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THE IMPACT OF ARTIFICIAL INTELLIGENCE RECOMMENDATIONS ON INDIVIDUAL INVESTOR DECISIONS

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ABSTRACT

Purpose- Although artificial intelligence technology is a new technology, it affects every aspect of our lives by finding a very fast field of activity. Artificial intelligence technology, which also shows its effect in the field of finance, is seen to have many applications. There are many alternatives in the investment markets, it will take a long time to make a profit in the markets and a certain amount of knowledge is required. People cannot master the data in all markets when they will invest, but technological developments provide the opportunity to invest by storing each data or observing their changes. This study aims to investigate the effects of artificial intelligence technology on individual investor decisions.
Methodology- The study consists of individual investors who live in Diyarbakır province and generally make investments. The questionnaire prepared in accordance with the scope of the study was applied to 1800 participants using face-to-face survey method. The 22 statements prepared in accordance with the scope of the study were applied to the participants. The questionnaires that 1616 participants answered correctly and accurately were included in the scope of the study. In order to ensure the reliability of the study statements, Cronbach's Alpha was calculated and this rate was determined as 91%. The answers given to the study statements were transferred to the tables as a result of the analyses. The transferred information was tried to be interpreted. In addition, frequency tables, t-test and anaova analysis were used in the analysis of the study data.
Findings- Thanks to artificial intelligence algorithms, which is one of this technology, it analyses the data in the market and enables the investor who wants to invest to trade in the market by giving buy and sell orders. Thus, artificial intelligence technology allows the investor to make more profitable investments by guiding the investor.
Conclusion- As a result, it is possible to say that the individual investors participating in the research do not have sufficient knowledge about artificial intelligence technologies, but they have an interest in investing using artificial intelligence technologies. In addition, it has been determined that the older the age, the lower the education level, the higher the income level and the married investors are insecure about investing using artificial intelligence technology.

Keywords: Artificial intelligence, markets, investment, technological developments, investment behaviour
JEL Codes: G10, G11, G41

1. INTRODUCTION

Artificial intelligence technology has become a technology that affects every aspect of our lives today. Artificial intelligence technology, which is also prominent in the finance sector, creates awareness about investments and helps investors make the most appropriate decision and shape their investments while making these decisions. Artificial intelligence technology analyses the data of investment instruments in the best way and creates an investment portfolio, which instruments are invested more in the investor and by analysing the investment graphs, it has an impact on the individual decision-making process of the investor. Thanks to artificial intelligence algorithms, by collecting information about the company to be invested in and analysing the risks and opportunities faced by investor portfolios, it allows investors to make analyses and comments by collecting more information about the company. It is almost impossible for investors to analyse and interpret large amounts of data. In terms of time, it is a tiring job in terms of making many transactions and taking time. Artificial intelligence technology allows the investor to invest in the most appropriate financial instrument by analysing important and complex data and making the data most suitable for the investor by revealing opportunities and threats.

Thanks to artificial intelligence algorithms, the role of the investor on investment decisions is shaped and enables the investor to make the right investment decision. Artificial intelligence technology analyses investor groups more comprehensively and creates a report about them, allowing the investor to shape his/her investment accordingly. With the inclusion of artificial intelligence systems in the investment field, it will create a sustainable investment area and will continue to advise investors on investment. Investors generally shape their investments by prioritising environmental factors or social factors when making decisions. However, artificial intelligence technology allows them to invest in the right investment instruments by comparatively analysing the data with algorithm models. It aims to discover the effect of artificial intelligence technology on investment instruments by collecting and analysing the data of investment companies thanks to artificial neural networks in artificial intelligence technology. Thanks to the technology, it aims to determine whether it is suitable for profitable investments by making suggestions to investors who will invest in companies. While investors are making investment decisions, this technology provides investors with a recommendation whether these decisions are taken correctly or not. Artificial intelligence technology is not known by many investors and this situation reveals the result that many investors cannot benefit from sufficient technology, but the investor should make the right decisions for the right investment by taking advantage of the data and investment forecasting models that artificial intelligence technologies reveal about them when buying a stock or bond by taking advantage of more technology. With the inclusion of artificial intelligence technology in the field of investment, it reveals that artificial intelligence-based systems should be used effectively by preventing investor loss with a correct decision of the investor by eliminating many risk factors.

By talking about the effects of artificial intelligence technology on investors, artificial intelligence technology allows individual customers who make investment decisions to make a more accurate decision and make predictions. Individual investors will help them make the right investment decision by analysing how to make better investment decisions by using artificial intelligence technology and how to get a better result in financial markets. While making an investment decision, the investor will be affected by psychological and sociological factors and will risk their existing savings by not making the right investment decision, but in artificial intelligence technology, they carry out the investment transactions without risking their savings. High frequency trading (HFT), one of the products of artificial intelligence technology, is one of the trading tools that make artificial intelligence-based algorithm trading. HFT analyses the markets and allows customers who trade in a short time period to make the right investment in the markets by making decisions without any human influence.

2. LITERATURE REVIEW

Ellezoğlu (2020), in his study, tried to determine whether the behaviour of individual investors in Ankara while making financial decisions affects this decision-making. In addition, he examined how investor risks appear and related changes due to the behaviour they exhibit. Gu, Kelly, & Xlu (2020), analyses how it will perform in the financial field from time series and cross-sectional models by predicting prices in the stock exchange with machine learning techniques in artificial intelligence technology. Güdelek (2019), in his study, approaches to financial problems were explained by examining time series. He states that the models created by developing deep learning models in financial data have achieved success in the financial field. Rasekhschaffe & Jones (2019), referring to the role of machine learning in the financial sector in the future, he mentioned the importance of artificial intelligence in the financial field and stated that the biggest effect of artificial intelligence is not realised in the financial field by giving the example of machine learning-supported Robo consultants of banks in the USA.

Sabharwal (2018), argues that the way to overcome the problem of compliance when using machine learning to predict income in stocks is the forecasting modelling to be created with data sets in machine learning methods. Korkulutaş (2018), made an application in Erzincan province by examining individual investor behaviours and evaluating investor behaviours in the financial context. By surveying 390 individual investors, he tried to investigate the behavioural effects on investment by examining the behavioural tendencies of investors. Aldemir (2015), investigated the factors affecting the civil servants and workers living in Tokat province while making investment decisions. According to the results of the surveys conducted with 400 participants and individual investors, the results of the financial profiles of investors on investment decisions were mentioned.

Küden (2014), in his study, examined the investor psychology of investment instruments by examining traditional and financial theories from a behavioural perspective. In the light of the data obtained as a result of the study, it was revealed that investors do not act rationally by being under the influence of psychological tendencies. Ayvalı (2014), tried to reveal the investment tendencies of individual investors in Bartın province with their level of knowledge and investment understanding while investing. In the light of the data obtained by conducting a questionnaire survey with investors and bank employees on investment, it was determined that investors in Bartın province are affected by factors such as past investment experiences and factors such as income levels and investor views, factors such as financial stability, and that investors keep their self-confidence at a high level by diversifying their investment and reducing risks. Çelik (2013), in the light of the data obtained as a result of his study by examining the psychology of individual investors in our country by examining the behavioural effects in the financial field, it was found that individual investors invest under the influence of psychological prejudices in their investment decisions and thus cannot achieve the desired result in the market.

Özer, Sarı, & Başakın (2017), in their study, evaluated the stocks of 8 developing countries on a weekly basis and made forecasts using fuzzy logic and artificial intelligence neural network technique and stated that the ii study management made similar predictions by trying to find the best stock in terms of investment among them. Shen, Jiang, & Zhang (2012), in his artificial intelligence study, revealed the investability of the next day's stock situation by predicting the profit margin of the stocks by predicting the profitability of the stocks by predicting the profit margin of the stocks by predicting these stock ratios of artificial intelligence technology by 74.4% for NASDAQ stock market, 77.6% for S&P and 77.6% for DJIA. Kutlu & Badur (2009), in his study, made a forecasting study for the Istanbul Stock Exchange 100 index and stated that the forecasts given for investment in stocks using artificial intelligence neural network technique are promising. Tsai & Wang (2009), There are many studies on making stock forecasts using artificial intelligence technology. He stated that by using neural techniques, using algorithms in decision tree models in investment using neural techniques, stocks in the Taiwan market were correctly inferred by 77%.

3. CONCEPTUAL ARTIFICIAL INTELLIGENCE

Artificial intelligence technology, unlike natural intelligence, can be defined as the ability of computers or computer-controlled robots to perform tasks related to entities in general. These robots created with the computer system are a technology created by thinking like humans and acting like them (Say, 2018). Artificial intelligence can be defined as a concept that produces technological devices using abilities such as communication and perception based on the mind (Kuşçu, 2015).

When we look at another definition of artificial intelligence; it is a device that performs operations through programming to perform logical and arithmetic operations of computer systems. Artificial intelligence is a technology that creates intelligent machines by imitating human behaviour. Intelligent machines are defined as machines that behave like humans, think like them and at the same time make decisions like humans. While artificial intelligence is given a task, we do not need to define it; instead, it is defined as a technological machine that creates machines with algorithms and programming that works on its own (Karakuş, 2023).

Artificial intelligence technologies are expressed as the transfer of human intelligence to machines to perform the given task. The purpose of artificial intelligence is to fulfil tasks and reason. Artificial intelligence technology is based on neural networks, deep learning and machine learning. In this way, it will be seen that artificial intelligence technology is taking place more and more in our lives every day and that this technology comes up with different models with software every day. Artificial intelligence is a technological tool that imitates the human brain by having functions such as thinking like a human and finding solutions to problems (Wisetsri, vd., 2021).

3.1. Artificial Intelligence Technology

Artificial intelligence technology has pushed the limits of machines to create an efficient and trouble-free technology. The aim of artificial intelligence is not to replace human beings, but to create a more efficient working environment due to increasing workloads in artificial intelligence. Artificial intelligence backs up a workload and ensures that things are planned and finished faster. Artificial intelligence technology, which minimises human error, produces solutions to many critical problems. The most important part of artificial intelligence is artificial neural networks, and it stands out as an indispensable part of artificial intelligence that makes independent decisions thanks to these self-developing and learned system networks. Artificial intelligence technology shows its presence in the field of investment and directs the investor to make the right investment with an analysis modelling (Think Tech, 2022). Artificial intelligence technology can be expressed as a comprehensive computer discipline by creating intelligent machines by imitating human intelligence. Artificial intelligence technology has become an area where every company invests in many areas, and it is in our lives as a technological field that every segment from the financial field to the health sector is interested in.

The basic concepts of artificial intelligence technology; John Searle is the first to introduce these concepts. Some experts explain artificial intelligence with these two concepts. Strong artificial intelligence: It is a machine that solves problems alone without any training. This artificial intelligence aims to find solutions by proposing new approaches to problems by going beyond various problems. Machines and programmes are a technological concept that overcomes complex tasks without any human intervention and produces solutions to problems by thinking like humans. Weak artificial intelligence: weak artificial intelligence is also called narrow artificial intelligence. Weak artificial intelligence, which operates in a limited area, is a simulation of human intelligence, such as a narrowly defined problem or transcribing human speech. This artificial intelligence focuses on performing a single task in the best way (Schroer, 2023).

It is possible to explain the techniques of artificial intelligence technology as follows;

Neural network technique: In this technique, it is a technical analysis used on the basis of mathematical models based on the way the human brain works. They operate like neurons in the human brain. With this technique, it is used as prediction modelling in the financial field by predicting and generalising the data related to an event and guiding investors.

Deep learning techniques: It is a sub-field created by using preloaded information to decide on machine learning. This learning technique is a continuation of the machine learning technique. In this technique, it is an analysis technique used to make data with a very complex structure more understandable in stock data or portfolio management.

Machine learning: In this technique, without any human intervention, the machine accesses information completely by its own means. It is defined as the process of making predictions about a situation by analysing the data collected in this technique and separating the necessary information. Machine learning is used in financial markets to make risk prediction or market analysis for an investment instrument and guide investors in financial decisions (Yıldız, 2022).

4. FACTORS AFFECTING INDIVIDUAL INVESTORS AND INVESTMENT BEHAVIOUR

Investors are people who invest some of their income in investment instruments for their own account in order to earn income in the future. While some of these investors make conscious investments, some of them are referred to as investors who make investment attempts to manage their own fund source without any knowledge (Karan, 2011).

The individual investor is an essential element in the basic building block of the market. Investors want to earn income in the future by investing in different investment instruments and valuing their savings in this field. Investors shape their investments according to their personality traits and factors affecting investor behaviour, but in this case, investors unknowingly put their savings at risk by investing according to the guidance of the environment or their personality traits behaviour. It is aimed to minimise the risk by using applications that make recommendations to investors in artificial intelligence technology that allows investors to invest with completely accurate data without being exposed to environmental influences that guide investors in order not to risk their savings (Özcan, 2011).

Individual investors try to become investors in the investment market by acting with the idea of buying and selling both in the short and long term while investing in the capital market. Individual investors cannot be expected to comprehend the market like companies because they are not experts and act entirely on their own efforts and personal guidance. In this case, it cannot be expected to predict the risk of the instruments to be invested in the market, which will cause investors to withdraw from the market early and result in disappointment. Individual investors are expected to take steps that minimise the risk in the investment market by requesting help from experts and using technological developments (Dizdarlar & Şener, 2016). Individual investors shape their investments by being influenced by three main factors when making investment decisions. It is stated what kind of effects these factors have on investors and which factors affect investors when they make investments. Another factor is that the investor makes an investment without any knowledge and without making use of experts.

Personal factors: We can state that the individual investor not having the necessary knowledge and information about the instruments to be invested in while investing in investment instruments will create a risk in terms of income and the investor's income will be at risk. The level of education of the investor has a very important factor in investment while making financial decisions, in other words, investment preferences and knowledge levels will differ according to the type of education received by the investor. The fact that the individual investor has no knowledge about the financial instruments that he/she will invest in will cause him/her to be deprived of the profit returns that he/she has determined, which will lead to negative factors such as the inability to bring small savings into the economy, which will pave the way for the formation of negative factors.

It will be seen that the lack of information for individual investors and their inability to dominate the market have a direct impact on financial decisions. Having knowledge about financial instruments and having a certain level of education will benefit individuals when making investment decisions and they can make the right investment decision without risking their savings by making use of technological developments (Böyükaslan, 2012).

Environmental factors: While making investments, investors generally shape their investments according to the information they see in the environment or the information circulated by word of mouth depending on external factors. When individuals cannot make decisions on their own, they shape their investments with the help of groups or by getting help advice from family members, but these financial decisions reveal a risk factor. Individuals are influenced by the social and cultural environment of the society in which they are located and make their investments according to the financial instruments specified by the environment by accepting the behaviours of the environment as correct.

Individuals also invest in financial instruments by making use of their friend groups and groups of people who are valued by the environment while making investment decisions, or they invest in financial instruments in line with investment advice by taking suggestions from people who invest in stock exchanges and shaping their investments in this direction, but this is extremely risky and will be an approach that jeopardises the return of the investor (Usul, Eroğlu, & Bekçi, 2002).

The effects of financial factors: Investors make their investment decisions in line with financial objectives in order to generate income. The investor who makes an investment decision can be defined as directing his/her investments in the form of a desire to maintain his/her capital and to ensure a continuous income from the deposits he/she holds. When individuals want to turn their savings into investments, they should make their investments in this direction without losing their capital, that is, by minimising the risk factors. While making an investment decision, the individual should always follow up and direct his/her investments cautiously.

The investor wants to continuously increase the value of his capital. This desire of the investor will bring along risk factors, causing him to make the wrong investment and thus risk all his savings. Investors should definitely invest in financial investment instruments by taking advantage of the applications offered by artificial intelligence technology and reducing the risk level by shaping their investments in line with the analyses and data offered by this technology to investors (Özaltın, Ersoy & Bekci, 2015).

4.1. Impact of Artificial Intelligence Technology on Individual Investor Decisions and an Example of Artificial Intelligence Applications

Investors cannot be expected to make a correct investment by encountering more data while buying and selling commodities or stocks in the markets, in this case, investments are under the control of intelligent machines that have the ability to think like humans, working on big data and analysing data thanks to artificial intelligence and neural network algorithms, allowing investors to make the right decision. With the widespread use of systems in artificial intelligence technology, investors using this technology continue their investments by making gains in the market environment. In this context, machine learning enables investors to make their investments accordingly by detecting complex investment patterns and providing real-time data to investors thanks to big data processing power (Chlu, 2020).

If we give an example of using artificial intelligence technology, the company named kavout makes daily stock recommendations that will earn the most by sorting the stocks and using the artificial intelligence system for price determination and pattern confusion. This company also uses artificial intelligence algorithms to create a portfolio in the same way. Epogue, another investment firm, developed a three-stage artificial intelligence system and developed the technique of observing and analysing potential investment options in the first stage, and in the second stage, they created purchase orders, and in the third stage, active purchase orders were carried out and performance analysis was performed through machine learning, allowing investors to invest in the right investment instruments (Thakar, 2020).

By using artificial intelligence-supported investment applications, investors can use machine learning techniques to monitor market conditions, investment strategies and data, analyse these data, predict the investment opportunity in the future and create the investment conditions themselves, allowing investors to invest with the right decisions. In artificial intelligence technology, it continues to operate independently without any human intervention in artificial intelligence technology, learns the trends in the market by analysing the market and reveals them with a good analysis technique and directs investors to make the right decision with their reasoning and decision-making abilities. With artificial intelligence technology, investors can perform their transactions very quickly and provide more reliable and faster service to customers by automating their transactions (platinum crypto academy.com, 2020)

As an example of a company operating in the field of artificial intelligence, Kavout uses artificial intelligence technology to rank stocks. This company uses artificial intelligence technology to detect complex patterns by detecting complex patterns and determining their prices and recommending the most profitable stocks, allowing the investor to make the right investment. Investors recommend the most profitable stocks for investment by using algorithms in artificial intelligence technology to create a new portfolio. If we give an example of another company in artificial intelligence technology, Epuque creates a three-stage artificial intelligence system, making observations and analyses on potential investors in the first stage, creating purchase orders in the second stage, and actively placing purchase orders in the third stage, and analysing performance through machine learning in artificial intelligence technology. With the deep learning technique, which is a sub-branch of artificial intelligence technology, the news on the internet or information on social media is to collect data from various sources and analyse how the market reacts to the reactions by analysing the past and trend data that brings them together and to ensure that the investor is prepared for the market conditions in the future in the long term.

Today, with the development in artificial intelligence technology, the investment volume of accounts managed by traditional investors corresponded to 10% of the investment volume, while in 2012 it corresponded to 55% of the transactions made in the USA. Since 2000, with the use of artificial intelligence technology in investment, investment robots with artificial intelligence have been more successful than individual investors in analysing large volumes of data, simplifying complex transactions and making technical analysis, allowing investments to be made faster with artificial intelligence technology. Artificial intelligence technology is a technology that is open to development. In this way, by identifying and correcting errors, it allows investors to invest by providing investors with simple, understandable and simple analysis data. It is known that investment instruments are using artificial intelligence by enabling the participation of serious investors in the financial world through investment practices in artificial intelligence technology (Walker, 2021).

5. DATA AND METHODOLOGY

The study consists of individual investors who live in Diyarbakır province and generally make investments. The questionnaire prepared in accordance with the scope of the study was applied to 1800 participants using face-to-face survey method. The 22 statements prepared in accordance with the scope of the study were applied to the participants. The questionnaires that 1616 participants answered correctly and accurately were included in the scope of the study.

In order to ensure the reliability of the study statements, Cronbach's Alpha was calculated and this rate was determined as 91%. The answers given to the study statements were transferred to the tables as a result of the analyses. The transferred information was tried to be interpreted. In addition, frequency tables, t-test and anaova analysis were used in the analysis of the study data.

6. FINDINGS AND DISCUSSIONS

The statements determined within the scope of the study were analysed and tabulated.

Table 1: Statistical Information on Research Statements

Descriptive Statistics			
Valid	N	Mean	Std. Deviation
Do I have enough knowledge about artificial intelligence technology	2616	2,42	1,251
I think that I invest according to environmental impacts when making financial investments	2616	2,52	1,396
I think that artificial intelligence technology invests in the right investment instruments	2616	2,65	1,371
I think that I will make a profit in financial investment by using artificial intelligence technology	2616	2,66	1,380
When making an investment decision, I invest by thinking that I have a high level of knowledge	2616	2,58	1,319
I think that artificial intelligence technology will make a difference in the financial investment world	2616	2,61	1,374
Thanks to the algorithms in artificial intelligence technology, I think that complex data is presented to investors in a simple and understandable way	2616	2,61	1,421
I am aware that artificial intelligence technology can perform analysis techniques that many investor experts cannot do	2616	2,61	1,368
I have information that artificial intelligence technology analyses the market by operating independently without any human intervention	2616	2,70	1,354
I think that with artificial intelligence technology, investors can perform their transactions very quickly and provide more reliable and faster service to customers	2616	2,63	1,464
I think that the demand for investment instruments will increase by enabling the participation of serious investors in the financial world through investment practices in artificial intelligence technology?	2616	2,66	1,406
I have information about Kavout, a company that ranks stocks in the field of artificial intelligence investment and reveals the 3 most profitable ones	2616	2,61	1,394
I think artificial intelligence technology will shape our investments in the future	2616	2,53	1,362
When investing, I invest without taking any technology recommendation as a basis	2616	2,73	1,406
When making an investment decision, I invest by following the decision of the majority	2616	2,64	1,388
When investing, I prefer to buy the most purchased investment instrument	2616	2,70	1,446
I think to get support from investment counselling companies while investing	2616	2,63	1,428
I prefer to invest in instruments with few investments	2616	2,60	1,389
I always think that I will win while investing	2616	2,63	1,419

I always think that I win thanks to my intuition in my investments	2616	2,72	1,366
When making investment decisions, I always act with the ambition that I will earn more	2616	2,39	1,368
I always consider it unlucky when I lose in investment	2616	2,52	1,369
Valid N	***2616***	***2,611***	***1,358***

According to Table 1, the participants stated, "I think that artificial intelligence technology will shape our investments in the future," which is the statement with the highest mean of 2.73. In addition, it was determined that "I have enough knowledge about artificial intelligence technology" was the statement with the lowest mean of 2.42. In this direction, although the participants stated that they did not have enough information about artificial intelligence technology, it was determined that they thought that artificial intelligence technology could be effective in their investment decisions in the future. In addition, it was determined that the individuals participating in the research were generally undecided about approving the research statements.

Table 2: Statistical Information about Participants

Gender	***n***	***%***	***Age***	***n***	***%***
Female	1620	62	*18 years and under*	372	14
Male	996	38	*19 years to 29 years*	768	29
Total	2616	100	*30 years to 39 years*	672	26
Level of Education	***n***	***%***	*40 years to 49 years*	516	20
Primary education	480	18	*50 and above*	288	11
Associate degree	864	33	**Total**	2616	100
Undergraduate	948	37	***Income Level***	***n***	***%***
Postgraduate	324	12	Between 0 - 9.000 TL	384	15
Total	2616	100	Between 10.000 - 19.000 TL	960	37
Marital Status	***n***	***%***	Between 20.000 - 29.000 TL	660	25
Married	960	37	Between 30.000 - 49.000 TL	444	17
Single	1284	49	50.000TL and Above	168	6
Other	372	14	**Total**	2616	100
Total	2616	100	**Which financial instruments do you invest in?**	***n***	***%***
Do you invest in financial investment instruments?	***n***	***%***	*Gold*	372	18
Yes	2076	79	*Repo*	272	13
No	540	21	*Stocks and shares*	612	30
Total	2616	100	*Bond*	172	8
Where do you get information about financial investment news?	***n***	***%***	*Foreign currency*	324	16
Television channels	732	28	*Virtual money*	264	12
Internet news sites	876	34	*Other*	60	3
social media news sites	948	36	***Total***	2076	100
other	60	2			
Total	2616	100			

Table 2 shows the demographic characteristics of the participants and their answers to the questions determined within the scope of the study. According to Table 2, the majority of the participants are women. Participants are generally between the ages of 19 and 40. Participants generally have an associate's degree and a bachelor's degree. It was also determined that the participants had an income between 10.000 TL and 19.000 TL. The majority of the participants are single. While 79% of the participants stated that they used financial investment instruments, it was determined that the instrument they used the most was stocks. However, it was determined that they generally follow financial instruments on the internet.

Table 3: T-Test and Statistical Information on Gender

Variables	Group	N	Mean	Std. Dev.	t	df	p
	Woman	1620	2,701	,798			
Gender	Man	996	2,702	,773	**824**	**2198**	**,260**
	Total	2616					

Table 3 shows the relationship between the gender factor of the participants and the effect of artificial intelligence on investor decisions. Table 3 shows no statistically significant effect of gender factors and artificial intelligence on investor decisions.

Table 4: ANOVA Analysis on Age Factor

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	23,456	4	5,864	9,546	,000
Within Groups	1603,975	2611	,614		
Total	1627,431	2615			

Table 4 shows the relationship between the age factor of the participants and the effect of artificial intelligence on investor decisions. Table 3 shows a statistically significant effect of the age factor and artificial intelligence on investor decisions. To determine between which age groups this effect exists, the Tukey HDS test was performed.

Table 5: Tukey HDS Analysis

(I) Age	(J) Age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
18 and under	19 - 29	-,17036	,04951	,005	-,3055	-,0352
	30 - 39	-,11233	,05065	,173	-,2506	,0259
	40 - 49	-,31208	,05331	,000	-,4576	-,1666
	50 and above	-,11828*	,06152	,305	-,2862	,0496
19-29	18 and under	,17036	,04951	,005	,0352	,3055
	30 - 39	,05804	,04140	,627	-,0550	,1710
	40 - 49	-,14172	,04461	,013	-,2635	-,0199
	50 and above	,05208*	,05416	,872	-,0957	,1999
30-39	18 and under	,11233	,05065	,173	-,0259	,2506
	19 - 29	-,05804	,04140	,627	-,1710	,0550
	40 - 49	-,19975	,04588	,000	-,3250	-,0745
	50 and above	-,00595*	,05520	1,000	-,1566	,1447
40-49	18 and under	,31208	,05331	,000	,1666	,4576
	19 - 29	,14172	,04461	,013	,0199	,2635
	30 - 39	,19975	,04588	,000	,0745	,3250
	50 and above	,19380*	,05765	,007	,0364	,3512
50 and above	18 and under	,11828*	,06152	,305	-,0496	,2862
	19 - 29	-,05208*	,05416	,872	-,1999	,0957
	30 - 39	,00595*	,05520	1,000	-,1447	,1566

40 - 49	-,19380*	,05765	,007	-,3512	-,0364

*The mean difference is significant at the 0.05 level.

According to Table 5, it is determined that there is an interaction between participants aged 50 and over and other age groups.

Table 6: ANOVA Analysis on Level of Education Factor

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	101,716	4	25,429	43,517	,000
Within Groups	1525,715	2611	,584		
Total	1627,431	2615			

Table 6 shows the relationship between the level of education factor of the participants and the effect of artificial intelligence on investor decisions. Table 6 shows a statistically significant effect of the level of education factor and artificial intelligence on investor decisions. To determine between which age groups this effect exists, the Tukey HDS test was performed.

Table 7: Tukey HDS Analysis

(I) Education	(J) Education	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
primary education	associate degree	,31111*	,04352	,000	,1923	,4299
	undergraduate	,24318*	,04586	,000	,1180	,3684
	postgraduate	-,17500*	,05496	,013	-,3250	-,0250
associate degree	primary education	-,31111*	,04352	,000	-,4299	-,1923
	undergraduate	-,06793	,03952	,422	-,1758	,0399
	postgraduate	-,48611*	,04980	,000	-,6220	-,3502
undergraduate	primary education	-,24318*	,04586	,000	-,3684	-,1180
	associate degree	,06793	,03952	,422	-,0399	,1758
	postgraduate	-,41818*	,05185	,000	-,5597	-,2766
postgraduate	primary education	,17500*	,05496	,013	,0250	,3250
	associate degree	,48611*	,04980	,000	,3502	,6220
	undergraduate	,41818*	,05185	,000	,2766	,5597

* The mean difference is significant at the 0.05 level.

According to Table 7, it is determined that there is an interaction between the participants with primary education levels and the participants with other education levels.

Table 8: ANOVA Analysis on Income Level Factor

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	51,448	4	12,862	21,309	,000
Within Groups	1575,983	2611	,604		
Total	1627,431	2615			

Table 8 shows the relationship between the income level factor of the participants and the effect of artificial intelligence on investor decisions. Table 8 shows a statistically significant effect of the income level factor and artificial intelligence on investor decisions. To determine between which age groups this effect exists, the Tukey HDS test was performed.

Table 9. Tukey HDS Analysis

(I) income	(J) income	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Between 0-9.000 TL	Between 10.000-19.000 TL	-,29375*	,04691	,000	-,4218	-,1657
	Between 20.000-29.000 TL	-,13125*	,04986	,065	-,2674	,0049
	Between 30.000-49.000 TL	-,34206*	,05414	,000	-,4898	-,1943
	50.000TL and Above	-,53125	,07187	,000	-,7274	-,3351
Between 10.000 - 19.000 TL	Between 0-9.000 TL	,29375*	,04691	,000	,1657	,4218
	Between 20.000-29.000 TL	,16250*	,03928	,000	,0553	,2697
	30.000-49.000 TL arası	-,04831*	,04459	,815	-,1700	,0734
	50.000TL and Above	-,23750	,06497	,002	-,4149	-,0601
Between 20.000 - 29.000 TL	Between 0-9.000 TL	,13125	,04986	,065	-,0049	,2674
	Between 10.000-19.000 TL	-,16250*	,03928	,000	-,2697	-,0553
	Between 30.000-49.000 TL	-,21081*	,04769	,000	-,3410	-,0806
	50.000TL and Above	-,40000	,06714	,000	-,5833	-,2167
Between 30.000-49.000 TL	Between 0-9.000 TL	,34206*	,05414	,000	,1943	,4898
	Between 10.000 -19.000 TL	,04831*	,04459	,815	-,0734	,1700
	Between 20.000 -29.000 TL	,21081*	,04769	,000	,0806	,3410
	50.000TL and Above	-,18919	,07037	,056	-,3813	,0029
50.000TL and Above	Between 0-9.000 TL	,53125	,07187	,000	,3351	,7274
	Between 10.000-19.000 TL	,23750	,06497	,002	,0601	,4149
	Between 20.000-29.000 TL	,40000	,06714	,000	,2167	,5833
	Between 30.000-49.000 TL	,18919	,07037	,056	-,0029	,3813

*. The mean difference is significant at the 0.05 level.

According to Table 9, it is determined that there is an interaction between the participants with an income level of 50.000 TL and above and the participants with other income levels.

Table 10. ANOVA analysis on marital status factor

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	33,658	2	16,829	27,591	,000
Within Groups	1593,774	2613	,610		
Total	1627,431	2615			

Table 10 shows the relationship between the marial status of the participants and the effect of artificial intelligence on investor decisions. Table 8 shows a statistically significant effect of the marial status factor and artificial intelligence on investor decisions. To determine between which age groups this effect exists, the Tukey HDS test was performed.

Table 11. Tukey HDS Analysis

(I) Marial Status	(J) Marial Status	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Married	Single	,07383*	,03332	,069	-,0043	,1520
	Other	-,26774	,04770	,000	-,3796	-,1559
Single	Married	-,07383*	,03332	,069	-,1520	,0043
	Other	-,34157	,04599	,000	-,4494	-,2337

Other	Married	,26774	,04770	,000	,1559	,3796
	Single	,34157	,04599	,000	,2337	,4494

*The mean difference is significant at the 0.05 level.

According to Table 11, it is determined that there is an interaction between married participants and single participants.

7. CONCLUSION AND IMPLICATIONS

Within the scope of the study, it was carried out to investigate whether artificial intelligence technology has effects on investments for individuals who live in Diyarbakır province and generally make investments. With this study, it was tried to determine which investment instruments investors use and what they pay attention to while making their investments.

Individual investors participating in the research believe that using artificial intelligence technologies while investing will make the right investment decisions. However, the majority of investors stated that they do not have enough knowledge about artificial intelligence applications. Therefore, investors need to receive training on artificial intelligence technologies. However, it is important to receive this training with the help of experts or teams. Because they should be aware that these trainings cannot be received at an adequate level from various social media, etc. platforms or with hearsay information.

The relationship between the gender of the participants and the effect of artificial intelligence on investor decisions could not be determined. However, a relationship between other factors determined within the scope of the study and the effect of artificial intelligence on investor decisions was determined. Accordingly, it was determined that investors aged 50 and over do not use or trust artificial intelligence technologies. Because it is possible to say that experience has a high impact on investment decisions as age progresses. However, as a result of the young population keeping up with the developing technology, it is possible to say that they make their investments by integrating technology.

It has been determined that participants with primary education level do not use technological developments while investing. It has been determined that investors with a high level of education generally follow technological developments and use artificial intelligence technologies while investing. In addition, it was determined that investors with high income levels do not utilise artificial intelligence technologies. It is thought that investors with high income levels try to keep the risk level at the lowest level. It is seen that they do not trust the investments they will make using artificial intelligence technologies. It has been determined that single participants invest more courageously than married participants and direct their investments using artificial intelligence technologies. However, married investors seem to lack confidence in artificial intelligence technologies by hesitating to take too much risk.

In addition, it was determined that the most frequently used investment instrument of the individual investors participating in the study was stocks. This situation shows that investors do not want to take too much risk. In addition, it has been determined that when they make investment decisions or when they want to invest, they usually benefit from the relevant platforms on the websites.

REFERENCES

Aldemir, S. (2015). Davranışsal Finans Açısından Yatırımcı Davranışlarının incelenmesi: Tokat ili örneği. Yayınlanmış Yüksek Lisans Tezi . Eskişehir: Gazi Osmanpaşa Üniveritesi Sosyal Bilimler Enstitüsü.

Ayvalı , A. (2014). Bireysel Yatırımcı Profili ve Yatırımcı Tercileri Üzerine Bir Araştırma: Bartın İli Örneği. Yüksek Lisans Tezi. Bursa: Bartın Üniversitesi Sosyal Bilimler Enstitüsü.

Böyükaslan, A. (2012). Bireysel yatırımcıları finansal yatırım kararına yönlendiren faktörlerin davranışsal finans açısından incelenmesi: Afyon karahisar örneği. Afyonkarahisar, Türkiye: Afyon Kocatepe Üniversitesi Sosyal Bilimler Enstitüsü, Afyon.

Chlu, J., (2020). Block; writings artificial intelligence. The Power of AI in Finance and Algorithmic Trading: https://www.datacamp.com/blog/the-power-of-ai-in-finance-and-algorithmic-trading adresinden alınmıştır

Çelik, Ç. (2013). İMKB'de İşlem Yapan Yatırımcıların Davranışlarını Belirlemeye Yönelik Bir Araştırma. Yüksek Lisans Tezi . İzmir: Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü .

Dizdarlar, H., & Şener , Ö. (2016). Yatırımcıların risk alma davranışı üzerine bir uygulama. International Journal of Social Sciences and Education Research, 8, 1-14.

Ellezoğlu, N. (2020). Bireysel yatırımcı davranışlarının finans kapsamında incelenmesi: Ankara İli uygulaması. Ankara , Türkiye : Yüksek Lisans Tezi. Gazi Üniversitesi.

Gu, S., Kelly, B., & Xlu, D. (2020). Empirical asset pricing through machine learning. TheReview of Financial Studies, 14, 2223-2273.

Güdelek, M. (2019). Zaman Serisi analiz ve tahmin : derin öğrenme yaklaşımı. Yüksek Lisans Tezi.

Karan, M. (2011). Yatırım Analizi ve Portföy Yönetimi. Ankara: Gazi Kitabevi.

Korkulutaş, D. (2018). Bireysel Yatırımcı Davranış ve Kararlarının Davranışsal Finans kapsamında değerlendirilmesi. Erzincan, Türkiye: Erzincan Binali Yıldırım Üniversitesi Sosyal Bilimler Enstitüsü.

Kuşçu, E. (2015). çeviride yapay zeka uygulamaları. Kazım Karabekir Eğitim Fakültesi Dergisi, 46, 212-235.

Kutlu, B., & Badur, B. (2009). Yapay Sinir Ağları ile Borsa Endeksi Tahmini. İstanbul Üniversitesi İşletme Fakültesi İşletme İktisadı Enstitüsü Dergisi, 8, 25-40.

Küden , M. (2014). Davranışsal Finans Açısından Bireysel Yatırım Tercihlerinin Değerlendirilmesi. Yüksek Lisans Tezi. İzmir: Gediz Üniversitesi.

Özaltın , S., Ersoy, E., & Bekci, İ. (2015). Kar Dağıtım Politikasının Bireysel Yatırımcıların Yatırım Kararları Üzerindeki Etkisi. Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Dergisi, 397-411.

Özcan, H. (2011). Davranışsal Finansın Bireysel Yatırımcıların Karar Mekanizmaları Üzerindeki Etkileri. Yüksek Lisans Tezi. Nevşehir, Türkiye: Nevşehir Üniversitesi Sosyal Bilimler Enstitüsü.

Rasekhschaffe, K., & Jones, R. (2019). Machine Learning for Stock Selection. Financial Analysts Magazine, 70-88.

Sabharwal, C. (2018). The rise of machine learning androbo-advisors in banking. IDRBT Banking Technologies Journal, 1-28.

Say, C. (2018). 50 soruda yapay zeka. istanbul: 7. Renk Basım Yayın ve Filmcilik Ltd. Şti,.

Schroer, A. (2023, Mart 03). Yapay Zeka nedir ? nasıl çalışır https://builtin.com/artificial-intelligence adresinden alınmıştır

Shen, S., Jiang, H., & Zhang, T. (2012). Stock market forecasting using machine learning algorithms. (Stanford University Working Paper). Retrieved from (s. 1-5). http://cs229.stanford.edu/proj2012/ShenJiangZhang-StockMarketForecastingusingMachineLearni.

Thakar, C. (2020). This Blog. Artificial Intelligence and Machine Learning in Commerce: https://blog.quantinsti.com/artificial-intelligence-machine-learning-trading/ adresinden alınmıştır

Think Tech . (2022, 9 5). STM Think Tech: https://thinktech.stm.com.tr/tr/yapay-zekanin-gelecegi adresinden alınmıştır

Tsai, C., & Wang, S. (2009). Stock price forecasting by hybrid machine learning techniques. International MultiConference of Engineers and Computer Scientists. http://www.iaeng.org/

Usul, H., Eroğlu, A., & Bekçi, İ. (2002). Bireysel yatırımcıların hisse senedi edimine yönelik yaklaşımlar. Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 135-150.

Walker , J. (2021). Polygant. Artificial Intelligence for Commerce: https://polygant.net/ai/artificial-intelligence-for-trading/ adresinden alınmıştır.

Wisetsri, W., Julie Aarthy, C., Thakur, V., Culati, K., & Pandey, D. (2021). Systematic analysis and future research directions in artificial ıntelligence formarketing. Turkish Journal of Computer and Mathematics Education, 43-55.

Yıldız, A. (2022). Finansal alanda yapay zeka teknolojisinin kullanımı:sistematik literatür incelemesi. Pamukkale Sosyal Bilimler Enstitüsü Dergisi, 52, 1-20.

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BANK TECHNICAL EFFICIENCY OF COUNTRY GROUPS: A META-REGRESSION ANALYSIS

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ABSTRACT

Purpose- This study endeavors to examine studies using Data Envelopment Analysis in calculating the banking sector efficiency across country groups and to determine the factors affecting their technical efficiency through meta-regression analysis.
Methodology- As of November 22, 2023, relevant works were systematically reviewed using Web of Science, Scopus, and Google Scholar. The literature review employed a comprehensive search encompassing all files with the keywords such as ‘’technical efficiency (All Field) AND bank (All Field)’’. The research process adhered to the PRISMA guidelines. This study reviewed all studies published between 1932 and 2023 identifying 64599 studies in the initial scan by the author. The author independently scrutinized the titles, abstracts, keywords, text, and references of all manuscripts to mitigate selection bias and reveal whether eligibility criteria were met. Exclusions from the scope encompassed duplicate downloads, papers, books and book chapters, together with studies having low quality scores, no full-text versions, and those that are irrelevant to the subject.
Findings- The results of meta-regression analysis revealed that the data collection year of the studies and the income groups of the countries did not have an impact on the mean technical efficiency. The number of banks, number of observations, publication year, and number of countries were statistically significant on the mean technical efficiency estimate.
Conclusion- The study further standardized variables and methodological assumptions used in bank sector efficiency studies within country groups through meta-regression analysis. Empirical findings in the literature were combined. This study enhances accessibility to the existing body of knowledge for researchers in the field

Keywords: Banks, technical efficiency, Data Envelopment Analysis, Tobit Analysis, Meta-Regression Analysis
JEL Codes: C01, D24, M10

1. INTRODUCTION

The banking system fosters economic growth by allocating savings to competitive firms, entrepreneurs, individuals and states, and thereby enhancing capital accumulation and profitability (Bumann et al. 2013; Pagano 1993; Rajan and Zingales 1998; Ho et al., 2021). The evaluation of efficiency measurement in the banking sector has become a focal point of research, given to its significant effects on both microeconomic and macroeconomic development within the economy (Aiello and Bonanno 2016; Iršová and Havránek 2010; Ho et al., 2021).

Efficiency was first defined in a study by Farrell (1957). According to Farrell (1957), efficiency is a measure of the ratio of weighted outputs to inputs. Decision-making units use similar inputs to produce similar outputs. Thanassoulis (2001) aimed at transforming inputs into outputs for each decision unit. A technically efficient business can produce more output than others with similar inputs (Cherchye and Abeele, 2005; Attah-Kyei et al., 2023). A technically efficient insurance company operates above the efficient production frontier (Farrell, 1957).

Bank efficiency studies commonly employ two methods. These are DEA, a non-parametric method (Horvat et al., 2023; Milenković et al., 2022; Cvetkoska et al., 2021) and SSA, a parametric method (Ben Mohamed et al., 2021; Sharma et al., 2020; Nguyen & Vo, 2020; Koutsomanoli-Filippaki et al., 2009). Meta-regression analysis (MRA) serves as a statistical tool that investigates the relationship between the key findings of studies and notable characteristics such as sample and year of data collection (Glass 1976; Glass et al. 1981; Stanley and Jarrell 1989). MRA synthesizes different studies into a unified model. It evaluates the impact of certain aspects of the studies on the results. MRA finds application in economics (Chaffai, 2022; Aiello and Bonanno, 2019; Fall et al., 2018), education (Villano and Tran, 2021; Mikušová, 2020), agriculture (Paz et al., 2023, Nguyen-Anh et al., 2022; Trong Ho et al., 2022), environment (Hübner et al., 2021; Zangeneh et al., 2021; Nyathikala & Kulshrestha, 2020).

This study aims at examining studies using the DEA method in measuring the efficiency of banks within country groups and determining the factors affecting bank sector efficiency scores in country groups through meta-regression analysis. The study also strives to enhance accessibility to the literature to researchers who will use the DEA method in measuring the efficiency of banking sector and to determine the variables affecting efficiency. The risk of bias and limitation inherent in a single study calculating bank sector efficiency with DEA were eliminated through a meta-regression analysis. This study is expected to contribute to the literature by providing an effective overview with effective, valid and reliable parameter estimates for future studies utilizing DEA for efficiency assessment in bank sectors (Moher et al., 2009; Kaya & Algın, 2022).

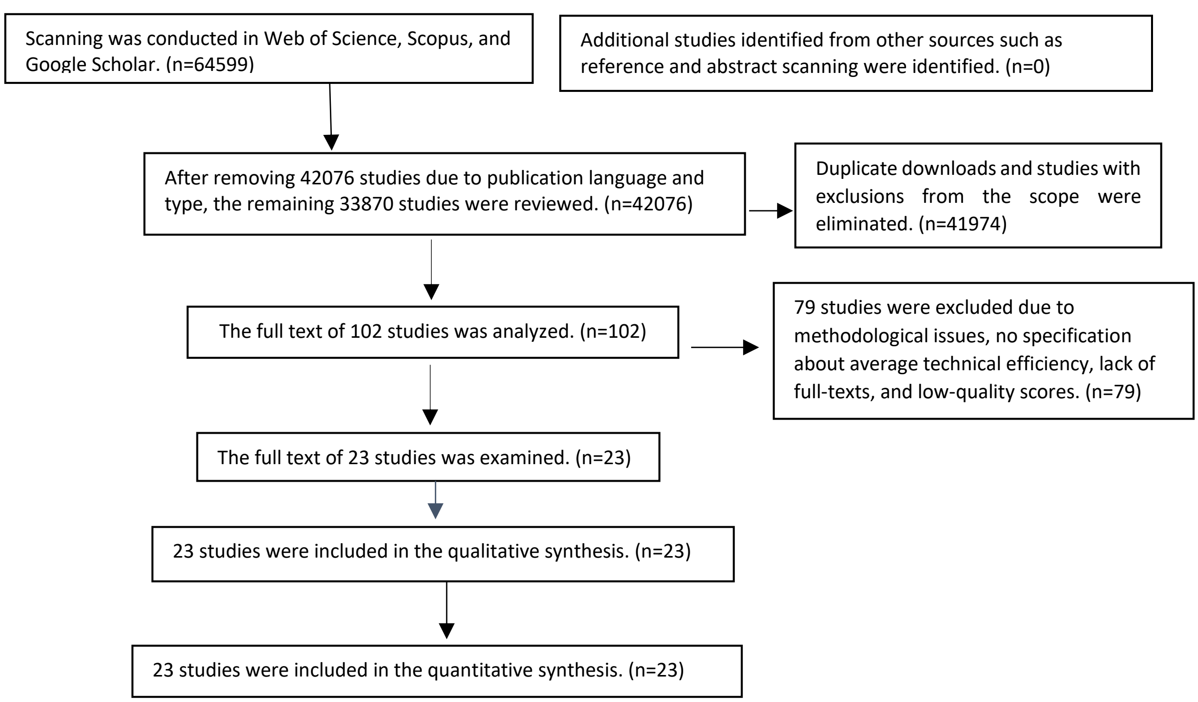
2. DATA AND METHODOLOGY

On November 22, 2023, relevant works were systematically reviewed using Web of Science, Scopus, and Google Scholar. The literature review employed a comprehensive search encompassing all files with the keywords such as ‘‘technical efficiency (All Field) AND bank (All Field)’’. The research process adhered to the PRISMA guidelines (Moher et al., 2009).

2.1. Selection of Studies

This study reviewed all studies published between 1932 and 2023 identifying 64599 studies in the initial scan by the author. The author independently scrutinized the titles, abstracts, keywords, text, and references of all manuscripts to mitigate selection bias and reveal whether eligibility criteria were met. Exclusions from the scope encompassed duplicate downloads, papers, books and book chapters, together with studies having low quality scores, no full-text versions, and those that are irrelevant to the subject. Figure 1 displays the selection process of studies.

Figure 1: Flow Diagram of the Study



Source: Moher et al., 2009; Kaya & Algın, 2022.

The author carried out a thorough review of all studies. After eliminating duplicate and irrelevant studies, 102 studies were chosen for full-text review. Studies with methodological issues and those possessing low quality scores and no specified mean technical efficiency were excluded during the full text review.

A 14-question quality checklist covering reporting, external validity, bias and power dimensions was deployed for calculating the quality score of the studies (Downs & Black, 1998; Varabyova & Müller, 2016). Each question in the checklist received a quality score (Table 1), with 1 point for meeting the criteria and 0 point for not meeting it(Table 2).

Table 1: Quality Checklist of Studies

Item	**Scoring** **yes (1)** **no/unclear (0)** **Not Applicable (N/A)**
Reporting	
1. Is the hypothesis/objective of the study clearly described?	23/23
2. Is the underlying economic theory of production/cost properly described? (e.g., is the economic justification for selecting input- vs. output orientation given?)	23/23
3. Are the input and output variables clearly defined and their inclusion justified?	23/23
4. Are the main findings of the study clearly presented with reference to study objectives?	23/23
5. Are the study limitations discussed (e.g., omitted variables)?	7/23
External validity	
6. Is the sample inclusive enough (appropriate benchmark)?	23/23
7. Is the assumption of a common technology addressed/tested (e.g., developing and developed countries analyzed together)?	23/23
Bias	
8. Are the data accurate enough to answer the questions, particularly the output data (only quantity or also quality output measures)?	23/23
9. Are the techniques (parametric, nonparametric or both) used to assess the main outcomes appropriate?	23/23
10. Has the dataset been examined for the presence of outliers?	1/23
11. Is the problem of convergence due to dimensionality properly addressed?	1/23
12. If the second-stage analysis is undertaken,are any statistical problems accounted for?	0/8 15 N/A
Power	
13. Have the sensitivity analyses been conducted?	2/23
14. Are the confidence intervals for efficiency estimates generated?	3/23

An overall quality score for the study was calculated by adding up the scores of all questions. 23 studies with a total quality score of 8 and above were selected for analysis (Table2).

Table 2: Quality Assessment Results

No	Author(s)	Reporting					External Validity		Bias					Power		Total Score
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
1	(Horvat et al., 2023)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
2	(Ul Hassan Shah, 2022)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
3	(Milenković et al., 2022)	1	1	1	1	1	1	1	1	1	0	0	1	0	1	11/14=0.79
4	(Cvetkoska et al., 2021)	1	1	1	1	0	1	1	1	1	1	0	0	0	0	9/14 =0.64
5	(Christopoulos et al., 2020)	1	1	1	1	0	1	1	1	1	0	0	1	0	1	10/16=0.71
6	(Banna et al., 2019)	1	1	1	1	1	1	1	1	1	0	0	1	0	1	11/14=0.79
7	(Fujii et al., 2018)	1	1	1	1	0	1	1	1	1	0	1	0	0	0	9/14 =0.64
8	(Loong et al., 2017)	1	1	1	1	0	1	1	1	1	0	0	1	1	1	11/14=0.79
9	(Kamarudin et al., 2017)	1	1	1	1	1	1	1	1	1	0	0	0	0	1	10/16=0.71
10	(Doumpos et al., 2017)	1	1	1	1	1	1	1	1	1	0	0	0	0	1	10/16=0.71
11	(Balcerzak et al., 2017)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
12	(Wong & Deng, 2016)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
13	(Kamarudin et al., 2015)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
14	(Rosman et al., 2014)	1	1	1	1	1	1	1	1	1	0	0	1	0	1	11/14=0.79
15	(Mobarek & Kalonov, 2014)	1	1	1	1	1	1	1	1	1	0	0	0	0	1	10/16=0.71
16	(Maghyereh & Awartani, 2014)	1	1	1	1	1	1	1	1	1	0	0	1	0	1	11/14=0.79
17	(Aghimien et al., 2014)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14=0.64
18	(Johnes, et al.,2014)	1	1	1	1	1	1	1	1	1	0	0	0	0	1	10/16=0.71
19	(Rahim et al., 2013)	1	1	1	1	0	1	1	1	1	0	0	1	0	0	9/14 =0.64
20	(Abu-Alkheil et al., 2012)	1	1	1	1	1	1	1	1	1	0	0	1	0	0	10/16=0.71
21	(Mostafa, 2011)	1	1	1	1	1	1	1	1	1	1	0	0	1	0	11/14=0.79

22	(Sufian et al., 2008)	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9/14 =0.64
23	(Al-Muharrami, 2008)	1	1	1	1	0	1	1	1	1	0	0	0	0	0	8/14=0.57

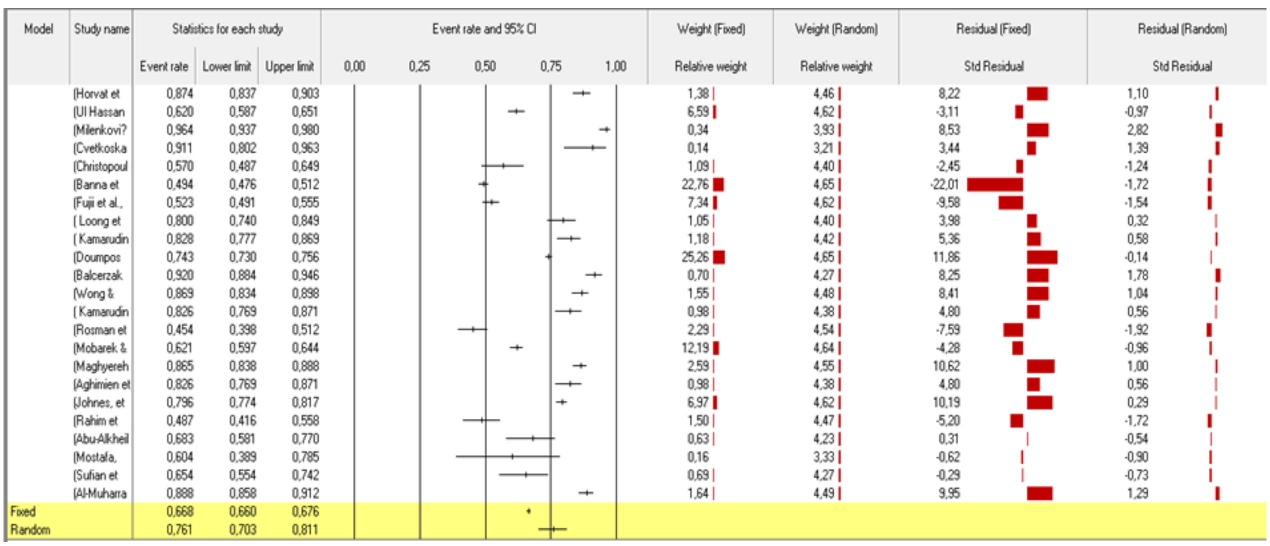
Note: 1=Yes, 0=No/Unspecified, N/A=Inapplicable

2.2. Data Analysis

The number of observations, number of variables, publication year, number of countries, country group, number of data collection year, mean technical efficiency score, software used, and quality score data were collected for each study. 21.73% of the studies using DEA in measuring bank technical efficiency in country groups were conducted in the Gulf Cooperation Council (GCC) countries. The studies in the pool of meta-regression analysis deployed R, Stata, DEAP, Dea Excel Solver, Dea-Max, MaxDEA, Frontier Analyst software to calculate bank technical efficiencies in country groups. Appendix1 shows the key features of the studies examined.

The data analysis encompassed two stages. Initially, analysis was conducted through the Random Effect Model (Table3). The mean effect size is 0.761 (95% CI: 0.703 to 0.811). Heterogeneity across studies was measured with the Q statistic (Q=1360,668 sd=22 p< 0.001).

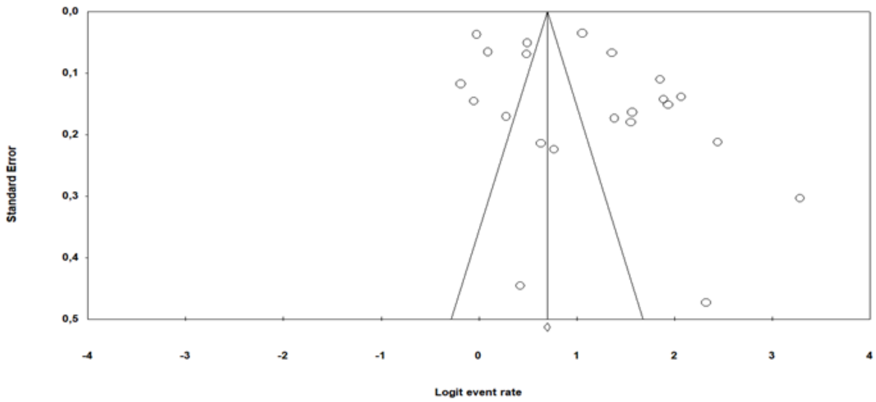
Table 3: Meta-Analysis Results of Studies



Model	Study name	Statistics for each study			Event rate and 95% CI	Weight (Fixed)	Weight (Random)	Residual (Fixed)	Residual (Random)
		Event rate	Lower limit	Upper limit	0,00 0,25 0,50 0,75 1,00	Relative weight	Relative weight	Std Residual	Std Residual
	(Horvat et	0,874	0,837	0,903		1,38	4,46	8,22	1,10
	(Ul Hassan	0,620	0,587	0,651		6,59	4,62	-3,11	-0,97
	(Milenkovi?	0,964	0,937	0,980		0,34	3,93	8,53	2,82
	(Cvetkoska	0,911	0,802	0,963		0,14	3,21	3,44	1,39
	(Christopoul	0,570	0,487	0,649		1,09	4,40	-2,45	-1,24
	(Banna et	0,494	0,476	0,512		22,76	4,65	-22,01	-1,72
	(Fuji et al.,	0,523	0,491	0,555		7,34	4,62	-9,58	-1,54
	(Loong et	0,800	0,740	0,849		1,05	4,40	3,98	0,32
	(Kamarudin	0,828	0,777	0,869		1,18	4,42	5,36	0,58
	(Doumpos	0,743	0,730	0,756		25,26	4,65	11,86	-0,14
	(Balcerzak	0,920	0,884	0,946		0,70	4,27	8,25	1,78
	(Wong &	0,869	0,834	0,898		1,55	4,48	8,41	1,04
	(Kamarudin	0,826	0,769	0,871		0,98	4,38	4,80	0,56
	(Rosman et	0,454	0,398	0,512		2,29	4,54	-7,59	-1,92
	(Mobarek &	0,621	0,597	0,644		12,19	4,64	-4,28	-0,96
	(Maghyereh	0,865	0,838	0,888		2,59	4,55	10,62	1,00
	(Aghimien et	0,826	0,769	0,871		0,98	4,38	4,80	0,56
	(Johnes, et	0,796	0,774	0,817		6,97	4,62	10,19	0,29
	(Rahim et	0,487	0,416	0,558		1,50	4,47	-5,20	-1,72
	(Abu-Alkheil	0,683	0,581	0,770		0,63	4,23	0,31	-0,54
	(Mostafa,	0,604	0,389	0,785		0,16	3,33	-0,62	-0,90
	(Sufian et	0,654	0,554	0,742		0,69	4,27	-0,29	-0,73
	(Al-Muharra	0,888	0,858	0,912		1,64	4,49	9,95	1,29
Fixed		0,668	0,660	0,676					
Random		0,761	0,703	0,811					

Publication bias was demonstrated by funnel plot and Egger's regression test (t=2,10760 df=21 p<0.05) (Figure 2).

Figure 2: Publication Bias of Studies



A meta-regression analysis was conducted to evaluate the estimate of mean technical efficiencies derived from the complied data. In the second stage, the Tobit model employed the mean technical efficiency as the dependent variable. Explanatory variables included the number of observations, the number of variables, the year of data collection, and the number of countries, all guided by relevant literature and model features. Besides, dummy variables such as the country group of the sample and the year of publication were incorporated into the model. The study serves under the key assumption that the reported functional form of technical efficiency scores in the literature can be explained by the characteristics of the studies, including the number of samples, the number of variables in the model and country groups. To explore this, the following 7 models are estimated (Table 4).

Model 1: $MTE = \alpha_0+\beta_1 V_i+\beta_2 O_i+\varepsilon_i$ (1)

Model 2: $MTE = \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 P_i +\varepsilon_i$ (2)

Model 3: $MTE= \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 P_i + \beta_4 C_i+\varepsilon_i$ (3)

Model 4: $MTE= \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 C_i + \beta_4 GC_i +\varepsilon_i$ (4)

Model 5: $MTE= \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 P_i + \beta_4 C_i + \beta_5 D_i+\varepsilon_i$ (5)

Model 6: $MTE= \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 P_i + \beta_4 C_i + \beta_5 GC_i+\varepsilon_i$ (6)

Model 7: $MTE= \alpha_0+\beta_1 V_i+\beta_2 O_i+ \beta_3 P_i + \beta_4 C_i + \beta_5 GC_i+ \beta_6 D_i+\varepsilon_i$ (7)

The following variables were used in the proposed model:
MTE: Mean technical efficiency
V: Number of variables
O: Number of observation
P: Year of publication
C: Number of countries
GC: Country group
D: Data collection year

Table 4: Tobit Analysis Results on Technical Efficiency

Variable	Model1		Model2		Model3		Model4	
	Tobit (S.E)	**p**	**Tobit (S.E)**	**p**	**Tobit (S.E)**	**p**	**Tobit (S.E)**	**p**
Constant	0.642883 (0.067479)	0.000***	0.489336 (0.086606)	0.000***	0.615679 (0.088555)	0.000***	0.0735405 (0.064621)	0.000***
V	0.027415 (0.014168)	0.053	0.036268 (0.013110)	0.005**	0.035763 (0.011409)	0.001**	0.028652 (0.012039)	0.017*
O	-0.000113 (0.0000525)	0.030**	-0.000159 (0.0000500)	0.001**	-0.000159 (0.0000435)	0.000***	-0.000123 (0.0000453)	0.006**

P			0.169066 (0.068725)	0.013*	0.119375 (0.062533)	0.056		
C					-0.008457 (0.003113)	0.006**	-0.010021 (0.003205)	0.001**
CG							0.031399 (0.061917)	0.612
D								
Log-likelihood	12.43566		15.12192		18.32193		16.75841	
Regression S.E	0.155137		0.141727		0.126894		0.135820	
Variable	**Model5**		**Model6**		**Model7**			
	Tobit (S.E)	**p**	**Tobit (S.E)**	**p**	**Tobit (S.E)**	**p**		
Constant	0.654106 (0.101500)	0.0000***	0.595774 (0.089641)	0.0000***	0.635024 (0.101568)	0.0000***		
V	0.036702 (0.011343)	0.0012**	0.034088 (0.011353)	0.0027**	0.035021 (0.011266)	0.0019**		
O	-0.000150 (0.0000447)	0.0008***	-0.000151 (0.0000438)	0.0006***	-0.000141 (0.0000449)	0.0017**		
P	0.122930 (0.061971)	0.0473**	0.129693 (0.062440)	0.0378**	0.133596 (0.061817)	0.0307*		
C	-0.009343 (0.003297)	0.0046**	-0.008013 (0.003096)	0.0096**	-0.008918 (0.003265)	0.0063**		
CG			0.053004 (0.057762)	0.3588	0.054190 (0.057020)	0.3419		
D	0.006759 (0.009047)	0.4550			-0.006982 (0.008878)	0.4316		
Log-likelihood	18.59763		18.73543		19.04058			
Regression S.E	0.129241		0.128469		0.130933			

As in Table 2, the models were estimated using the Tobit method given that the technical efficiency scores of Models 1, 2 and 3 are limited between 0 and 1 (Kaya & Algın, 2022; Bravo-Ureta et al., 2007; Greene, 1991). Considering the data used in the analysis, Tobit is considered as the most methodologically appropriate. Year of publication, number of countries, country group, data collection year were omitted in Model 1. Similarly, Model 2 excluded the number of countries, country group and data collection year; whereas Model 3 ignored country group and data collection year. Moreover, Model 4 did not include publication year and data collection. Moving on to Model 5, the variables of collection year and country group were disregarded, and data collection year was excluded in Model 6. Notably, all variables were encompassed in Model 7, reflecting a comprehensive consideration of their effects.

Most of the variables in the models were significant at least at 5% level. Across all models, variables associated with the data collection year and country groups showed no significant impact on the mean technical efficiency estimate. The number of variables in Model 1, year of publication in Model 3, country group in Model 4, year of data collection in Model 5, and country group in both Models 6 and 7 demonstrated no statistical significance. Notably, most variables in the models exhibited significance at a minimum level of 5%. Conversely, the data collection year and country group variables consistently lacked significant influence on the mean technical efficiency estimate across all models. The number of variables and the number of observations maintained statistical significance in each model.

3. CONCLUSION

The trend towards measuring technical efficiency in banks' country groups has increased since 2008. The study analyzed 23 empirical articles published between 1932 and 2023 employing DEA in calculating the bank efficiency within country groups that adhere to the predefined inclusion criteria. A meta-regression analysis was used to discern the variables affecting mean technical efficiencies across the reviewed articles. This study aims at evaluating the studies that calculate the bank efficiency of country groups with DEA using the meta-analysis method. All studies related to the subject in the literature were reviewed. 73.91% of the sample of studies using DEA in bank efficiency focused on Asian country groups. Western Balkan countries, including Serbia, Bosnia and Herzegovina, Montenegro, North Macedonia and Armenia, possessed the highest mean technical efficiency. The study revealed significant negative associations between mean technical efficiency scores and the number of banks and number of countries, while positive and significant correlations were observed with the number of variables and the year of publication. Importantly, the articles analyzed tended to overlook variations in sample sizes over the years and disparities in economic levels and political structures among countries within the same group. There is no such a meta-analysis study specifically published on bank efficiency in country groups. In this study, variables and methodological assumptions used in bank sector efficiency studies in country groups were standardized through meta-regression analysis. Empirical findings in the relevant literature were combined. The literature was made accessible to researchers.

REFERENCES

Aiello, F., & Bonanno, G. 2019. Explaining differences in efficiency: A meta-study on local government literature. Journal of Economic Surveys, 33(3), 999-1027. https://doi.org/10.1111/joes.12310

Aiello, F., & Bonanno, G. (2016). Efficiency in banking: a meta-regression analysis. InternatIonal Review of Applied Economics, 30(1), 112-149. https://doi.org/10.1080/02692171.2015.1070131

Attah-Kyei, D., Andoh, C., & Kuttu, S. (2023). Risk, technical efficiency and capital requirements of Ghanaian insurers. Risk Management, 25(4), 22-35. https://doi.org/10.1057/s41283-023-00127-z

Ben Mohamed, E,, Meshabet, N,, & Jarraya, B, (2021). Determinants of technical efficiency of Islamic banks in GCC countries. Journal of Islamic Accounting and Business Research, 12(2), 218-238. https://doi,org/10,1108/JIABR-12-2019-0226

Bravo-Ureta, B. E., Solís, D., Moreira López, V. H., Maripani, J. F., Thiam, A., & Rivas, T., (2007). Technical efficiency in farming: a meta-regression analysis. Journal of Productivity Analysis, 27(1), 57-72. https://doi.org/10.1007/s11123-006-0025-3

Bumann, S., Hermes, N., & Lensink, R., (2013). Financial liberalization and economic growth: A meta-analysis. Journal of International Money and Finance, 33, 255-281. https://doi.org/10.1016/j.jimonfin.2012.11.013

Chaffai, M. E. (2022). New evidence on Islamic and conventional bank efficiency: A meta-regression analysis. Bulletin of Economic Research, 74(1), 221-246. https://doi.org/10.1111/boer.12291

Cherchye, L., & Abeele, P. V. (2005). On research efficiency: A micro-analysis of Dutch university research in economics and business management. Research Policy, 34(4), 495-516. https://doi.org/10.1016/j.respol.2005.03.005

Cvetkoska, V., Čiković, K, F., & Tasheva, M., (2021). Efficiency of commercial banking in developing countries. Mathematics, 9(14), 1597-1615. https://doi,org/10,3390/math9141597

Downs, S. H., & Black, N., (1998). The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. Journal of Epidemiology & Community Health, 52(6), 377-384. http://dx.doi.org/10.1136/jech.52.6.377

Egger, M., Smith, G. D., Schneider, M., & Minder, C., (1997). Bias in meta-analysis detected by a simple, graphical test. Bmj, 315(7109), 629-634. https://doi.org/10.1136/bmj.315.7109.629

Fall, F., Akim, A. M., & Wassongma, H. (2018). DEA and SFA research on the efficiency of microfinance institutions: A meta-analysis. World Development, 107, 176-188. https://doi.org/10.1016/j.worlddev.2018.02.032

Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society Series A: Statistics in Society, 120(3), 253-281. https://doi.org/10.2307/2343100

Glass, G. (1976). Primary, secondary, and meta-analysis of research. Educational Researcher, 5, 3–8.

Glass, G., Barry McGaw, and Mary Lee Smith. 1981. Meta-Analysis in Social Research. Beverly Hills: Sage Publications.

Greene, W. H. (1991). LIMDEP User's Manual and Reference Guide: Version 6.0. Econometric Software.

Haidich, A. B. (2010). Meta-analysis in medical research. Hippokratia, 14(Sup1), 29-37.

Ho, T. H., Nguyen, D. T., Ngo, T., & Le, T. D. (2021). Efficiency in Vietnamese banking: A meta-regression analysis approach. International Journal of Financial Studies, 9(3), 41-55. https://doi.org/10.3390/ijfs9030041

Horvat, A, M., Milenković, N., Dudić, B., Kalaš, B., Radovanov, B, & Mittelman, A., (2023). Evaluating bank efficiency in the West Balkan countries using data envelopment analysis. Mathematics, 11(1), 151-165, https://doi,org/10,3390/math11010015

Hübner, R., Kühnel, A., Lu, J., Dettmann, H., Wang, W., & Wiesmeier, M. (2021). Soil carbon sequestration by agroforestry systems in China: A meta-analysis. Agriculture, Ecosystems & Environment, 315, 107437. https://doi.org/10.1016/j.agee.2021.107437

Iršová, Z., & Havránek, T. (2010). Measuring bank efficiency: a meta-regression analysis. Prague Economic Papers, 19(10), 307-328. DOI: 10.18267/j.pep.379

Kaya, N., & Algın, A. (2022). Kamu Hastanelerinde Teknik Etkinlik: Bir Meta-Regresyon Analizi, Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi, 17(3), 810-821. DOI: 10.17153/oguiibf.1094736

Koutsomanoli-Filippaki, A., Margaritis, D., & Staikouras, C. (2009). Efficiency and productivity growth in the banking industry of Central and Eastern Europe. Journal of Banking & Finance, 33(3), 557-567. https://doi.org/10.1016/j.jbankfin.2008.09.009

Mikušová, P. (2020). The efficiency of public higher education ınstitutions: a meta-analysis. Ekonomický časopis, 68(09), 963-977.

Milenković, N., Radovanov, B., Kalaš, B., & Horvat, A., M., (2022). External Two Stage DEA Analysis of Bank Efficiency in West Balkan Countries. Sustainability (Switzerland), 14(2), Article 978. https://doi,org/10,3390/su14020978

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2010). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. International Journal of Surgery, 8(5), 336-341. https://doi.org/10.1016/j.ijsu.2010.02.007

Nguyen-Anh, T., Hoang-Duc, C., Tiet, T., Nguyen-Van, P., & To-The, N. (2022). Composite effects of human, natural and social capitals on sustainable food-crop farming in Sub-Saharan Africa. Food Policy, 113, 102284. https://doi.org/10.1016/j.foodpol.2022.102284

Nguyen, T. L. A., & Vo, X. V. (2020). Does corporate governance really matter for bank efficiency? Evidence from ASEAN countries. Eurasian Economic Review, 10(4), 681-706. https://doi.org/10.1007/s40822-020-00151-4

Nyathikala, S. A., & Kulshrestha, M. (2020). Performance measurement of water supply services: a cross-Country comparison between India and the UK. Environmental Management, 66(4), 517-534.

Pagano, M. (1993). Financial markets and growth: An overview. European economic review, 37(2-3), 613-622. https://doi.org/10.1007/s00267-020-01333-1

Paz, B., Hailu, A., Rola-Rubzen, M. F., & Rashid, M. M. (2023). Conservation agriculture-based sustainable intensification improves technical efficiency in Northern Bangladesh: The case of Rangpur. Australian Journal of Agricultural and Resource Economics. https://doi.org/10.1111/1467-8489.12537

Sharma, P., Manoa, S., Taleniwesi, S., & Nghiem, S. (2020). Technical efficiency of banking institutions in a Pacific Island Country: a distance function stochastic frontier analysis. Journal of the Asia Pacific Economy, 25(1), 1-15. https://doi.org/10.1080/13547860.2018.1528661

Stanley, Tom D., and Stephen B. Jarrell. 1989. Meta-regression analysis: A quantitative method of literature surveys. Journal of Economic Surveys, 3, 161–70.

Stanley, T. D., Doucouliagos, H., Giles, M., Heckemeyer, J. H., Johnston, R. J., Laroche, P.,Nelson, J. P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R. S., & Rost, K. (2013). Meta-analysis of economics research reporting guidelines. Journal of Economic Surveys, 27(2), 390-394. https://doi.org/10.1111/joes.12008

Tatsioni, Aathina, and John P. A. Ioannidis. 2017. Meta-analysis. In International Encyclopedia of Public Health. Edited by S. R. Quah. Oxford: Academic Press, pp. 117–24. https://doi.org/10.1016/B978-0-12-803678-5.00291-5

Thanassoulis, E. (2001). Introduction to the theory and application of data envelopment analysis. Dordrecht: Kluwer Academic Publishers.

Trong Ho, P., Burton, M., Ma, C., & Hailu, A. (2022). Quantifying heterogeneity, heteroscedasticity and publication bias effects on technical efficiency estimates of rice farming: A meta-regression analysis. Journal of Agricultural Economics, 73(2), 580-597. https://doi.org/10.1111/1477-9552.12468

Varabyova, Y., & Müller, J. M. (2016). The efficiency of health care production in OECD countries: a systematic review and meta-analysis of cross-country comparisons. Health Policy, 120(3), 252-263. https://doi.org/10.1016/j.healthpol.2015.12.005

Villano, R. A., & Tran, C. D. T. (2021). Survey on technical efficiency in higher education: A meta-fractional regression analysis. Pacific Economic Review, 26(1), 110-135. https://doi.org/10.1111/1468-0106.12310

Zangeneh, M., Banaeian, N., & Clark, S. (2021). Meta-Analysis on Energy-Use Patterns of Cropping Systems in Iran. Sustainability, 13(7), 3868. https://doi.org/10.3390/su13073868

Appendix 1: Studies Examined in Meta Regression Analysis

Author(s)	Region	Method	Publication Period	Sample Size	MTE	Software
(Horvat et al., 2023)	West Balkan Countries	DEA	2015-2019 (t=5)	395	0.874	x
(Ul Hassan Shah, 2022)	South Asia Countries	Meta-Frontier DEA	2013-2018 (t=6)	882	0.620	DEA-Max
(Milenković et al., 2022)	West Balkan Countries	DEA, Tobit Analysis	2015-2019 (t=5)	312	0.964	DEAMax
(Cvetkoska et al., 2021)	Developing Countries EU	DEA	2015-2019 (t=5)	55	0.911	MaxDEA 8, Excel
(Christopoulos et al., 2020)	PIIGS Countries	DEA, MPI, Truncated Regression Analysis	2009-2015 (t=7)	140	0.570	x
(Banna et al., 2019)	Sino-ASEAN (Association of Southeast Asian Nations) Countries	DEA, Tobit Analysis	2000-2013 (t=4)	2870	0.494	DEAP 2.1, STATA15
(Fujii et al., 2018)	EU Countries	DEA	2005-2014 (t=10)	927	0.523	x
(Loong et al., 2017)	Neighboring Countries – (Malaysia, Indonesia and	DEA, OLS Regression Analysis	2006-2014 (t=9)	207	0.800	x
(Kamarudin et al., 2017)	Southeast Asian Countries	DEA	2006-2014 (t=9)	261	0.828	x
(Doumpos et al., 2017)	Organisation of Islamic Cooperation Countries	DEA, SFA	2000-2011 (t=12)	4170	0.743	x
(Balcerzak et al., 2017)	EU Countries	DEA, MPI	2014-2015 (t=10)	302	0.920	x
(Wong & Deng, 2016)	ASEAN (Association of Southeast Asian Nations) Countries	DEA	2000-2010 (t=11)	429	0.869	x
(Kamarudin et al., 2015)	GCC (Gulf Cooperation Council Countries)	DEA	2007-2011 (t=5)	215	0.826	DEAP 2.1
(Rosman et al., 2014)	Middle Eastern and Asian Countries	DEA, Tobit Analysis	2007-2010 (t=4)	291	0.454	x

(Mobarek & Kalonov, 2014)	OIC	DEA, SFA	2004-2006 / 2007-2009 (t=4)	1632	0.621	R
(Maghyereh & Awartani, 2014)	GCC	DEA, Truncated Regression Analysis	2000-2009 (t=10)	700	0.865	x
(Aghimien et al., 2014)	GCC	DEA	2007-2011 (t=5)	215	0.826	DEAP 2.1
(Johnes, et al.,2014)	Islamic and Conventional Bank (18 Country)	DEA	2004–2009 (t=6)	1353	0.796	x
(Rahim et al., 2013)	MENA and Asian Countries	DEA, OLS Regression Analysis	2006-2009 (t=4)	189	0.487	STATA 10
(Abu-Alkheil et al., 2012)	Europe and Muslim-Majority Countries Countries	DEA, MPI, OLS Regression Analysis	2005-2008 (t=4)	92	0.683	DEAP 2.1
(Mostafa, 2011)	GCC	DEA	2009 (t=1)	21	0.604	Frontier Analyst DEA 3.0
(Sufian et al., 2008)	MENA and Asian Countries	DEA	2001-2006 (t=6)	96	0.654	DEAP 2.1
(Al-Muharrami, 2008)	GCC	DEA	1993-2002 (t=10)	520	0.888	DEA Excel Solver

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EXAMINING THE NEXUS BETWEEN CORPORATE SOCIAL RESPONSIBILITY DISCLOSURE AND EARNINGS MANAGEMENT: EVIDENCE FROM THE STATE-OWNED ENTERPRISES OF BANGLADESH

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ABSTRACT

Purpose- The purpose of the study is to examine the association between corporate social responsibility (CSR) disclosure and the practice of earnings management in the listed state-owned enterprises (SOEs) of Bangladesh.
Methodology- All the listed SOEs (17 firms) of Dhaka Stock Exchange (DSE) for the years 2017-2022 were considered in the study, resulting in observations of 102 firm-years. Content analysis was used to assess the level of CSR disclosure in the annual reports. For measuring earnings management, Beneish M-score model was used as the proxy variable. To investigate the association between CSR disclosure and earnings management, multivariate regression analysis was conducted using pooled OLS model, random effects model and lag model.
Findings- The regression outcomes of the study found a positive and significant association between CSR disclosure and earnings management. This study shows how managers can use CSR disclosures as a competitive advantage by manipulating earnings while also fostering positive relationships with stakeholders.
Conclusion- Investors and governments alike are increasingly demanding ethical business practices and full disclosure from corporations. The study concludes that managers' opportunistic behavior is a primary motivation for using CSRD to cover their tracks. This study will provide valuable insights to the policy-makers, regulators, investors and other stakeholders on how CSR reporting can be used as a medium to hide management's manipulative practices and, why it is important to implement a more comprehensive guideline on CSR reporting and effective governance to eliminate such practices.

Keywords: Corporate social responsibility (CSR) disclosure, earnings management, Beneish M-Score, state-owned companies (SOEs), Bangladesh.
JEL Codes: G38, M14, M41

1. INTRODUCTION

Corporate Social Responsibility (CSR) encompasses a diverse array of initiatives undertaken by companies with the aim of mitigating adverse effects and enhancing positive contributions to society (Carroll, 1999). Over the past few decades, there has been a noticeable trend in the business world toward a heightened understanding of CSR. Because of this increased knowledge, businesses are now approaching the creation and distribution of profits with greater care. Organizations these days exhibit a greater concern for their moral and ethical behavior, especially when it comes to their dealings with relevant stakeholder groups. Companies that implement CSR aim to satisfy the implicit social contract and stakeholder expectations. As a result, the argument makes the case that a business that exhibits social responsibility and cares about its stakeholders is more likely to release transparent financial data, which will enable it to provide a true picture of its overall financial situation (Salewski & Zulch, 2014). However, there is a claim that CSR could serve as an entrenchment mechanism, manipulating earnings data to further management' self-interested goals (Choi et al., 2013). When managerial discretion is used to change financial statements through transaction structuring and financial reporting, earnings management (EM) takes place. The purpose of this manipulation is to influence contractual outcomes that depend on reported accounting data or to deceive stakeholders about the true economic performance of the company (Healy & Wahlen, 1999).

The relationship between CSR and earnings management has been explored by some studies in recent times. However, the outcomes of the studies cannot be generalized as some studies found a positive relationship whereas some found a negative relationship. According to one group, firms involved in high-level of CSR reporting are more ethical and transparent and thus, do not get involved in earnings management (Alsaadi et al., 2017; Cho & Chun 2016; Choi et al., 2013). In contrast, another group thinks that firms that disclose more about CSR activities tend to do so to obscure their practice of earnings manipulation (Muttakin et al., 2015; Gargouri et al., 2010; Prior et al., 2008). Due to these contrasting findings, the relationship between CSR disclosure and earnings management remains a debatable topic in the existing field of literature.

State-owned enterprises have been considered to have substantial influence over vital industries including communications, energy, and transportation (OECD, 2014). According to Kowalsky et al. (2013), state-owned enterprises are a major factor in the rapid economic development of countries like China, Russia, Brazil, India, Malaysia, Indonesia, and the United Arab Emirates. Bangladesh has made significant contributions to its economic growth since gaining independence, and the country is now recognized as a globally competitive market. Although the private sector is flourishing, state-owned enterprises (SOEs) have accrued losses due to difficulties in institutional management. The continuous accumulation of losses by most of the SOEs and increased pressure from stakeholders increases the possibility of earnings management by the firms. Existence of weak capital markets, inefficient monitoring, and minimal activity in the managerial labor market practices can also provide opportunity for the management to take such manipulative actions (Farooque et al., 2007). So, management can use disclosure mechanisms like CSR reporting as a medium to evade the attention of stakeholders from such earnings management practices.

Over the years, a good number of studies have analyzed the impact of CSR disclosure on earnings management practice by firms. However, most of the studies were conducted in the context of developed countries (Habbash & Haddad, 2019; Almahrog et al., 2018; Moratis & Egmond, 2018). Only a handful of studies can be found in the context of developing countries. In Bangladesh, Muttakin et al. (2015) conducted such study using 135 non-financial companies. This is the only study conducted in the context of Bangladesh as per the best knowledge of authors. Besides, currently there are no studies that have investigated such relationship by exclusively considering the SOEs of Bangladesh only. The dearth of existing research in this area accompanied by the importance of SOEs in Bangladesh have encouraged the authors to explore the area and contribute to the field of research.

The primary objective of this study is to investigate whether there exists a relationship between CSR disclosure and earnings management practices by listed SOEs in Bangladesh. The study also looks into the nature and level of CSR reporting by the SOEs in Bangladesh. In addition, the study sheds light on the earnings management practice by firms using Beneish M-Score. The study has found a positive and significant association between CSR disclosure and earnings management implying that firms that provide more disclosures on CSR tend to do so to conceal their earnings management practices. The study also found an increasing pattern in the level of CSR disclosure as well as earnings management practices by the sample firms.

The study will contribute to the existing field of literature in several ways. First, this is the first study that explores the association between CSR reporting and earnings management in the listed SOEs of Bangladesh. The outcomes of the study will provide valuable insights on the reasons behind such relationship. Second, the study demonstrates the current picture of CSR reporting by the listed SOEs in Bangladesh. Third, the study investigates the level of earnings management practiced by the SOEs in Bangladesh. Finally, the study addresses the issue of autocorrelation and endogeneity using appropriate regression models to provide more robust results on this matter.

The rest of the study is organized in the following way: Section 2 discusses the theoretical framework used in the study. Section 3 gives a brief overview of the findings of previous studies and draws a hypothesis based on the discussion. Section 4 presents the sample, data and research methods used in the study. Section 5 presents the key findings of the study using descriptive statistics, bivariate analysis and multivariate analysis and discusses the results. Finally, section 6 provides the concluding remarks and possible implications of the study.

2. THEORETICAL FRAMEWORK

2.1. Agency Theory

Agency theory encourages opportunity-based management approaches (Jensen & Meckleng, 1976). According to Velayutham (2018), managers would conceal their own opportunistic actions within the company by using CSR reporting and financial success as smokescreens. Because of this, CSR management provides managers with protection for their professional reputations, which in turn allows them to more skillfully manage profits and report inflated financial data. According to Kim et al. (2012), managers who engage in profit management do so covertly by inflating CSR reports and padding the books. Those in charge of a company's bottom line risk losing investors' faith if they lose sway over the company's outcomes. CSR reporting and performance that value several stakeholder groups will attract and retain a wider audience.

2.2. Stakeholder Theory

Stakeholder demand has a significant impact on businesses' decisions to use CSR practices and the amount of information they choose to share. Stakeholder theory is applied to the study of how state-owned businesses' financial results change after adopting CSR policies (Brown & Deegan, 1998). Businesses may improve their status in the market by listening to and responding to the needs of their stakeholders. There is increasing pressure on businesses to reduce the negative effects of externalities while maximizing the positive ones from a wide range of interested parties, including customers, workers, rivals, suppliers, and governments. Stakeholder theory provides a theoretical basis for assessing a firm's actions in relation to the stakeholders it has identified and the actions it has taken as a result (Neu et al., 1998). Participation in CSR initiatives is essential for organizations to effectively manage stakeholder relationships and create value. According to stakeholder theory, companies can reduce agency costs by implementing social activities, especially Corporate Social Responsibility (CSR), which improves and influences their relationships with various stakeholders (Scholtens & Kang, 2013). Unlike agency theory that focuses on the opportunistic hypothesis, the stakeholder theory emphasizes on the ethical hypothesis which assumes that firms that provide more CSR disclosure are unlikely to manage earnings as this is regarded as an unethical act (Kumala & Siregar, 2020).

3. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT:

Whether or not there is a connection between CSR reporting and a company's performance has been the subject of interest for researchers of different countries. Prior studies have found contrasting results while assessing such relationship. Table 1 shows the brief summaries of different studies that investigated the relationship between CSR disclosure and earnings management. Two different perspectives can be used to explain such differences in findings. According to the first perspective, organizations with strong commitments to CSR show a lower inclination to manipulate earnings. This tendency results from their refusal to engage in the practice of earnings management, which is to hide negative earnings realizations (Chih et al., 2008). Choi et al. (2013) argue that companies that exhibit a strong commitment to CSR are more likely to adopt responsible practices in the reporting of their financial statements, given the perceived irresponsibility associated with earnings management in line with CSR principles. Businesses that commit time, money, and energy to developing and implementing CSR programs that address stakeholders' ethical concerns tend to be more inclined to provide accurate and open financial reporting. Furthermore, these businesses are less inclined to engage in earnings management practices (Kim et al., 2012). García-Sánchez and García-Meca (2017) and Sun et al. (2010) stated that CSR is perceived as a mechanism for elucidating the broader concerns of the organization to stakeholders and underscoring its commitment to accountability, thereby compelling the firm to conduct itself in a socially responsible manner. Almahrog et al. (2018) conducted a study on listed UK firms and found a negative association between CSR reporting and earnings management. They stated that organizations disseminating an extensive volume of CSR data reduce information asymmetry and foster stronger connections with stakeholders, putting these goals ahead of just maximizing profits. Ding et al. (2007) and Wang and Yung (2011) found a negative correlation between these two factors at state-owned businesses but a positive one at privately held companies that are more likely to push profit-boosting financial strategies.

The second perspective, managerial opportunism, implies that executives involved in earnings manipulation may purposefully use information from CSR to conceal their self-serving behavior (Prior et al., 2008). According to Choi et al. (2013), engaging in CSR activities might strengthen the status of managers who manipulate earnings information for personal gain. Based on the investigation conducted on a sample of 593 firms in 26 countries, Prior et al. (2008) found a positive relationship between the variables and identified two reasons behind such relationship. First, stakeholder activism may arise as a result of earnings manipulation, thereby undermining the stakeholders' standing inside the firm. One way to stop this kind of action is to speak to and satisfy stakeholders' interests. Second, for entrenchment reasons, managers are more likely to work together with other stakeholders as a hedging tactic to lessen the impact of shareholder disciplinary measures against them for profits management methods. According to the predictable earnings hypothesis, companies with high levels of CSR tend to use earnings smoothing mechanisms (Goel & Thakor, 2003). This reduces earnings volatility and information asymmetry between insiders and uninformed investors. This procedure helps to disclose to the investing community more consistent earnings. Habbash and Haddad (2019) conducted a study on Saudi Arabian companies and found that companies that take CSR actions are more prone to earnings management. In order to win over stakeholders, executives who manipulate earnings are driven to foster a positive social image. As a result, there is a decreased chance of managerial termination; this is why Corporate Social Responsibility (CSR) is used as a means of entrenchment. Based on the mixed findings of different studies, the following hypothesis is drawn:

H1: Ceteris Paribus, there exists a significant association between the level of CSR disclosures and earnings management in the listed state-owned firms of Bangladesh.

Table 1: Review of Previous Studies on CSR Disclosures and Earnings Management

Author(s) and Year	Sample	Variables	Significant Findings
Prior et al. (2008)	593 firms, 26 countries, 2002-2004	Earnings Management and CSR performance	Earnings management positively impacts CSR, as managers manipulating earnings for their own benefit motivate participation as these activities counter shareholder demand.

Chih et al. (2008)	46 countries, 1653 firms	CSR index, Earnings smoothing, and Earnings decrease avoidance	Increased CSR disclosures boost earnings aggressiveness, potentially enabling socially conscious businesses to manipulate earnings and conceal profit-seeking actions. Unrelated institutional variables may influence earnings management.
Laksmana And Yang (2009)	USA, 1304 firm-year observations, 2001-2002	CSR disclosure and Earnings management	Companies with high CSR disclosures experience more consistent, smooth, and predictable earnings than those with low CSR.
Wang and Yung (2011)	China has 142 listed firms.	firm ownership, CSR performance, CSR disclosures, and Earnings management	No relationship between CSRD and earnings management in state-owned enterprises, whereas a positive relationship in privately owned firms prone to promoting financial plans that unfairly increase earnings has been found.
Hong and Andersen (2011)	USA, 8078 firm-year observations, 1995-2005	CSR performance and Earnings Management (dependent)	Higher-quality accruals and fewer uses of activity-based earnings management are factors that affect financial reporting quality in socially responsible businesses.
Choi and Pae (2011)	Korea, 1432 firm-year observations	CSR (ethical commitment list) disclosure and earnings management (accounting Accuracy)	In comparison to businesses with lesser ethical commitment, companies with stronger commitment report earnings cautiously and correctly forecast future cash flows.
Yip et al. (2011)	USA, 110 firms	CSR reporting, Earnings management, Political cost, and ethical predisposition	There is a negative relationship between CSR disclosures and earnings management in the oil and gas industry but a positive relationship in the food industry. This data suggests that, besides ethical issues, there are other factors that affect the result.
Kim et al. (2012)	USA, 23392 firm-year observations, 1991–2009	CSR Disclosures (independent) and Earnings Management	Companies with a social conscience are less likely to influence operations, control earnings, or face SEC investigations. They argue that ethical and reputational reasons motivate managers to produce high-quality financial reports, aligning with the legitimacy hypothesis.
Salewski and Zulch (2012)	258 firms, 10 developed countries	CSR performance and earnings management (dependent)	Companies with higher CSR levels are more likely to manipulate results and delay negative news releases.
Pyo and Lee (2013)	Korea, 4257 firm-year observations, 2004-2010	CSR performance (independent), Accounting conservatism	Found a positive relationship between CSR disclosure and Earnings Management. Firms with high CSR performance tend to manipulate earnings.
Scholtens and Kang (2013)	Asia, 39 firms, 10 countries	CSR performance and Earnings management	Companies that practice social responsibility are less likely to manipulate earnings because CSR can diminish earnings management incentives, possibly dealing with agency problems between managers and shareholders.
Hoang et al. (2014)	Vietnam, 142 listed firms	firm ownership, CSR disclosure, and earnings management	Found an insignificant relationship in a state-owned firm, and a significant positive relationship in a private owned firm.
Muttakin et al. (2015)	Bangladesh, 116 firms, 580 firm-year observations, 2005–2009	CSR disclosure score and Earnings management	Managers in emerging economies manage earnings by increasing CSR disclosures. (Relationships are Positive.) And adverse links with export-focused industries and influential stakeholders.
Suteja et al. (2016)	Indonesia,55 firm-year observations,2010-2014	CSR performance and earnings management	Found a positive relationship between bank CSR disclosure and earnings manipulation.

4. RESEARCH METHODOLOGY

4.1. Sample Size and Data Collection

For the purpose of the study, all 17 state-owned manufacturing firms listed in Dhaka Stock Exchange (DSE) have been considered. The study has covered the timeframe of 2017-2022 resulting in a sample size of 102 firm-years. Data were collected from secondary sources (annual reports of the firms). As none of the firms disclosed their CSR related information in separate CSR reports, only annual reports were considered for content analysis. Data regarding earnings management and control variables were collected from financial statements of the firms. Table 2 depicts the industry-wise sample composition for the study.

Table 2: Industry-wise Category of Selected SOEs

Industry	Total Firms
Fuel and Power	7
Engineering	4
Food and Allied	2
Miscellaneous	4
Total	**17**

4.2. Definition of Variables

4.2.1. Dependent Variable (M-Score)

While several alternatives exist for measuring earnings quality, the Beneish M-Score has been chosen for this research because of its superior specification and less precise requirements for data. When it comes to the identification of possible fraudulent activity in financial accounts, the Beneish M-Score model offers a more complete tool for forensic accounting than traditional measurements used in fraud detection systems (Özcan, 2018; Akra & Chaya, 2020). Studies conducted by Kamal et al. (2016), Repousis (2016), Mamo and Sehu (2017), Arman and Sharmin (2019) used the M-Score as a proxy for earnings management. According to the model, a score higher than-2.22 indicates the existence of earnings management (Beneish, 1999). Eight factors taken from the income statement, balance sheet, and statement of cash flows are needed to compute the M-Score. The level of earnings manipulation was then determined by calculating the M-Score for the company using the following model:

Beneish M Score Formula = -4.84 + 0.92 * DSRI + 0.528 * GMI + 0.404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI + 4.679 * TATA - 0.327 * LVGI (1)

Table 3 represents the detailed components of Beneish M-Score Model:

Table 3: Beneish M-score Model Variables

Variable Name	Definition	Formula
DSRI	Days Sales Ratio Index	(Net Receivales$_t$ /Sales$_t$) / (Net Receivales$_{t-1}$/sales$_{t-1}$)
GMI	Gross Margin Index	(Gross Margin$_t$/Sales$_t$)
AQI	Asset Quality Index	[1-(Current Asset$_t$+PP&E$_t$+Securities$_t$)/Total Asset$_t$}] / [1-(Current Asset$_{t-1}$ +PP&$_{t-1}$+Securities$_{t-1}$)/Total Asset$_{t-1}$}]
SGI	Sales Growth Index	(Sales$_t$/Sales$_{t-1}$)
DEPI	Depreciation Index	[Depreciation$_{t-1}$/(PPE$_{t-1}$+Depreciation$_{t-1}$)] / [Depreciation$_t$/(PPE$_t$+Depreciation$_t$)]
SGAI	Sales, General Administration Index	(SGA Expense$_t$/Sales$_t$)/ (SGA Expense$_{t-1}$/Sales$_{t-1}$)
TATA	Total Accruals to Total Assets	(Income from continuing operations$_t$ -Cash Flow from Operations$_t$)/Total Asset$_t$
LVGI	Leverage Index	(Total Debt$_t$/Total Asset$_t$)

4.2.2. Independent Variable (CSRD)

CSR disclosure index (CSRD) served as the independent variable in the study. To assess the number of disclosures by firms, content analysis has been performed. A checklist containing 20 items have been used for the content analysis (see Appendix). The checklist was derived from the study conducted by Muttakin et al. (2015). The reason behind selecting this checklist was the similarity in context as the study has also been conducted in context of Bangladesh. Although the weighted method was used by some of the previous studies for content analysis (Fayad et al., 2022; Qaderi et al., 2022), the unweighted method has been used in this study to minimize subjectivity (Elsayed and Hoque, 2010; Omran et al., 2021) . An item was scored one if the sample company disclosed the same information mentioned in the checklist, otherwise it was scored zero. The scores were cross-checked by the authors to ensure the content analysis's reliability. After the analysis, an index was prepared based on the ratio of the total score achieved and the maximum achievable score. The calculation of CSRD for each firm can be represented using the following formula:

$$CSRD_j = \sum_{t=1}^{n_j} \frac{X_{ij}}{n_j} \tag{2}$$

Where,
$CSRD_j$ = corporate social disclosure index for j-th firm.
n_j= number of items expected for j-th firm, where n=20;
X_{ij} = 1, if i-th items are disclosed for firm j, otherwise 0; and

4.2.3. Control Variables

Four control variables namely leverage, return on assets (ROA), firm size and firm age have been considered for the study. There exist opposite views on the relationship between leverage and earnings management. Studies conducted by Becker et al. (1998) and Sweeney (1998) found a positive relationship between leverage and earnings management as highly levered firms tend to manipulate earnings to respond to debt contracting. On the other hand, Dechow and Skinner (2000) found a negative association between the variables stating that high levered firms are closely monitored by the creditors, leaving little scope for management to get engaged in earnings management. According to Dechow et al. (1995), in order to increase ROA, management may use accrual-based and real earnings management. Contrasting views also exist regarding the impact of firm size on earnings management. Larger firms tend to engage in earnings management due to excessive pressure from capital markets (Richardson et al., 2002). In contrast, Lee and Choi (2002) found that larger firms are less likely to get involved in earnings management as they are strongly monitored by the outsiders. As for firm age, older firms tend to manage earnings more compared to newer ones as they need to maintain their reputation (Yunietha & Palupi, 2017).

4.3. Model Specification

In consistent with the studies conducted by Habbas and Haddad (2019) and Moratis and Egmond (2018), the following model was used to test the hypotheses:

$$\text{M-Score}_{it} = \alpha + \beta_0 CSRD_{it} + \beta_1 LEV_{it} + \beta_2 ROA_{it} + \beta_3 FSIZE_{it} + \beta_4 FAGE_{it} + \varepsilon_{it} \tag{3}$$

The definitions of variables are presented in Table 4.

Table 4: Definition of Variables

Variables	Description	Notation	Expected Relationship	Reference
Dependent Variable				
M-Score	Value derived from Beneish M-Score model	IRI		
Explanatory Variable				
CSR Disclosure	Index value using content analysis	CSRD	+/-	Muttakin et al. (2015)
Control Variables				
Leverage	The ratio of total book value of debt to total book value of asset.	LEV	+/-	Becker et al. (1998)
Profitability	The ratio of profit before tax to total asset	ROA	+/-	Dechow et al. (1995)
Firm Size	Natural logarithm of total book value of asset	FSIZE	+/-	Lee and Choi (2002)
Firm Age	Natural logarithm of firm's age since inception	FSIZE	+	(Yunietha & Palupi, 2017)

5. FINDINGS AND DISCUSSION

5.1. Descriptive Statistics

5.1.1. Descriptive Statistics of Dependent Variable (Earnings Management)

Table 5 presents annual descriptive data pertaining to the mean of the dependent variable (M-score) across the time span from 2017 to 2022. It has been observed that the average values of DSRI, GMI, AQI, SGI, DEPI, TATA, and LVGI showed a decline in the initial three years. However, in 2020, these average values have shown an upward trend, resulting in a rise in the average value of the M-score. Following the year 2019, there has been a discernible upward trend in the average M-score value. This observation implies a corresponding increase in the prevalence of earnings manipulation throughout successive years. In contrast to the initial three-year period, the average value of the M-score exhibited a downward trend.

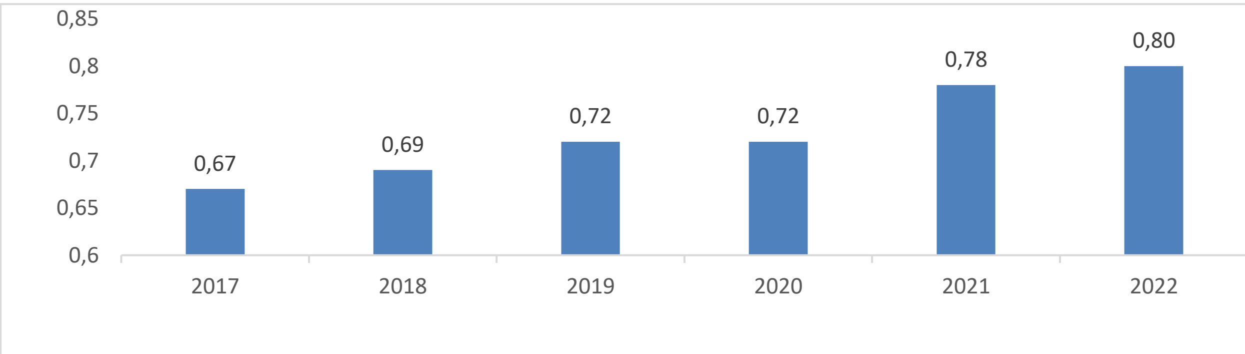
Table 5: Component-wise Beneish M-Score (Annual Average)

Year	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
2017	-1.26	1.91	0.34	1.05	1.17	1.23	1.11	0.11	0.92
2018	-1.52	1.43	0.31	1.97	1.15	1.27	1.02	0.08	0.97
2019	-1.90	1.42	0.28	1.64	1.15	1.23	1.16	0.04	1.04
2020	1.27	1.30	0.27	9.96	1.22	1.19	1.15	0.02	1.05
2021	0.65	1.27	0.26	8.62	1.25	1.19	1.16	0.00	1.05
2022	2.62	2.73	0.94	7.13	2.48	4.31	2.66	-0.08	0.91

5.1.2. Descriptive Statistics of Independent Variable (CSRD)

Figure 1 shows the year-wise index value of CSR disclosure by the sample firms. It can be seen that the level of disclosure has increased over the years, particularly during the COVID period and post-COVID period. This is a positive sign particularly for a developing country like Bangladesh. The major rise during 2021 and 2022 suggests that the SOEs became more involved in CSR activities due to pandemic and thus disclosed more information in the annual reports to demonstrate their contribution to the community.

Figure 01: CSR Disclosure Index over the Years



5.1.2. Descriptive Statistics of the Model

Table 6 presents the descriptive statistics of the dependent, independent, and control variables used in the study. The mean value of the M-score, which serves as the dependent variable, is 1.036 percent. The range of values spans from -22.4 to 42.19. The standard deviation, which is calculated to be 4.811, represents the extent of variation from the mean value. In a similar vein, the mean value of the independent variable CSRD is observed to be 0.7289, with a corresponding standard deviation of 0.156. The lower bound of the range is 0.35, while the upper bound is 1, implying a full disclosure of checklist items by a firm. The average values of the control variables are as follows: 2.0289% for leverage (LEV), -0.1868% for return on asset (ROA), BDT 49613 million for firm size (FSIZE), and 44 years for firm age (FAGE). The minimum values observed in the dataset are as follows: 0.07% for the variable LEV, -7.06% for the variable ROA, BDT 233 million for the variable FSIZE, and 9 years for the variable FAGE. Likewise, the maximum are: 26.3% for LEV, 1.2% for ROA, BDT 431868 million for FSIZE, and 63 years for FAGE. A negative mean value of ROA implies the poor level of performance by the listed SOEs in Bangladesh.

Table 6: Descriptive Statistics of the Variables

Variable	Observation	Mean	Std. Dev.	Minimum	Maximum
M-score (%)	102	1.036	4.8113	-22.41	42.19
CSRD (%)	102	.7289	0.1558	.35	1
LEV (%)	102	2.0292	4.5959	.07	26.3
ROA (%)	102	-.1869	.8331	-7.06	1.2
FSIZE (in million)	102	49613	79386	233	431868
FAGE (in years)	102	44	13.3848	9	63

5.2. Bivariate Analysis

5.2.1. Correlation Matrix

Table 7 shows the correlation matrix of the dependent and independent variables used in the study at 10%, 5%, and 1% significance levels. The analysis of the correlation matrix shows that CSRD has a positive and significant correlation with earnings management (r =.1166, p< 0.1, p< 0.05). Which gives a good indication that increasing CSR disclosure has a significant impact on earnings manipulation. Correlation between leverage and ROA has the highest value (-0.6140). According to Gujarati (2003), the highest acceptable value is 0.7. So, the problem of multicollinearity is not an issue for the study.

Table 7: Pearson Correlation Matrix

	mscore	csrd	lev	roa	fsize	fage
mscore	1					
csrd	0.1166**	1				
lev	-0.03	-0.2971***	1			
roa	-0.0351*	0.2888***	-0.6140***	1		
fsize	-0.0383	0.3914***	-0.4645**	0.3488***	1	
fage	-0.0065	0.4289***	-0.0462	-0.0587	-0.0351	1

Note: ***, **, and * indicate level of significance at 1%, 5% and 10% respectively. For definition of variables, refer to table 4.

5.2.2. Multicollinearity

Variance inflation factor (VIF) is a powerful quantitative indicator for analyzing the existence and magnitude of multicollinearity in the context of regression research. If the VIF value is more than 10, it suggests that there is a multicollinearity problem in the model. And if the VIF value is less than 1, it suggests that biases are present in the regression equation (Gujarati, 2003). Table 8 shows the VIF values of the independent and control variables used in the study. As the mean VIF is 1.6 (less than 10) and values of each VIF is in between 1.35 to 1.84 (less than 2), it can be said that no multicollinearity exists among the variables of the research model.

Table 8: Variance Inflation Factor

Variable	Symbol	VIF	1/VIF
Leverage	LEV	1.84	0.544126
Return on assets	ROA	1.7	0.587858
CSR disclosure	CSRD	1.62	0.616507
Firm size	FSIZE	1.48	0.677162
Firm age	FAGE	1.35	0.740777
Mean VIF		**1.6**	

5.3. Multivariate Analysis

Table 9 demonstrates the regression result of the models used in the study. Pooled-OLS method was used to estimate the equation in Model-1 and random effects method was used to estimate the equation in Model-2. The selection of random effects model was confirmed by using Huasman test.

The results show a positive and significant association between CSR disclosure and earnings management practice by the sample companies in both models. The relationship is significant at 10%, 5% and 1% level respectively. This implies that SOEs that make more disclosures regarding CSR activities are involved in earnings management practices. This is in consistent with the findings of the studies conducted by Habbash and Haddad (2019), Uyagu and Dabor (2017), Prior et al. (2008), Goel and Thakor (2003) etc. The implementation of CSR may intensify agency issues by increasing the incentives for insiders to participate in earnings management. This is driven by the motivation to conceal rent-seeking activities from external stakeholders (Jensen, 2001). Participation in CSR activities by managers may mask their opportunistic actions. Based on agency theory, it is expected that managers who engage in earnings manipulation will disclose more information about their companies in order to further their own goals (Habbash & Haddad, 2019). This result is in variance with the ethical perspective, which expects CSR and earnings management to be negatively correlated. SOEs extensively involved in earnings management practices often seek to conceal such activities through increased CSR disclosure. This situation is particularly pertinent in markets characterized by a lack of stringent regulations and investor protection measures like Bangladesh.

Among the control variables, only ROA has a negative and significant relationship with earnings management. Firms with strong financial performance have less tendency to manipulate earnings compared to the poor performing firms. Leverage, firm size and firm age did not have any significant impact on earnings management.

Table 9: Regression Results Using the Pooled-OLS model and Random Effects Model

Independent Variables	Model-1	Model-2
	(Coefficients)	**(Coefficients)**
CSRD	2.4930***	2.3769***
	(0.3770)	(0.2751)
LEV	-0.2430	-0.2431
	(0.7578)	(0.4561)
ROA	-0.2390***	-0.2391**
	(0.9030)	(0.1532)
FSIZE	-1.5440	-1.5449
	(0.3558)	(0.5152)
FAGE	-2.0540	-6.0057
	(0.9185)	(0.7175)
CONSTANT	0.5204*	0.4157*
	(0.1758)	(0.2316)
Year Dummy	Yes	Yes
Observations	102.0000	102
R-squared	0.3308	0.2915

This table represents the result of the relationship between earnings management and CSR disclosure using equation 3. Model 1 is estimated by using the Pooled OLS Model with Driscoll–Kraay standard errors and Model 2 is estimated by using Random Effects Model. Standard errors are in parentheses. ***, **, and * indicate level of significance at 1%, 5% and 10% respectively. For definition of variables, refer to table 4.

7. ROBUSTNESS TEST

Table 10 presents the results of the regression equation using the lag model and the pooled-OLS model with panel corrected standard errors (PCSE). The results of all these models are in consistent with the results of Model 1 and Model 2. The consistency of results of the lag model used in Model 3 and main two models ensure that there is no endogeneity problem among the variables. The findings suggest that whether a firm is involved in earnings management or not can also be predicted by its CSR disclosure of last year. Model 4(a) is estimated by using PCSE model with independent autocorrelation structure whereas Model 4(b) is estimated by using PCSE model with first-order autocorrelation structure. So, both the probability of endogeneity and autocorrelation problems have been addressed in this study.

Table 10: Regression Results Using the Lag model and Pooled-OLS with PCSE Model

Independent Variables	Model-3	Model-4(a)	Model-4(b)
	(Coefficients)	**(Coefficients)**	**(Coefficients)**
CSRD	3.4130**	2.4930***	2.2327***
	(0.1099)	(0.3992)	(0.9018)
LEV	-0.3414	-0.2430	-0.0705

	(0.8632)	(0.5316)	(0.6203)
ROA	-0.3445**	-0.2390**	-0.2629*
	(0.3787)	(0.3426)	(0.9159)
FSIZE	-1.8173	-1.5440	-0.1045
	(0.6696)	(0.8307)	(0.5186)
FAGE	-6.6918	-2.0540	-3.5877
	(0.6211)	(0.8114)	(0.0494)
CONSTANT	0.6383	0.5204	0.8882
	(0.8615)	(0.9914)	(0.0523)
Observations	85	102	102
R-squared	0.2538	0.3308	0.2915

This table represents the result of the relationship between earnings management and CSR disclosure using equation 3. Model 3 is estimated by using Lag Model whereas Model 4(a) is estimated by using PCSE model with independent autocorrelation structure and Model 4(b) is estimated by using PCSE model with first-order autocorrelation structure. Standard errors are in parentheses. ***, **, and * indicate level of significance at 1%, 5% and 10% respectively. For definition of variables, refer to table 4.

7. CONCLUSION AND IMPLICATIONS

The aim of the research is to investigate the relationship between CSR disclosure and earnings management practices by listed SOEs of Bangladesh. The study used all 17 listed SOEs in DSE for the years 2017-2022 which resulted in a sample size of 102 firm-years. The study has used Beneish M-Score as a proxy of earnings management practice. Content analysis has been conducted using a checklist to measure the extent of CSR reporting by the firms. Finally, leverage, ROA, firm size and firm age have been used as the control variables in the study. Multivariate analysis using pooled-OLS model and random effect model have been conducted to assess the relationship among the variables.

The study found a positive and significant association between CSR disclosure and earnings management practices by the SOEs. This lends credence to the argument that managers may be tempted to take advantage of situations and utilize CSR reporting to divert attention away from more pressing issues like earnings manipulation. The findings are in line with the agency theory suggesting that managers engaged in earnings manipulations are anticipated to augment corporate disclosures as a strategic maneuver to pursue personal gains. To garner stakeholder support, managers who manipulate revenues are motivated to project a positive social image. As a result, there is less chance of a manager being fired, which presents CSR disclosure as a means of entrenchment (Habbash & Haddad, 2019).

The study has several implications for the regulators, policy-makers, practitioners and investors. It is advisable for investors to refrain from making assumptions on the engagement of firms in CSR initiatives, ethical behavior, or the disclosure of pertinent information in their financial reports. The evaluation of firms' CSR programs should be approached with care, given our research findings that indicate the potential for certain corporations to manipulate earnings and provide shareholders with less open financial disclosures. Managers may be further motivated to engage in opportunistic activities by the implementation of policies that promote socially responsible practices, rather than just relying on coercive measures to encourage desirable actions. Hence, it is imperative for regulators to exercise caution about this opportunistic behavior and intensify monitoring measures in order to uphold social conformity. CSR disclosures should be based on genuine implementation rather than serving as superficial statements aimed at deceiving stakeholders. To achieve this, it is advisable to establish criteria that can be used to verify the authenticity and sincerity of CSR disclosures. Effective corporate governance structure and strict monitoring and auditing can play vital role to prevent the opportunistic behavior of management and meaningful reporting of CSR related information.

There are some limitations to this study. The study used unweighted method for content analysis which prevented the deeper investigation of disclosure of each item in the checklist. A larger sample size could have provided a better result. Finally, the study used only two models for assessing earnings management. Using other models could have provided more comprehensive results.

The study paves the way for future research in different ways. A comparative analysis can be conducted using cross-country samples for a broader understanding of the nature of relationship between CSR reporting and earnings management. Corporate governance variables like board characteristics and ownership structure can be used as moderators to observe their role in such regard. Finally, in-person interviews with management, stakeholders and regulators can provide valuable insights on the probable reasons behind such outcome.

REFERENCES

Akra, R. M., & Chaya, J. K. (2020). Testing the effectiveness of Altman and Beneish models in detecting financial fraud and financial manipulation: Case study Kuwaiti stock market. International Journal of Business and Management, 15(10), 70–81. https://doi.org/10.5539/ijbm.v15n10p70

Almahrog, Y., Ali Aribi, Z. & Arun, T. (2018). Earnings management and corporate social responsibility: UK evidence. Journal of Financial Reporting and Accounting, 16(2), 311-332. https://doi.org/10.1108/JFRA-11-2016-0092

Alsaadi, A., M. S. Ebrahim, & A. Jaafar. (2017). Corporate Social Responsibility, Shariah- Compliance, and Earnings Quality. Journal of Financial Services Research, 51(2), 169-194. https://doi.org/10.1007/s10693-016-0263-0

Arman, M., & Sharmin, S. (2019). Likelihood of a company's manipulation of its financial statement: An empirical analysis using Beneish M-score model. International Conference on Management and Information Systems September (Vol. 29, pp. 30).

Becker, C. L., DeFond, M. L., Jiambalvo, J., & Subramanyam, K. (1998). The effect of audit quality on earnings management. Contemporary Accounting Research, 15(1), 1–24. https://doi.org/10.1111/j.1911-3846.1998.tb00547.x

Beneish, M. (1999). The detection of earning manipulation. Financial Analyst Journal, 55(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

Brown, N. & Deegan, C. (1998). The public disclosure of environmental performance information: a dual test of media agenda setting theory and legitimacy theory. Accounting and Business Research, 2(1), 21-41. https://doi.org/10.1080/00014788.1998.9729564

Carroll, A. B. (1999). Corporate social responsibility evolution of a definitional construct. Business & Society, 38(3), 268–295. https://doi.org/10.1177/000765039903800303

Chih, H., Shen, C., & Kang, F. (2008). Corporate social responsibility, investor protection, and earnings management: Some international evidence. Journal of Business Ethics, 79(1-2), 179–198. https://doi.org/10.1007/s10551-007-9383-7

Cho, E., & S. Chun. 2016. Corporate social responsibility, real activities earnings management, and corporate governance: evidence from Korea. Asia-Pacific Journal of Accounting & Economics, 23(4), 400-431. https://doi.org/10.1080/16081625.2015.1047005

Choi, B. B., D. Lee, & Y. Park. (2013). Corporate Social Responsibility, Corporate Governance and Earnings Quality: Evidence from Korea. Corporate Governance: An International Review. 21(5), 447-467. https://doi.org/10.1111/corg.12033

Choi, T.H., & Pae, J. (2011). Business ethics and financial reporting quality: evidence from Korea. Journal of Business Ethics, 103(3), 403–427. http://dx.doi.org/10.1007/s10551-011-0871-4

Dechow, P. M., & Skinner, D. J. (2000). Earnings management: Reconciling the views of accounting academics, practitioners, and regulators. Accounting Horizons, 14(2), 235–250. https://doi.org/10.2308/acch.2000.14.2.235

Dechow, P., Sloan, R., & Sweeney, A. (1995). Detecting earnings management. Accounting Review, 70(2), 193–225.

Ding, Y., Zhang, H., & Zhang, J. (2007). Private vs. state ownership and earnings management: evidence from Chinese listed companies. Corporate governance: an international review, 15(2), 223–38. https://doi.org/10.1111/j.1467-8683.2007.00556.x

Elsayed, M.O. and Hoque, Z. (2010). Perceived international environmental factors and corporate voluntary disclosure practices: An empirical study. The British Accounting Review, 42(1), 17–35. Available at: https://doi.org/10.1016/J.BAR.2010.01.001

Farooque, O.A., Zijl, T.V., Dunstan, K. & Karim, A.K.M.W. (2007). Corporate governance in Bangladesh: link between ownership concentration and financial performance. Corporate Governance: An International Review, 15(6), 1453-1468. https://doi.org/10.1111/j.1467-8683.2007.00657.x

Fayad, A.A.S., Binti Mohd Ariff, A.H. & Ooi, S.C. (2022). Dose board characteristics influence integrated reporting quality? Empirical evidence from an emerging market. Cogent Economics & Finance, 10(1). Available at: https://doi.org/10.1080/23322039.2022.2140907

García-Sánchez, I.-M., & E. García-Meca. (2017). CSR Engagement and Earnings Quality in Banks. The Moderating Role of Institutional Factors. Corporate Social Responsibility and Environmental Management, 24(2), 145-158. https://doi.org/10.1002/csr.1405

Gargouri, R. M., C. Francoeur, & R. Shabou. (2010). The Relationship between Corporate Social Performance and Earnings Management. Canadian Journal of Administrative Sciences, 27(4), 320-334. https://doi.org/10.1002/cjas.178

Goel, A.M. & Thakor, A.V. (2003). Why do firms smooth earnings? The Journal of Business, 76(1), pp. 151-192. https://doi.org/10.1086/344117

Gujarati, D. N. (2003). Basic Econometrics (4th ed.). New York: McGraw-Hill.

Habbash, M. & Haddad, L. (2020). The impact of corporate social responsibility on earnings management practices: evidence from Saudi Arabia. Social Responsibility Journal, 16(8), 1073-1085. https://doi.org/10.1108/SRJ-09-2018-0232

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. Accounting Horizons, 13(4), 365–383. https://doi.org/10.2308/acch.1999.13.4.365

Hoang, T. C., Abeysekera, I. A., & Ma, S. (2014). State ownership and earnings management: Empirical evidence from Vietnamese listed firms. Proceedings of the 1st International Conference on Finance and Economics, Ho Chi Minh City, Việt Nam, 2–3 June.

Hong, Y. & Andersen, M.L. (2011). The relationship between corporate social responsibility and earnings management: an explanatory study. Journal of Business Ethics, 104, 461–471. https://doi.org/10.1007/s10551-011-0921-y

Jensen, M.C., & Meckling, W.H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305-360. https://doi.org/10.1016/0304-405X(76)90026-X

Kamal, M. E. M., Salleh, M. F. M., & Ahmad, A. (2016). Detecting financial statement fraud by Malaysian public listed companies: The reliability of the Beneish M-Score model. Jurnal Pengurusan, 46, 23–32.

Kim, Y., Park, M. S., & Wier, B. (2012). Is earnings quality associated with corporate social responsibility? The Accounting Review, 87(3), 761–796. http://dx.doi.org/10.2308/accr-10209

Kowalski, P., Büge, M., Egeland, M., & Sztajerowska, M. (2013). State-Owned Enterprises: Trade Effects and Policy Implications. OECD Trade Policy Papers n. 147, Paris: OECD Publishing.

Kumala, R. & Siregar, S.V. (2021). Corporate social responsibility, family ownership and earnings management: the case of Indonesia. Social Responsibility Journal, 17(1), 69-86. https://doi.org/10.1108/SRJ-09-2016-0156

Laksmana, I. & Yang, Y. (2009). Corporate citizenship and earnings attributes. Advances in Accounting, 25(1), 40-48. https://doi.org/10.1016/j.adiac.2009.02.001

Lee, B. B., & Choi, B. (2002). Company size, auditor type, and earnings management. Journal of Forensic Accounting, 3, 27–50.

Mamo, J., & Shehu, I. (2017). An estimating model for accounting manipulation phenomena. Case of Albania. Interdisciplinary Journal of Research and Development, 4(2), 130–44.

Moratis, L., & van Egmond, M. (2018). Concealing social responsibility? Investigating the relationship between CSR, earnings management and the effect of industry through quantitative analysis. International Journal of Corporate Social Responsibility, 3(8). https://doi.org/10.1186/s40991-018-0030-7

Muttakin, M. B., A. Khan, & M. I. Azim. (2015). Corporate social responsibility disclosures and earnings quality: Are they a reflection of managers' opportunistic behavior? Managerial Auditing Journal, 30(3), 277-298. https://doi.org/10.1108/MAJ-02-2014-0997

OECD, (2014). The size and sectoral distribution of SOEs in OECD and partner countries.

Omran, M. et al. (2021). Integrated reporting and board characteristics: evidence from top Australian listed companies. Journal of Applied Accounting Research, 22(4), 732–758. Available at: https://doi.org/10.1108/JAAR-04-2020-0077/FULL/XML

Özcan, A. (2018). The use of Beneish model in forensic accounting: Evidence from Turkey. Journal of Applied Economics and Business Research, 8(1), 57–67.

Prior, D., Surroca, J., & Tribó, J. A. (2008). Are socially responsible managers really ethical? Exploring the relationship between earnings management and corporate social responsibility. Corporate Governance: An International Review, 16(3), 160–177. https://doi.org/10.1111/j.1467-8683.2008.00678.x

Pyo, G., & Lee, H.-Y. (2013). The Association Between Corporate Social Responsibility Activities and Earnings Quality: Evidence from Donations and Voluntary Issuance Of CSR Reports. Journal of Applied Business Research (JABR), 29(3), 945–962. https://doi.org/10.19030/jabr.v29i3.7793

Qaderi, S.A. et al. (2022). Board Characteristics and Integrated Reporting Strategy: Does Sustainability Committee Matter? Sustainability, 14(10), 6092. https://doi.org/10.3390/SU14106092

Repousis, S. (2016). Using Beneish model to detect corporate financial statement fraud in Greece. Journal of Financial Crime, 23(4), 1063–1073. https://doi.org/10.1108/JFC-11-2014-0055

Richardson, S. A., Tuna, A., & Wu, M. (2002). Predicting earnings management: The case of earnings restatements. In Min, predicting earnings management: the case of earnings restatements (October 2002).

Salewski, M., & Zülch, H. (2014). The association between corporate social responsibility and earnings quality – Evidence from European blue chips. Leipzig: HHL Working Paper Series No. 112, HHL.

Scholtens, B. & Kang, F. (2013). Corporate social responsibility and earnings management: evidence from Asian economics. Corporate Social Responsibility and Environmental Management, 20(2), 95-112. https://doi.org/10.1002/csr.1286

Scholtens, B. & Kang, F.C. (2013). Corporate social responsibility and earnings management: evidence from Asian economies. Corporate Social Responsibility and Environmental Management, 20(2), 95-112. https://doi.org/10.1002/csr.1286

Sun, N., Salama, A., Hussainey, K., & Habbash, M. (2010). Corporate environmental disclosure, corporate governance and earnings management. Managerial Auditing Journal, 25(7), 679–700. https://doi.org/10.1108/02686901011061351

Suteja, J., Gunardi, A., & Mirawati, A. (2016). Moderating effect of earnings management on the relationship between corporate social responsibility disclosure and profitability of banks in Indonesia. International Journal of Economics and Financial Issues, 6(4), 1360-1365.

Sweeney, A. P. (1994). Debt-covenant violations and managers' accounting responses. Journal of Accounting and Economics, 17(3), 281–308. https://doi.org/10.1016/0165-4101(94)90030-2

Uyagu, B. & Dabor, A.O. (2017). Earnings management and corporate social responsibility, Romanian Economic Journal, 20(65), 70-87

Velayutham, E. (2018). Sustainability disclosure and earnings management. In Boubaker, S., Cumming, D., & Nguyen, D. K. (Eds.), Research handbook of finance and sustainability. Cheltenham, the UK: Edward Elgar Publishing.

Wang, l., & Yung, K. (2011). Do state enterprises manage earnings more than privately owned firms? The case of China. Journal of business finance & accounting, 38(7-8), 794-812. https://doi.org/10.1111/j.1468-5957.2011.02254.x

Yip, E., Staden, C.V. & Cahan, S. (2011). Corporate social responsibility reporting and earnings management: the role of political costs. Australasian Accounting Business and Finance, 5(3), 17-33.

Yunietha, & Palupi, A. 2017. Pengaruh Corporate Governance dan Faktor LainnyaTerhadap Manajemen Laba Perusahaan Publik Non Keuangan. Jurnal Bisnis DanAkuntansi, 19(4), 292–303. http://jurnaltsm.id/index.php/JBA

APPENDIX

CSR disclosure items:

(1) Community involvement:

- Charitable donations and subscriptions.
- Sponsorships and advertising.
  - Community program (health and education)

(2) Environmental:

- Environmental policies.

(3) Employee information:

- Number of employees/human resources.
- Employee relations.
- Employee welfare.
- Employee education.
- Employee training and development.
- Employee profit sharing.
- Managerial remuneration.
- Workers' occupational health and safety.
  - Child labor and related actions.

(4) Product and service information:

- Types of products disclosed.
- Product development and research.
- Product quality and safety.
- Discussion of marketing networks.
- Focus on customer service and satisfaction.
  - Customer award/rating received.

(5) Value-added information:

- Value-added statement.

Source: Muttakin et al. (2015)

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UNDERPRICING OF IPOS (INITIAL PUBLIC OFFERING) IN BORSA ISTANBUL: THE EFFECT OF COVID-19 PANDEMIC PERIOD

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ABSTRACT

Purpose- The research investigates the impact of the COVID-19 pandemic on Initial Public Offering (IPO) mispricing in the Turkish IPO market from 2010 to 2022. The study aims to offer valuable insights into the behavior of IPOs during this period, aiding investors and issuers in understanding the effects of the pandemic on IPO pricing. The findings may empower stakeholders, including investors, regulators, and market participants, to make more informed decisions in times of market volatility and uncertainty.
Methodology- The study utilizes two methods, ordinary least squares (OLS) and quantile regression (QR), to analyze the impact of independent variables on IPO mispricing. OLS focuses on average effects, overlooking nuances in mispricing distribution. In contrast, QR allows the exploration of variable effects at different mispricing levels, accommodating the asymmetric distribution of returns. Employing QR helps identify specific impacts of variables on IPOs within distinct mispricing levels, addressing distribution heterogeneity observed in the sample. This robust approach enhances the study's ability to capture a more comprehensive understanding of the relationship between independent variables and IPO mispricing.
Findings- The study reveals a substantial increase in IPO mispricing during the COVID-19 period, attributed to factors like heightened asymmetric information, reduced IPO volume, and decreased demand. Notably, the impact extends beyond the pandemic period, indicating a lasting effect on IPO mispricing. Sector-specific effects are observed, with all sectors, except Consumer Non-Cyclicals, showing significance in first-day returns. However, for 1-year returns, only the Finance and Energy sectors exhibit significance, with the latter slightly exceeding the 10% limit.
Conclusion- The study provides robust evidence of increased IPO mispricing during the COVID-19 pandemic, highlighting the persistent impact of the crisis on financial markets, as well as sector-specific nuances influencing mispricing levels.

Keywords: IPOs, mispricing, pandemic, initial returns, long-term returns
JEL Codes: C21, C23, D81

1. INTRODUCTION

IPO (Initial Public Offering) mispricing has been a topic of interest in the finance and economics literature for several decades. Researchers have examined various factors that contribute to IPO mispricing, the consequences of mispricing, and potential explanations for the phenomenon. IPO mispricing refers to the deviation of the offer price from the actual market value of newly issued shares. It is typically measured as the difference between the offer price and the first-day closing price or the initial return of the stock. Underpricing is a common form of IPO mispricing, where the offer price is set below the stock's market value. This results in a significant initial return for investors who are allocated shares in the IPO. Overpricing, on the other hand, occurs when the offer price is set above the stock's market value, leading to negative initial returns.

Numerous factors have been identified as contributing to IPO mispricing. These include:

- **a** **Information asymmetry:** Information disparities between issuers and investors can lead to mispricing. Investors may struggle to accurately assess the true value of the company due to limited information.
- **b** **Market conditions:** The overall state of the stock market can impact IPO mispricing. During bullish market conditions, demand for IPO shares tends to be higher, leading to greater underpricing.

c **Book-building process:** The process of setting the offer price through book-building involves interactions between issuers, underwriters, and institutional investors. These negotiations can result in mispricing.

d **Investor sentiment:** Market sentiment and investor behavior play a role in IPO mispricing. Positive sentiment can drive up demand for IPO shares, contributing to underpricing.

e **Reputation signaling:** Companies with higher reputations and better-known underwriters may deliberately underprice their IPOs to signal quality and attract investors.

f IPO mispricing has implications for various market participants:

a. **Issuers:** Underpricing can result in missed capital-raising opportunities, whereas overpricing can lead to a lack of investor interest in future offerings.

b. **Investors:** Those who receive IPO allocations benefit from underpricing, while subsequent investors may experience negative returns if the initial price is inflated.
c. **Underwriters:** Mispricing affects underwriters' reputation and their ability to accurately price future offerings.
d. **Market efficiency:** IPO mispricing challenges the efficient market hypothesis, suggesting that markets are not always fully reflective of fundamental values.

In March 2020, the World Health Organization declared the COVID-19 outbreak a pandemic, which led to a global economic downturn and heightened uncertainty in financial markets worldwide, including the IPO market. Researchers have examined the effects of the pandemic on IPO underpricing, exploring how market conditions, investor sentiment, and other factors have influenced the mispricing phenomenon.

Understanding the impact of the pandemic on IPO underpricing can provide insights into changes in market dynamics, investor behavior, and the overall functioning of the IPO market during times of crisis.

The long-term implications of the pandemic on IPO underpricing are still unfolding. The extent to which the changes observed during the pandemic will persist in the post-pandemic period remains uncertain. Further research is needed to evaluate the lasting effects and potential adjustments in IPO pricing dynamics as markets recover and stabilize.

This research paper specifically examines the impact of the pandemic on IPO activity, with a focus on the increase in information uncertainty. To measure this effect, we use underpricing and post-IPO stock return volatility as proxies.

2. LITERATURE REVIEW

Researchers have proposed several theories to explain IPO mispricing, including:

a. **Information-based explanations:** Information asymmetry, uncertainty, and the presence of informed traders contribute to mispricing.
b. **Behavioral finance theories:** Investor sentiment, herding behavior, and overreaction to news can drive mispricing.
c. **Signaling models:** Underpricing as a deliberate strategy to signal quality and attract investors.
d. **Institutional factors:** Regulatory requirements, underwriter reputation, and the role of investment banks in setting IPO prices.

2.1. Literature Review: IPO Underpricing

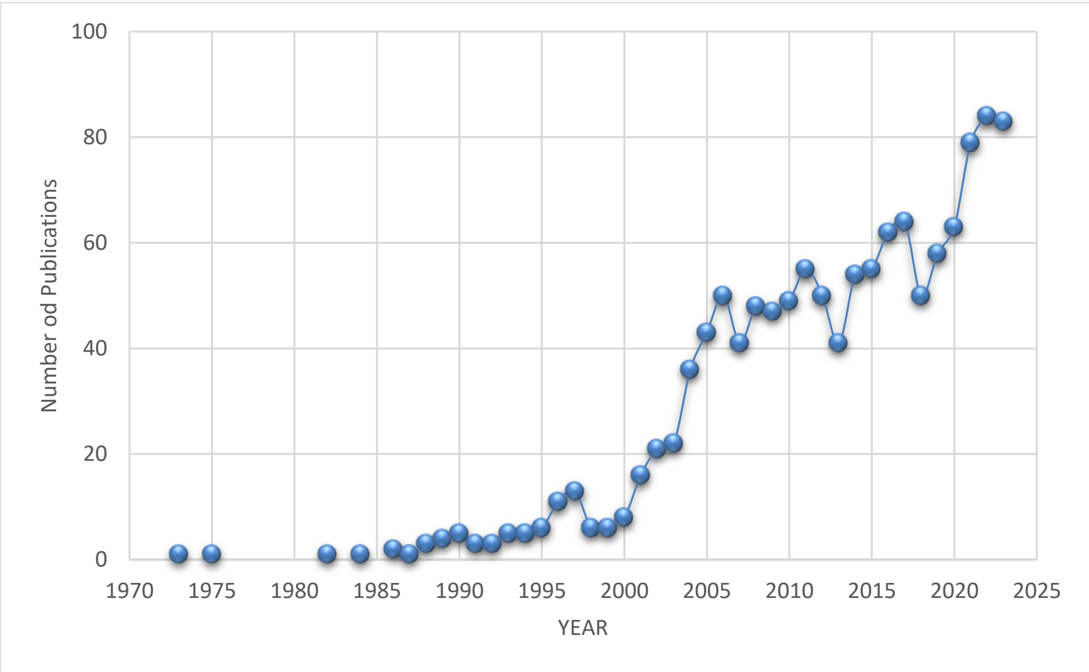
The phenomenon known as IPO underpricing is widely recognized as empirical evidence of high first-day returns for IPO firms. Since the Securities and Exchange Commission conducted a study in 1971, it has been evident that IPO stocks are initially priced lower than their subsequent sale price in the secondary market. This trend of IPO mispricing has persisted over time, as demonstrated by the frequency of studies analyzing the mispricing of IPOs in Figure 1.

In 1973, Dennis Logue (Logue, 1973) published the first academic paper on the subject of IPO mispricing. Titled "On the Pricing of Unseasoned Equity Issues: 1965-1969," the study examined 250 IPOs released between 1965 and 1969. Upon conducting a text search of the article, it is found that the terms "underpricing" and "overpricing" are mentioned six times and once, respectively. Notably, Logue referred to the IPOs as the "first public offering of common stock" instead of using the term "initial public offering."

The search yielded a second article, namely Ibbotson's (Ibbotson, 1975) study named "Price Performance of Common Stock New Issues." In this study, the author analyzed a sample of 120 IPOs released between 1960 and 1969. Ibbotson's findings revealed an average initial positive return of 11.4%. Throughout the article, he used the term "underpricing" to refer to mispricing, which was mentioned seven times.

After Ibbotson's work, numerous studies have confirmed the significant initial day returns for IPO stocks. These studies have put forth various explanations for underpricing, including information asymmetry among investors (Rock, 1986), the reputation of underwriters (Beatty et al., 1986) signaling by qualitative firms (Grinblatt and Hwang, 1989; Welch, 1989), and other factors. Several firm-level characteristics have also been identified as potential contributors to IPO underpricing, such as the pre-issuance uncertainty of the issuing firms (Beatty et al., 1986), uncertainty surrounding future growth opportunities, and firm age (Ritter, 1984; Loughran and Ritter, 2004), higher P/E ratios (Chen et al., 2004; Engelen, 2003), and the proportion of insider shareholding (Habib and Ljungqvist, 2001). These explanations are rooted in competitive theories like information asymmetry, signaling, market timing, agency theory, and others.

Figure 1: Frequency of Publications by years Related to "IPO Mispricing/Underpricing"



Source: Scopus Data; Filter: "IPO" & "Mispricing" and "IPO" & "Underpricing", As of 13/06/2023

Previous studies have revealed significant disparities in IPO mispricing, particularly when comparing the mean and median levels of mispricing. To illustrate, in Australia, Lee, Taylor, and Walter (1996) found a mean mispricing of 16.41% and a median mispricing of 10%. In China, Wang (2005) reported a mean mispricing of 271.90% and a median mispricing of 123.90%. In Canada, Kooli and Suret (2001) observed a mean mispricing of 20.57% and a median mispricing of 5%. Malaysia had a mean mispricing of 95.20% and a median mispricing of 76.50% according to Ahmad-Zaluki, Campbell, and Goodacre (2007). South Korea, as reported by Lin, Pukthuanthong, and Walker (2013), had a mean mispricing of 55.83% and a median mispricing of 36.19%. Taiwan, according to Lee and Kuo (2010), experienced a mean mispricing of 28.42% and a median mispricing of 17.89%. In the United States, Miller and Reilly (1987) found a mean mispricing of 9.87% and a median mispricing of 2.78%, whereas Chang et al. (2014) reported a mean mispricing of 13.36% and a median mispricing of 6.27% (Table 1).

Recent studies have primarily focused on the impact of sentimental data on prices when examining the mispricing/underpricing of IPOs. Ikeda (2022) found that IPO performance worsens as the average level of optimism and the divergence of investors' opinions increase. Another study revealed that media-connected firms receive more frequent and positive media coverage compared to their unconnected counterparts, resulting in reduced IPO underpricing. However, these media-connected firms experience poorer post-IPO market performance. Despite their better pre-IPO accounting performance, these firms engage in more earnings management with the support of their connected media (Chao et al., 2023). It has also been observed that companies with fluent names tend to be more profitable (Green and Jame, 2013), yet some investors seem to overlook this information. Consequently, stocks with fluent names generate higher abnormal returns relative to stocks with non-fluent names (Montone et al., 2023).

When an investment banker shares a social connection with a mutual fund manager, the manager is significantly more likely to (1) participate in the IPO, (2) submit bid prices above the average, and (3) achieve lower IPO returns. The influence of social relationships between investment bankers and fund managers is more prominent when the issuer has low accounting quality or when the underwriter is a small bank. Additional evidence suggests that these social connections between investment bankers and fund managers reduce IPO underpricing. In summary, the findings suggest that social interactions enable individual investment bankers to effectively exchange value-relevant information with IPO investors (Wu, 2023).

Table 1: Mispricing Across Time and Markets

Country	Study	Year	Period	Mean(%)	Median(%)
US	Miller & Reilly	1987	1982-1983	9,87	2,78
Hong Kong	McGuinness	1992	1980-1990	17,60	
US	Michaely & Shaw	1994	1984-1988	7,27	
Australia	Lee et al.	1996	1976-1989	16,41	10,00
Germany	Ljungqvist	1997	1970-1993	9,20	
Japan	Hamaoi Packer, Ritter	2000	1989-1995	15,70	
Malaysia	Jelic, Saadouni & Briston	2001	1980-1995	99,25	79,04
Canada	Kooli & Suret	2001	1991-1998	20,57	5,00
Belgium	Engelen	2003	1996-1999	14,32	
China	Wang	2005	1994-1999	271,90	123,90
UK	Hill & Wilson	2006	1991-1998	11,41	
Malaysia	Ahad-Zaluki et al.	2007	1990-2000	95,20	76,50
China	Guo & Brooks	2008	1984-2005	378,40	119,37
Turkiye	Kucukkocaoglu	2008	1993-2005	7,01	7,67
France	Chahine and Filatotchev	2008	1997-2000	22,70	9,80
Taiwan	Lee & Kua	2010	1997-2007	28,42	17,98
China	Lee, Hsieh & Yen	2010	1993-2005	144,42	108,16
Brazil	Boulton, Smart & Zutter	2010	2000-2004	13,70	13,90
China	Gao	2010	2006-2008	157,00	
India	Hopp & Dreher	2013	1988-2005	96,74	
Singapore	Hopp & Dreher	2013	1988-2005	22,43	
South Korea	Lin et al.	2013	1991-2011	55,83	36,19
New Zealand	Lin et al.	2013	1991-2011	17,95	31,51
Indonesia	Husnan, Hanafi & Muhandar	2014	1995-2012	23,06	15,42
Greece	Autore et al.	2014	1998-2008	58,30	
Taiwan	Chang, Chen, Kao & Wu	2014	2006-2010	50,60	34,00
US	Chang et al.	2014	2006-2010	13,36	6,27
Australia	Bird & Ajmal	2016	1995-2013	25,51	8,62

Furthermore, research indicates a significant relationship between board members and underpricing. A board with a strong reputation and extensive experience tends to help companies reduce uncertainty and decrease IPO underpricing in China (Wang et al., 2023). Additionally, firms without venture capital support exhibit a 2.4% lower IPO underpricing effect compared to firms with venture capital support.

2.2. Literature Review: IPO Underpricing during COVID-19

Existing studies on equity, debt, and derivative markets demonstrate that the severity of the COVID-19 outbreak, coupled with government policy measures, resulted in higher levels of volatility and uncertainty (Baig et al., 2021; Baig et al., 2022; Zaremba et al., 2021). Several studies have analyzed the impact of COVID-19 on IPO underpricing. Findings suggest mixed effects, with some studies reporting an increase in underpricing, while others find a decrease or no significant change. The variations in results may be attributed to differences in sample periods, regional markets, and the severity of the pandemic's impact. However, there is a consensus that the pandemic and the government initiatives that preceded it have had a negative impact on the quality and effectiveness of markets and institutions, due to the increased uncertainty it has caused. Based on previous market observations and IPO theories, it is anticipated higher levels of underpricing and volatility for IPOs that were issued during the pandemic. This is because increased uncertainty is typically associated with higher levels of IPO underpricing, and it is natural to expect greater underpricing during times of economic distress (Beatty & Ritter, 1986).

Government intervention and stimulus measures implemented in response to the pandemic could have influenced IPO underpricing. These measures aimed to stabilize financial markets and support economic recovery. The provision of liquidity and favorable market conditions resulting from government actions may have positively impacted IPO underpricing.

The COVID-19 pandemic compelled governments to swiftly adapt and take action to protect both the health and the economy of their respective countries. However, there were notable variations in how different countries handled the crisis, resulting in divergent outcomes. Therefore, our paper focuses on analyzing the IPO changes in Turkiye, to identify the underlying factors behind these changes. It is apparent that informational shocks and government responses related to the pandemic have had a significant impact on the IPO markets, and our research aims to shed light on these effects.

Table 2: First-Day Returns: 1992-2016

Country	# of IPO	First-Day Returns (%)
Australia	1138	0,18
Brazil	88	0,06
Canada	193	0,21
China	1533	0,57
Denmark	26	0,02
France	95	0,04
Germany	35	0,02
Greece	28	0,16
India	363	0,29
Indonesia	103	0,34
Italy	63	0,18
Japan	1913	0,6
Mexico	28	0,03
Poland	64	0,35
Russia	31	0,56
Saudi Arabia	102	2,13
South Africa	29	0,17
South Korea	689	0,37
Sweden	57	0,06
Turkiye	24	0,06
United Kingdom	404	0,27
USA	3206	0,24
Average		*0,38*
Median		*0,14*
Max		*16,8*
Min		*-0,89*
Developed Countries	7191	
Average		*0,32*
Median		*0,1*
Max		*13,5*
Min		*-0,89*
Developing Countries	3021	
Average		*0,51*
Median		*0,32*
Max		*16,8*
Min		*-0,88*

Source: Jamaani, F. & Abdullahi Dahir A. (2021)

2.3. Literature Review: Underpricing in the Turkish IPO Market

The first study conducted on the IPO market in Turkiye emerged in the year 2000 (Kiymaz, 2000). In his research, he took 163 firms listed and traded on the Istanbul Stock Exchange between 1990 and 1996. This research again focused on initial (first trade date) return and the results show that the Turkish IPOs are underpriced on the initial trading day by an average of 13.1%. In his research, he also made a sub-sector analysis for IPO underpricing.

Then in 2006, M. Banu Durukan (Durukan, 2006) showed that the relationship between ownership structure and underpricing is weak and Mehmet Orhan (Orhan, M, 2006) investigated underpricing on the Istanbul Stock Exchange for 18 sectors for the period 1996–2005. His analysis showed that half of the sectors provided a negative first-day return.

Other research regarding Turkish IPO Market Underpricing is also mainly concentrated on “Initial Returns” and “Ownership” and commitment period. Finally, in 2023, there is research (Ilbasmış, M., 2023) related to the effect of uncertainty on IPO underpricing, short-term performance after IPO, and hot-and-cold-IPO market cycles. Empirical results show that short-term market-adjusted abnormal returns of IPO firms during the pandemic are much larger than those before the pandemic.

3. THEORETICAL FRAMEWORK

3.1. Underpricing as a Proxy for Information Uncertainty

Underpricing is a common phenomenon in IPOs, often associated with information asymmetry between issuers and investors. In times of uncertainty, such as during the pandemic, information asymmetry is likely to be exacerbated. Thus, underpricing can be utilized as a proxy for induced information uncertainty caused by COVID-19.

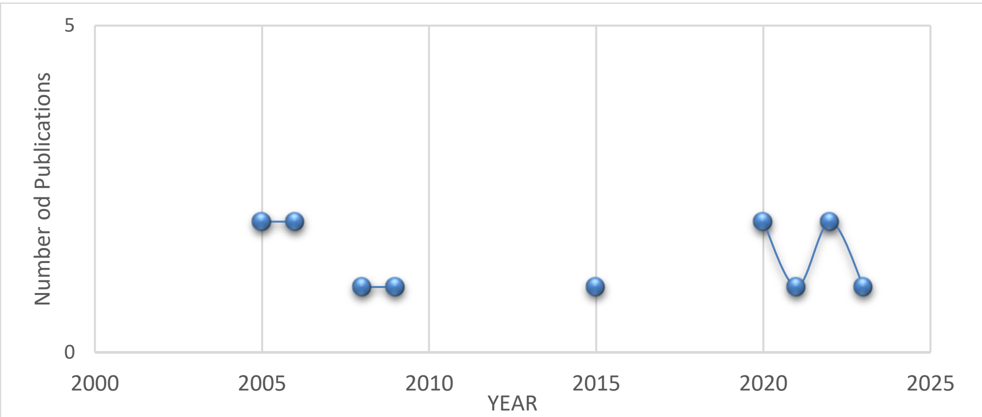
3.2. Volatility as a Proxy for Information Uncertainty

Volatility measures the fluctuations in stock prices and reflects the uncertainty in the market. Increased volatility during the pandemic can indicate higher information uncertainty, as investors struggle to assess the impact of COVID-19 on firms' prospects. Thus, volatility can serve as a proxy for induced information uncertainty caused by the pandemic.

4. MOTIVATION & OBJECTIVES

The primary objective of this study is to determine whether the COVID-19 pandemic has had a significant impact on IPO mispricing in the Turkish IPO market in the longer run, which means up to 1 year. As is seen in the Literature Review, most of the research was made by the comparison of first-day returns as the definition of “IPO mispricing” and there were a limited number of research had been done for the Turkish IPO market (Figure 2).

Figure 2: Frequency of Publications by years Related to IPO Mispricing/Underpricing in “Turkish Market”



Source: Scopus Data; Filter: “IPO” & “Mispricing” and “IPO” & “Underpricing”, as of 17/05/2023

This will be achieved through the following specific objectives:

a. To analyze the IPOs that were listed on the Borsa Istanbul between January 2010 and December 2022.

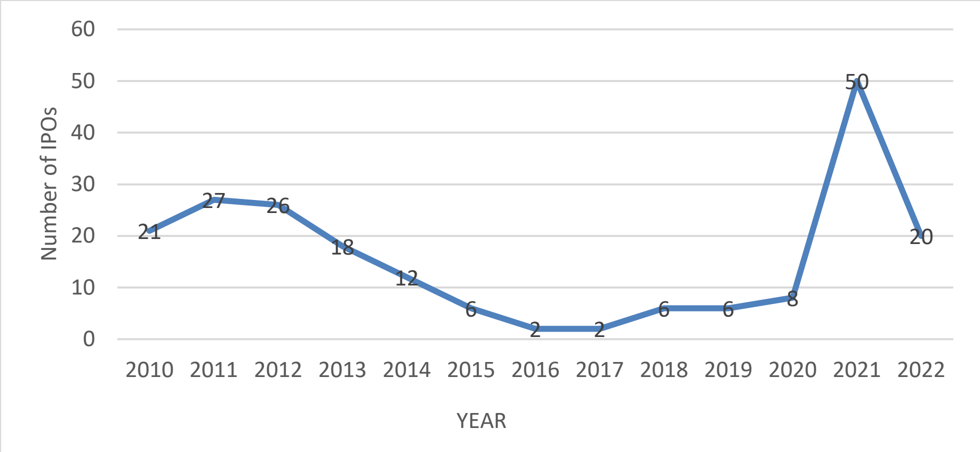
b. To examine the pricing of these IPOs to determine if there was any significant mispricing during this period for the long run (up to 1 year).

c. To identify the factors contributing to IPO mispricing in the Turkish market during the pandemic.

d. To examine the influence of COVID-19-related factors on investor sentiment and IPO pricing in Turkiye.

e. To propose potential measures or strategies to mitigate IPO mispricing in the face of future crises.

Figure 3: Frequency of IPOs by years in “Turkish Market”



Source: Borsa Istanbul (Istanbul Stock Exchange)

Table 3: Frequency of IPOs by sectors in "Turkish Market"

Sector	Pre-COVID	During&After-COVID	TOTAL
Financials	15	6	21
Basic Materials	16	12	28
Real Estate	16	3	19
Utilities	5	8	13
Consumer Non-Cyclicals	17	8	25
Industrials	23	12	35
Consumer Cyclicals	21	10	31
Technology	6	7	13
Healthcare	5	4	9
Energy	3	7	10
TOTAL	**127**	**77**	**204**

5. DATA & METHODOLOGY

5.1. Data Collection

The study uses a quantitative research approach, and data will be gathered on IPOs launched in the Turkish market during the period from January 2010 to December 2022 from the Borsa Istanbul website, company prospectuses, and financial news reports. BIST-ALL, BIST-100, and BIST-Sector returns have also been included in the research for the determination of the actual return performances of IPOs for the relevant time period. Additionally, pandemic-related data such as stock returns, offer prices, and market conditions.

5.2. IPO Initial Return Calculation

The study will employ regression analysis to determine whether there is a significant relationship between the COVID-19 pandemic and IPO mispricing. The analysis will also control for other variables such as market conditions, company size, and industry sector. The first step is calculating the initial returns of IPOs as a measure of mispricing. Then compare the IPO offer price with the closing price on the first day, on the week-end, on the month-end, on the 3-month-end, on the 6-month-end, and year-end trading.

$Initial\ Return_i = \frac{CP_i - AOP}{CP_i}$ where CP_i is the closing price on the trading date and AOP is the Adjusted-Offer-Price. (1)

Adjusted-Offer-Price (AOP) is the retroactively corrected version of the initial public offering (IPO) price due to subsequent capital increases through paid-in and bonus share issuances, as well as dividend payments by the company. So,

$AOP = OP\ x\ PAF$ where OP is the Offer-Price and PAF is the Price-Adjustment-Factor. (2)

$Adjusted\ Initial\ Return_i = Initial\ Return_i -\ MR_i$, where MR_i is the Market Return for the related time period. (3)

For this study, for market returns, the "Adjusted Returns" calculation includes not only the BIST-100 but also the BIST-ALL, calculated by considering all stocks, and sector-specific BIST-Sector indices.

5.3. Empirical Analysis

Utilize quantitative techniques such as event study methodology, regression analysis, and statistical modeling to investigate the relationship between COVID-19 and IPO mispricing. Explore factors such as market sentiment, industry characteristics, IPO characteristics, and pandemic-related variables.

The study involves employing two methods: the traditional ordinary least squares (OLS) and the more appropriate quantile regression (QR). The OLS method focuses on assessing the average impact of independent variables on mispricing, disregarding the unexplored latent characteristics of the mispricing distribution, especially when it deviates from a normal distribution. In contrast, the QR method allows us to investigate the diverse effects of independent variables at different levels of mispricing due to the asymmetric distribution of returns. By employing the QR approach, it can be identified the specific impacts of each variable on IPOs within particular levels of mispricing. This robust method is capable of handling potential heterogeneity in the distribution, which was observed in the sample. The QR method also facilitates the examination of various segments of the mispricing distribution, including the tail regions, enabling a comparison of the effects of explanatory factors on IPOs that range from extremely overpriced to extremely underpriced.

5.4 Variables Used in Equations

Y1: Return on first trade date
Y2: Return on first week
Y3: Return on first month
Y4: Return on Month-3
Y5: Return on Month-6
Y6: Return on first year

SEC1	Basic Materials
SEC2	Consumer Cyclicals
SEC3	Consumer Non-Cyclicals
SEC4	Energy
SEC5	Financials
SEC6	Healthcare
SEC7	Industrials
SEC8	Real Estate
SEC9	Technology
SEC10	Utilities

$DYEAR_t$: Dummy variable for the year of IPO (t = 2010, 2011, …, 2022)
$DSEC_i$: Dummy variable for the sector/industry of Equity
P_0: Initial Return of the equity on a specific time period (First trade date, first week, first month, third month, sixth month, and first year)
P_{ALL}: Initial Return of the overall stock exchange on a specific time period (First trade date, first week, first month, third month, sixth month, and first year)
P_{100} : Initial Return of the BIST 100 (Borsa Istanbul 100 index) on a specific time period (First trade date, first week, first month, third month, sixth month, and first year)
P_{SEC}: Initial Return of the related Equity's Sector Index on a specific time period (First trade date, first week, first month, third month, sixth month, and first year)

5.5. Hypothesis and Equations

This research aims to analyze below hypothesis:

H01: In the long run (1-year) there is mispricing(underpricing) in Turkish IPO Market

H02: The COVID-19 pandemic has led to increased IPO mispricing in the Turkish market.

Based on these hypotheses, in the first section of the research, clarity will be provided regarding whether there is an error in the pricing of IPOs in the long term. While conducting this study, on the one hand, returns will be taken into account, and on the other hand, the effects of year and sector factors will be eliminated. In the second section, the impact of the COVID-19 period on this pricing will be examined based on the final values obtained.

For our research's specific analysis, data characteristics, and modeling techniques being employed, it is used Log returns, or logarithmic returns, which are commonly used in financial analysis, especially when analyzing equity investments, for several reasons:

- **Stationarity:** Log returns help stabilize the variance of the returns over time, making them more suitable for statistical analysis. In financial markets, asset prices often exhibit volatility clustering, where periods of high volatility are followed by periods of low volatility. Log returns help to mitigate this issue and make the data more stationary, which is a key assumption in many statistical models.
- **Symmetry:** Logarithmic returns have a symmetric distribution, which makes them easier to work with in mathematical and statistical models. This symmetry assumption simplifies many modeling techniques, such as linear regression.
- **Interpretability:** Log returns are additive over time. This means that if you have a series of log returns for different time periods, you can sum them to get the overall return for the entire period. This property is not true for simple percentage returns.
- **Compounding:** Log returns are particularly useful for understanding the effects of compounding. When you invest in an asset, your wealth grows or declines exponentially over time. Log returns allow you to easily track this compounding effect and calculate the final wealth based on a series of returns.
- **Normality assumption:** Many financial models assume that returns follow a normal distribution. While this assumption is not always valid, log returns tend to be closer to a normal distribution compared to simple percentage returns, making them more amenable to these models.
- **Comparability:** Log returns make it easier to compare the performance of different assets or investments over various time periods because they are additive and have consistent units (e.g., natural logarithms of wealth ratios).
- **Mathematical properties:** Logarithmic returns are mathematically convenient for various financial calculations, such as risk assessment (e.g., calculating volatility) and portfolio optimization.

Since the dummy variables DYEAR and DSEC are included in the equations, a constant term is not used in the equations to avoid the perfect **multicollinearity** problem.

Equations for IPO Mispricing and COVID Impact

Y1 First Trade Date

$$\Delta LnP_0 = COVID + \beta_1 \Delta LnP_{ALL} + \beta_2 \Delta LnP_{100} + \beta_3 \Delta LnP_{SEC} + \sum_{t=2010}^{2022} DYEAR_t + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (4)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$

Y2 Week 1

$$\Delta LnP_0' = COVID + \Delta LnP_0 + \beta_1 \Delta LnP_{ALL}' + \beta_2 \Delta LnP_{100}' + \beta_3 \Delta LnP_{SEC}' + \sum_{t=2010}^{2022} DYEAR_t + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (5)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$
H_0: $\alpha_1=0$

Y3 Month 1

$$\Delta LnP_0'' = COVID + \alpha_1 \Delta LnP_0 + \alpha_2 \Delta LnP_0' + \beta_1 \Delta LnP_{ALL}'' + \beta_2 \Delta LnP_{100}'' + \beta_3 \Delta LnP_{SEC}'' + \sum_{t=2010}^{2022} DYEAR_t + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (6)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$
H_0: $\alpha_1= \alpha_2=0$

Y4 Month 3

$$\Delta LnP_0''' = COVID + \alpha_1 \Delta LnP_0 + \alpha_2 \Delta LnP_0' + \alpha_3 \Delta LnP_0'' + \beta_1 \Delta LnP_{ALL}''' + \beta_2 \Delta LnP_{100}''' + \beta_3 \Delta LnP_{SEC}''' + \sum_{t=2010}^{2022} DYEAR_t + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (7)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$
H_0: $\alpha_1= \alpha_2= \alpha_3=0$

Y5 Month 6

$$\Delta LnP_0'''' = COVID + \alpha_1 \Delta LnP_0 + \alpha_2 \Delta LnP_0' + \alpha_3 \Delta LnP_0'' + \alpha_4 \Delta LnP_0''' + \beta_1 \Delta LnP_{ALL}'''' + \beta_2 \Delta LnP_{100}'''' + \beta_3 \Delta LnP_{SEC}'''' + \sum_{t=2010}^{2022} DYEAR_t + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (8)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$
H_0: $\alpha_1= \alpha_2= \alpha_3= \alpha_4=0$

Y6 Year 1

$$\Delta LnP_0''''' = COVID + \alpha_1 \Delta LnP_0 + \alpha_2 \Delta LnP_0' + \alpha_3 \Delta LnP_0'' + \alpha_4 \Delta LnP_0''' + +\alpha_5 \Delta LnP_0'''' + \beta_1 \Delta LnP_{ALL}''''' + \beta_2 \Delta LnP_{100}''''' + \beta_3 \Delta LnP_{SEC}''''' + \sum_{t=2010}^{2022} DYEAR_t \ldots + \sum_{i=1}^{10} DSEC_i + \varepsilon_j \quad (9)$$

H_0: $COVID\ has\ a\ significant\ impact\ on\ IPOs$
H_0: $\beta_1=\beta_2=\beta_3=0$
H_0: $\alpha_1= \alpha_2= \alpha_3= \alpha_4= \alpha_5=0$

6. EMPIRICAL RESULTS

6.1. Delisted Companies

Before starting the empirical results, it would be more useful to provide more detailed information about the IPO data used in terms of evaluating the results. As mentioned before, the study examines the data of a total of 204 companies for the relevant periods between 2010 and 2022. However, a total of 20 companies are currently delisted from Borsa Istanbul. It is planned to conduct a separate study on the reasons for this (Figure 4 & Table 4).

Figure 4: Enlisted IPOs by years in "Turkish Market"

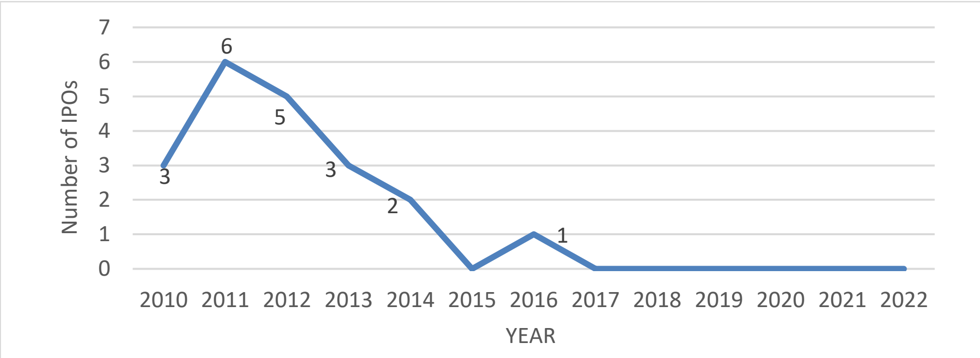


Table 4: Frequency of Delisted IPOs by Sectors

Sector	# of Companies
Financials	2
Basic Materials	2
Real Estate	1
Utilities	0
Consumer Non-Cyclicals	4
Industrials	4
Consumer Cyclicals	4
Technology	1
Healthcare	1
Energy	1
TOTAL	**20**

6.2 Further Analysis

The pandemic has led to increased uncertainty and volatility in financial markets, which could have resulted in mispricing. The study finds evidence of increased IPO mispricing during the Covid-19 pandemic. Additionally, the study may reveal differences in mispricing levels before and after the outbreak of the pandemic.

The results include:

- As seen in Table 5 and in Figure 5, statistical results present a detailed analysis of returns, BIST-ALL adjusted returns, BIST-100 adjusted returns, and BIST-Sector adjusted returns for three different periods: Full Period (n=204), Pre-Covid (n=127), and During-After Covid (n=77).
    - Full Period (n=204):
        - The mean returns range from 6% to 244%, indicating significant variation across different time intervals.
        - The standard deviations are also large, suggesting considerable dispersion in returns.
        - Minimum and maximum values show the range of returns, with some extreme values.
        - Positive kurtosis values indicate relatively peaked distributions.
        - Positive skewness values indicate a skew to the right in the distribution.
    - Pre-Covid (n=127):
        - Similar to the Full Period, there is variation in mean returns and standard deviations across different time intervals.
        - Minimum and maximum values show the range of returns during the pre-COVID period.
        - Positive kurtosis values suggest relatively peaked distributions.
        - Positive skewness values indicate a skew to the right in the distribution.
    - During-After Covid (n=77):
        - The mean returns range from 7% to 244%, showing variation across different time intervals.
        - Standard deviations are relatively high, indicating significant dispersion in returns.
        - Minimum and maximum values illustrate the range of returns during and after the Covid period.
        - Positive kurtosis values suggest relatively peaked distributions.
        - The skewness values vary, indicating different skewness in the distribution.

  In summary, there are significant differences in Means and Standard Deviations in “Adjusted Market Returns” which means IPO companies have higher returns compared to the market or in other words, IPOs in general were underpriced during offerings.

- COVID impact tested for each equation and the results show that we cannot reject the H0, which means COVID-19 pandemics have a significant impact on IPO results (Table 6). For Equation 1, the variable “COVID” has a negative coefficient (-0.059) with a significant probability (0.009), suggesting that it is associated with a decrease in the dependent variable. For Equation 2, “COVID” has a strong negative impact (-1.219) with a highly significant probability (0.000), indicating a significant association with a decrease in the dependent variable. For Equation 3, “COVID” has a positive coefficient (1.142) with a significant probability (0.001). For Equation 4, “COVID” has a negative coefficient (-2.122) with a significant probability (0.003). For Equation 5, “COVID” has a positive coefficient (2.018) with a significant probability (0.001) and finally in Equation 6, “COVID” has a very negative coefficient (-6.113) with a highly significant probability (0.001). This result is predictable since, the impact of COVID-19, including increased asymmetric information, reduced IPO volume, and decreased demand, is expected to result in a higher rate of “IPO underpricing” in IPOs conducted during the COVID-19 period compared to the periods before and after the pandemic.
- H0: $\beta1 = \beta2 = \beta3 = 0$ also tested for each equation and when the H0 cannot be rejected the equation is estimated as the restricted form.
- “Y3” (Month-End Returns) has a positive coefficient (0.782) with a strong significant probability (0.001) in Equation 4 and “Y1” (First Date Returns) has a positive coefficient (3.036) with a significant probability (0.032) in Equation 6.
- While all index values are insignificant for Equation 4, we see that only the Borsa Istanbul-All Index is significant in our equation in Equation 9, that is when we consider 1-year returns. Due to the broadened definition of “IPO underpricing” in this study (considering not only initial day returns but also returns for various periods, including up to one year), the previously observed high values of “IPO underpricing” in earlier studies are lower.

- Equation-4:
  - ΔLnP_ALL has a coefficient of 0.832 with a probability of 0.823. The coefficient is positive, suggesting a positive relationship with the dependent variable.
  - Other variables in the equation are not significantly different from zero, as their p-values are greater than the conventional significance level of 0.05.
- Equation-5:
  - ΔLnP_100 has a negative coefficient (-1.026), but the probability value is 0.759, indicating that it is not statistically significant at the 0.05 level.
  - The variable with the lowest p-value in this equation is ΔLnP_SEC with a coefficient of 0.109 and a p-value of 0.776, suggesting it is not a significant predictor.
- Equation-6:
  - ΔLnP_ALL has a substantial coefficient of 16.600 with a highly significant probability of 0.001, indicating a strong positive relationship with the dependent variable.
  - Other variables in the equation do not appear to be statistically significant, as their p-values are greater than 0.05.

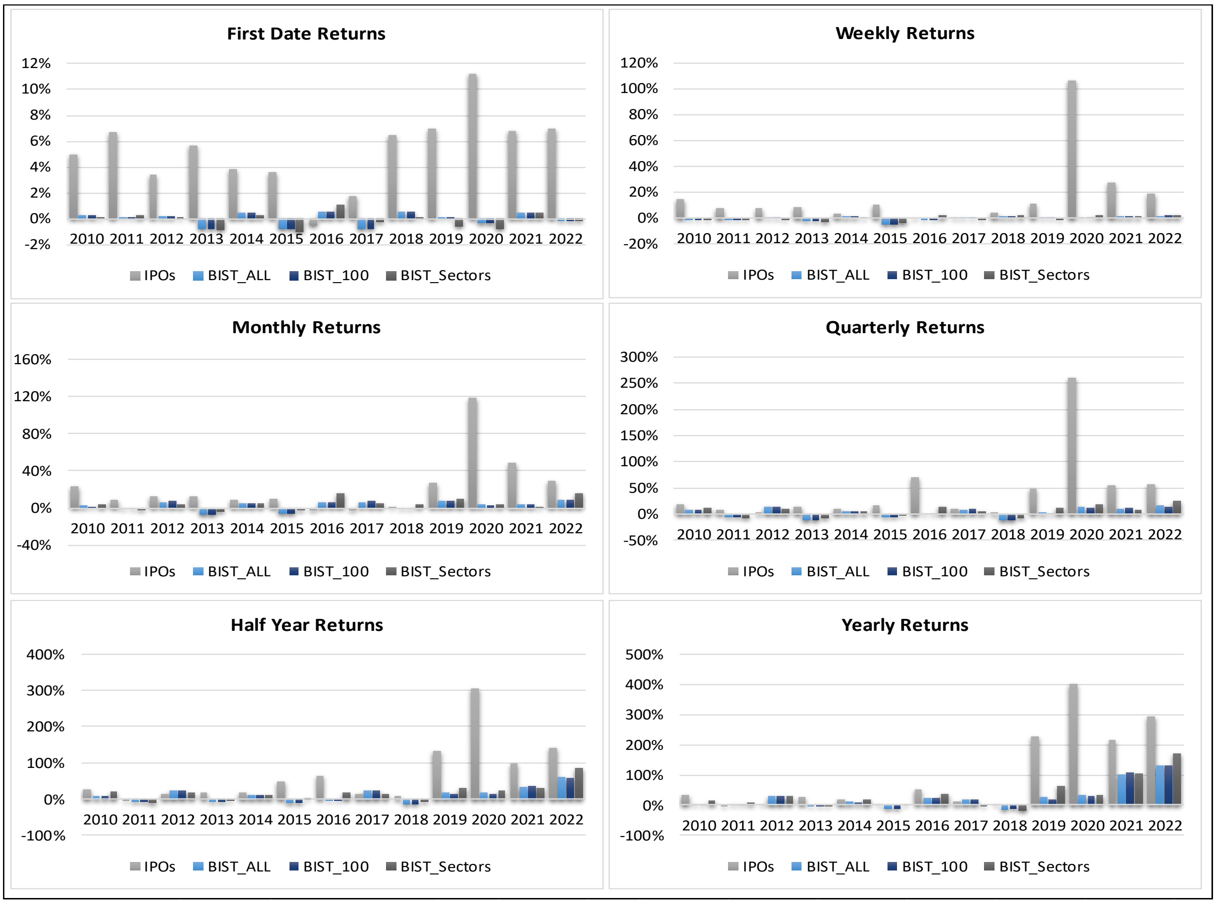
Table 5: Descriptive Statistics of IPO Returns in "Turkish Market"

	Returns						BIST-ALL Adjusted Returns						BIST-100 Adjusted Returns						BIST-Sector Adjusted Returns					
	D1	W1	M1	M3	M6	Y1	D1	W1	M1	M3	M6	Y1	D1	W1	M1	M3	M6	Y1	D1	W1	M1	M3	M6	Y1
Full Period (n=204)																								
Mean	6%	18%	27%	36%	62%	110%	6%	18%	25%	31%	45%	66%	6%	18%	24%	31%	45%	65%	6%	18%	24%	30%	41%	58%
Std	8%	35%	55%	87%	131%	234%	9%	35%	55%	85%	125%	212%	9%	35%	55%	85%	126%	213%	9%	34%	54%	84%	124%	213%
Min	-17%	-29%	-35%	-100%	-59%	-75%	-17%	-23%	-38%	-96%	-86%	-110%	-17%	-23%	-38%	-96%	-88%	-119%	-17%	-23%	-55%	-99%	-156%	-354%
Max	41%	240%	314%	749%	895%	1543%	40%	241%	323%	726%	878%	1381%	40%	241%	323%	726%	878%	1376%	41%	226%	319%	741%	893%	1343%
Median	5%	4%	8%	12%	18%	41%	5%	5%	7%	9%	8%	1%	5%	5%	7%	9%	7%	0%	5%	4%	7%	12%	3%	0%
Kurtosis	1.08	8.37	5.81	26.10	16.15	11.82	1.30	8.69	6.36	26.36	18.68	13.19	1.31	8.71	6.30	26.12	18.37	13.03	1.36	7.46	6.38	28.81	19.96	12.13
Skewness	0.66	2.36	2.22	4.12	3.36	3.16	0.71	2.37	2.27	4.15	3.61	3.39	0.71	2.37	2.26	4.13	3.57	3.37	0.76	2.26	2.24	4.30	3.73	3.13
Pre-Covid (n=127)																								
Mean	5%	10%	13%	15%	24%	31%	5%	11%	12%	14%	20%	22%	5%	11%	12%	14%	20%	23%	5%	11%	12%	13%	16%	16%
Std	10%	30%	40%	57%	74%	126%	10%	31%	40%	58%	74%	123%	10%	31%	40%	58%	75%	125%	10%	30%	40%	55%	70%	119%
Min	-17%	-29%	-35%	-100%	-59%	-75%	-17%	-23%	-38%	-96%	-86%	-100%	-17%	-23%	-38%	-96%	-88%	-101%	-17%	-23%	-38%	-99%	-106%	-203%
Max	41%	240%	231%	459%	398%	1020%	40%	241%	222%	471%	404%	983%	40%	241%	221%	473%	410%	995%	41%	226%	228%	441%	368%	952%
Median	1%	2%	3%	0%	2%	-8%	2%	3%	2%	-1%	2%	-9%	2%	3%	2%	-1%	2%	-8%	1%	3%	0%	0%	-2%	-16%
Kurtosis	0.60	26.50	9.29	28.16	6.35	30.94	0.78	26.17	8.07	29.86	6.19	30.07	0.79	26.11	7.96	29.71	6.24	29.86	0.77	22.98	8.91	27.92	5.68	30.78
Skewness	0.95	4.31	2.71	4.05	2.19	4.69	0.97	4.26	2.54	4.14	2.03	4.59	0.97	4.25	2.53	4.13	2.03	4.57	0.99	4.03	2.63	3.95	1.98	4.55
During-After Covid (n=77)																								
Mean	7%	31%	49%	71%	126%	244%	7%	29%	44%	59%	88%	139%	7%	29%	44%	58%	86%	135%	7%	29%	44%	57%	83%	126%
Std	5%	38%	68%	112%	173%	304%	5%	38%	69%	111%	173%	294%	5%	38%	69%	112%	173%	295%	5%	38%	68%	112%	174%	300%
Min	-10%	-25%	-28%	-32%	-43%	-15%	-9%	-23%	-34%	-44%	-72%	-110%	-9%	-23%	-35%	-49%	-78%	-119%	-9%	-23%	-55%	-89%	-156%	-354%
Max	10%	135%	314%	749%	895%	1543%	15%	142%	323%	726%	878%	1381%	15%	141%	323%	726%	878%	1376%	16%	142%	319%	741%	893%	1343%
Median	10%	19%	32%	38%	61%	126%	9%	17%	31%	27%	32%	27%	9%	17%	31%	27%	30%	21%	9%	17%	31%	33%	29%	36%
Kurtosis	1.79	- 0.21	2.70	17.53	8.92	5.02	1.13	- 0.14	3.32	17.11	9.97	5.04	1.03	- 0.15	3.24	16.90	9.78	4.97	1.34	- 0.08	3.25	18.32	10.16	4.28
Skewness	- 1.62	0.85	1.59	3.49	2.67	2.21	- 1.32	0.84	1.68	3.44	2.84	2.25	- 1.30	0.84	1.67	3.42	2.81	2.24	- 1.27	0.86	1.62	3.54	2.85	1.96

Note: The table presents a summary statistic of the dependent variable underpricing. The sample is divided into three categories: (1) the average of all IPOs in the full period of time. (2) IPOs issued pre-COVID-19, meaning IPOs before March 2020. (3) IPOs issued during IPO, IPOs after March 2020. It includes simple returns and marked adjusted returns for each period. We include the market adjusted Return, which is adjusted for interim market movement, by using the IPO-specific indexes (BIST-All, BIST-100, and BIST-Sectors).

- Equation-7:
  - ΔLnP_SEC has a negative coefficient (-0.226) with a probability of 0.516, indicating that it is not statistically significant.
  - Other variables in the equation do not appear to be statistically significant.
- Equation-8:
  - ΔLnP_ALL has a positive coefficient of 7.681 with a probability of 0.032, indicating a statistically significant positive relationship.
  - ΔLnP_100 also has a negative coefficient of -7.560 with a probability of 0.027, suggesting a statistically significant negative relationship.
  - Other variables are not statistically significant.
- Equation-9:
  - ΔLnP_ALL has a positive coefficient of 8.220 with a probability of 0.063, suggesting a positive relationship, but the p-value is slightly above the conventional significance level.
  - Other variables in the equation do not appear to be statistically significant.

Figure 5: Average Returns of IPOs by years in "Turkish Market" compared with BIST-ALL, BIST-100, and BIST-Sector



- In addition to this, it can be seen that the dummy variables D2020, D2021, and D2022 are also significant in all equations. These results had already emerged while conducting the COVID-19 analysis. However, it is understood from these results that the impact of COVID continues not only in the relevant period but also in 2022 (Table 6).
- Considering the first-day returns of IPOs, all sector values except SEC 3 (Consumer Non-Cyclicals) are significant (SEC 3 has a non-significant p-value (0.142)), while based on 1-year returns, it is possible to say that the effect of only SEC5 (Financials) and SEC4 (Energy), which is slightly above the 10% limit, continues. Particularly in recent times, there has been an increasing demand for energy companies, which may lead to higher levels of "IPO underpricing" in specific IPOs, especially those conducted in these sectors.
    - For Equation 1 Except SEC 3, all sectors have significant p-values
    - For Equation 2 SEC 3 and SEC 7 have significant p-values (0.018;0.042). SEC 2 and SEC 4 are also considered significant since the p-values are 10% level.
    - For Equation 3, only SEC 2 has a significant p-value (0.024)
    - For Equation 4, SEC 2 (0.018) and SEC 8 (0.050) has significant p-values.
    - For Equation 5, only SEC 6 has a significant p-value (0.005)
    - For Equation 6, none of the sectors have a significant p-value in a 95% confidence interval. But Sec 4 and SEC 5 have a significant 90% confidence interval.

Table 6: Results of Equations – IPO Mispricing and COVID Impact

	Equation-1			Equation-2			Equation-3			Equation-4			Equation-5			Equation-6		
Variable	Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.	
COVID	-0.059	0.009		-1.219	0.000		1.142	0.001		-2.122	0.003		2.018	0.001		-6.113	0.001	
Y1				1.770	-		-0.150	0.607		-0.854	0.280		-0.077	0.897		3.036	0.032	
Y2							1.258	-		0.217	0.553		-0.543	0.104		-0.830	0.134	
Y3										0.782	0.001		-0.057	0.430		0.373	0.204	
Y4													1.281	-		-0.187	0.435	
Y5																1.284	-	
∆LnP_ALL	0.832	0.823		5.902	0.096	**	16.600	0.001	***	-0.156	0.987		7.681	0.032	***	8.220	0.063	**
∆LnP_100	-1.026	0.759		-5.838	0.145		-15.653	0.000	***	1.096	0.909		-7.560	0.027	***	-5.663	0.202	
∆LnP_SEC	0.240	0.709		0.663	0.549		0.109	0.776		-0.226	0.516		0.451	0.036	***	-0.010	0.964	
D2011	0.009	0.038	***	-0.101	0.000	***	0.049	0.212		0.103	0.282		0.033	0.636		0.142	0.723	
D2012	-0.024	0.000	***	-0.050	0.001	***	0.046	0.118		-0.191	0.111		0.179	0.021	***	-0.621	0.149	
D2013	0.003	0.558		-0.050	0.019	***	0.062	0.215		0.178	0.040	***	0.166	0.011	***	0.247	0.562	
D2014	-0.010	0.181		-0.085	-	***	0.009	0.766		0.033	0.276		0.126	0.012	***	-0.179	0.710	
D2015	-0.024	0.060	**	0.009	0.765		-0.022	0.714		0.101	0.073	**	0.369	-	***	-0.143	0.817	
D2016	-0.055	0.000	***	-0.060	0.023	***	0.034	0.577		-0.006	0.947		-0.293	0.128		-0.244	0.859	
D2017	-0.035	0.008	***	-0.059	0.093	**	-0.025	0.378		0.186	0.003	***	0.089	0.162		-0.261	0.789	
D2018	0.009	0.369		-0.136	0.000	***	-0.080	0.196		0.177	0.140		0.197	0.022	***	0.328	0.598	
D2019	0.010	0.206		-0.091	0.027	***	-0.062	0.281		0.199	0.157		0.236	0.075	**	-0.853	0.238	
D2020	0.110	0.000	***	1.833	-	***	-1.353	0.001	***	3.345	-	***	-1.786	0.002	***	5.163	0.006	***
D2021	0.072	0.005	***	1.319	0.000	***	-0.943	0.005	***	2.169	0.010	***	-1.413	0.016	***	4.935	0.006	***
D2022	0.072	0.004	***	1.219	0.001	***	-1.078	0.002	***	2.324	0.001	***	-1.750	0.003	***	3.785	0.041	***
SEC1	0.028	0.104		0.012	0.732		-0.037	0.614		-0.028	0.553		-0.060	0.583		0.031	0.936	
SEC2	0.073	0.000	***	0.064	0.093	**	-0.137	0.024	***	-0.076	0.472		-0.122	0.251		-0.420	0.299	
SEC3	0.034	0.142		0.104	0.018	***	0.045	0.691		-0.244	0.018	***	-0.043	0.385		-0.385	0.325	
SEC4	0.039	0.025	***	0.074	0.103		0.080	0.407		0.226	0.080	**	-0.125	0.692		0.901	0.102	
SEC5	0.078	0.048	***	0.045	0.430		-0.067	0.287		0.115	0.151		-0.058	0.661		-0.702	0.089	**
SEC6	0.077	0.009	***	0.046	0.330		0.087	0.562		-0.134	0.232		-0.336	0.005	***	-0.144	0.796	
SEC7	0.070	0.000	***	0.091	0.042	***	0.083	0.424		0.291	0.183		-0.020	0.875		-0.275	0.474	
SEC8	0.030	0.023	***	0.030	0.264		0.025	0.590		-0.178	0.050	***	-0.087	0.225		-0.170	0.658	
SEC9	0.090	0.001	***	0.099	0.325		-0.053	0.540		0.045	0.699		0.766	0.114		0.070	0.890	
SEC10	0.036	0.076		-0.020	0.781		-0.038	0.443		0.075	0.623		-0.554	0.089		-0.252	0.598	

***: Significant at 95% confidence level

** : Significant at 90% confidence level

7. CONCLUSIONS

Understanding the effects of COVID-19 on IPO mispricing in the Turkish market is crucial for developing effective strategies to mitigate pricing anomalies during future crises. This research proposal outlines the objectives, research methodology, results, and implications of the study.

Market Returns Analysis: There are significant differences in means and standard deviations in "Adjusted Market Returns" across various periods, indicating that IPO companies had higher returns compared to the market. This implies a trend of underpricing during offerings.

COVID-19 Impact Analysis: The study tests the impact of COVID-19 on IPO results for each equation. The results suggest a significant impact, with coefficients and probabilities varying across equations. Notably, the impact includes increased asymmetric information, reduced IPO volume, and decreased demand, leading to higher rates of IPO underpricing during the COVID-19 period compared to before and after the pandemic.

Equation-Specific Results: Each equation reveals specific insights into the factors influencing IPO underpricing. For instance, Equation 3 shows a substantial positive relationship between ΔLnP_ALL and the dependent variable, while Equation 4 indicates that ΔLnP_SEC is not statistically significant. The results vary across equations, emphasizing the importance of considering different variables.

D2020, D2021, D2022 Impact: The dummy variables D2020, D2021, and D2022 are found to be significant in all equations, indicating that the impact of COVID-19 continues not only in the relevant pandemic period but also extends into 2022.

Sector-Specific Analysis: The study explores sector-specific impacts on IPO returns. While the first-day returns of IPOs across sectors are mostly significant, 1-year returns show continued effects primarily in the Financials and Energy sectors.

Month-End and First-Date Returns: Specific variables, such as "Y3" (Month-End Returns) in Equation 4 and "Y1" (First-Date Returns) in Equation 6, demonstrate significant positive coefficients, indicating their influence on the dependent variables.

Limitations and Implications: The study notes that the broadened definition of "IPO underpricing," considering returns for various periods, has led to lower values compared to earlier studies. This underscores the importance of refining measurement metrics.

Continued Impact of COVID-19: The results highlight that the impact of COVID-19 continues, as evidenced by the significant coefficients associated with the "COVID" variable in various equations.

In conclusion, the study provides valuable insights into the dynamics of Turkish IPOs during and after the COVID-19 pandemic. The findings contribute to the understanding of market behavior, IPO underpricing trends, and the persistent impact of external shocks on financial markets.

REFERENCES

Autore, D. M., Boulton, T. J., Smart, S. B. & Zutter, C. J. (2014). The impact of institutional quality on initial public offerings. Journal of Economics and Business, 73(C), 65–96.

Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2021). Deaths, panic, lockdowns, and US equity markets: The case of COVID-19 pandemic. Finance Research Letters, 38, 101701.

Baig, A. S., Butt, Mengxi, C. (2022). Did the COVID-19 pandemic (really) positively impact the IPO Market? An Analysis of information uncertainty. Finance Research Letters, 46, 102372.

Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. Journal of Financial Economics, 15(1–2), 213–232.

Bird, R. & Ajmal, H. (2016). Mispricing of Australian IPOs. JASSA: The Finsia Journal of Applied Finance, (1), 27-33.

Boulton, T. J., Smart, S. B. & Zutter, C. J. (2010). IPO underpricing and international corporate governance. Journal of International Business Studies, 41(2), 206–222.

Campbell, T. S. & Kracaw, W. A. (1980). Information production, market signaling, and the theory of financial intermediation. The Journal of Finance, 35(4), 863–882.

Chahine, S. and Filatotchev, I. (2008), The Effects of Information Disclosure and Board Independence on IPO Discount. Journal of Small Business Management, 46: 219-241.

Chang, H. H., Chen, A., Kao, L. & Wu, C. S. (2014). IPO price discovery efficiency under alternative regulatory constraints: Taiwan, Hong Kong, and the US. International Review of Economics & Finance, 29, 83–96.

Chao, Y., Jiaxin, W., Zhi, W., Kam, C. C. (2023), Do media connections help? Evidence from IPO pricing in China, Journal of Accounting and Public Policy, 42(3), May-June 2023, 107075.

Chen, G., Firth, M. & Kim, J.-B. (2004). IPO underpricing in China's new stock markets. Journal of Multinational Financial Management, 14(3), 283–302.

Durukan, M. B., (2006), 16 - IPO underpricing and ownership structure: Evidence from the Istanbul Stock Exchange, Editor(s): Greg N. Gregoriou, In Quantitative Finance, Initial Public Offerings, Butterworth-Heinemann.

Engelen, P. J. & van Essen, M. (2010). Underpricing of IPOs: Firm-, issue- and country-specific characteristics. Journal of Banking & Finance, 34(8), 1958–1969.

Esterling, E. (2022, January). Volatility in Perspective. Crestmont Research. https://www.crestmontresearch.com/docs/Stock-Volatility-Perspective.pdf [Date Accessed: August 4, 2023].

Gao, Y. (2010). What comprises IPO initial returns: Evidence from the Chinese market. Pacific-Basin Finance Journal, 18(1), 77–89.

Green, T.C., Jame, R. (2013), Company name fluency, investor recognition, and firm value. Journal of Financial Economics, 109 (2013), 813-834.

Grinblatt, M., & Hwang, C. Y. (1989). Signaling and the Pricing of New Issues. The Journal of Finance, 44(2), 393–420.

Guo, H. & Brooks, R. (2008). Underpricing of Chinese A-share IPOs and short-run underperformance under the approval system from 2001 to 2005. International Review of Financial Analysis, 17(5), 984–997.

Habib, M. A. & Ljungqvist, A. P. (2001). Underpricing and entrepreneurial wealth losses in IPOs: Theory and evidence. Review of Financial Studies, 14(2), 433–458.

Hamao, Y., Packer, F. & Ritter, J. R. (2000). Institutional affiliation and the role of venture capital: Evidence from initial public offerings in Japan. Pacific-Basin Finance Journal, 8(5), 529–558.

Hill, P. & Wilson, N. (2006). Value gains on flotation and IPO underpricing. Journal of Business Finance & Accounting, 33(9-10), 1435–1459.

Hopp, C. & Dreher, A. (2013). Do differences in institutional and legal environments explain cross-country variations in IPO underpricing? Applied Economics, 45(4), 435–454.

Husnan, S., Hanafi, M. M. & Munandar, M. (2014). Price stabilization and IPO underpricing: An empirical study in the Indonesian stock exchange. Journal of Indonesian Economy and Business, 29(2), 129.

Ibbotson, Roger G., (1975). Price performance of common stock new issues. Journal of Financial Economics. Volume:2 Issue:3, 235–272.

Naoshi, I. (2022), Optimism, divergence of investors' opinions, and the long-run underperformance of IPOs, Journal of Financial Markets, Volume 64, 2023.

Ilbasmış, M. (2023), Underpricing and aftermarket performance of IPOs during the Covid-19 period: Evidence from Istanbul stock exchange, Borsa Istanbul Review, 23(3), 662-673.

Jamaani, F. & Abdullahi Dahir A. (2021), Modifier Effects of Country-level Transparency on Global Underpricing Difference: New Hierarchical Evidence, International Review of Financial Analysis, 74(C): 1016-1067.

Jelic, R., Saadouni, B. & Briston, R. (2001). Performance of Malaysian IPOs: Underwriters reputation and management earnings forecasts. Pacific-Basin Finance Journal, 9(5), 457–486.

Kiymaz, H., (2000), The initial and aftermarket performance of IPOs in an emerging market: evidence from Istanbul stock exchange, Journal of Multinational Financial Management, Volume 10, Issue 2, 213-227.

Kooli, M. & Suret, J. M. (2001). The underpricing of initial public offerings: Further Canadian Evidence. CIRANO Working Paper No. 2001-50. https://ideas.repec.org/p/cir/cirwor/2001s-50.html [Date Accessed: August 8, 2023].

Kucukkocaoglu, G., (2008), Underpricing in Turkiye: A Comparison of the IPO Methods, Money Macro and Finance (MMF) Research Group Conference 2006 8, Money Macro and Finance Research Group.

Lee, J. S. & Kuo, C. T. (2010). Determinants of high and low IPO initial returns: Evidence from Taiwan's stock markets. Journal of Information and Optimization Sciences, 31(6), 1189–1207.

Lee, P. J., Taylor, S. L. & Walter, T. S. (1996). Australian IPO pricing in the short and long run. Journal of Banking & Finance, 20(7), 1189–1210.

Lin, H. L., Pukthuanthong, K. & Walker, T. J. (2013). An international look at the lawsuit avoidance hypothesis of IPO underpricing. Journal of Corporate Finance, 19, 56–77.

Ljungqvist, A. P. (1997). Pricing initial public offerings: Further evidence from Germany. European Economic Review, 41(7), 1309–1320.

Logue, D. E. (1973). On the Pricing of Unseasoned Equity Issues: 1965-1969. The Journal of Financial and Quantitative Analysis, 8(1), 91–103.

Loughran, T. & Ritter, J. R. (2002). Why don't issuers get upset about leaving money on the table in IPOs? Review of Financial Studies, 15(2), 413–444.

McGuinness, P. (1992). An examination of the underpricing of initial public offerings in Hong Kong: 1980-90. Journal of Business Finance & Accounting, 19(2), 165–186.

Michaely, R. & Shaw, W. H. (1994). The pricing of initial public offerings: Tests of adverse-selection and signaling theories. Review of Financial Studies, 7(2), 279–319.

Miller, R. E. & Reilly, F. K. (1987). An examination of mispricing, returns, and uncertainty for initial public offerings, Financial Management, 16(2), 33–38.

Montone, M., van den Assem, M.J., Zwinkels, R.C.J. (2023), Company name fluency and stock returns. Journal of Behavioral and Experimental Finance, 39, 100819, September 2023.

Orhan, M., (2006), 4 - Short- and long-run performance of IPOs traded on the Istanbul Stock Exchange, Editor(s): Greg N. Gregoriou, In Quantitative Finance, Initial Public Offerings, Butterworth-Heinemann, 2006.

Ritter, J. R. (1984). The "Hot Issue" Market of 1980. The Journal of Business, 57(2), 215–240.

Rock, K., (1986). Why new issues are underpriced. Journal of Financial Economics Volume:15 Issues:1–2, 187–212.

Wang, C. (2005). Ownership and operating performance of Chinese IPOs. Journal of Banking & Finance, 29(7), 1835–1856.

Wang, S., Wang, P., Cebula, R.J., Foley, M. (2023), Board characteristics and IPO underpricing in China: The perspective of the moderating effect of venture capitalists, Finance Research Letters, 52, 103491.

Welch, I., (1996), Equity offerings following the IPO theory and evidence, Journal of Corporate Finance, Volume 2, Issue 3, 227-259.

Wu, S. (2023), Impact of serial entrepreneurs on IPO valuation: Evidence from U.S. IPOs, The North American Journal of Economics and Finance, 64, 101857.

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. Finance Research Letters, 35, 101597.