conduct the in-depth analysis [6–8] of texts of research publications and to create slides showing the interrelations of their keywords. The advantage of VOSviewer is that it can be employed to process big bibliographic data sets. It is particularly useful for analysing large numbers of bibliographic objects (over a hundred items) [9–12]. The smart processing of scientific databases normalizes the links between the keywords so as to create maps [12our results showed that a comprehensive bibliometric and visualization investigation was required. The literature on KM has grown rapidly since the 1970s. The United States of America, as the original contributing country, has also internationally collaborated the most in this field of study. The National Cheng Kung University has made the highest number of contributions. The majority of authors contributed a small number of publications. Additionally, the most common category in KM research was management. The main publications for KM research include Journal of Knowledge Management, and Knowledge Management Research & Practice. A keywords analysis determined that \"knowledge sharing\", \"innovation\", \"ontology\", and \"knowledge management\" were consistent hotspots in knowledge management research. Through a document co-citation analysis, the intellectual structures of knowledge management were defined, and four emerging trends were identified that focus on new phenomenon, the practice of knowledge management, small and medium enterprises (SMEs] of relations between scientific terms. We processed sets of keywords taken from the Web of Science database. A search using such keywords as Computer Architecture and Network Security identified 1,275 academic papers and surveys for 2016–2021. We also conducted a search using such keywords as Computer Security, Intrusion Detection, Blockchain, and Deep Learning. Moreover, a search in the International Patent Database (WIPO) uncovered 1,842 and 14,095 patents related to computer architecture and network security, respectively. Patent analysis was conducted with the tools of the Questel Orbit patent database, which comprises over 100 sources from world patent collections. The Amadeus database (Bureau van Dijk, Moody's Analytics) was used to define the relation between the number of patents and the financial performance achieved by electronics manufacturers.

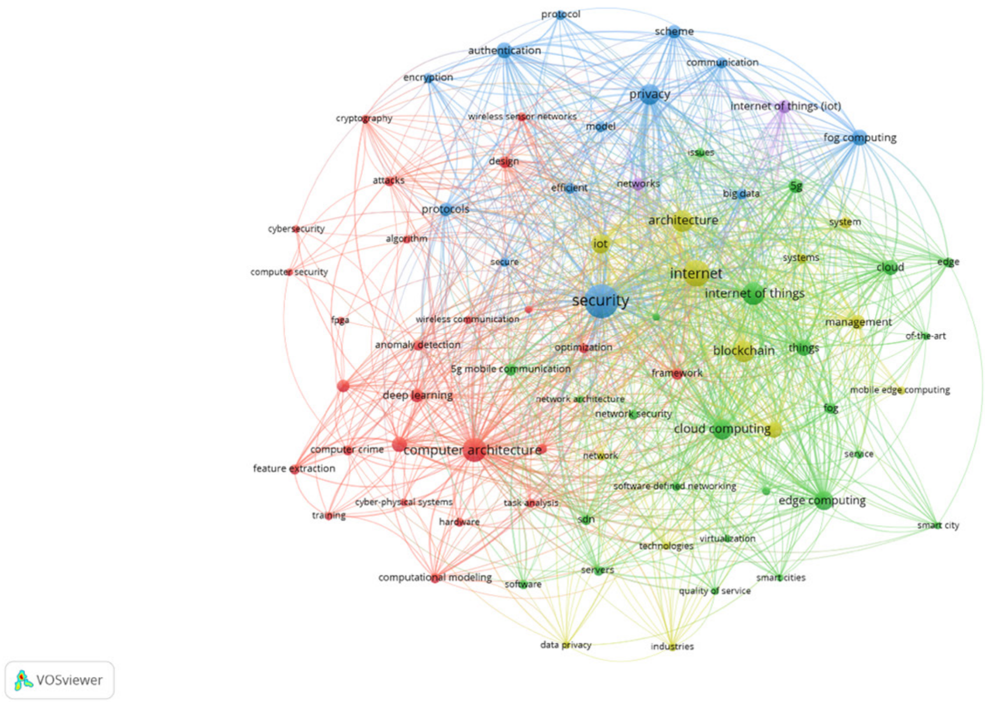
Results

The initial database of 2,208 keywords was compiled by processing bibliographic data from a set of 1,275 documents using the VOSviewer programme. The threshold was then limited to ten occurrences. With these criteria, VOSviewer showed the semantic nodes of 77 keywords (Figure 1). The results of network analysis were grouped into five clusters, which are shown in the figure in different colours. The most important cluster connected the notions of "computer architecture", "Internet of things", and "security".

A natural hypothesis would be that studies mainly focus on the emergence of the global structure of the big data network for artificial devices. In our opinion, artificial intelligence should not be connected too closely with computer-aided learning and security so as not to jeopardize human life. Technological development should be directed at laying the groundwork for sustainable human development, not the development of mechanisms. This shows the importance of such R&D sectors as computer architecture and big data. Scientists have shown that value creation by single enterprises is increasingly rare today due to the growth of industrial cooperation [13]. Bibliometric analysis was used to determine the relation between industrial clusters and global value chains. The creation of industrial conglomerations simultaneously raises the issue of competition and the management of interdependent facilities. In any event, all scientific research results are subjective, and the trustworthiness of their conclusions need to be confirmed by large-scale scientific surveys. On the other hand, big data processing is becoming difficult due to the insufficiency of data storage systems and computing power [14].

[1] Statistics Data Center of WIPO: URL: https://www3.wipo.int

Figure 1. Keywords network



Source: developed by the author using VOSviewer.

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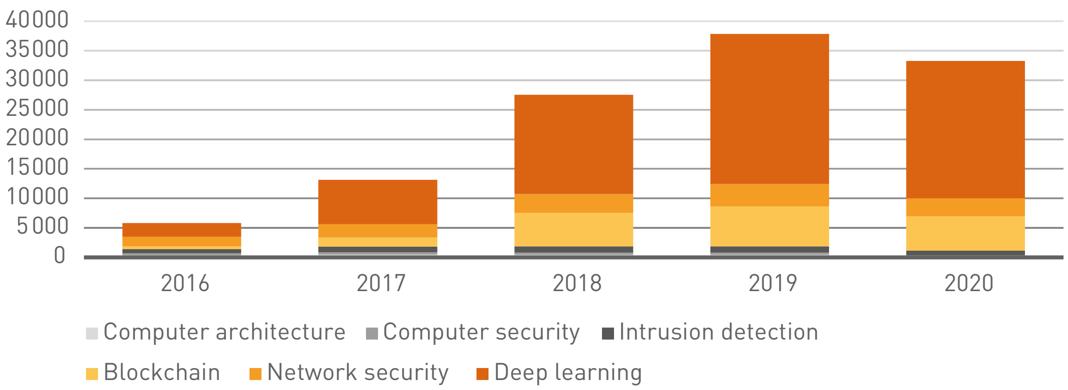
In any event, all scientific research results are subjective, and the trustworthiness of their conclusions need to be confirmed by large-scale scientific surveys. On the other hand, big data processing is becoming difficult due to the insufficiency of data storage systems and computing power [14]. Nevertheless, as the Internet of things develops, big data processing increases, while scholarly analytics help to evaluate the role of big data in technical processes. Researchers [15] have warned that the growth of the collection of technical network data and a rapid increase in the number of IoT devices can create difficulties for computer networks. To solve this problem, it is necessary to increase the maintenance service capacities for data processing infrastructure. The uninterrupted functioning of computers, cloud storage and data processing systems is very important for manufacturing companies. The factor of data confidentiality is highly significant for the design of computer networks in the IoT domain, as it would otherwise be meaningless to discuss the creation and development of remote-controlled high-tech facilities. Engineers and scientists are focusing their efforts on creating an open reference architecture for big data to provide managers of facilities, programmers, and system engineers with solutions in a compatible big data ecosystem [16]. The general structure of applications for big data integrates weakly connected economic sectors and closely connected corporate data analysis systems and manufacturing control systems. The value of the big data structure for business lies in the fact that available computing and analytical services analyse and visualize data, i.e., help to make more efficient management conclusions for creating value. However, the advantages of network innovations pose serious problems related to security and data reliability [17]. Big data analysis threatens to violate confidentiality at various stages of the life cycle of information units: collection, storage, analysis, use and elimination. Researchers have developed a security taxonomy, which can be used as a methodological guideline for evaluating research results related to the big data life cycle. They also plan to develop a security architecture for the big data life cycle. Adding data mechanically [18] for solving industrial problems does not always yield results. The analysis and interpretation of data are related closely to good database management. Studies [19] have shown that a simple blockchain (Fusion Chain) may improve the security of devices in the Internet of things. Such devices ensure the reliability and integrity of databases without a centralized server. Devices for high-speed transactions are also being developed. Another cluster includes algorithms, network intrusion detection systems, machine learning, network security, and modelling. Assuring the stable functioning of industrial databases, the reliable operation of technological equipment, and the error-free detection and counteraction of malicious computer intrusions is of great importance. Scientists [20] have developed tools for the ongoing monitoring of information security for public and private corporations. Timely incident management will assist companies in ensuring information confidentiality in the long term. Artificial intelligence specialists [21] are shifting their attention to heuristic solutions, neural networks, and logical reasoning. For over 60 years, considerable success has been attained in these research areas, yet the field of artificial intelligence looks quite vague at present. This leads to the following key question: what is the role of human knowledge with regard to artificial intelligence? Technology 4.0 serves as a basis for integrating smart machines, manufacturing facilities, physical objects, and people to organise value creation processes at a higher level [22]. The Internet of things, cloud systems, and virtual media are offering new opportunities and posing new threats. Information and data security are of utmost importance for industrial production. Industry 4.0 requires architecture and design security in order to protect smart manufacturing systems. The main problem is that malicious programmes may manipulate technical process data, triggering the production of modified products and changing the duration of the manufacturing cycle. The study [23] assessed the influence of Russian capital markets on investment potential by examining 514 manufacturing companies over the period 2014–2018. The results showed a positive correlation between the cash flows of affiliated companies and investments. These conclusions are of practical importance for large and medium-size companies, which are looking for tools to increase the availability of financial resources in a faltering economy. In particular, a low efficiency of intellectual property is observed in the public sector [24] due to its underdeveloped accounting and analysis system. Patent analysis is another method that can be used for intellectual property analysis to solve economic problems. The use of the dynamic innovation theory should clarify the development areas of public enterprises.

Patent activity in the hi-tech sphere is showing impressive dynamics (Figure 2). The number of publications as well as the number of deep learning patents grew approximately tenfold, with blockchain demonstrating the highest growth. Over 2016–2020, the number of patents decreased by 60% in computer architecture and by 40% in computer security. An insignificant growth of 15% occurred in the field of intrusion detection. However, patent activity in network security grew significantly – by 183%. A qualitative increase has been observed in the number of innovative products related to blockchain and deep learning – by almost 13 and 10 times, respectively. On the whole, over 5 years (2016–2020) the increase in the number of academic papers was marked by a strong positive correlation of 0.799. However, it is always necessary to check the significance of the correlation ratio by applying the zero-hypothesis validation rule. In our calculations, n = 5 because we analyse statistics over five years:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0,799\sqrt{\frac{5-2}{1-0,638}} \right| = 2,30 \,. \quad (1)$$

The boundary of the criterion $t_{кр}$ (α; k) is calculated using Student's t-distribution. $t_{кр}$ is defined by the significance level and depends on the degree of freedom of k, which in our case is equal to $n - 2$ where $n = 5$ (the number of years from 2016 to 2020). It is convenient to calculate the indicator of Student's t-distribution by applying the following function: Microsoft Excel T.INV.2T. (0.01; 3) = 5.841, i.e. $t_{кр} = t_{кр}(0.01; 5 - 2) = 5.841$. As long as $T < t_{кр}$ the relation is not considered to be significant at a 1% significance level.

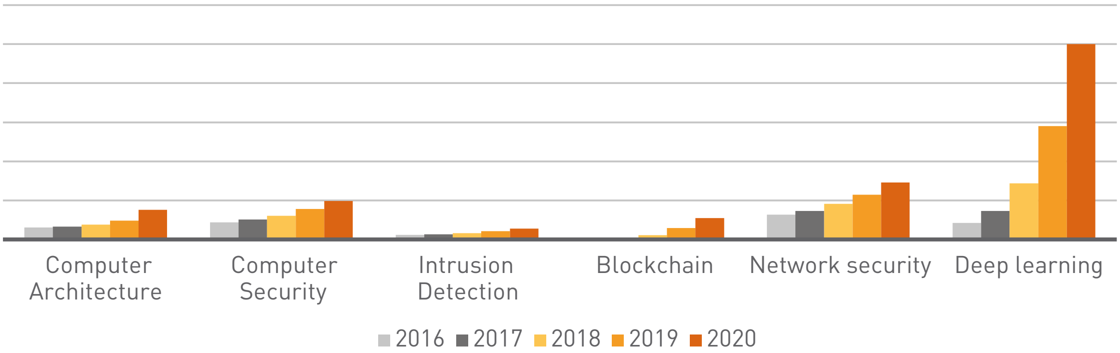
Figure 2. Number of patents



Source: compiled by the author using Orbit Intelligence.

The number of research publications increased for all keywords (Figure 3), albeit the rates of growth were different. Computer architecture grew by 2.5 times, while computer and network security expanded by 224 and 229%. The interest in intrusion detection increased by a similar factor: 244%. Blockchain demonstrated an explosive and steady growth, with the number of publications increasing by approximately 66 times. Deep learning publications grew by almost 12 times.

Figure 3. Number of academic papers and surveys



Source: compiled by the author on the basis of the WoS database.

The correlation between the number of research publications and valid patents is rather ambiguous. Over 2016–2020, the number of valid patents in the Orbit database and the number of research publications in WoS in the sections Computer Architecture and Computer Security show a strong negative dependence: –0.885 and –0.770, respectively. How objectively do these figures reflect the correlation between intellectual property rights and research publications? Usually the zero-hypothesis verification rule is used to verify the significance of the correlation ratio. In our calculations $n = 5$, because we analysed statistics over five years and more:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0{,}885\sqrt{\frac{5-2}{1-0{,}783}} \right| = 3{,}29\,. \qquad (2)$$

The boundary of the criterion $t_{кр}$ (α; k) was calculated on the basis of Student's t-distribution. $t_{кр}$ is defined by the significance level and depends on the degree of freedom of k, which in our case is equal to $n - 2$, where $n = 5$ (number of years from 2016 to 2020). It is easy to calculate the value of $t_{кр}$ by applying the function: Microsoft Excel T.INV.2T.(0.01; 3) = 5.841, which corresponds to $t_{кр} = t_{кр}(0.01; 5–2) = 5.841$. We have $T < t_{кр}$; therefore, the relation cannot be objectively considered to be significant at a 1% significance level.

In the field of Intrusion Detection, the number of patents virtually does not depend on the number of research publications (correlation ratio of 0.083). For the field of Blockchain, we calculate significance using the following formula:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0{,}083\sqrt{\frac{5-2}{1-0{,}007}} \right| = 0{,}14\,. \qquad (3)$$

0.14 < 5.841, and so the relation cannot be considered significant at a 1% significance level. Similarly, the correlation between the number of Network Security patents (0.713) and the number of studies dedicated to this topic seems to be indicative of a strong express positive relation at first sight. We make the following simple calculations in order to prove this hypothesis:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0{,}713\sqrt{\frac{5-2}{1-0{,}508}} \right| = 1{,}76\,, \qquad (4)$$

and for Deep Learning with the ratio of 0.704:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0{,}704\sqrt{\frac{5-2}{1-0{,}496}} \right| = 1{,}72\,. \qquad (5)$$

The values of the random variable T are significantly less than the critical value of Student's criterion in both cases, and so the correlation indicator cannot be considered significant. A longer period of analysis may be necessary – much longer than five years.

Researchers naturally take an interest in the influence of intellectual property on corporate financial performance. However, it is impossible to assess here the whole range of research work and the scope of implementation of innovative technologies. The economy must be stable in the long term, and the global survey *Digital Trust* by the audit and business consulting firm PWC[2] suggests some general conclusions. Information security is ensured by means of innovative cryptography, a technology which has been preventing hacker attacks for almost 40 years (the Massachusetts Institute of Technology in the USA obtained a patent for cryptographic protection in 1983). The PWC survey is based on a 2020 poll of 3,249 company directors who were actually engaging in business digitalization. The COVID-19 pandemic necessitated automatization to cut costs (47% in Russia, 35% in the world). 26% of Russian companies and 37% of companies across the globe consider the quality of information to be the #1 concern. Breakthrough technologies using zero-trust architecture to analyse risks online allow the introduction of preliminary protective measures to prevent criminals from committing unlawful acts. Investments in technology lead to reduced operating costs. The PWC survey speaks of 25 innovative approaches in the sphere of information security – for example, the quality of risk management has improved greatly (approximately by 76%) along with confidence in digital technologies (by 81% in Russia and by 76% in the world).

[2] Research by PWC: URL: https://www.pwc.ru

Table 1. Dynamics of the return on assets of electronic equipment element manufacturers and the number of valid patents

OKVED (Russian National Classifier of Types of Economic Activity) 26.11	2016	2017	2018	2019	2020
Return on assets*	7.59	6.90	6.49	9.99	10.87
Number of patents	397	57	341	16.279	4.305

*On the basis of net profit.

Source: database: URL: https://amadeus.bvdinfo.com

Table 2. Dynamics of return on assets of manufacturers of electronic printed circuit boards and of the number of valid patents

OKVED (Russian National Classifier of Types of Economic Activity) 26.12	2016	2017	2018	2019	2020
Return on assets*	**	**	6.64	6.57	12.33
Number of patents	**	**	24	821	52

* On the basis of net profit

** No data available.

Source: database. URL: https://amadeus.bvdinfo.com

This has led to a staff shortage in the sphere of cloud services and the analysis of security factors. It has been estimated that there will be approximately 3.5 million "digital" vacancies in the world in 2021. The PWC survey polled directors in Western Europe (34%), North America (29%), Asia (18%), Latin America (8%), Eastern Europe (4%), the Middle East (3%) and Africa (3%).

The *DIGITAL IQ in Russia 2020* joint study[3] by PWC and ABBYY (February 2021) surveyed 106 top managers of large Russian companies in the following sectors: information technology (19%), industry (14%), telecommunications, financial sector, transport, education (approximately 7% each), marketing, services for businesses, construction (approximately 6% each) and other types of economic activity (20%). It conjectured that the digital intelligence strategy is shaped by three factors: employees' digital mindset, software infrastructure and available innovations. Today, digitalization (the improvement of technology and management processes) is playing a significant role in Russian business. The most relevant advanced technologies are artificial intelligence, the Internet of things and robots. Ideally, advanced technologies should be used systemically at enterprises (according to about 81% of managers) and, at the same time, should work harmoniously together (according to 74% of managers). Due to the demand for real-time technical process analysis, the highest growth (140%) is forecast for Process Mining. Naturally, advanced technology shall be used to increase labour productivity (by 74%) and cut costs (by 58%). Artificial intelligence should show a growth of 76% over the two coming years.

In 2019, CRI Electronics (an analytic centre of the radio-electronic industry) compiled a rating[4] of 69 radio-electronic enterprises with a total revenue of RUB 150 billion and approximately 62.5 thousand employees. Industrial goods accounted for about 64% of the revenue, and R&D for approximately 24%. JSC RPC Istok had the greatest income of RUB 12.3 billion, the Mikron Group came in second with RUB 11.7 billion, while the Research Institute of Communication and Control Systems was third with RUB 8.5 billion. The majority of enterprises invest little into new technologies at their own initiative – about only 5% of their revenues, which hinders the introduction of successful competitive products.

Let us now turn to the patent analysis of the computer industry. From the Amadeus database (August 2021), we obtained the financial indicators and number of patents in several advanced industries, including 26.11 (2017 OKVED (Russian National Classifier of Types of Economic Activity)) – production of electronic device parts, 26.12 – production of electronic printed circuit boards, 26.20 – production of computers and peripheral equipment, and 26.70 – production of optical equipment. The study period was the five years from 2016 to 2020. Table 1 presents the data of 118 profitable sectoral enterprises (with a positive return on assets).

The correlation between the return on assets and the number of patents is definitely positive, amounting to 0.669.

[3] Research by PwC and ABBYY. URL: https://www.abbyy.com/ru

[4] Analytical materials of CRI Electronics. URL: https://www.instel.ru

Does this figure reliably measure the correlation between intellectual property rights and corporate financial performance? We can use the zero-hypothesis verification rule to check the significance of the correlation ratio. In our calculations $n = 5$, because we analysed statistics over five years.

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0,669\sqrt{\frac{5-2}{1-0,552}} \right| = 1,56\,. \qquad (6)$$

The boundary of the criterion $t_{кр}$ (α; k) was calculated using Student's t-distribution. $t_{кр}$ is defined by the significance level and depends on the degree of freedom of k, which in our case is equal to $n - 2$, where $n = 5$ (number of years from 2016 to 2020). We calculate the value of the indicator by applying the function: Microsoft Excel T.INV.2T. (0.01; 3) = 5.841. As we have $T < t_{кр}$ (1.56 < 5.84), the relation cannot be considered significant at a 1% significance level. Probably, the analysis period needs to be significantly longer than five years. Unfortunately, the Amadeus database lacks the required data in this case. For the purposes of comparison, let us take a look at the analogous indicators of other groups of electronics and optics manufacturers. While the database comprises 132 enterprises manufacturing electronic printed circuit boards (26.12), Table 2 presents only 21 profitable companies.

Using Table 2, Excel calculations for three years show a negative correlation of –0.482, i.e., if $n = 3$, the random variable is equal to

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0,482\sqrt{\frac{3-2}{1-0,232}} \right| = 0,55\,. \qquad (7)$$

In this case, calculations using Microsoft Excel T.INV.2T. (0.01; 1) show that T = 63.657 and $T < t_{кр}$ (0.55 < 63.657), and so the relation cannot be considered significant at a 1% significance level. We repeat that larger data sets are needed to calculate the significance of the statistical correlation between factors and results. Table 3 presents the indicators of computer manufacturers: 41 profitable enterprises out of 308 (Amadeus database). In this sector, the correlation between patents and the return on assets is positive and quite strong: 0.622. Therefore, for small samples the following is true: if $n = 4$,

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0,622\sqrt{\frac{4-2}{1-0,387}} \right| = 1,12\,. \qquad (8)$$

Table 3. Dynamics of the return on assets of computer manufacturers and of the number of valid patents

OKVED (Russian National Classifier of Types of Economic Activity) 26.20	2016	2017	2018	2019	2020
Return on assets*	**	3.96	12.47	8.54	13.99
Number of patents	**	13	82	1,412	4,459

* On the basis of net profit

** No data available.

Source: database: URL: https://amadeus.bvdinfo.com

The calculations show $T < t_{кр}$ (1.12 < 63.657), and so the relation cannot be considered significant at a 1% significance level. Table 4 represents profitable enterprises manufacturing optical equipment (111 out of 274) and the number of valid patents in their assets.

Table 4. Dynamics of the return on assets of optical equipment manufacturers and of the number of valid patents

OKVED (Russian National Classifier of Types of Economic Activity) 26.70	2016	2017	2018	2019	2020
Return on assets *	8.01	**	3.14	9.77	10.22
Number of patents	2	**	4	69	111

* On the basis of net profit.

** No data available.

Source: database: URL: https://amadeus.bvdinfo.com

The correlation over the period of 2018–2020 is close to 1: 0.942. So, calculations yield the following result:

$$T = \left| r\sqrt{\frac{n-2}{1-r^2}} \right| = \left| 0,942\sqrt{\frac{3-2}{1-0,936}} \right| = 3,66. \qquad (9)$$

We have $T < t_{кр}$ (3.66 < 63.657), and so the relation cannot be considered significant at a 1% significance level.

Conclusion

In 2016–2020, patents and academic papers were closely connected with each other, as shown by the positive correlation ratio of 0.799. On the one hand, intellectual property exerts some influence on corporate financial performance as well as promoting the dynamic development of the innovation technological paradigm in the Russian economy. On the other, an increasing number of patents requires improving the actual legal protection of intellectual results to make the expenditures on developing intellectual property reasonable and economically viable.

Of the academic papers and surveys dealing with the topic of Intellectual Property in the Web of Science Core Collection in recent years (2016–2021), 11% were dedicated to economics and another 11% to management problems. Our analysis of patent landscapes and research publications related to computer technologies generated five clusters of keywords connected with the terms Computer Architecture and Network Security. The number of publications and the number of patents related to Deep Learning and Blockchain increased by an order of magnitude.

Over 2016–2020, research publications and valid patents relating to Computer and Network Security, Blockchain, Deep Learning, and Intrusion Detection showed a strong positive correlation of 0.799. However, the calculated values of T and $t_{кр}$ show that the correlation cannot be considered significant at a 1% significance level. In the opinion of the directors of Russian companies working in the area of information technology, the most relevant and prospective technologies are artificial intelligence, the Internet of things, and robots. However, according to 2019 data, 69 Russian radio-electronic enterprises invested no more than 5% of their net profits in R&D.

According to Amadeus data on electronics manufacturers in 2016–2020, the net profit margin and the number of valid patents of enterprises showed a correlation of 0.669. Firms manufacturing electronic printed circuit boards had a negative correlation of –0.482. In this case, data for calculations was available only for 2018–2020. There is a positive dependence of 0.662 among computer manufacturers. The highest correlations between profitability and the number of patents (0.942) were found among enterprises manufacturing optical equipment. The significance of the correlation has been calculated for all industry sectors: the obtained values of T and $t_{кр}$ show that the correlation cannot be considered significant at a 1% significance level. The results of the present study are both qualitative and quantitative in nature. The qualitative results show the expediency of the systemic use of innovative equipment, materials and technologies in manufacturing. The quantitative results provide calculations of the impact of innovative machines, mechanisms, materials, and technologies (created on the basis of patents) on the actual production of high-tech products that are in demand today.

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