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Meta-Analysis of the Use of Logit-Probit Models in the Impact of Financial Indicators on Credit Rating

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ABSTRACT

The diversity of tools and measurement methods has created new opportunities in studies, often leading to different results and causing confusion in understanding the overall outcomes. Meta-analysis is a set of statistical methods for integrating the results of various studies and identifying moderating factors in the relationships between financial indicators and credit ratings. In this research, we will use the methodology of meta-analysis (meta-analysis), which is considered a quantitative statistical approach. To implement the meta-analysis method, all studies conducted in the field of research using keywords such as financial ratios, credit rating models; Logit-Probit models, and factors affecting credit rating will be identified and collected from domestic and international journal websites (in the time period from 2008 to 2023) as the statistical population of the research. Finally, out of the total studies collected, 22 studies were analyzed systematically with certain limitations applied. The results of the examination of these studies indicate that most of these studies are heterogeneous. Moreover, the Logit and Probit models accurately and acceptably predict the impact of financial ratios on credit rating. Additionally, it was determined that there is a significant relationship between financial indicators and credit rating.

Keywords: Meta-analysis; Logit-Probit Models; Financial Indicators; Financial Ratios; Credit Rating.

1. Introduction

Financial ratios are metrics used by financial analysts to assess the performance of a company and evaluate its financial health. These indicators can signify trends, risks, and financial opportunities for an organization. In the same vein, credit rating is used as a tool to assess the quality and financial strength of a company. However, the precise impact and how financial ratios affect a company's credit rating have not yet been fully explored.

Nowadays, external financing and credit allocation play a significant role in the economies of countries. The globalization of the economy and the introduction of new service channels like the internet have enabled credit seekers to search for credit providers without temporal or spatial limitations. Consequently, credit institutions have been inclined to expand their activities to other countries worldwide. Credit rating models provide a significant part of the information needed by credit institutions for effective credit management. These models are used to predict the risk size of a credit applicant and encompass a wide range of qualitative and quantitative methods. The approach currently used in Western banks involves ratings conducted by external institutions, presented as a risk grade for each company. S&P, Fitch, and Moody's are the most reputable institutions that measure and provide specific ratings of the credit risk of various companies internationally. Calculating a company's credit risk can have numerous benefits, including estimating the likelihood of loan repayment in banks or the growth of stock value in stock market organizations for investors. The increased demand for external financing, heightened competition, and the emergence of new channels in the modern economic space have created new opportunities for credit institutions and, conversely, necessitated new tools and methods. This issue has driven these institutions towards revising, empowering, and incorporating new technologies in credit management processes.

Understanding a company's credit status helps users make lower-risk decisions. The capability and willingness to fulfill obligations indicate a company's credit status, determined by the credit rating index. A company's credit rating is an independent assessment of its ability to timely pay off debts, and the primary and appropriate function of credit rating is to enhance the efficiency and transparency of capital markets by reducing information asymmetry between borrowers and lenders (Gray, Mirkovic, and Ragnathan, 2006; Keller, 2005). Information asymmetry has posed challenges to credit grantors and borrowers in making accurate lending and borrowing decisions, which credit rating can resolve by clarifying the creditworthiness and desirability of the borrower.

The financial status of companies is highly correlated with their ability to meet their obligations to investors, creditors, and other stakeholders. The rating of companies is a measure of their financial status and helps users, especially investors, make better investment decisions (Mokhatab Rafiei et al., 2012). Comparing the credit risk of companies facilitates investor decision-making. On the other hand, a company's rating determines the cost it must pay for financing in the capital market.

Study Contradictions: Researchers over the years have made considerable efforts in credit rating but have not yet reached an accurate conclusion. (World Bank Report, 2017) Generally, the methods used for rating are divided into parametric and non-parametric categories. Parametric methods are based on statistics and have various examples. For instance, logit, probit, discriminant analysis, and logistic regression are among the parametric models used in this field. Non-parametric and data mining methods have been employed subsequently. Decision trees, neural networks, and expert systems are the most important non-parametric models used for analyzing companies' credit ratings. (Sabzvari et al., 2006) Foreign research such as Salschinberger (1992), Quants and Fant (1993), Altman et al. (1994), Lacher et al. (1995), Desai (1996), Piramota (1998), David West (2000), Tian Xiong Li et al. (2002), and domestic research like Ali Mansouri (2003), Pouneh Roueintan (2005), and Pouya Hosseini (2008) have indicated that non-parametric and data mining research, due to more precise analysis and consideration of qualitative aspects, can better analyze companies' credit ratings than parametric methods. Several points need attention: Firstly, non-parametric credit assessment models are highly diverse, each with its advantages and disadvantages. This has led to a lack of consensus among researchers in credit rating on a specific method. Secondly, the general methods used have structural errors. For example, most modern research aims to utilize fuzzy logic in their studies, but there are criticisms of fuzzy logic's performance. For instance, Sharma et al. in 2005 attempted to model linguistic

fuzzy for selecting appropriate NET strategies in process industries. They found that fuzzy logic leads to the quantitative translation of ambiguous and qualitative information, ultimately rendering the research results ineffective. This issue can also occur in credit rating. Thirdly, most methods used have a hierarchical nature and do not consider relationships between variables. For example, the TOPSIS method is one of the main models used in past research. This method uses the concepts of "ideal solution" and "similarity to the ideal solution." The ideal solution, as its name suggests, is the solution that is best in every way, which generally does not exist in practice, and the aim is to approach it. There is no precise consensus on defining the "ideal solution" in stating companies' credit status. By reviewing specialized texts of credit rating research, it can be seen that there is no collective opinion among researchers regarding the parameters analyzed. Undoubtedly, the results of this research can be useful for the Securities and Exchange Organization, banks, financial and credit institutions, and financial analysts. The main goal of this research is to answer the contradictions and inconsistencies in research related to credit rating, contributing to the growth and elevation of research in accounting and finance.

The primary goal of this research is to combine and compare the findings of previous research and establish a link between studies to derive a coherent conclusion from the scattered results of studies, using statistical methods to ascertain the actual effects of the variables in this research. To achieve this goal, this research will use the method of meta-analysis to reach a unified conclusion. In this method, the results of various and numerous research are combined, and new, more coherent results are extracted using statistical methods. In meta-analysis research, the researcher begins by recording the characteristics and findings of a mass of research in quantitative concepts, preparing them for the use of powerful statistical methods. The main task of the meta-analysis method is to harmonize and unify the results of research. Meta-analysis research is inherently applied and falls under quantitative research. The results of this research can increase the knowledge of university professors, audit managers, PhD students in accounting, CEOs and board members of companies, and managers and analysts of banks, investment companies, brokers, and investment funds regarding the quality of information. With more knowledge in the above area, companies may adopt better policies, procedures, and measures, subsequently increasing the confidence of investors and financial analysts and consequently the prosperity of the Iranian capital market. Moreover, policymakers (Securities and Exchange Organization) and standard-setters (Audit Organization) can use the results of this research to establish more beneficial and effective reporting requirements and regulations to improve decision-making quality. On the other hand, the results of this research can be important for users (professors, students, and researchers) and enrich the accounting literature on the transparency of financial reporting.

This research aims to answer the following questions:

- Do financial ratios have a significant impact on credit rating?
- Do the Logit and Probit models accurately and acceptably model the impact of financial ratios on credit rating?

A researcher begins the process of data analysis and synthesis by calculating the effect size, computing the distribution of effect size, and examining the homogeneity and moderating variables (Kierkegaard and Yaprak, 2010).

Stages of Work:

For the meta-analysis, the research will follow these steps:

1) **First Step**: Initially, all research studies available on the subject will be reviewed.
2) **Second Step**: In the next step, statistical measures of effect size (like P-Value, Z, Kai-square, F, and t) should be transformed.
3) **Third Step**: If feasible, the average effect size should be calculated. However, it should be noted that usually these coefficients' distribution is not normal and should be transformed to Fisher's z transformation.
4) **Fourth Step**: The significance of the overall effect size value will be tested, and an estimate of the confidence interval will be determined.
5) **Fifth Step**: It's important to consider the issue of homogeneity or heterogeneity of effect sizes before combining them. If they are homogeneous, they can be combined together. Otherwise, steps two to four will be undertaken to determine if the researches are homogeneous.

6) **Sixth Step**: The studies will be divided into subgroups if there's any variance in effect size that remains unexplained and they are homogeneous. The key variables based on which the studies will be divided will be identified. This step involves using the QW (within-group homogeneity test) and QB (between-group homogeneity test) statistics. If the value of QW is not significant, it indicates that the studies within the classes are homogeneous, and the researcher can proceed with identifying key variables for a good overall effect size estimation. QB is also a helpful statistic for subgroup analysis.

2. Research Methodology

This research is fundamentally applied in terms of its goal and is an empirical study in the field of accounting and finance in terms of its research method. The first part of the research, conducted as a literature review, focuses on extracting determinants of credit ratings. For this purpose, literature related to credit ratings, including leading rating agencies and research conducted in this field, was studied. The impactful indices on credit ratings consist of five groups of financial ratios derived from the audited financial statements of companies. These five groups of financial indicators, along with the variables of each index, are elucidated in Table Number One.

Table Number (1) – Financial Indices Affecting Credit Rating

Profitability Indices	Liquidity Indices	Activity Indices	Leverage Indices	Growth Indices
Operating Margin	Current Ratio	Inventory Turnover	Financial Leverage	Sales Growth Rate
Return on Investment	Quick Ratio	Accounts Receivable Turnover	Long-Term Debt to Total Assets	Operating Profit Growth Rate
Return on Equity	Cash Ratio	Fixed Asset Turnover	Long-Term Debt to Equity	Asset Growth Rate
Return on Assets	Current Asset Ratio	Working Capital Turnover	Debt to Equity	Equity Growth Rate
Earnings Per Share	Working Capital	Total Asset Turnover	Equity to Fixed Assets	
Net Profit Margin	Current Liabilities to Assets	Operating Cycle	Ownership Ratio	
Gross Profit Margin	Current Liabilities to Equity			
	Current Liabilities to Working Capital			
	Working Capital to Total Assets			
	Operating Cash Flows to Equity			

Risk and Credit Rating

The term risk, specifically in financial markets, often relates to the potential loss of an investor. Credit risk is the likelihood of a default by the issuer, which involves the failure to pay interest or principal on the commitment. In financial markets, investors are often interested in measuring a company's risk to decide on their investment level. Since the 1980s, there has been a significant increase in demand for information related to credit risk analysis, and numerous methodologies have been developed in response to this demand (Marcia et al., 2014). Choi et al. (2006) assert that studies on the rating process indicate a clear correlation between credit ratings and the subsequent default probability; that is, companies with higher credit ratings have a lower likelihood of default and vice versa.

Logit and Probit Models

Logit and probit models are two logistic regression methods used to examine the dependency between a binary response variable (like the occurrence or non-occurrence of an event) and one or more explanatory variables. These models can be employed to investigate the impact of financial ratios on credit ratings.

Logit and probit models for predicting the financial and credit status of companies were introduced in the late 1970s. The logit model is a multivariate analysis that considers all predictive factors simultaneously in a

problem. Unlike multiple discriminant analysis, the weight given to each independent variable in logit analysis is probabilistic, considering the likelihood assigned to each category. These models were aimed at estimating the probability of failure in fulfilling company commitments. A key difference between logit and probit regression models is that probit models assume that the information follows a normal distribution. Ohlson (1988) is among those who used this model to predict company bankruptcy. Winington (1990) compared the validation results of discriminant analysis models with logistic regression. He concluded that logistic regression has a lower error percentage than discriminant analysis methods. Joos et al. (1998) compared the efficiency of the logit regression model with decision tree results. Using data from Belgium's largest banks, they demonstrated that the logit model's results were more accurate. Westgaard, Van Der Wijst, Latinen, and others, like Henley, have used logistic regression for credit assessment of legal and natural persons.

Amiri (2003) in his research developed a model to predict bankruptcy in Iran. He selected 60 samples for his model, half of which were financially distressed. Using 5 financial ratios, he presented a model based on multiple regression. The model's test results showed that it correctly classified 93% of the total sample. Falah Shams (2005), in his article, examined the efficiency of linear probability models, logit, and artificial neural networks for predicting credit risk. In his research, using financial and credit information of 316 legal clients of banks, he tested the mentioned models. His research findings indicate that the relationship between variables in the credit risk prediction model is not linear, and exponential and sigmoid functions are more suitable models for predicting credit risk. Rai and Falahpour (2008), in their research, examined the use of the Support Vector Machine in predicting financial distress of companies. They presented a model using data from 40 manufacturing companies. The overall prediction accuracy of the presented model compared to the results of the logit regression model in one, two, and three years was examined, and it was found that the overall prediction accuracy of the model one year before bankruptcy was higher than that of the logistic regression model.

In this research, logit and probit models have been used to examine the dependent variable. Logit and probit models are used when the dependent variable is binary or dummy. In this research, field studies and library research have been used to select influential variables. The method used for data collection in this research is library-based. In this research, the focus is on research conducted on the specific topic of meta-analysis of financial indices affecting credit ratings of companies. Meta-analysis methods are very interactive in many stages (Glass and Smith, 1980). Initially, the topic is selected, then formulated, and studies related to the topic are collected that have examined a similar hypothesis. Then, the characteristics of the studies are coded and extracted, statistical measures and averages, and other statistical data are converted to effect size, and finally, the effect sizes are combined and interpreted. It should be noted that in the meta-analysis method, there is no particular limitation in relation to the number of studies. For data collection, several different combinations of keywords related to financial reporting have been used: the keywords of this research are credit rating, credit risk, credit rating model, which will be searched in various sources and in first-hand and reputable accounting journals, as well as from professors active in this field regarding the identification of related articles. Finally, the references section of the collected articles will be used to identify other experimental studies related to the topic to complete the research data. Meta-analysis or meta-analysis is a set of statistical and analytical techniques for combining the results of research in a specific field, with a relatively unified research question, to increase the narrative power, validity, generalizability, and practical use of research findings. This research method was first presented in 1976 by Mr. Glass, an American statistician. There are many software and systems used at different stages of data collection, organization, analysis, and final report presentation in meta-analysis. The software CMA is one of the most comprehensive meta-analysis software in the world. It is used to compile a dataset of meta-analytical data to calculate the effect size for each of the experimental studies and identify probable moderating variables (Buckley and colleagues, 2010). The effect size is a measure used to display and standardize the findings of research (Lipsey and Wilson, 2001) and provides information related to the extent of the relationship between the dependent variable and explanatory variables related to each study.

Data collection includes identifying published works on a specific topic. This stage is important as it will initially reveal the number of research studies; to create a sample, authors will use several databases, specialized journals, and published reviews. After selecting the relevant articles, the reference list of these studies will be reviewed to identify other related articles (Buckley and his colleagues, 2013). Research methods generally include using keyword searches in several databases and other sources. The population under study in this research is articles (from empirical research conducted) related to credit rating worldwide. More specifically, these articles will be from first-hand and reputable management and accounting journals. This research is based on sampling, and all collected information will be used for summarization and conclusion. To implement the meta-analysis method, all studies conducted in the research topic area using keywords such as credit rating, credit risk, credit rating model, and factors affecting credit rating from foreign journal websites (articles published in the time period 2008 to 2023) and the website of domestic scientific research journals (articles published during the years 2008 to 2023) will be identified and collected as the statistical population of the research. Finally, out of a total of 231 collected studies, after applying the limitations outlined in Table Number (2) and using a systematic elimination method, ultimately 22 studies will be analyzed.

This table provides a summary of the process used to select the final sample of studies for the research, highlighting the total number of studies initially considered and the criteria used to narrow down these studies to a final sample of 22.

Table Number (2) – Research Population and Sample

Studies	Number
Total number of studies	231
Total studies in foreign journals from 2008 to 2023	152
Criteria for eliminating foreign studies	
Number of articles that did not have the indices required for this research	(73)
Articles that did not have a consistent statistical method	(44)
Articles that were not related to the variables of the research topic	(23)
Final number of foreign articles	**12**
Total studies in domestic journals from 2008 to 2023 (Iranian Calendar: 1387 to 1402)	79
Criteria for eliminating domestic studies	
Number of articles that did not have the indices required for this research	(33)
Articles that did not have a consistent statistical method	(31)
Articles that were not related to the variables of the research topic	(5)
Final number of domestic studies	**10**
Final sample	**22**

3. Research Hypotheses

Based on the research questions, the following hypotheses are presented:

- **Main Hypothesis 1**: Financial ratios play a decisive role in determining the credit rating of companies. In this study, to clarify how the meta-analysis of financial indicators affecting the credit rating of companies is conducted, and in light of the previously mentioned discussions and theoretical foundations of the research, the following hypotheses are proposed:
  - **Sub-Hypothesis 1**: Profitability indicators play a decisive role in determining the credit rating of companies.
  - **Sub-Hypothesis 2**: Growth indicators play a decisive role in determining the credit rating of companies.
  - **Sub-Hypothesis 3**: Activity indicators play a decisive role in determining the credit rating of companies.
  - **Sub-Hypothesis 4**: Liquidity indicators play a decisive role in determining the credit rating of companies.

- **Sub-Hypothesis 5**: Leverage indicators play a decisive role in determining the credit rating of companies.
- **Main Hypothesis 2**: Logit and probit models accurately and acceptably predict the impact of financial ratios on the credit rating.

4. Research Findings

Cohen (1977) defines effect size as the magnitude of the relationship in the population or the degree of deviation from the null hypothesis. The results from the table below indicate that the value of the Q statistic for all variables is greater than the table value, and the significance level of the Q test is less than 0.05. However, since this index is sensitive to the increase in the number of effect sizes, the power of this test to reject homogeneity increases with more effect sizes. Therefore, the squared I statistic is another index used for this purpose; the I^2 value for the variables in question is greater than 75 percent, indicating that the heterogeneity of effect size is at a relatively high level; thus, the null hypothesis is rejected, and the alternative hypothesis concerning the heterogeneity of the effect sizes of the mentioned variables is confirmed.**H0**: There is no significant difference between the obtained effect sizes.

H1: There is a significant difference between the obtained effect sizes.

Furthermore, at this stage, the strength of the relationship between independent and dependent variables is assessed. In the meta-analysis approach for testing research hypotheses, the heterogeneity of the effect size is initially tested to determine the type of meta-analysis model used for testing the hypothesis under consideration. If the data are homogeneous, the fixed effects model is used, and if heterogeneous, the random effects model is utilized.

Table No. (3) Heterogeneity Test of Effect Size

Hypothesis Name	Relationship Between Independent and Dependent Variable	Heterogeneity Test of Effect Size	I^2 Value	Q Statistic Significance Level
Sub-Hypothesis 1: Profitability Indicators and Credit Risk	Random Effects	80.58	0.000	41.19
Sub-Hypothesis 2: Growth Indicators and Credit Risk	Random Effects	89.01	0.000	191.08
Sub-Hypothesis 3: Activity Indicators and Credit Risk	Random Effects	82.26	0.000	95.83
Sub-Hypothesis 4: Liquidity Indicators and Credit Risk	Random Effects	82.26	0.000	22.55
Sub-Hypothesis 5: Leverage Indicators and Credit Risk	Random Effects	78.53	0.000	27.95

It's worth mentioning that in meta-analysis, we have two models: the fixed-effect model and the random-effects model. It's important to note that in the fixed-effect model, the assumption is that all observed differences between effect sizes in various studies are solely due to sampling error. In other words, it assumes there is no heterogeneity. However, in the random-effects model, the assumption is that heterogeneity exists. Considering that after reviewing the assumptions of meta-analysis we concluded that the random-effects model should be used to combine results for reporting effect size, therefore, the table below presents the effect size reports of studies conducted in the random-effects model. Given the results of the above table, the hypothesis testing of the study based on the random-effects model and employing the CMA2 software is shown in the table below.

This table provides a clear and organized overview of the research findings related to the influence of different financial indices on credit risk.

Based on the results obtained from the use of meta-analysis models, point estimates (weighted average based on the sample size) and interval estimates (confidence interval) of the effect size from various studies are presented, along with test statistics and significance levels. These are utilized for judging the significance of the obtained estimates. If the calculated confidence interval includes zero, it can be inferred that the effect size is not equal to zero, and there is no significant relationship between the variables of the study, thus rejecting the research hypothesis. However, if the confidence interval does

not include zero, it is concluded that the effect size is not zero, indicating a significant relationship between the study variables, thereby confirming the research hypothesis. If the calculated mean effect size is positive, the relationship between the two variables is positive, and if it is negative, the relationship is negative. In the interpretation of the effect size, a value less than 0.1 (greater than -0.1) is typically considered small, between 0.1 and 0.3 (between -0.1 and -0.3) as medium, and more than 0.3 (less than -0.3) as large.

Table No. (4) Testing of Subsidiary Hypotheses Based on the Model of Fixed or Random Effects

Result	Significance Level	Z-Statistic	Effect Size Confidence Interval	Weighted Mean Effect Size	Relationship Between Variables	Hypothesis Name
Confirmed	0.000	3.55	(0.097 to 0.326)	0.214	Profitability Indices and Credit Risk	Subsidiary 1
Confirmed	0.000	8.35	(0.254 to 0.160)	0.208	Growth Indices and Credit Risk	Subsidiary 2
Confirmed	0.000	6.12	(0.225 to 0.118)	0.172	Activity Indices and Credit Risk	Subsidiary 3
Confirmed	0.003	2.97	(0.538 to 0.123)	0.347	Liquidity Indices and Credit Risk	Subsidiary 4
Confirmed	0.001	3.39	(0.356 to 0.099)	0.232	Leverage Indices and Credit Risk	Subsidiary 5

Table No. (5) - Frequency Distribution of Effect Size Categories

Frequency Percentage	Frequency	Range of Effect Size Intensity
0.06%	3	Low intensity (less than 0.1 or greater than -0.1)
0.84%	42	Medium intensity (between 0.1 to 0.3 or between -0.1 and -0.3)
0.10%	5	High intensity (more than 0.3 or less than -0.3)
100%	50	Total

Based on the table mentioned earlier, out of 22 articles, 3 cases (equivalent to 10%) fall into the 'small' category, 16 cases (equivalent to 80%) fall into the 'medium' category, and finally, 3 cases (equivalent to 10%) fall into the 'large' category. Therefore, the effect size obtained in the first range (i.e., less than 0.1) is small, and the hypothesis under study lacks sufficient strength. Also, when the value of r is in the second range (i.e., between 0.1 and 0.3), the effect size is considered medium, and finally, when the value of r is in the third range (i.e., more than 0.3), the impact is assessed as strong. According to this classification, 84% of the effect sizes are evaluated as medium; therefore, it can be said that based on the results of this meta-analysis, financial indicators and credit ratings have a medium-level relationship.

For a better understanding of the conceptual model of the research, the statistical description of the variables seemed necessary, as it provides a better understanding for the analyses conducted to test the conceptual model. In this research, a quantitative effect size has been calculated for each field study; the quantity of the calculated effect sizes and their frequency indicate that out of the 22 research cases considered, in total, a quantitative effect size was calculable in 22 cases. The average effect size calculated for different studies in this research is 0.165. According to Cohen's (1988) criterion, the combined effect size of the random effects model, which is 0.165 for the entire sample, is considered a relatively medium effect size. Also, to examine publication bias, a funnel plot was drawn using comprehensive meta-analysis software; Chart No. 1, which relates to all research, is distributed in a nearly symmetrical shape, indicating the absence of bias. Whereas, if there were publication bias, the dispersion of research at the bottom of the chart would have been noticeable. This issue is related to small and limited research in terms of sample size. Therefore, in the mentioned research, it can be said that publication bias has been minimized. Thus, the statistical results are significant and reliable.

The examination of 22 studies conducted on the relationship between financial ratios and credit risk indicates that these studies are heterogeneous. Therefore, combining the correlation statistics documented in these studies does not lead to a definitive conclusion regarding the existence and extent of such a relationship. In order to identify the cause of this heterogeneity, the studies can be categorized based on different credit risk criteria, and the within-group variance statistic can be calculated. This approach helps us to investigate whether these different criteria used in the studies for measuring credit risk are one of the factors contributing to the inconsistency in the research results. Thus, to test the primary hypothesis of the research and examine whether these criteria for categorizing, namely the different credit risk assessment criteria, are the moderating factor in the relationship between the two main variables of the research (financial ratios and credit risk), the values of the between-group and within-group homogeneity tests have been calculated and presented. As explained in the Methodology section about the meta-analysis tests, it is observed that the value of the within-group homogeneity test is insignificant - as shown in Table No. 5. Therefore, the different criteria used in the studies are one of the factors contributing to the inconsistency in the research results. Hence, the studies within the categories are homogeneous, and the researcher has performed well in identifying the key variables (i.e., financial ratios), and the first primary hypothesis of the research is confirmed.

Chart No. 1 - Publication Bias in All Studied Research

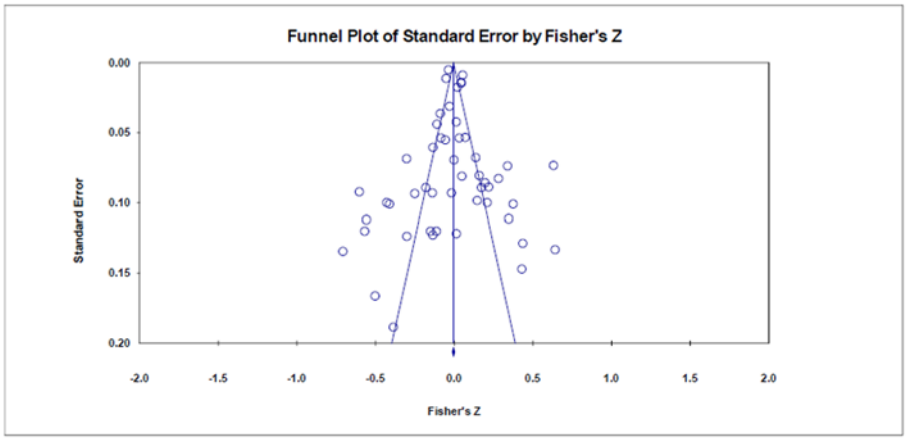

Table No. (6) - Results from the Homogeneity Test of Subgroups for the First Main Hypothesis

Index	Sum of Squares	F-Statistic Value	Significance Level
Within-Group	37.61	0.601	0.699
Between-Group	650.5		

5. Conclusion and Discussion

Investors, managers, and credit grantors each consider different criteria for assessing the performance of a business unit. Among these, an effective analysis of financial ratios is a suitable solution and the first step for evaluating and rating companies, emphasizing the importance of rating companies and economic institutions using comprehensive rating models based on financial performance evaluation (Hosseini et al., 2016). A review of the research literature shows that in the field of the relationship between financial indicators and credit risk, despite various studies conducted, the results are usually confusing and contradictory. Therefore, this study aimed to identify the reasons for such differences by employing a meta-analysis approach. Overall, this research sought to analyze financial indicators and credit risk through meta-analysis, leading to the following conclusions:

- Financial ratios (indicators) play a decisive role in determining the credit rating of companies.

- There is a significant relationship between profitability indicators and the credit rating of companies.
- There is a significant relationship between growth indicators and the credit rating of companies.
- There is a significant relationship between activity indicators and the credit rating of companies.
- There is a significant relationship between liquidity indicators and the credit rating of companies.
- There is a significant relationship between leverage indicators and the credit rating of companies.

Examination of the Second Primary Hypothesis
Second Primary Hypothesis: Logit and Probit models accurately and acceptably predict the impact of financial ratios on credit rating.

The examination of 22 studies conducted on the relationship between financial ratios and credit risk indicates that these studies are heterogeneous. Therefore, combining the correlation statistics documented in these studies does not lead to specific conclusions regarding the existence and extent of such a relationship. To identify the cause of this heterogeneity, the studies are categorized based on different criteria, and the within-group variance statistic is calculated. This method helps to investigate whether the different criteria used in the studies to measure credit risk are one of the factors causing inconsistency in the research results.

Given the data related to model testing and the performance evaluation metrics presented in the table above, it can be concluded that the Probit model exhibits greater accuracy compared to the Logit model presented.

Thus, to test the second primary hypothesis of the research and examine whether these criteria for categorization, namely different models for measuring financial ratios on credit risk, the values of the between-group and within-group homogeneity tests have been calculated and presented. As explained in the Methodology section about the meta-analysis tests, it is observed that the value of the within-group homogeneity test is insignificant; therefore, the different criteria used in the studies are one of the factors contributing to the inconsistency in the research results. Hence, the studies within the categories are homogeneous, and the researcher has performed well in identifying the key variables (i.e., financial ratios), and the second primary hypothesis of the research is confirmed.

The results obtained in this research are consistent with the theoretical framework and financial literature referenced in the study. Therefore, as a general conclusion and considering the points mentioned in the research literature, it can be inferred that financial ratios derived from financial statements have an impact on the credit risk of a company. These results can enhance the understanding and knowledge of investors and researchers in the capital market area, and possibly lead to the identification of other factors capable of explaining credit risk.

The practical results of this research can be of interest to two main groups. The first group includes users of financial information, such as investors, credit grantors, bank managers, and financial and credit institutions. These individuals are directly related to credit risk, financial effects, and the outcomes of company performance. The second group consists of researchers, policymakers, compilers of financial and credit standards, rating agencies, and institutions like stock exchanges that are interested in economic and financial issues. A significant part of the results of this research is in line with the theoretical foundations and, while filling the research gaps in this field, can assist managers in proper management and shareholders in investing and determining the policies and procedures of the company.

Table No. (7): Results from the Second Main Hypothesis Test

Metric	Logit Model	Probit Model
Mean Absolute Error (MAE)	0.48	0.501
Determination Coefficient (R^2)	0.69	0.75
Normalized Mean Squared Error (NMSE)	0.31	0.25
Root Mean Squared Error (RMSE)	675.0	672.0
Mean Squared Error (MSE)	456.0	452.0

Table No. (8) - Results from the Homogeneity Test of Subgroups for the Second Main Hypothesis

Index	Sum of Squares	F-Statistic Value	Significance Level
Within-Group	77.44	1.35	0.254
Between-Group	662.2		

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