Financial Internet Quarterly

UNIVERSITY of INFORMATION TECHNOLOGY and MANAGEMENT in Rzeszow, POLAND

Financial Internet Quarterly

Financial Internet Quarterly 2023, vol. 19 / no. 4

Financial Internet Quarterly Editorial Office
University of Information Technology and Management in Rzeszów
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10.2478/fiqf-2023-0023

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DIFFERENCES IN BUSINESS FRAUD BETWEEN STATE-OWNED AND PRIVATE COMPANIES: CASE OF CROATIA

Marijana Bartulović[1], Dijana Perkušić[2], Ivan Kovačević[3]

Abstract

Fraud presents a serious problem and arising issue for all of society at national and global levels. According to global fraud research conducted by the Association of Certified Fraud Examiners, it is estimated that the average company loses about 5% of its annual revenue due to different types of business fraud. Total estimated annual fraud losses according to global ACFE research reaches about 4.7 trillion dollars. Business frauds also present an important issue for the Croatian economy, business community and society as a whole. Thereby, considerable attention should be given to this issue with the aim of raising awareness throughout society on fraud and its negative and destructive impact on all of society. The main purpose of this paper is to examine differences in fraud characteristics between state-owned and private companies in the Republic of Croatia. Research was based on data on business frauds obtained by the Association of Certified Fraud Examiners Croatia which included 124 respondents. Data were related to frauds that occurred in Croatian companies in 2021 and 2020. In this paper we focused on fraud characteristics such as fraud loss, type of fraud, fraud duration and methods of fraud detection in order to determine whether fraud in privately owned companies differs significantly from fraud in state-owned companies. Research results revealed how differences in fraud characteristics among privately and state-owned companies exist. Based on a sample of Croatian companies that were victims of fraud, it is noted how fraud in state-owned companies lasts longer and creates greater loses in comparison to fraud in private owned companies. Moreover, data related to estimated fraud loss and fraud duration were statistically significant in terms of differentiating these two groups of companies. Based on data on discriminatory variables a logistic regression model correctly classified 78.46% of companies in the group of companies that are privately or state-owned.

JEL classification: M41, K42
Keywords: Frauds, State-owned Companies, Private Companies

Received: 23.07.2023 Accepted: 14.09.2023

Cite this:
Bartulović M., Perkušić D., Kovačević I. (2023) Differences in business fraud between state-owned and private companies: case of Croatia. Financial Internet Quarterly 19(4), pp. 1-8.

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Introduction

In today's turbulent times and challenging business environment where companies are moving from one crisis to another, business fraud presents a serious problem. Karpoff (2021, p.1) emphasizes that "COVID-19 pandemic and resulting economic shutdown" will increase fraud in the next period. These same predictions are pointed out in research performed by the Association of Certified Fraud Examiners (ACFE) and Grant Thornton (2021). Soltani pointed out how "corporate fraud goes on at a deeper level within the company and the environment in which it operates (Soltani, 2014, p. 252) while Grandstaff and Solsma (2021, p. 421) indicate how the main characteristics of fraud are that it lasts longer, generates greater fraud losses and the number of companies affected by fraud increases over time. According to global fraud research conducted by the ACFE, total estimated annual fraud losses reach about 5% of its annual revenue or 4.7 trillion dollars (ACFE, 2022, p. 8). However, these are only estimates and most frauds remain undetected since fraud perpetrators use various schemes to hide the fraud. Fraud is a global problem since "it has devastating consequences for shareholders, employees, firms and communities" (Bekiaris & Papachristou, 2017, p. 473).

No organization, regardless of industry or region, is resistant to the issue of fraud. It is considered that "financial reporting fraud and other forms of financial reporting misconduct are a significant threat to the existence and efficiency of capital markets" (Amiram et al., 2018, p. 2). According to ACFE (2022, p. 6) "occupational fraud is very likely the costliest and most common form of financial crime in the world". Fleming et al. (2016) state how fraud causes losses to employees, customers, suppliers and society as a whole. Occupational frauds can be defined as "frauds that are committed by individuals against the organizations that employ them" (ACFE, 2022, p. 6). According to the Institute of Internal Auditors (IIA, 2017, p. 23) fraud is defined as "any illegal act characterized by deceit, concealment, or violation of trust. These acts are not dependent upon the threat of violence or physical force. Frauds are perpetrated by parties and organizations to obtain money, property, or services; to avoid payment or loss of services; or to secure personal or business advantage." Fraud, as part of white collar crime, presents a serious problem, and it can be classified in three main categories (ACFE, 2022, p. 10): 1) asset misappropriation, 2) corruption, and 3) financial statement fraud. Asset misappropriation is the most common type of fraud and occurs in about 86% of cases. However, this type of fraud generates the lowest losses with median loss of USD 100.000 per case. Financial statement fraud is represented in only 9% of cases but according to results, it is the costliest category of fraud. This type of fraud generates a median loss of USD 593,000 per case. Corruption falls between these two categories since it happens in 50% of cases and causes a loss of USD 150,000 per case. Bekiaris and Papachristou (2017, p. 473) state how three conditions need to be present to commit fraud: opportunity or motive, pressure, rationalization and capability. According to Wolfe and Hermanson (2004, p. 38) "opportunity opens the doorway to fraud, and incentive and rationalization can draw the person toward it. But the person must have the capability to recognize the open doorway as an opportunity and to take advantage of it by walking through, not just once, but time and time again".

The Association of Certified Fraud Examiners Croatia (ACFE Croatia) performed its first survey on fraud in the Republic of Croatia according to ACFE methodology in 2021. The sample included 124 respondents, i.e., companies in which fraud occurred during 2021 and 2020. Results were presented in the report "How do we steal? Research on Business Fraud in the Republic of Croatia". The report gives information on types of fraud, costs, methods, perpetrators and other fraud characteristics in Croatia. The aim of this paper is to examine differences in fraud characteristics between state-owned and privately owned companies in the Republic of Croatia. We focused on fraud characteristics such as fraud loss, type of fraud, fraud duration and methods of fraud detection in order to determine whether fraud in privately owned companies differs significantly from fraud in state-owned companies.

The paper is organized as follows: after the introductory part of the paper, the second chapter presents previous research in this area. In the third chapter, research sample, methodology and results are presented, while the last, fourth part of the paper, gives concluding remarks.

Previous research

Previous scientific research in this area is quite rare. The reason for this can be found in the unavailability of data on fraud and companies victimized by fraud. One of the main characteristics of fraud is concealment and fraud perpetrators use various schemes to hide the fraud. ACFE has been conducting empirical research on fraud since 1996. In their research, they analyse and present different characteristics of fraud committed around the world: type of fraud, loss caused by fraud, methods of concealing fraud, effectiveness of control mechanisms, perpetrators, etc. Their research contributes to understanding characteristics of professional fraud in order to improve fraud detection and prevention. For years their research has shown how asset misappropriation is the most common type of fraud. It assumes stealing assets from an employer and occurs in around 86% of fraud cases (ACFE, 2022). Financial statement fraud, according to ACFE research, presents the least common type (it occurs in around 9% of cases) but the most expensive fraud scheme. Financial statement fraud can be defined as "a scheme in which an employee intentionally causes a misstatement or omission of material information in the organization's financial reports" (ACFE, 2022, p. 94). Corruption, as a type of occupational fraud is defined as "scheme in which an employee misuses their influence in a business transaction in a way that violates their duty to the employer in order to gain a direct or indirect benefit" (ACFE, 2022, p. 94) and it happens in 50% of fraud cases and causes a median loss of USD 150.000.

Authors in their fraud research point out how fraud causes significant losses in market value of a firm (Karpoff et al., 2008), impact image and financial position of the company (Beasley et al., 2010) and "have significantly eroded the public trust in financial statements that are disclosed by firms" (Ozcan, 2016, p. 130). Research on fraud performed by Fleming et al. (2016) was based on data gathered by the ACFE. The aim of their research was to determine differences in fraud characteristics among private and public companies. According to results public companies have stronger anti-fraud controls, are exposed to greater fraud losses, experience fraud with a larger number of perpetrators and have less fraud that is discovered by accident. Giriūnas and Mackevičius (2014) examined fraud in the public sector of Lithuania. According to results, fraud in the public sector is more frequent when compared to fraud in the private sector and in most of the cases is initiated from the side of upper management. Based on analysis of corporate fraud in India, Gupta and Gupta (2015) conclude that weak regulatory systems and weak coordination between different regulatory bodies make fertile ground for fraud. Ozcan (2016) conducted research on characteristics of a company and accounting fraud on a sample of 144 firms listed on Borsa Istanbul in the period 2005 to 2015. According to research results, firms that achieve low liquidity ratios, have negative financial performance and have high debt to equity ratios are more vulnerable to fraud. Also, results revealed how smaller firms are more exposed to fraud as well as those with lower accounts receivable turnover and inventory turnover.

Characteristics of corporate fraud, causes of fraud and fraudster business profiles were examined by Bekiaris and Papachristou (2017). Based on reports of the ACFE in the period from 2004 to 2016 they examined fraud evolution and concluded how in the observed period asset misappropriation was the most often fraud scheme. They also point out that the banking industry as well as the government sector were in other side the communication and utilities sectors are the least exposed to fraud. Moreover, according to research results, owners involved with fraud cause the greatest fraud losses. Tenure and position are found to be positively related to fraud loss and authors point out how "to commit fraud a person should be trusted and have gained access to valuable information, to overlap controls" (Bekiaris & Papachristou, 2017, p. 473). Junger et al. (2020) examined characteristics of fraud on a sample of 300 fraud cases related to Dutch companies. The authors focused on three fraud categories: CEO fraud, fraudulent contracts and ghost invoices. According to results, fraud committed by CEOs are conducted online, while most fraudulent contract and ghost invoices are conducted offline.

Halar et al. (2022) performed a comprehensive analysis of ACFE reports in the period 2014-2022. By analyzing reports on fraud during this period, the authors also came to the conclusion that asset misappropriation is the most common form of fraud in all periods of observation. Furthermore, the longer the fraud goes undetected, the greater the fraud loss is. Fraud reports have indicated that tips are the most common way of fraud detection and the key control mechanisms that companies had at the time when the fraud occurred are external audit, formal code of conduct and internal audit. Results of this research have shown that most fraud cases (about 70%) occurred in the for-profit sector (private or state-owned companies). It is followed by the government sector, and the non-profit sector is according to research results least exposed to fraud. Analysis of specific industries within ACFE reports in the period 2014-2022 has shown that the banking industry is most exposed to fraud which is in line with the results of Bekiaris & Papachristou (2017). It is followed by government and public administration and the manufacturing industry.

Bartulović et al. (2022) compared characteristics and trends in fraud in the Republic of Croatia with global results. They concluded that the main features of fraud in Croatia do not deviate significantly from global fraud trends, but certain differences exist. Misappropriation of assets is in Croatia also the most common type of fraud and it occurred in 52% of cases. Corruption as a form of fraud occurred in 31% of fraud cases and is the second most represented form of fraud. Differences compared to the global results are observed in the third place. More precisely, on a global level financial statement fraud is the third most common type of fraud while in Croatia the third most common type of fraud is computer fraud which occurred in 22% of cases. Also, Croatian results showed that more than 50% of organizations that were fraud victims had no adequate control mechanisms at the time when the fraud occurred. The authors point out how "different control mechanisms present fraud detection and prevention measures, and are being imposed as an indispensable tool in the fight against fraud on a global level… in the practice of Croatian companies, this form of fraud prevention and detection has proved to be insufficiently represented and ineffective" (Bartulović et al., 2022, p. 117).

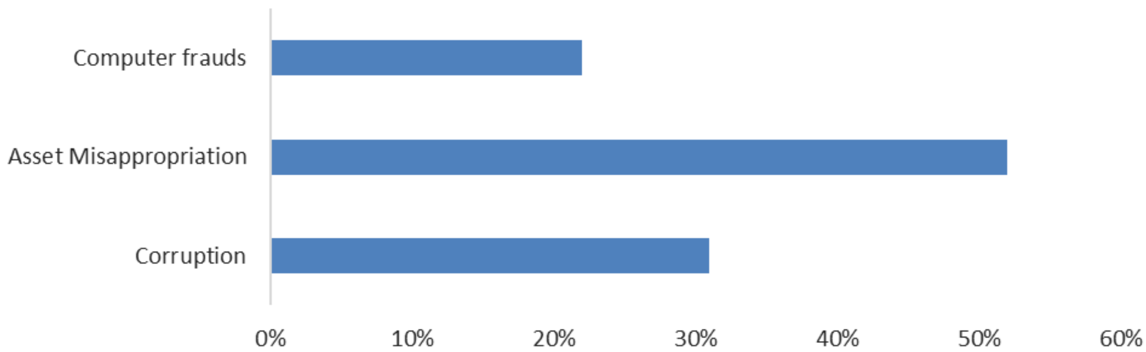
Methodology & empirical results

Research sample and methodology

Research was based on data gathered by Association of Certified Fraud Examiners Croatia (ACFE Croatia). They performed comprehensive fraud research according to the methodology of ACFE for the first time in the Republic of Croatia in 2021. Within the research fraud that happened during 2021 and 2020 were analyzed and a total of 124 companies from 16 different industrial sectors were included in the research. Results of the research were presented in the report "How do we steal? Research on Business Fraud in the Republic of Croatia" (ACFE Croatia, 2022). Business or occupational fraud is usually divided into three main categories: corruption, misappropriation of assets, and financial statement fraud (ACFE, 2022, 10). These three categories have dominated for years, although it must be pointed out how in recent years, new forms of fraud related to computer fraud have been detected. Misappropriation of assets has been for years the most prevalent type of occupational fraud. This type of fraud is present in 86% of cases at the global level and in 52% of fraud cases in Croatia.

Croatian survey results show how corruption as a type of fraud is represented in 31% of analyzed fraud cases while at the global level corruption is represented in 50% of cases. Moreover, research of fraud in Croatia has shown that computer fraud or cybercrime is the third most common type of fraud in Croatia, and it was noticed in 22% of cases. It should be noted how on a global level, financial statement fraud is in third place, and it is represented in 9% of cases. According to Croatian fraud results this type of fraud is represented in 16% of cases. Croatian results are in some aspects similar to global results and follow global fraud trends. However, some specificities can be pointed out. For example, at the global level 42% of fraud is initially detected by tip-offs. In Croatia this percentage is much lower and amounts to 22% meaning that 22% of fraud in Croatian companies was detected by tip-off. Also, it should be pointed out that half of the analyzed companies at the time when fraud was detected did not have any type of anti-fraud controls. Results have shown that Croatia significantly lags behind global trends in the implementation of anti-fraud controls (ACFE Croatia, 2022) and there is significant space for improving anti-fraud systems in Croatian companies. Also, when estimated loss is observed, differences for the Croatian sample in comparison to global trends can be observed. At the global level it is estimated that the average company loses 5% of its annual revenue to fraud while in Croatia these estimates go to 13 % (ACFE Croatia, 2022, p. 5).

Figure 1: Most common types of business fraud in Croatia



Source: ACFE Croatia, 2022, p. 8.

In this paper we focused on analysis of differences in fraud between state-owned and private companies. In determining differences in fraud characteristics between these two groups we focused on the following parameters: fraud loss, type of fraud, fraud duration and methods of fraud detection. In further analysis we eliminated all companies with missing data on some of the required parameters. Finally, our sample consisted of 65 observations. Out of the total number of companies 49 companies, or 75.38% ,were privately owned companies and the other 16, or 24.62%, were state-owned. Distribution of companies due to ownership status is shown in Table 1.

Table 1: Ownership structure of analyzed companies

Ownership	Number of observations	%
Private	49	75.38
State-owned	16	24.62
Total	65	100.00

Source: Author's own work.

The aim of the paper was to determine differences in fraud characteristics between private and state-owned companies. In order to determine differences among these two groups logistic regression was used. Logistic regression is a statistical method used for predicting outcomes of a categorical dependent variable. In logistic regression the dependent variable can have two or more outcomes and in our research the dependent variable is binary – the company is privately owned or not. Logistic regression is used to obtain the probability that a unit from the sample (in our case a certain company) belongs to a certain group (group of companies in state or private ownership). Value 1 is assigned to state-owned companies and value 0 to those that were privately owned. The independent variables that predict the outcome of the dependent variable are the following: fraud loss, type of fraud, fraud duration and methods of fraud detection. Descriptive statistics for independent variables are presented in Table 2. Fraud loss refers to total financial loss caused by fraud in the affected company. The variable type of fraud indicates the way fraud was committed: by asset misappropriation, corruption, financial statements fraud or some other form of fraud. Fraud duration indicates the time that elapses between the start of the fraud and its detection while variable methods of fraud detection indicate the way the fraud was initially discovered.

Table 2: Group statistics

Total sample	No. of obs.	Mean	Std. Dev.	Min	Max
Fraud loss	65	3.5692	1.6767	1	6
Type of fraud	65	2.5077	1.8125	1	6
Fraud duration	65	17.4769	24.1150	1	100
Methods of fraud detection	65	4.5692	3.4595	1	11

Source: Author's own work.

In performing logistic regression, using several independent variables can lead to the problem of high collinearity among two or more independent variables. Due to fact that in practice there is usually a smaller or larger dependence of independent variables it was necessary to test the level of multicollinearity. Therefore, before running logistic regression, multicollinearity between the independent variables was analyzed. Table 3 shows the results of multicollinearity analysis.

Table 3: Correlation matrix

	Fraud loss	Type of fraud	Fraud duration	Methods of fraud detection
Fraud loss	1.0000			
Type of fraud	-0.0246	1.0000		
Fraud duration	-0.1892	-0.1197	1.0000	
Methods of fraud detection	-0.0298	-0.0942	0.2861	1.0000

Source: Author's own work.

As shown in Table 3, there is no problem of multicollinearity between the observed variables so all independent variables were included in the next step of analysis. In the next step, logistic regression was performed, and the results are presented in the following part of the paper.

Research results

The aim of this paper was to determine differences in fraud characteristics between private and state-owned companies. As presented in Table 4, the logit regression model is statistically significant. The variables fraud loss and fraud duration are statistically significant in the context of differentiating between the observed two groups of companies.

Table 4: Logit regression model

Type of ownership~p	Coef.	Std. Err.	z	P > z	[95% Conf.	Interval]
Fraud loss	-0.4943	0.1973	-2.51	0.012	-0.8810	-0.1076
Type of fraud	-0.0476	0.1877	-0.25	0.800	-0.4155	0.3202
Fraud duration	0.0236	0.0129	1.81	0.070	-0.0019	0.0490
Methods of fraud detection	-0.0113	0.0938	-0.12	0.905	-0.1951	0.1726
_cons	0.1731	0.9743	0.18	0.859	-1.7365	2.0827

Number of observations = 65, LR chi2 (4) = 12.70, Probability > chi2 = 0.0128, Log likelihood -29.92429, Pseudo R2=0.1751

Source: Author's own work.

The other two variables, type of fraud and methods of fraud detection were not statistically significant in the context of differentiating privately and state-owned companies. Classification results are shown in Table 5. Classification accuracy shows how many companies from the sample were correctly classified by the logistic regression model into the group of private or state-owned companies. Accuracy of logistic regression model amounts to 78.46%. This means that 78.46% of companies were correctly classified in the group of companies that are privately or state-owned according to available data on the independent – discriminatory variables fraud loss and fraud duration. From total number of state-owned companies (16 observations) the model correctly classified 4 cases. In the group of privately owned companies, out of 49 observations the model correctly classified 47 cases.

Table 5: Classification results

Privately companies - 0 State owned companies - 1			Predicted group membership 1	Predicted group membership 0	Total
Original	Count	1	4.00	12.00	16.00
		0	2.00	47.00	49.00
	%	1	25.00	75.00	100.00
		0	4.08	95.92	100.00

Source: Author's own work.

Thus, based on the research results, it can be concluded that differences in fraud characteristics exist among privately owned and state-owned companies. Estimated fraud loss and fraud duration are variables that are statistically significant in terms of differentiating these two groups of companies. Fraud duration is presented by the number of months or time that passes between the initiation of fraud and its detection. According to the results of fraud research in Croatia the average duration of fraud is 8 months, which is shorter than the global trend. According to global fraud results for 2022, average fraud duration is 12 months. In our analysis we focused on differences between publicly and state-owned companies. According to available data, average fraud duration for the sample of privately owned companies is 6 months and in state-owned companies this period reaches 12 months. So, differences in fraud duration among two groups of companies exist and these differences are statistically significant in terms of differentiating among private and state -owned companies. Private companies in most of the detected fraud cases were faced with losses under 200,000 HRK while in state-owned companies, the loss usually was in the range of HRK 1 to 5 million. It can be noticed how state-owned companies are exposed to greater fraud loss and this variable is also statistically significant in terms of distinguishing private and state-owned companies. It should be emphasized that results are in line with results obtained by Fleming et al. (2016) who also revealed that public companies are exposed to greater fraud losses.

Conclusions

The aim of this paper was to analyze data gathered by ACFE Croatia in order to determine differences in fraud characteristics among privately and state-owned companies. Results of the first fraud research conducted according to ACFE methodology show how Croatian companies lose 13% of their annual revenue due to different types of fraud. So, fraud research shows how Croatian companies follow global trends and that no organization is resistant to fraud. As Bekiaris and Papachristou (2017, p. 473) state, frauds are "complex in structure, difficult to detect and difficult even for a specialist to fully comprehend them". Various organizations (for example ACFE, The IIA…) emphasize the issue of fraud and its destructive impact on all of society and researchers in this area try to point out different characteristic of fraud, fraud perpetrators, detection methods and so on, in order to contribute to better understanding of this phenomenon.

Within this research we analyzed differences in fraud among privately and state-owned companies. Results of the conducted logistic regression indicate that differences in fraud characteristics among two observed groups of companies exist. Moreover, estimated fraud loss and fraud duration were statistically significant in terms of differentiating these two groups of companies. Based on data on independent – discriminatory variables the logistic regression model correctly classified 78.46% in a group of companies that are privately or state-owned. According to results, fraud in state-owned companies have fraud duration of 12 months and generate losses from 1 to 5 million HRK. On the other side, in private companies it takes 6 months from the moment when fraud occurs to the time when it is detected. Moreover, state-owned companies are exposed to greater fraud losses which is in line with ACFE (2022, p. 13) observation that the longer a fraud remains undetected, the greater financial loss is.

Grandstaff and Solsma (2021, p. 421) also point out that fraud lasts longer and generates greater losses so it can be concluded that the anti-fraud community should respond to these issues by a stronger fight against fraud. However, certain limitations should be pointed out. In the research sample there is a difference between the number of state-owned and privately owned companies. It should be noted that the research is based on data on fraud that occurred in the Republic of Croatia in the years 2020 and 2021 and included 124 respondents. Most of them were from the private sector which created disproportion in our final sample. Also, we eliminated all companies missing data on some of the required parameters which resulted in 65 observations. It should be noted that certain variables that could be relevant to our research (such as size, financial result, etc.) were not included due to lack of data.

In the end, the aim of this paper is to contribute to a better understanding of fraud characteristics in Croatia and to our best knowledge this is first research on fraud differences between state-owned and privately owned companies in Croatia. Also, the authors emphasize the fraud issue and its destructive effect on companies, employees and society as a whole and thus this paper aims to contribute to raising awareness about fraud and the importance of fighting fraud at all levels of society. The authors encourage future research in this area aware of the fact that researchers are faced with unavailability of the data on fraud and companies victimized by fraud. Future research in this area could focus on more in-depth analysis of fraud cases and fraud characteristics in order to highlight fraud characteristics and the destructive impact of fraud on company performance and society as a whole.

Acknowledgment

The authors would like to thank the Association of Certified Fraud Examiners Croatia, who provided us with the results of the research on fraud in the Republic of Croatia, as well as COMPING and SAS, who contributed to conduct the first research on fraud according to the ACFE methodology.

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Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 9-24
10.2478/fiqf-2023-0024

Financial Internet Quarterly

DOMESTIC CAPITAL VS. FOREIGN CAPITAL NEW ENTERPRISE CREATION: THE CASE OF FDI IN INDIA

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Abstract

The attempt of this paper is to find an empirical relationship between Foreign Direct Investment and New Firms (Paid up Capital) and Gross Capital Formation (proxy for business growth) and Credit to Commercial Sector and Gross Capital Formation using the test of stationarity (ADF, PP, and KPSS methods), Johansen Cointegration and Granger's Causality. The results show that FDI crowds out creation of new firms and capital formation and it is the Credit flow to the commercial sector that causes Gross Capital Formation at current price. It shows domestic flow of credit is more influential in capital formation rather than foreign capital inflow.

JEL classification: E22

Keywords: Foreign Direct Investment; Gross Capital Formation; Commercial Sector; Savings-Investment Gap; Paid-Up Capital

Received: 23.07.2023 Accepted: 14.09.2023

Cite this:

Sajikumar T. & Silva A.F.C. (2023) Domestic capital vs. foreign capital new enterprise creation: the case of FDI in India. Financial Internet Quarterly 19(4), pp. 9-24.

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Introduction

India has liberalized the foreign direct investment (FDI) regime for rapid increase in economic growth, industrialization, creation of employment and growth of income, from 1991. For a developing country, FDI not only helps in bridging the saving-investment gap, but also brings in the technology, new managerial techniques, improvises marketing techniques, capital formation, boosts exports, enhances competition in the domestic market, increases the quality of human capital, promotes research and development, structural changes and has other spillover effects (Romer, 1993). FDI brings about increase in the total factor productivity of inputs (Rappaport, 2000). FDI is desirable because it ushers technical progress through introducing advanced technology and competitive management practices emulated by domestic firms (Findlay, 1978). The neoclassical growth model assumes that increase in knowledge is embodied in the production function attributed to foreign direct investment (Wang, 1990). However, most companies start by serving a new market via exports, before investing in it, via FDI. With the liberalization of the Indian economy, there was a boost in companies willing to export their products to India, and eventually, in investing in it, via FDI (Conconi et al., 2016).

Through the new firm entry, it is possible to have an insight into the spillover effects of FDI and how domestic entrepreneurship is enhanced through innovation and it is also possible to exploit new opportunities to generate employment and income (Markusen & Venables, 1999) and thereby reaching the main objective of achieving GDP growth (Baumol & Strom, 2007; Minniti & Levesque, 2010). Findlay (1978) wrote that when the foreign direct investment increases, it boosts new technology creation and its multiplier effect on the domestic economy is seen, as well as the new innovative business practices used by the foreign firms. Wang (1990) says that according to neoclassical growth model, knowledge is part of the production function attributed to foreign direct investment.

However, there is literature and empirical finding that FDI crowds out capital formation and new enterprise creation. It is also important for a country to achieve a threshold level of development and undergo appropriate reforms in terms of ease of doing business in order to assimilate and realize the benefits of FDI for economic growth. It is equally important that in an era of globalization, the external shocks do not destabilize the domestic economy (Christopherson et al., 2010). One of the advantages for domestic economies is that foreign direct investment helps it to tide over the external crises and shocks (Mata & Freitas, 2012; Phelps et al., 2003). It is important to have the capability of the domestic entrepreneurship to help the home economy bounce back (Martin, 2012; Martin & Sunley, 2014). The domestic entrepreneurship needs to be resilient to absorb the shock of external crises (Huggins & Thompson, 2015). The more robust the influence of FDI, the greater will be the birth rate of new firms than the death rate, and the recovery of the economy will be easy and rapid (Thompson & Wenyu, 2014).

Using the Augmented Dickey-Fuller test and non-parametric tests, we attempt to study whether foreign direct investments influence new enterprise formation (paid-up capital) at current prices, gross capital formation at current prices and if the gross capital formation is affected by credit to the commercial sector. The article starts with the literature survey and the attractiveness of the country for FDI, followed by the analysis of the data and the testing of the hypotheses and the conclusions of the study. Even though India ranks second next to China in attracting FDI, such investments do not help in gross capital or new enterprise formation and credit to the commercial sector mainly helps in domestic investments which are inhibited by foreign ones.

Literature survey

The dynamism of the modern economy is essential in creating entrepreneurship, the more the addition of new firms, more will be the competition, productivity and innovation (Klapper et al., 2006). Entrepreneurship is defined as the activities of an individual or a group, initiating an economic enterprise in the formal sector, under a legal form of business (Klapper & Love, 2011).

In order to understand the relationship between FDI inflows and domestic investment, it is necessary to understand how the profitability of the domestic firms is enhanced. By the acquisition of the ownership of domestic firms, FDI channelizes more funds for gross capital formation. There are empirical evidences that FDI crowds out domestic investment (Apergis et al., 2006). A study by Desbordes (2022) for the period of 2002-2014, shows that FDI in the retail banking sector of developing countries is associated with better relative economic performance of externally financially dependent manufacturing sectors. This happens because the entry of foreign financial institutions increases local financial development and in doing so, fosters economic growth of the host country.

The overall effect of FDI can be divided into the agglomeration effect and the competition effect, the former being moderated by the absorptive capacity of domestic firms (Lu et al., 2017). To counteract the competition effect, the local entrepreneurs may rise to the challenge posed by FDI and hence increase the domestic investment (Mello, 1999). The resources available could be used for building the requisite infrastructure mix and thus increase the profitability of domestic firms (Blomstrom, 1989). This will eventually go a long way in increasing the demand for local inputs and thereby enhance local income (Cardoso & Dornbusch, 1989). The total factor productivity growth is one of the benefits accrued to the domestic economy (OECD, 2002). An economy which has an ideal mix of resources and inputs would attract FDI and create compatible resources for the domestic firms (Markusen & Venables, 1999). It is the extent of free trade that attracts more FDI (Bhagwati, 1978), however, the evolution of political disagreement among policymakers on topics such as tariffs, subsidies, and trade agreements can have the opposite effect (Azzimonti, 2019). The extent of development in the financial markets and the extent of availability of technically and skill trained labor force will dictate the level of superiority of the foreign firms that can better exploit the resources and elbow out the domestic firms, given the fact that they are willing to pay better wages than the domestic firms (Fry, 1992). This would constrain the domestic investment (Aitken & Harrison, 1999) and domestic firm may lose market share. A superior foreign firm can attract the local skilled labor creating shortages for local firms. Moreover, the wage rate in the domestic economy will increase and local firms´ cost of production will go up leading to unprofitability and closure, which in turn may increase the unemployment (Borensztein et al., 1998; Kokko, 1994).

A study at aggregate and intra industry level shows that FDI has negative effect on entrepreneurship (Hülya et al., 2013). Countries that have undergone inadequate reforms may hamper the growth of new firms despite FDI inflows (Klapper & Love, 2011). It has been observed that the presence of FDI increases the imports adversely impacting the balance of payments and eventually, there will be an increase in the cost of imported capital and in the cost of production, coupled with a reduction in domestic investment. Finally, FDI would replace the domestic firms. It is important that the country encourages development of infrastructure and other availability of sophisticated financial instruments for the domestic economy (Suliman & Elian, 2014) and labor markets that would encourage FDI to create more firms. Sometimes the technology ushered in by FDI is able to exploit the economies of scale and creates technological barriers to entry for the domestic firms (Ayyagari & Kosová, 2010). The superior technology of the foreign firms is capable of realizing economies of scale and cannot be emulated by the domestic firm, hence creating entry barriers for the domestic players. It is the state of domestic firms that would attract FDI. Sometimes the size of domestic investment, extent of openness to trade and the size of local market has no impact on FDI (Harrison & Revenga, 2015). Many a times, FDI does not accelerate economic growth (Carkovic & Ross, 2002; Mansfield & Romeo, 1980). A country will have to frame policies to ensure that FDI benefits the economic growth. If the FDI is attracted to areas and sectors that would not be otherwise attract investment, the economic growth can be assured, so the government can always try to restrict the FDI to unattractive sectors (Crescenzi et al., 2021). Sustainable economic development cannot rely solely on the introduction of FDI and should instead emphasize the importance for firms to improve value capture so as to better capitalize on the positive spillovers generated by foreign investment (Lu et al., 2022).

Until the late nineties of the last century, India fared poorly in attracting FDI, despite offering a large domestic market, rule of law, low labor costs, and a well working democracy. This was mainly due to a restrictive FDI regime, high import tariffs, exit barriers for firms, stringent labor laws, poor quality infrastructure, centralized decision-making processes, and a very limited scale of export processing zones (Bajpai & Sachs, 2000).

However, with the gradual opening of the economy since 1991, and the governmental focus on liberalization of policies to welcome FDI, India has been able to fare better in attracting investments at a positive growth rate, through technology transfer, employment generation, improved access to managerial expertise, global capital, product markets and distribution networks. It is rated as the second most favored destination in the world for FDI after China, but in future, it is expected to surpass it, as it has a large proportion of young population (Azhar & Marimuthu, 2012). By 2019, the country ranked as the 9th largest recipient of FDI (and 7th by 2021) with inflows around $ 83.6 billion, both in horizontal and vertical types of investments, and in 2020, the government is now scrutinizing every FDI under the Ministry of Commerce and Industry to ensure that opportunistic takeovers or acquisitions of Indian companies do not take place. Our study is thus limited to the period up to 2018-19, before the changes in the FDI regulations.

Table 1: FDI, New Firms, Gross Capital Formation and Credit to Commercial Sector

Time Series of	Denotation	Units	Data Span	Data Source
FDI (Current Price)	FDI	Rs. Cr.	2000 to 2018	Department of Industrial policy and planning
New Firms (Paid up Capital)	NF	Rs. Cr.	2000 to 2018	India stat.com
FDI (Current Price)	FDI	Rs. Cr.	2000-01 to 2018-19	Handbook of Statistics on Indian Economy 1999-20
Gross Capital Formation (Current price)	GCFRNT	Rs. Cr.	2000-01 to 2018-19	Handbook of Statistics on Indian Economy 1999-20
Credit to Commercial Sector (Current price)	CCS	Rs. Cr.	2000-01 to 2018-19	Handbook of Statistics on Indian Economy 1999-20

Note: Rs. Cr. (Rupees in Crores. A Crore is an Indian unit that is equal to 10 million)

Source: Author's own work.

Test hypothesis

In our hypotheses, we aim to test the bidirectional causality between FDI and several domestic factors like new enterprise creation, gross capital formation and increase in credit to the commercial sector, while most studies rely only on the effects of FDI on the local economies.

H_1: There is bidirectional causality between FDI and New Enterprise Creation (paid up capital) at current price.

As per the OECD (2002), the overall benefits of FDI for developing economies can be seen via technology spillovers, human capital formation, contribution to international trade integration, creation of more competitive business environments and enhancement in enterprise development, as well as the transfer of cleaner technologies and leading to more socially responsible corporate policies.

In a study on a sample of African countries by Munemo (2015), it was found out that FDI significantly crowds-in new domestic firms, when business start-up regulations are lower.

H_2: There is bidirectional causality between FDI and Gross Capital Formation at current price.

As per Khan (2007), FDI is the most important source of external funds flow for the developing countries over the years and becomes a significant part of capital formation, being widely recognized as a growth-enhancing factor for developing economies.

An empirical study by Krkoska (2001) in Eastern European economies showed that FDI, domestic credit and local capital markets are all important financing sources for capital formation, with FDI having a greater impact as compared to domestic credit and capital market financing.

Similarly, Ntamwiza and Masengesho (2002) discovered a significant positive effect between capital formation, foreign direct investment and economic growth, in the long run, in Rwanda. A study in India by Khan and Masood (2022) found out that FDI have a great impact and are deep rooted in the economy and are essential for the growth of the economy.

H_3: There is bidirectional causality between Credit to Commercial Sector and Gross Capital Formation current price.

According to OECD (2001), gross capital formation measures the value of acquisitions of new or existing fixed assets by the business sector, governments and households less disposals of fixed assets, or in other words, how much new value is added to the economy rather than consumed. The higher the cost of credit, lower will be the gross capital formation.

Analytical model

Augmented Dickey Fuller test (ADF)

In order to test the data for stationarity, as the first step of data analysis in economics and financial research, formal or informal methods can be used. While informal methods encompass charts and diagrams, the formal way to test the stationarity can be accomplished using the Dickey-Fuller test or the Augmented Dickey-Fuller test, with the latter being used more commonly to test the unit root. In this study, the Augmented Dickey-Fuller (ADF) stationarity test and the nonparametric test will be used. The first considers the autoregressive models of an order greater than the unity, as shown by the expression:

$$\Delta Y = \alpha_0 + \gamma Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \tag{1}$$

In which:

$$\gamma = -(1 - \sum_{i=1}^{p} \alpha_i), \; and \; \beta_i = \sum_{i=1}^{p} \alpha_i \tag{2}$$

being that α_0 is the intercept γ, order of the autoregressive model which describes the behavior of the temporal series; Y - dependent variable; Δ - difference operator; and ε_t - error structure, which is identically and independently distributed.

The ADF test requires us to take the first differences of Y_t, $(Y_t - Y_{t-1}) = \Delta Yt$ and regress them on lagged values of ΔY_t , and Y_{t-1} and see if the estimated slope coefficient in this regression (= ˆ δ) is zero or not. If it is zero, we conclude that Y_t is nonstationary. But if it is negative, we conclude that Y_t is stationary. Where t is the time or trend variable and ε_t is a pure white noise error term. If the null hypothesis is rejected, it means that Y_t is a stationary time series. The MacKinnon (1996) one sided p-values are taken to reject/accept the null hypothesis.

This hypothesis should be rejected when the calculated value of the t statistic exceeds the critical value of Dickey-Fuller, signaling that the series will be stationary; otherwise the series will not be stationary (Dickey & Fuller, 1981).

MacKinnon (1991) provided finite-sample critical values for the ADF test. The analysis yields the estimates of critical values not for only a few sample sizes but for any sample size. Like Fuller (1976), the critical values can be based with k = 1 only, for the ADF test. While proper correction for the lag effect in implementing the ADF is desirable, the analysis is useful for researchers in practical applications as the appropriate critical values for ADF can be computed with reasonable accuracy from response surface equations for any sample size and lag length (Cheung & Lai, 1995).

KPSS test

We propose a test of the null hypothesis that an observable series is stationary around a deterministic trend. The series is expressed as the sum of deterministic trend, random walk, and stationary error, and the test is the Lagrange Multiplier test of the hypothesis that the random walk has zero variance. The asymptotic distribution of the statistic is derived under the null and under the alternative hypotheses that the series is difference stationary.

The KPSS test (Kwiatkowski et al., 1992) differs from the other unit root tests described here in that the series y_t is assumed to be (trend-) stationary under the null hypothesis. The KPSS statistic is based on the residuals from the OLS regression of yt on the exogenous variables x_t.

$$y_t = x_t'\delta + u_t \quad (3)$$

The LM statistic is be defined as:

$$LM = \sum_t S(t)^2 / (T^2 f_0) \quad (4)$$

Where f_0, is an estimator of the residual spectrum at frequency zero and where S(t), is a cumulative residual function:

$$S(t) = \sum_{r=1}^{t} u_r \quad (5)$$

based on the residuals ut = yt - xt' δ(0), We point out that the estimator of δ, used in this calculation differs from the estimator for δ used by GLS detrending since it is based on a regression involving the original data and not on the quasi-differenced data.

To specify the KPSS test, one must specify the set of exogenous regressors xt, and a method for estimating f_0. The KPSS test is therefore considered as a suitable complement for unit root tests not only due the fact that it directly tests the stationarity, but especially because it can be used for shorter time series.

In the case where samples are small or medium-sized, finite-sample size distortions that arise in the stationarity test are by and large a consequence of the poor properties of the long-run variance estimator applied to the small samples. The size distortions can be controlled in small and medium-sized samples by conditioning the distribution of the KPSS test on the sample size and the choice of truncation lag. However, there is always a possibility of having a considerable loss of power, that can be quite severe that the test may become biased (Kristian, 2006).

Cointegration test

Further to estimate the long-run relationships, i.e., to run the regression on the equations on FDI and new firms (paid up capital), FDI and gross capital formation at current price, gross capital formation and credit flow to commercial sector, the cointegration test is run. Two sets of variables are cointegrated if a linear combination of those variables has a lower order of integration. For example, cointegration exists if a set of I(1) variables can be modeled with linear combinations that are I(0). The order of integration here - I(1) - tells one that a single set of differences can transform the non-stationary variables to stationarity.

A cointegration means the two series shift from short run equilibrium to long run equilibrium (Dickey et al., 1991).

$$\Delta e_t = \beta_1 + \beta_2 t + \delta e_{t-1} + \sum_{i=1}^{m} \alpha \Delta et - 1 + \varepsilon t \quad (6)$$

We tested whether the residuals are stationary using again the standard ADF test. The software E-views provides the default lag length of 11 in our test and it is sufficient to get rid of auto-correlation problem in the annual data series being used here. The Johansen Cointegration Test for the above-mentioned variables is done with trend assumption of no deterministic trend (restricted constant), linear deterministic trend and linear deterministic trend (restricted). The hypothesized number of cointegrating equations (CE) is at None and At most 1. The Eigen values, Max-Eigen

Statistic and Trace statistic at 5% Critical Value and 1% Critical Value are used to accept or reject the hypothesis of no cointegration.

As compared to the Engle Granger´s test of causality, Johansen´s tests tend to find spurious cointegration more often and the results hold asymptotically as well as in finite samples (Gonzalo & Lee, 2000).

Engle Granger's test of causality

A variable X is said to cause another variable Y, with respect to a given information set that includes X and Y, if current Y can be predicted better by using past values of X than by not doing so, given that all other past information in the information set is used (Granger, 1969).

$$(X)t = \alpha + \sum_{i=1}^{m} \beta i(X)_{t-1} + \sum_{j=1}^{n} \tau j(Y)_{t-1} + \mu 1t \quad (7)$$

$$(Y)t = \theta + \sum_{i=1}^{p} \phi i(Y)_{t-i} + \sum_{j=1}^{q} \psi j(X)_{t-j} + \mu 2t \quad (8)$$

where it is assumed that the disturbances u1t and u2t are uncorrelated. In passing, note that, since we have two variables, we are dealing with bilateral causality. In this case there is Granger causality, thus

$$\sum_{j=1}^{n} \tau j \neq 0, \text{ and } \sum_{j=1}^{q} \psi j \neq 0 \quad (9)$$

Table 2: Augmented Dickey Fuller Test of Stationarity for FDI inflow and new enterprises paid up capital

Variables	Level		
	Intercept	Trend and intercept	None
FDI INFLOW	-2.27**	-3.49**	-1.04**
New enterprises paid up capital	4.14	2.10	4.49
Variables	**First difference**		
	Intercept	**Trend and intercept**	**None**
FDI INFLOW	-3.02**	-1.08**	-1.57**
New enterprises paid up capital	1.16	-4.35	2.51
Variables	**Second difference**		
	Intercept	**Trend and intercept**	**None**
FDI INFLOW	-2.89**	-3.15**	-2.91
New enterprises paid up capital	-5.35**	-5.94**	-6.57**

** Reject the null hypothesis of unit root and is significant at 1% level

Source: Own compilation.

The null hypothesis unit root exists and if the calculated value is less than the table value, the null hypothesis is rejected, and the series is stationary.

Both the above mentioned time series are stationary after second difference, hence they are integrates of order I(2).

Table 3: Results from cointegration test. Trend assumption: No deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	27.2500 (0.0001)	02	22.7200 (0.0003)	02
1	4.5300 (0.0395)		4.5300 (0.0395)	

Source: Author's own work.

Table 4: Trend assumption: No deterministic trend (restricted constant)

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	28.0500 (0.0034)	01	22.9100 (0.0033)	01
1	5.1400 (0.2677)		5.1400 (0.2677)	

Source: Author's own work.

Table 5: Trend assumption: Linear deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	22.560000 (0.003600)	01	20.1700 (0.0052)	01
1	2.391664 (0.122000)		2.3900 (0.1220)	

Source: Author's own work.

Table 6: Trend assumption: Linear deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	31.1500 (0.0100)	01	20.5000 (0.0343)	01
1	31.1500 (0.1008)		10.6400 (0.1008)	

Source: Author's own work.

The above table shows at least one cointegrating equation in each of the above-mentioned trend assumptions. Hence it is possible to test the Engle Granger Causality.

Table 7: Granger's Test of Causality

Sr No.	Null Hypothesis:	Observation	F-Statistic	Probability
1	No. of new enterprises (paid up capital) does not cause FDI inflow	17	1.16935	0.3436
2	FDI inflow does not cause new entepirse formation	17	1.78286	0.2099

Source: Author's own work.

Since the P value is greater than 0.05, we accept the null hypothesis, there is no bidirectional causality between FDI Inflow and New Enterprise creation. Hence H_1 is not satisfied.

Table 8: Augmented Dickey Fuller Test of Stationarity for FDI inflow and gross capital formation

Variables	Level		
	Intercept	Trend and intercept	None
Gross capital Formation	1.27	-0.51	1.97
Foreign Direct invesment	-0.70	-7.26	1.56
Variables	First difference		
	Intercept	Trend and intercept	None
Gross capital Formation	-5.88**	-3.60	-5.25**
Foreign Direct invesment	-3.83*	-7.26**	-5.81**
Variables	Second difference		
	Intercept	Trend and intercept	None
Gross capital Formation	-5.57**	-5.37**	-5.25**
Foreign Direct invesment	-5.51**	-5.88**	-5.84**

** Stationary at 1% significance level.

Source: Author's own work.

Since the timeseries are stationary in the ADF Test and KPSS Test, attempt is made to run the cointegration test on the two time series data of the variables mentioned above. Here the null hypothesis is satisfied, and as such H_2 is not accepted.

Table 9: KPSS test for foreign capital inflow

	Exogenous	LM-Stat	Critical values		
			0.01	0.05	0.10
Level	Intercept only	0.53**	0.73	0.46	0.34
Level	Constant, Linear Trend	0.10**	0.20	0.14	0.11
First Difference	Intercept	0.22**	0.73	0.46	034
First Difference	Constant, Linear Trend	0.18**	0.21	0.14	0.11
Second Difference	Intercept	0.13**	0.73	0.40	0.34
Second Difference	Constant, Linear Trend	0.10**	0.21	0.14	0.11

** Accepting the null hypothesis of stationarity at 1 percent significance.

Source: Author's own work.

Table 10: KPSS test of stationarity for gross capita formation

	Exogenous	LM-Stat	Critical values		
			0.01	0.05	0.10
Level	Intercept only	0.57**	0.73	0.46	0.34
Level	Constant, Linear Trend	0.18**	0.21	0.14	0.11
First Difference	Intercept	0.27**	0.73	0.46	0.34
First Difference	Constant, Linear Trend	0.20**	0.21	0.14	0.11
Second Difference	Intercept	0.24**	0.73	0.46	0.34
Second Difference	Constant, Linear Trend	0.22	0.21	0.14	0.11

** Accepting the null hypothesis of stationarity at 1 percent significance.

Source: Author's own work.

Table 11: Cointegration test between FDI and gross capital formation (since they do not cointegrate there is no causality test to be conducted). Trend assumption: No deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	11.197940 (0.070000)	none	10.081790 (0.070000)	none
1	1.116154 (0.330000)		1.116154 (0.330000)	

Source: Author's own work.

Table 12: Trend assumption: No deterministic trend (restricted constant)

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	13.714800 (0.300000)	none	10.083970 (0.320000)	none
1	3.630829 (0.460000)		3.630829 (0.460000)	

Source: Author's own work.

Table 13: Trend assumption: Linear deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	10.351060 (0.250000)	none	6.738058 (0.520000)	none
1	3.613007 (0.050000)		3.613007 (0.050000)	

Source: Author's own work.

Table 14: Trend assumption: Linear deterministic trend (restricted)

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	16.31 (0.46)	none	12.260 (0.390)	none
1	4.05 (0.73)		4.050 (0.730)	

Source: Author's own work.

Table 15: ADF and KPSS test for credit flow to commercial sector and gross capital formation

Variables	Level		
	Intercept	Trend and intercept	None
Gross capital Formation	1.27	-0.51	1.97
Credit flow to commercial sector	6.85	-1.41	1.52
Variables	**First difference**		
	Intercept	**Trend and intercept**	**None**
Gross capital Formation	-5.88**	-3.60	-5.25**
Credit flow to commercial sector	-0.42	-3.60	1.46

Variables	Second difference		
	Intercept	Trend and intercept	None
Gross capital Formation	-5.57**	-5.37**	-5.25**
Credit flow to commercial sector	-3.78*	-3.59	-3.10**

** Stationary at 1% significance level.

Source: Author's own work.

Interpretation of the results

In KPSS the null hypothesis series are stationary, hence if the calculated value is greater than the table value, the null hypothesis is rejected in favor of the alternative hypothesis, that time series are non-stationary. So H_3 is accepted.

Table 16: KPSS test of stationarity for credit to commercial sector

	Exogenous	LM-Stat	Critical values		
			0.01	0.05	0.10
Level	Intercept only	0.57**	0.73	0.46	0.34
Level	Constant, Linear Trend	0.19**	0.21	0.14	0.11
First Difference	Intercept only	0.67**	0.73	0.46	0.34
First Difference	Constant, Linear Trend	0.11**	0.21	0.14	0.11
Second Difference	Intercept	0.11**	0.21	0.14	0.11
Second Difference	Constant, Linear Trend	0.10**	0.21	0.14	0.11

** Accepting the null hypothesis of stationarity at 1 percent significance.

Source: Author's own work.

Since the time series on credit to commercial sector and gross capital formation are stationary and integrated of order I(0).

Cointegration test between credit to commercial sector and gross capital formation

Table 17: Trend assumption: No deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	16.376510 (0.000000)	one	14.104590 (0.010000)	one
1	2.271919 (0.150000)		2.271919 (0.150000)	

Source: Author's own work.

Table 18: Trend assumption: No deterministic trend (restricted constant)

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	20.237190 (0.050000)	none	14.683880 (0.070000)	none
1	5.553315 (0.220000)		5.553315 (0.220000)	

Source: Author's own work.

Table 19: Trend assumption: Linear deterministic trend

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	18.614660 (0.010000)	02	14.537430 (0.040000)	02
1	4.077228 (0.040000)		4.077228 (0.040000)	

Source: Author's own work.

Table 20: Trend assumption: Linear deterministic trend (restricted)

Null Hypothesis	J trace	Trace Statistic: No. of cointegrating equation at 0.05 level	J max-eigen value	Max-eigen test: No. of cointegrating equation at 0.05 level
0	25.464020	none	18.814010	none
1	6.650014		6.650014	

Source: Author's own work.

The results show that the time series data are cointegrated at 5% significance level under the assumption of no deterministic trend and linear deterministic trend.

Since there is cointegration between the above mentioned two variables, attempt is made to test for Engle grangers causality test.

Table 21: Granger's test of causality

Sr No.	Null Hypothesis	Observation	F-Statistic	Probability
1	CCS does not Granger Cause GKF	17	8.35117	0.0053
2	GKF does not Granger Cause CCS	17	0.29519	0.7496

Source: Author's own work.

In the above table, first row, we reject the null hypothesis, hence the credit to commercial sector does not cause Gross capital Formation (proxy for business creation). However, in the second row, the null hypothesis is accepted.

Results

1. In India as believed theoretically, FDI do not help in creating new firms and in gross capital formation (domestic investment).

As per Bhattarai and Negi (2020), FDI contributed positively to sales, profit, employment and wages of firms in India from 2004 to 2018. While the authors discuss the benefits brought in by advanced technology and skill management practices brought in by foreign promoters, they do not discuss the impact that FDIs had in creating new firms or in gross capital formation (domestic investment).

Chakraborty and Nunnenkamp (2008) analyzed the booming FDI in post-reform India and concluded that the results are industry-specific, with growth effects varying across sectors. While the manufacturing sector has seen good growth, the primary sector was not affected, and the services sector had only transitory effects, but the impact on new firms is not studied.

A similar study by Pradhan (2002) on the production function, shows that the Indian economy benefitted positively from FDI.

A comparison between India and China regarding foreign invested enterprises by Huang and Tang (2011), show that while China adopted a more proactive policy towards FDI than India, the latter pursued a more comprehensive domestic reforms policy, establishing a ministry devoted to privatization and undertook a deeper financial liberalization that resulted even in bank privatizations. This was an initiative of the government and not a direct effect of FDI inflows.

Based on these articles, it is clear that the Indian economy, which has a tremendous potential, had a positive impact due to FDI. While FDI inflows supplement domestic capital and bring in new technology and skills to existing companies, and ought to have a positive impact on new firms´ creation and gross capital formation, our results show that FDI has stifled domestic capital.

2. Flow of credit to commercial sector helps to promote domestic investment (proxy for business creation).

India is a country that needs large scale investments in infrastructure for accelerating inclusive growth aimed at poverty alleviation and improvement in quality of life. Given the fiscal constraints that leave little room for expanding public investment at the required scale, public-private partnership (PPP) is required, with most of the funding being raised from domestic financial institutions (Roy, 2015). A study of the British International Investment regarding their participation in lending for micro, small and medium enterprises in India, found out that between 2013 and 2015, credit had a significant relationship with job creation, SME exhibited impressive financial performance, first-time borrowers could be reached and investment in female managed enterprises increased.

As per Liu et al. (2019), bank loans, as compared to stimulate enterprises technological innovations to a greater extent than equity financing and internal financing, both for listed companies and SMEs. Several Indian studies, including those by Ramcharran (2017) and Singh et al. (2002) proved that the flow of credit to the commercial sector helps in promoting domestic investments, or in other words, new business creation. These conclusions match the findings of our study, where FDI result in a crowd out effect that does not support the domestic business enterprises. However, with the domestic policy adopted by the Indian government, domestic businesses have been growing mainly due to bank credit to the commercial sector.

3. Policy changes and more reforms are required so that FDI is better absorbed and helps to create new firms, rather than the crowd out effect. Based on the results, FDI inhibits the domestic investment and new enterprise creation in India.

After the gradual opening of the economy, India witnessed a huge inflow of FDI funds, mainly in the manufacturing sector (Conconi et al., 2017), but due to improper regulations, there is a tendency for FDI to crowd out capital formation and new enterprise creation. It is important for a country to achieve a threshold level of development and undergo appropriate reforms in terms of ease of doing business in order to assimilate and realize the benefits of FDI for economic growth. It is equally important that in an era of globalization, the external shocks do not destabilize the domestic economy (Christopherson et al., 2010).

To counteract the competition effect, the local entrepreneurs may rise to the challenge posed by FDI and hence increase the domestic investment (Mello, 1999). The resources available could be used for building the requisite infrastructure mix and thus increase the profitability of domestic firms (Blomstrom, 1989). A country will have to frame policies to ensure that FDI benefits the economic growth. If the FDI is attracted to areas and sectors that would not be otherwise attract investment, the economic growth can be assured, so the government can always try to restrict the FDI to unattractive sectors (Crescenzi et al., 2021).

By 2019, India ranked as the 9th largest recipient of FDI (and by 2021, the 7th), with inflows around $83.6 billion, both in horizontal and vertical types of investments, and in 2020, the government is now scrutinizing every FDI under the Ministry of Commerce and Industry to ensure that opportunistic takeovers or acquisitions of Indian companies do not take place. While the new rules tried to simplify the existing regulations, some restrictions were imposed on FDI from neighboring countries (countries sharing land borders with India) and the investment horizon was broadened to erstwhile restricted areas like public insurance companies, defense and pharmaceuticals, and further restricted sectors may be opened in future. The end result may be a boost to new firms´ creation and domestic capital formation, that is not seen at present.

Conclusion

Our study concludes that FDI stifles domestic capital due to the fact that local firms do not have the financial backing that foreign firms have. While the entry of FDI backed companies in India brings in new technology and foreign funds, the benefits for the local industry are not seen. Similar results by (Hernández-Catá, 2000; Serván, 1996; Odentha, 2001) found that FDI crowds out domestic investment in African countries. Domestic firms may be constrained by the weak financial intermediation and the inadequate availability of funds could prevent them from taking advantage of the opportunities created by the FDI.

On the other side, domestic flow of capital is helpful in encouraging domestic investment. This domestic investment is mainly supported by local bank loans and financing. It is evident from the empirical work of (Alfaro et al., 2004), that underdeveloped financial markets may be a deterrent to take the advantage of foreign capital inflows. It is a case of negative spillover of international capital inflows (Demirguc et al., 2006).

Finally, the new rules of the government of India tried to simplify the existing regulations and some restrictions were imposed on FDI from neighboring countries (countries sharing land borders with India) and the investment horizon was broadened to erstwhile restricted areas like public insurance companies, defense and pharmaceuticals, and further restricted sectors may be opened in future. The end result may be a boost to new firms´ creation and domestic capital formation, that is not seen at present.

Limitations and further study

Our study had some limitations, due to data availability and was restricted to the period of 2000-2019, before the new FDI regulations came into force. It would be interesting to continue the study for the period after or including 2023 to see if the new regulations on FDI have improved the inflows to the country. The impact of the Covid-19 pandemic could also be a topic of study. Another lead would be the study of FDI inflows for a specific sector of the Indian economy or a study comparing India and China or any other neighboring country.

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Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 25-48
10.2478/fiqf-2023-0025

Financial Internet Quarterly

HOW COVID-19 AFFECTED CORPORATE DIVIDEND DECISIONS: NOVEL EVIDENCE FROM EMERGING COUNTRIES

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Abstract

The study aims to investigate the corporate dividend policy decisions in emerging countries during the COVID-19 pandemic. Our sample consists of 5,869 publicly listed firms from 29 emerging countries to explicate the observed trends in dividend policy during the pandemic. Logistic regressions are used to investigate the main factors that drive the propensity to change dividend payouts. Our analysis reveals that most firms opted to either increase or decrease their dividends, with a minority proportion deciding to maintain dividends. Notably, our findings demonstrate that firm profitability is the main driver of all types of dividend changes, except when firms opt to maintain or decrease dividends. Moreover, we find that when firms reduce dividends by over 70%, profitability emerges as a crucial determinant, thus bolstering the signaling hypothesis. The results are robust to sample size sensitivity and different levels of dividend changes. The findings of the study might have practical implications for corporate managers and policymakers in designing dividend decisions and policies under uncertain conditions. This research underscores the impact of the COVID-19 pandemic on corporate dividend policy in emerging countries and emphasizes the need to consider the level of dividend changes in exploring the dividend puzzle.

JEL classification: G30, G32, G35
Keywords: Dividend policy, COVID-19, Pandemic, Profitability, Emerging countries

Received: 01.06.2023 Accepted: 08.09.2023

Cite this:
AlGhazali M.A. & Yilmaz I. (2023) How COVID-19 Affected Corporate Dividend Decisions: Novel Evidence from Emerging Countries. Financial Internet Quarterly 19(4), pp. 25-48.

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Introduction

COVID-19 has been one of the most challenging uncertainties for corporations in recent years. It was first detected in December 2019, and its effects became more concrete by February 2020. The World Health Organization (WHO) officially declared it a pandemic in March 2020. To cope with this pandemic, governments announced several actions to prevent the virus's spread, including partial or complete lockdowns, which led to significant effects on economies and corporations. This resulted in declines in economic growth worldwide by 4.2%, in the US by 3.4%, in Europe by 7.5%, in the G-20 by 3.8%, and in India by 9.9%. Yilmazkuday (2020) reports the negative impact of COVID -19 on the global economy, while Mazur et al. (2021), Tripathi and Pandey (2021), and Baker et al. (2020) demonstrate a robust increase in equity market volatility in the US.

The uncertainty caused by COVID-19 has affected various industries and regions in disparate ways. Pan (2021) has reported a significant drop in manufacturing PMI since 2011, with the effect being more pronounced in developed rather than developing markets. However, the MSCI emerging markets index has underperformed the MSCI world index during the pandemic (Pan, 2021). This effect has extended to internal and external capital chains, prompting firms to review their financial policies (Jiang et al., 2021). During 2020, leverage decreased significantly in the US (Haque & Varghese, 2021). Firms with high leverage experience a high level of risk (Huang & Ye, 2021). The flow of credit to industrial sectors remained robust (Deghi et al., 2021), and stock markets have reacted negatively to the pandemic (Harjoto et al., 2021; Prabheesh et al., 2020).

Wigglesworth et al. (2020) reported a reduction in firms' dividends globally during the pandemic. The emerging empirical research on the impact of COVID-19 on corporate dividend policy has focused on developed countries (e.g. Ali, 2022; Ntantamis & Zhou, 2022). However, few studies have explored its effects on emerging countries and have used a single-country setting, such as Ali et al. (2022) in Pakistan, and Tinungki et al. (2022) in Indonesia. Scholars have demonstrated salient differences between developed and developing countries regarding corporate governance mechanisms, legal protection, voting rights, ownership structure, and the role of institutional shareholders (Glen et al., 1995; Mitton, 2004; Adjaoud & Ben-Amar, 2010). These issues are not independent of how corporate dividend policy is determined and deserve further investigation. For instance, Aivazian et al. (2003) have demonstrated that the sensitivity of dividend policy determinants differs in emerging compared to developed markets.

The agency theory of dividends, proposed by Jensen (1986), contends that firms with excess cash can resolve the principal-agent problem by maintaining or increasing dividends. In contrast, the signaling theory of dividends, advanced by Bhattacharya (1979), asserts that changing dividends can convey valuable information about a firm's prospects. In this context, our objective is to investigate the corporate dividend policies during the COVID-19 pandemic, utilizing a substantial sample from emerging countries. Our study seeks to provide new insights into the effect of the pandemic on corporate dividend policies in emerging countries, where empirical research in this domain is relatively limited. To the best of our knowledge, our study is the first of its kind to explore the impact of the pandemic on corporate dividend policy across 29 emerging countries.

The present study represents a significant contribution to the literature on corporate dividend policy. Specifically, it is the first study to investigate the impact of unexpected exogenous shocks, such as the COVID-19 pandemic, on dividend policy using a large sample from emerging countries. The empirical findings of our study demonstrate that the majority of firms in these countries either increase or cut dividends during the pandemic. Additionally, the number of firms that maintain dividends is lower than those that omit dividends, which underscores the impact of the pandemic on firms' dividend stability in these countries.

Our study also sheds light on the importance of considering the levels of dividend changes to explain the variation in dividend policy across firms and countries. The results reveal that at a higher level of dividend reduction (> 75%), there is a significant negative growth in the profitability of firms that decrease dividends compared to those that maintain dividends. Furthermore, at a higher level of dividend increases and decreases (> 75%), profitability and asset turnover are the primary drivers of corporate dividend decisions. However, the decision to increase or maintain a dividend is primarily attributed to the profitability and size of a firm. Therefore, splitting dividend changes into levels may provide further insights into the mixed evidence on corporate dividend policy.

Lastly, our study highlights the variation in dividend policy between developing (Ali, 2022) and developed countries, which merits further consideration. These findings have significant implications for policymakers, investors, and other stakeholders, particularly regarding the impact of unexpected exogenous shocks on dividend policy in developing economies. Overall, our study makes a valuable contribution to the literature on corporate finance and dividend policy, and its findings have important implications for future research in this area.

This paper is structured as follows: Section 2 provides a review of the relevant literature, while Section 3 describes the data and methodology used in our analysis. In Section 4, we present our empirical results, and Section 5 reports on the robustness checks we conducted. Finally, Section 6 concludes the paper.

Literature review

Dividend policy is one of the financial policy challenges faced by corporations. Some studies have focused on the question of whether dividend policy affects firm value, while others have focused on the determinants of dividend policy. In their seminal work, Miller and Modigliani (1961) argue that in a perfect market, corporate dividend policy is irrelevant and does not have any impact on corporate value. However, in the real world with market imperfections such as taxes, transaction costs, asymmetric information, and principal-agent conflict, dividend policy has been shown to affect shareholders' value.

The existing literature documented that there are significant differences in dividend policies and decisions of the firms in emerging countries and developed countries, particularly the firms in emerging countries follow less stable dividend policies and the most important determinant of the dividend decision is the current year earnings, also the firms in emerging countries are subject to higher financial constraints (Adaoglu, 2000; Aivazian et al., 2003; Glen & Singh, 2004). Jabbouri (2016) investigated the determinants of dividend policy in MENA region countries and reported that firm size, profitability, and liquidity have a positive effect on dividend payments while firm growth and leverage have a negative effect. The responses of the firms in their dividend policies during economic slumps are also different in emerging and developed countries. The firms in developed countries tend to reduce dividends in such periods while the counterparts in emerging countries tend to increase the payout to pacify the investors (Chemmanur & Tian, 2014; Jabbouri, 2016).

Agency and signaling theories have been widely used in the literature to justify the relevance of corporate dividend policy. Agency theory explains dividend decisions in principal-agent problems (Jensen, 1986). In this context, firms should continue to pay or increase dividends to prevent self-interested managers from investing excess cash in negative NPV projects or obtaining private benefits. The signaling theory argues that dividend changes convey signals about firms' prospects, suggesting a positive link between dividends and earnings (Bhattacharya, 1979).

Several empirical studies have examined corporate dividend policy during the financial crisis of 2007-2009 and provided empirical evidence of the adverse impact of this crisis on dividend policy (e.g. Hauser, 2013; Floyd et al., 2015). For instance, Hoberg and Prabhala (2009) detect a lower propensity of firms to pay dividends after the financial crisis, and Hauser (2013) finds consistent results with this conjecture. Bistrova et al. (2013) show that there was a reduction in the payout policy during the financial crisis in European firms. COVID-19 has been a similar turmoil period for corporations, and they have encountered financial policy challenges, including dividend decisions (Cejnek et al., 2021; Ali, 2022; Eugster et al., 2022; Ntantamis & Zhou, 2022).

Ali (2022) investigates the impact of COVID-19 on dividend policy in G-12 countries and finds that while the majority of firms maintain or increase dividends, there is a significant increase in the number of firms that decrease or omit dividends compared to the pre-COVID-19 period. Her findings reveal that firms' profitability plays a crucial role in determining the decision to change dividends. Using US data, Krieger et al. (2021) study the impact of COVID-19 on the payout policy of US firms, reporting that the proportion of dividend cuts or omissions during 2020 was three to five times higher than in the periods 2015-2019.

Ntantamis and Zhou (2022) examine the effect of COVID-19 on the payout policies of firms in G-7 countries, considering dividends and share repurchases. They find that more companies decreased their payout after the pandemic started and point out that the scale of adjustments varies across countries. They also find that cash holdings helped mitigate the negative effects of the pandemic, with the effect being more significant in North America and Japan compared to Europe.

In developing countries, Tinungki et al. (2022) examine the impact of COVID-19 on dividend policy in Indonesia and find that the pandemic does not have a significant effect on firms' dividend policy. However, Ali et al. (2022) demonstrate that the majority of listed firms in Pakistan omit dividends during the pandemic, while firms that decide to maintain dividends account for less than 6% of the sample. They further show that firms that increase (decrease) dividends experience a positive (negative) profitability compared with firms that decrease (maintain) dividends. However, they find no robust evidence on other dividend change groups.

Data and methodology

The sample

The study's sample comprises listed firms from 29 countries that were obtained from Refinitiv Eikon during the 2015-2020 period. We follow the recent studies that examine the impact of COVID-19 on dividends and choose the period 2015-2020 (e.g. Krieger et al., 2020; Ali, 2022). The initial sample consisted of

14,208 firms, from which 738 financial and real estate firms were removed. We excluded firms that never paid dividends or engaged in share repurchases in 2020 (N = 6,738) from the sample. Additionally, we removed firms that chose to omit dividends in 2019 or initiate dividends only in 2020, following Ali's (2022). We retained only firms with complete accounting data and restricted the sample to investable firms by excluding those with total assets and total equity of less than 0.5 and 0.25 million, respectively. To counter the influence of potential outliers, we implemented a winsorization procedure on all non-dummy variables, limiting extreme values to the 1st and 99th percentiles. This technique effectively mitigates the impact of any errant observations, thereby promoting a more robust and reliable dataset for subsequent analyses. As a result, our final sample comprised 5,869 firms from 29 countries. We utilized the Industry Classification Benchmark (ICB) to categorize firms into nine distinct groups, as reported in Table 1.[3]

Table 1: Sample Details

Panel A: Sample distribution per country							
Country	Freq.	Percent	Cum.	Country	Freq.	Percent	Cum.
Argentina	22.0	0.4	0.4	Morocco	22.0	0.4	80.7
Bahrain	13.0	0.2	0.6	Oman	39.0	0.7	81.4
Bangladesh	69.0	1.2	1.8	Pakistan	145.0	2.5	83.9
Brazil	120.0	2.0	3.8	Peru	55.0	0.9	84.8
Bulgaria	14.0	0.2	4.1	Philippines	60.0	1.0	85.8
Chile	88.0	1.5	5.6	Poland	90.0	1.5	87.3
China	2620.0	44.6	50.2	Qatar	19.0	0.3	87.7
Colombia	29.0	0.5	50.7	Romania	41.0	0.7	88.4
Egypt	54.0	0.9	51.6	Russia	63.0	1.1	89.4
Hungary	6.0	0.1	51.7	Saudi Arabia	50.0	0.9	90.3
India	1085.0	18.5	70.2	South Africa	90.0	1.5	91.8
Indonesia	172.0	2.9	73.1	Thailand	389.0	6.6	98.5
Kuwait	20.0	0.3	73.5	Turkey	72.0	1.2	99.7
Malaysia	358.0	6.1	79.6	UAE	19.0	0.3	100.0
Mexico	45.0	0.8	80.3	Total	5869.0	100.0	
Panel B: Sample distribution per industry							
ICB Industry name	**Freq.**	**Percent**	**Cum.**	**ICB Industry name**	**Freq.**	**Percent**	**Cum.**
Basic Materials	929.0	15.8	15.8	Industrials	1553.0	26.5	82.7
Consumer Discretionary	1089.0	18.6	34.4	Technology	524.0	8.9	91.7
Consumer Staples	630.0	10.7	45.1	Telecommunications	166.0	2.8	94.5
Energy	187.0	3.2	48.3	Utilities	323.0	5.5	100.0
Health Care	468.0	8.0	56.3	Total	5869.0	100.0	

Source: Author's own work.

Descriptive statistics

Table 2 provides a comprehensive overview of summary statistics by dividend-change groups for the 2015-2020 period. Notably, the vast majority of firms in markets have exhibited a propensity for a dividend increase, aligning with the findings reported in extant research conducted on developed markets (Ali, 2022). However, contrary to these previous studies, firms exhibiting a decrease (or no-change) in dividends represent the second (or third) largest group. Additionally, in 2020, the number of firms with dividend increase (DIC) stood at 2,353, surpassing all other types of dividends-change groups, a trend that aligns with Ali's (2022) observations in G-12 countries. However, this pattern has remained relatively flat since 2019, diverging from that observed in developed countries.

[3] The majority of firms in Table 1 are from China and India which account for 63% of the sample. This might lead our estimations to be biased. Hence, we consider the overrepresentation of the sample in the robustness section.

Table 2: Number of Firms per Dividend-Change Group

Dividend	2015		2016		2017		Total
	Obs	%	Obs	%	Obs	%	Obs
DIC	1571	42.3	2294	45.5	2605	47.3	13775
DNC	557	15.0	946	18.8	1026	18.6	5545
DDC	1104	29.7	1277	25.3	1364	24.8	8584
DOM	483	13.0	525	10.4	514	9.3	4165
Total	3715	100.0	5042	100.0	5509	100.0	32069
Dividend	**2018**		**2019**		**2020**		**Total**
	Obs	**%**	**Obs**	**%**	**Obs**	**%**	**Obs**
DIC	2670	44.4	2282	38.6	2353	40.1	13775
DNC	1020	17.0	1125	19.0	871	14.8	5545
DDC	1562	26.0	1652	27.9	1625	27.7	8584
DOM	763	12.7	860	14.5	1020	17.4	4165
Total	6015	100.0	5919	100.0	5869	100.0	32069

DIC: Dividend increase, DDC: Dividend decrease, DNC: Dividend no change, DOM: Dividend omissions.

Source: Author's own work.

Table 2 shows that the number of firms that opted not to change dividends (DNC) in 2020 stood at 871, in contrast to the 1,125 recorded the previous year. This finding contradicts that reported in G-12 nations (Ali, 2022), where the number of firms that maintained dividends in 2019 and 2020 was almost identical. Dividend-decreasing firms (DDC) remained relatively stable both during the pandemic and preceding years, diverging from the sample observed in developed countries (Ali, 2022). Conversely, dividend-omitting firms (DOM) increased over the period, reaching their highest levels during the pandemic year, a trend that aligns with the results of research conducted in the US (Pettenuzzo et al., 2021) and developed countries (Ali, 2022). For the remainder of this study, we will focus on the pandemic year: 2020.[4]

Table 3 presents the descriptive statistics for each dividend group during the pandemic year, which includes firms that increased dividends (Panels A), firms that maintained dividends (Panels B), firms that decreased dividends (Panels C), and firms that omitted dividends (Panels D). All variables used in the analysis are defined in Appendix A. Among the different dividend-change groups, the firms that increased dividends were found to be more profitable and larger, this is consistent with the findings reported in developed countries (Ali, 2022). The firms that decided not to change dividends were observed to be more liquid during the COVID-19 year. However, their profitability, assets turnover, size, and market-to-book ratio were found to be very similar to the dividend-decreasing firms, which contradicts the findings of Ali (2022) in G-12 countries. These results suggest that there are similarities in the characteristics of firms that maintain dividends and those that cut dividends, which is not in line with Ali's (2022) findings that show that firms that decide not to change dividends are much more profitable, have higher assets turnover, are smaller, and experience lower market-to-book ratios. On the other hand, the dividend-omitting firms were found to have negative profitability, lower liquidity, more debt, and a high market-to-book ratio.

[4] The total number of firms paying dividends in our study, including DIC, DDC, and DNC, decreased from 5,059 to 4,849 in 2019 and 2020, respectively. This finding is consistent with the results obtained by Ntantamis and Zhou (2022) in G-7 countries. However, the numbers in each dividend-change group differ significantly from those reported in developed countries (Ali, 2022), indicating differences in dividend behavior between developing and developed markets.

Table 3: Descriptive statistics

Characteristics	Mean	Median	Min	Max	Std. Dev.
Panel A: Dividend increases (DIC)					
ROA %	7.8	6.6	-34.0	27.5	5.8
chE %	3.2	2.5	-87.2	82.2	9.1
ROE %	14.2	12.2	-145.7	61.8	11.2
Operpm %	15.8	12.8	-267.1	65.6	14.4
AstTvr	0.8	0.7	0.0	3.5	0.5
Lev %	43.1	42.6	3.0	94.0	19.5
Size	20.1	20.1	14.6	23.9	1.8
Liq	2.6	1.8	0.2	25.5	2.6
MktBk	0.7	0.4	0.0	9.6	0.9
Panel B: No change in dividends (DNC)					
ROA%	5.3	4.5	-32.1	27.5	5.0
chE%	-1.2	-0.1	-109.8	50.4	8.4
ROE%	9.2	8.6	-145.7	46.7	10.2
Operpm %	10.3	9.3	-267.1	65.6	16.2
AstTvr	0.8	0.7	0.0	3.5	0.6
Lev %	41.6	41.0	3.0	94.0	19.9
Size	19.6	19.6	14.4	23.9	1.8
Liq	2.9	1.8	0.2	25.5	3.4
MktBk	0.8	0.6	0.0	9.6	0.8
Panel C: Dividend decreases (DDC)					
ROA %	4.8	3.9	-34.0	27.5	5.3
chE %	-4.3	-2.5	-109.8	90.1	11.9
ROE %	9.1	7.2	-85.6	61.8	11.3
Operpm %	10.9	9.0	-192.5	65.6	16.0
AstTvr	0.7	0.6	0.0	3.5	0.5
Lev %	43.5	43.8	3.0	94.0	20.8
Size	19.9	19.8	14.7	23.9	1.8
Liq	2.6	1.7	0.2	25.5	2.8
MktBk	0.8	0.6	0.0	9.6	1.0
Panel D: Dividend omissions (DOM)					
ROA %	-0.4	0.4	-34.0	27.5	8.2
chE %	-11.3	-6.2	-109.8	90.1	21.0
ROE %	-2.9	0.9	-145.7	61.8	22.7
Operpm %	-3.5	2.6	-267.1	65.6	33.7
AstTvr	0.7	0.6	0.0	3.5	0.6
Lev %	47.8	48.3	3.0	94.0	20.9
Size	19.2	19.3	14.4	23.9	1.9
Liq	2.3	1.5	0.2	25.5	3.1
MktBk	1.1	0.7	0.0	9.6	1.3

The table presents several characteristics of the sample. It reports the mean, median, maximum, minimum and standard deviation of variables for each dividend's category. All variables are defined in Appendix A. Panels A, B, C, and D present the groups of firms that chose to increase, not change, decrease and omit dividends, respectively.

Source: Author's own work.

Pairwise correlations

Table 4 (see: Appendix) presents the pairwise correlations among the variables used in the analyses during the COVID-19 period. The dividend increases are positively correlated with all profitability measures, asset turnover, and size, but negatively correlated with leverage, liquidity, and market-to-book ratio. Dividend no-change cases have a similar pattern, with the exception that they have a positive correlation with liquidity. Dividend cuts have a positive association with ROA, ROE, operating profit margin, and size, but are negatively associated with changes in earnings, asset turnover, leverage, liquidity, and market-to-book ratio. Dividend omissions display an opposite pattern compared to the other three categories; they have negative correlations with all profitability measures, asset turnover, and liquidity, but positive correlations with leverage, size, and market-to-book ratio. These findings reveal that the no-change dividend and dividend decrease groups exhibit similar correlations with all of the used variables, except for ChE, size, and liquidity. These statistics confirm some differences from those in developed markets (Ali, 2022), which show that firms that decrease dividends are negatively correlated with all profitability measures, firm size, and market-to-book ratio.

Methodology

To examine the impact of the pandemic on corporate dividend policy, we follow the recent study by Ali (2022). We calculate the dividend changes following Nissim (2001), as the difference between dividends in fiscal year t and the dividends in the previous year, scaled by the dividend in the previous year. Then, dividend changes are sorted into four groups: (I) dividend increases, (II) dividend no changes, (III) dividend decreases, and (IV) dividend omission. Next, dichotomous variables are constructed based on each two groups of dividend changes (DivChange). Our dependent variable is a categorical variable that equals 1 or 0. Thus, we apply logistic regression to investigate what factors drive the variation in dividend decisions in emerging countries during the COVID-19 pandemic. The model is specified as follows:

$$Pr(DivChange_i = 1) = \beta_0 + \beta_1 Profitabitliy_i + \Sigma\theta X_i + Industry\ Dummies_j + Country\ Dummies_k + \eta_i \quad (1)$$

Where is a dichotomous variable that takes the value of 1 and 0 for each two groups: dividend increases (= 1) versus dividend no change (= 0); dividend increases (= 1) versus dividend decreases (= 0); dividend omissions (= 1) versus dividend no changes (= 0); dividend omission (= 1) versus dividend decreases (= 0); and dividend decreases (= 1) versus dividend no change (= 0). We have used four different measures of profitability following the recent literature (i.e. Return on assets (ROA %); Change in earnings (chE %); Return on equity (ROE %); Operating profit margin (Operpm %)). ROA % is defined as net income over total assets (Krieger et al., 2021), and chE % is defined as the change in the net income scaled by the book value of equity (Ali, 2020). ROE % is defined as net income scaled by the book value of equity (Richard et al., 2014). Operpm % is operating profit divided by revenue (Fairfield & Yohn, 2001).[5] Control variables, include assets turnover, firm size, leverage, liquidity, and market-to-book ratio (DeAngelo et al., 2004; Denis & Osobov, 2008; Ali, 2022). All other variables are defined in Appendix A. Furthermore, we control for country and industry fixed effects in all regressions.

Empirical results

The estimates for the logistic regression are displayed in Table 5 (see: Appendix), Panels A to D. Considering the results in Panels A to E (Models 1 to 16), we found strong associations between firms' profitability and the propensity to change dividends in emerging countries during the COVID-19 pandemic, which is in line with Ali's recent study (2022) in G-12 countries. Panel A reveals that profitability measures are positive and statistically significant at the 1% level, indicating that firms with higher profitability are more likely to increase dividends than to maintain them. Models 5 to 8 in Panel B document that the likelihood of increasing dividends is more pronounced in firms with higher profitability, as opposed to decreasing them. Firms with lower profitability, as stated in models 9 to 12 of Panel C, are more likely to omit dividends than to maintain their levels. Moreover, Panel D detects that lower profitability increases the likelihood of firms omitting dividends rather than decreasing them. The regression outputs in models 17 to 20 demonstrate that the coefficients of profitability measures are not robustly significant. These findings provide little support for the impact of profitability on the likelihood of firms decreasing dividends compared to maintaining them, which is inconsistent with the findings in developed countries (Ali, 2022). Study (2022) in G-12 countries. Panel A reveals that profitability measures are positive and statistically significant at the 1% level, indicating that firms with higher profitability are more likely to increase dividends than to maintain them. Models 5 to 8 in Panel B document that the likelihood of increasing dividends is more pronounced in firms with higher profitability, as opposed to decreasing them. Firms with lower profitability, as stated in models 9 to 12 of Panel C, are more likely to omit dividends than to maintain their levels. Moreover, Panel D detects that lower profitability increases the likelihood of firms omitting dividends rather than decreasing them. The regression outputs in models 17 to 20 demonstrate that the coefficients of profitability measures are not robustly significant. These findings provide little support for the impact of profitability on the likelihood of firms decreasing dividends compared to maintaining them, which is inconsistent with the findings in developed countries (Ali, 2022).

[5] We have employed different measures of profitability to provide robust evidence of the impact of profitability on corporate dividend policy. The majority of the previous studies have demonstrated the significant influence of profitability on corporate dividend policy (e.g. Fama & French, 2001; DeAngelo et al., 2004; Al-Ghazali, 2014).

The effect of firms' characteristics on the likelihood of firms to change dividends in panel A of Table 5 (see: Appendix) shows that the propensity of firms to increase rather than maintain dividends is positively associated with assets turnover as shown in models 2 and 3, indicating that firms with high assets turnover are more likely to increase dividends. Size bears positive and significant coefficients indicating that larger firms are more likely to increase than maintain dividends. Furthermore, the coefficients of liquidity are statistically insignificant at 10%, suggesting that firms that increase compared to those that maintain dividends do not exhibit significant liquidity differences. The market-to-book ratio is lower in firms that increase rather than maintain dividends. As shown in models 5 to 8 of panel B, the likelihood of firms to increase than decrease dividends is positively (negatively) correlated with assets turnover, size, and market-to-book ratio. Panels C and D reveal that the propensity of firms to omit rather than maintain dividends (penal C) and omit rather than decrease dividends (panel D) is negatively (positively) and significantly related to assets turnover and size (leverage and market-to-book ratio). Panel E reports that asset turnover reduces the propensity of firms to decrease rather than maintain dividends while other factors are not statistically significant.

We extended our analysis to investigate the inconsistent results with Ali's study on the impact of firms' profitability on the likelihood of firms decreasing rather than maintaining dividends. We divided dividend reductions into four groups: (I) reduction less than 25%; (II) reduction between 25% and less than 50%; (III) reduction between 50% and less than 75%; and (IV) reduction greater than 75% and less than 100%. We ran a logistic regression using Eq. (1), where the explanatory variables are (I) a dichotomous variable that is 1 for dividend reduction less than 25% and 0 if dividends are not changed; (II) a dichotomous variable that is 1 for dividend reduction between 25% and less than 50% and 0 if dividends are not changed; (III) a dichotomous variable that is 1 for dividend reduction between 50% and less than 75% and 0 if dividends are not changed; and (IV) a dichotomous variable that is 1 if dividend reduction between 75% and less than 100% and 0 if dividends are not changed.

The estimated outputs of the logistic regression are presented in Table 6 Panel A to D (see: Appendix). We find strong evidence indicating that at a lower level of dividend reduction, Panel A, higher profitable firms are more likely to cut than maintain dividends. The coefficients of leverage and size are positive and significant only in models 1 and 2, respectively. These findings might suggest that a small reduction in dividends could be used by firms not to convey their prospect about future profitability: signaling. The relationship between the propensity of firms to change dividends and profitability diminishes at moderate and high levels of dividend reductions (25% ≤ DDCD < 50% and 50% ≤ DDCD < 75%) as reported in Panel B and C. Specifically, we find that at these levels of dividend reductions, the profitability measures are not robustly significant. Assets turnover is negative and statistically significant in panel B indicating that firms at moderate levels of dividend reduction exhibit lower assets turnover than those that maintain dividends. Panel C shows that size and liquidity bear statistically negative coefficients.

In the case of extreme dividend reduction (a decrease ≥ 75%), as in Panel D, the findings demonstrate a robust significant negative correlation between all the profitability measures and the propensity of firms to decrease rather than maintain dividends, consistent with developed markets (Ali, 2022). Furthermore, firms with extreme dividend reductions exhibit lower asset turnover than those that maintain dividends.

Robustness Check

In the preceding section, we presented compelling evidence of the impact of the COVID-19 pandemic on the dividend policies of corporations in nations except in one group: Dividend decreases vs. dividend no-change. Nonetheless, it is plausible that our findings are attributable to alternative explanations. To fortify our results, we address two critical factors in this section: (1) the sensitivity of sample size; and (2) the distinction between the levels of dividend increases and the maintenance of existing dividend levels.

Sample size sensitivity

The present study encompasses data from 29 distinct countries, albeit with variations in the number of observations for each country, as indicated in Table 1. The preponderance of data from China and India in our sample warrants scrutiny, as this may introduce a potential bias into our estimation through overrepresentation. To address this concern, we re-examine our analysis, as reported in Table 5 (see: Appendix), by omitting data from the aforementioned countries. The estimated outputs from this refined analysis are subsequently presented in Table 7 (see: Appendix). Our findings, which align with those reported in Table 5 (see: Appendix), furnish compelling evidence of the impact of profitability measures on corporate dividend policy, except in one category, i.e., dividend decreases vs. dividend no-change. Moreover, the remaining estimated coefficients demonstrate consistent signs and levels of significance. In light of these findings, we affirm that our estimations remain robust, notwithstanding the potential for overrepresentation in our sample.

The level of dividend increases versus no-change dividends

The relationship between firms' profitability measures and corporate dividend policy has been investigated in Table 6 (see: Appendix), revealing an inconsistency in impact across varying levels of dividend reduction. To provide a more in-depth examination of this phenomenon, Table 7 (see: Appendix) was employed, revealing the pronounced impact of firms' profitability on dividend reduction in the context of extreme reduction. This pattern may also be observed in the case of dividend increases, prompting a replication of the analysis using dividend increases in Table 7 (see: Appendix). Specifically, the dividend increases were partitioned into four distinct groups based on their percentage increase, ranging from less than 25% to greater than 75%. Table 8 (see: Appendix) presents the estimated results based on the specified model, using a dichotomous variable that is 1 for each group of dividend increases and 0 if dividends are not changed.

The results demonstrate that all profitability measures exhibit positive and significant coefficients at all levels of dividend increases, indicating that the impact of corporate profitability on dividend increases is consistent across all levels. These findings provide further support for the results presented in Table 5 (see: Appendix). Moreover, it was found that the primary drivers of increasing dividends at higher levels were profitability and asset turnover, aligning with the findings in the context of dividend reduction.

Conclusion

In this study, we have undertaken an analysis of the impact of the COVID-19 pandemic on dividend policy, drawing upon a large sample of firms from emerging countries. Our investigation has yielded several notable findings. Firstly, we have observed that a majority of firms in our sample have either increased or decreased their dividends during the pandemic. Additionally, we have noted a significant rise in the number of firms that have opted to omit dividends, surpassing those that have maintained their dividend payments during the pandemic. Our regression analyses have further revealed that profitability and firm size are the primary determinants of changes in dividend policy, except for the decision to reduce or maintain dividends.

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Appendix

Appendix: Variable definitions

Variable	Abbreviation	Definition/Calculation
DivChange	DICD vs. DNCD	Dummy variable equals to 1 for dividend increases and 0 for dividend no change
	DICD vs. DDCD	Dummy variable equals to 1 for dividend increases and 0 for dividend decreases
	DOMD vs. DNCD	Dummy variable equals to 1 for dividend omissions and 0 for dividend no changes
	DOMD vs. DDCD	Dummy variable equals to 1 for dividend omission and 0 for dividend decreases
	DDCD vs. DNCD	Dummy variable equals to 1 for dividend decreases and 0 for dividend no change.
Return on Assets (%)	ROA%	(Net Income scaled by total assets) * 100
Change in Earnings (%)	chE%	(Change in the net income over book value of equity) * 100
Return on Equity (%)	ROE%	(Net income divided by book value of equity) * 100
Operating Profit Margin (%)	Operpm%	(Operating profit scaled by revenue) * 100
Asset Turnover	AstTvr	Revenue over total assets
Leverage	Lev%	(Long-term debt scaled by total assets) * 100
Firm Size	Size	Natural logarithm of total assets
Liquidity	Liq	Current assets divided by current liabilities
Market-to-book ratio	MktBk	Market capitalization scaled by book value of equity

Source: Author's own work.

Table 4: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
DIC	1												
DNC	-0.1637*	1											
DDC	-0.2064*	-0.1181*	1										
DOM	-0.1407*	-0.0805*	-0.1015*	1									
ROA%	0.2918*	0.0816*	0.0790*	-0.1140*	1								
chE%	0.1004*	0.0010	-0.0643*	-0.1448*	0.4270*	1							
ROE%	0.2269*	0.0704*	0.0813*	-0.0786*	0.8232*	0.4999*	1						
Operpm%	0.1729*	0.0635*	0.0805*	-0.0405*	0.6031*	0.2537*	0.5108*	1					
AstTvr	0.0621*	0.0242*	-0.0221*	-0.0222*	0.2018*	0.0499*	0.1824*	0.1131*	1				
Lev%	-0.0591*	-0.0523*	-0.0435*	0.0281*	-0.2332*	-0.0433*	-0.1782*	-0.0341*	0.1891*	1			
Size	0.2129*	0.0347*	0.1305*	0.0312*	0.0981*	0.0080	0.1055*	0.1862*	-0.1610*	0.2703*	1		
Liq	-0.0184*	0.0133*	-0.0020	-0.0333*	0.0826*	0.0102*	0.0429*	-0.0532*	-0.1516*	-0.5539*	-0.2186*	1	
MktBk	-0.1166*	-0.0468*	-0.0558*	0.0010	-0.1722*	-0.0187*	-0.0953*	-0.1315*	-0.0900*	-0.0380*	-0.1189*	0.0247*	1

Source: Author’s own work.

Table 5 (A): Dividend Changes during COVID-19

Variables	Panel A: DICD vs. DNCD				Panel B: DICD vs. DDCD			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ROA	0.1310***				0.1250***			
	(8.5200)				(10.4900)			
chE		0.0883***				0.1310***		
		(6.5100)				(9.3800)		
Operpm			0.0341***				0.0337***	
			(5.1100)				(6.3300)	
ROE				0.0657***				0.0498***
				(6.0900)				(7.2000)
AstTvr	-0.0025	0.1940*	0.4870***	0.0111	0.2410***	0.3800***	0.7890***	0.3120***
	(-0.0200)	(1.9200)	(4.3100)	(0.1100)	(2.7800)	(3.9600)	(7.4000)	(3.3900)
Lev%	0.0097***	-0.0063*	-0.0016	-0.0052	0.0058**	-0.0078***	-0.0028	-0.0090***
	(2.7700)	(-1.9400)	(-0.4700)	(-1.5700)	(2.0300)	(-2.8100)	(-1.0600)	(-3.3300)
Size	0.0590*	0.1150***	0.0765**	0.0666*	0.0738***	0.1120***	0.0789***	0.0852***
	(1.7200)	(3.3500)	(2.2600)	(1.9600)	(2.6700)	(3.9200)	(2.8700)	(3.1300)
Liq	-0.0130	-0.0275	-0.0352	-0.0226	-0.0033	-0.0157	-0.0220	-0.0158
	(-0.6400)	(-1.4300)	(-1.5800)	(-1.1700)	(-0.1800)	(-0.9100)	(-1.1800)	(-0.9200)
MktBk	0.0881	-0.1320*	-0.0488	0.0575	0.0894*	-0.0957	-0.0110	0.0438
	(1.1400)	(-1.7600)	(-0.7400)	(0.7200)	(1.8200)	(-1.6100)	(-0.2400)	(0.8900)
Constant	-1.9120*	-1.3500	-1.4550	-1.4600	-2.9500**	-0.9580	-2.5660**	-2.5240**
	(-1.9300)	(-1.3800)	(-1.4500)	(-1.4800)	(-2.5700)	(-0.3800)	(-2.4300)	(-2.0700)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2939.0000	2939.0000	2939.0000	2939.0000	3699.0000	3699.0000	3699.0000	3699.0000
PseudoR2	0.1300	0.1290	0.1070	0.1240	0.1010	0.1590	0.0774	0.0845
chi2	316.8000	280.3000	272.3000	276.0000	326.5000	278.9000	251.7000	286.0000
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Variables	Panel C: DOMD vs. DNCD				Panel D: DOMD vs. DDCD			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
ROA	-0.1380***				-0.1590***			
	(-9.2600)				(-11.4600)			
chE		-0.0609***				-0.0313***		
		(-6.0100)				(-6.3600)		
Operpm			-0.0386***				-0.0444***	
			(-7.0000)				(-7.2800)	
ROE				-0.0635***				-0.0729***
				(-6.7500)				(-9.4900)

Variables	Panel C: DOMD vs. DNCD				Panel D: DOMD vs. DDCD			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
AstTvr	-0.2480**	-0.4380***	-0.5360***	-0.2890**	-0.1040	-0.3840***	-0.4120***	-0.1130
	(-2.0900)	(-3.5600)	(-4.3300)	(-2.4100)	(-0.9900)	(-3.5500)	(-3.8600)	(-1.0300)
Lev%	0.0136***	0.0212***	0.0218***	0.0207***	0.0127***	0.0213***	0.0193***	0.0198***
	(3.3700)	(5.4100)	(5.6400)	(5.2300)	(3.8200)	(6.4600)	(5.8700)	(5.7600)
Size	-0.3570***	-0.4060***	-0.3750***	-0.3630***	-0.3060***	-0.3580***	-0.3100***	-0.3070***
	(-7.9600)	(-9.0400)	(-8.4500)	(-8.1500)	(-8.3400)	(-9.7300)	(-8.6900)	(-8.1000)
Liq	-0.0263	-0.0232	-0.0328	-0.0211	0.0011	-0.0019	-0.0082	0.0063
	(-1.2000)	(-1.1500)	(-1.2300)	(-1.0300)	(0.0600)	(-0.1000)	(-0.3000)	(0.3300)
MktBk	0.1240**	0.2990***	0.1850***	0.1410**	0.0898**	0.2570***	0.1530***	0.1010**
	(2.0200)	(4.1900)	(2.9300)	(2.2100)	(1.9800)	(5.0300)	(3.3400)	(2.2100)
Constant	5.9000***	5.9960***	5.3350***	5.8990***	6.9260***	6.4310***	6.5090***	6.6760***
	(4.2400)	(4.7600)	(3.0700)	(4.7200)	(6.1100)	(6.1600)	(5.8200)	(5.6500)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1728.0000	1728.0000	1728.0000	1728.0000	2437.0000	2437.0000	2437.0000	2437.0000
PseudoR2	0.2100	0.1950	0.1840	0.2030	0.2010	0.1310	0.1730	0.2000
chi2	276.4000	237.4000	281.7000	231.9000	344.3000	283.4000	313.5000	314.0000
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's own work.

Table 5 (B): Dividend Changes during COVID-19

Variables	Panel E: DDCD vs. DNCD			
	Model 17	Model 18	Model 19	Model 20
ROA	-0.00950			
	(-0.90000)			
chE		-0.04430***		
		(-4.02000)		
Operpm			0.0014	
			(0.4400)	
ROE				0.0023
				(0.4400)
AstTvr	-0.17900*	-0.16200	-0.1960*	-0.2110**
	(-1.72000)	(-1.59000)	(-1.9400)	(-2.0300)
Lev	0.00110	0.00140	0.0021	0.0019
	(0.35000)	(0.44000)	(0.6700)	(0.6300)
Size	-0.00840	-0.01090	-0.0136	-0.0138
	(-0.24000)	(-0.31000)	(-0.3900)	(-0.4000)
Liq	-0.02490	-0.02230	-0.0248	-0.0248
	(-1.34000)	(-1.19000)	(-1.3300)	(-1.3300)
MktBk	-0.00741	0.03070	0.0169	0.0191
	(-0.12000)	(0.48000)	(0.2800)	(0.3100)
Constant	0.82200	0.55000	0.8680	0.8610
	(0.84000)	(0.55000)	(0.9000)	(0.8900)
Industry & Country Dummies	Yes	Yes	Yes	Yes
N	2261.00000	2261.00000	2261.0000	2261.0000
PseudoR2	0.06960	0.08680	0.0694	0.0694
chi2	181.50000	184.30000	181.0000	181.2000
P-value	0.00000	0.00000	0.0000	0.0000

Source: Author's own work.

Table 6: Dividend reductions vs. No-change dividends

Variables	Panel A: (25% > DDCD) vs. DNCD				Panel B: (25%≤ DDCD <50%) vs. DNCD			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ROA	0.0685***				-0.0134			
	(4.7400)				(-0.8700)			
chE		-0.0083				-0.0447***		
		(-0.9800)				(-2.6100)		
Operpm			0.0127*				0.0061	
			(1.7800)				(1.4200)	
ROE				0.0393***				0.0015
				(5.1800)				(0.2000)
AstTvr	-0.1190	0.0440	0.1010	-0.1230	-0.3370*	-0.3410**	-0.3440**	-0.3790**
	(-0.8300)	(0.3300)	(0.7300)	(-0.8600)	(-1.9300)	(-2.0200)	(-2.0400)	(-2.1600)
Lev%	0.0081*	0.0005	0.0022	0.0003	-0.0017	-0.0014	0.0005	-0.0004
	(1.7900)	(0.1300)	(0.5100)	(0.0800)	(-0.3600)	(-0.3000)	(0.1100)	(-0.1000)
Size	0.0670	0.1050**	0.0809	0.0652	-0.0301	-0.0379	-0.0475	-0.0377
	(1.3100)	(2.0900)	(1.5700)	(1.2700)	(-0.5700)	(-0.7200)	(-0.8900)	(-0.7100)
Liq	0.0007	-0.0042	-0.0078	-0.0052	-0.0221	-0.0214	-0.0229	-0.0225
	(0.0300)	(-0.1700)	(-0.2800)	(-0.2000)	(-0.9000)	(-0.8600)	(-0.8900)	(-0.9200)
MktBk	0.0886	-0.0642	-0.0058	0.0939	-0.0756	-0.0497	-0.0122	-0.0363
	(1.0800)	(-0.7000)	(-0.0700)	(1.1500)	(-0.7100)	(-0.4800)	(-0.1300)	(-0.3600)
Constant	-2.0020	-2.3200*	-1.9110	-1.7160	0.1180	-0.0367	0.3920	0.2080
	(-1.5500)	(-1.7800)	(-1.4700)	(-1.3100)	(0.0800)	(-0.0200)	(0.2800)	(0.1400)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1315.0000	1315.0000	1315.0000	1315.0000	1246.0000	1246.0000	1246.0000	1246.0000
PseudoR2	0.1020	0.0896	0.0933	0.1050	0.0816	0.0945	0.0825	0.0812
chi2	147.9000	129.0000	134.9000	151.7000	111.6000	113.9000	112.3000	110.3000
P-value	0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Variables	Panel C: (50% ≤ DDCD < 75%) vs. DNCD				Panel D: (75% ≤ DDCD < 100%) vs. DNCD			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
ROA	-0.0764***				-0.1110***			
	(-3.7600)				(-3.6300)			
chE		-0.0537***				-0.0706***		
		(-3.0500)				(-3.5600)		
Operpm			-0.0071				-0.0168*	
			(-1.2200)				(-1.6500)	
ROE				-0.0196				-0.0238*
				(-1.3900)				(-1.7700)

Variables	Panel C: (50% ≤ DDCD < 75%) vs. DNCD				Panel D: (75% ≤ DDCD < 100%) vs. DNCD			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
AstTvr	-0.0335	-0.1090	-0.2000	-0.1010	-0.6770**	-0.6250*	-0.9510***	-0.8010**
	(-0.2100)	(-0.6800)	(-1.2300)	(-0.6100)	(-2.0600)	(-1.9000)	(-2.7500)	(-2.2700)
Lev%	-0.0033	0.0009	0.0019	0.0020	0.0036	0.0052	0.0104	0.0096
	(-0.6500)	(0.1800)	(0.3900)	(0.4100)	(0.4900)	(0.6700)	(1.4500)	(1.3000)
Size	-0.1020*	-0.1160**	-0.1210**	-0.1130**	-0.0554	-0.0706	-0.0708	-0.0750
	(-1.9100)	(-2.1500)	(-2.2400)	(-2.1000)	(-0.6800)	(-0.8700)	(-0.8700)	(-0.9100)
Liq	-0.0687**	-0.0589*	-0.0671*	-0.0687*	-0.0201	-0.0200	-0.0238	-0.0263
	(-2.0000)	(-1.6500)	(-1.9100)	(-1.9400)	(-0.4700)	(-0.4200)	(-0.5200)	(-0.5900)
MktBk	-0.0042	0.1530*	0.1090	0.0688	-0.2610	0.0443	-0.0811	-0.0936
	(-0.0400)	(1.6700)	(1.2500)	(0.6900)	(-1.4400)	(0.3000)	(-0.5200)	(-0.6200)
Constant	1.3010	0.9340	1.2920	1.4390	0.8260	-0.2670	0.3680	0.5740
	(0.8700)	(0.6500)	(0.8900)	(1.0400)	(0.4400)	(-0.1500)	(0.2000)	(0.3000)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1208.0000	1208.0000	1208.0000	1208.0000	927.0000	927.0000	927.0000	927.0000
PseudoR2	0.0992	0.1150	0.0864	0.0890	0.1370	0.1830	0.1170	0.1170
chi2	116.5000	109.7000	110.8000	107.1000	86.1800	83.2500	75.2400	80.7300
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's own work.

Table 7 (A): Dividend Changes during COVID-19: Sample Sensitivity

Variables	Panel A: DICD vs. DNCD				Panel B: DICD vs. DDCD			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ROA	0.13800***				0.0788***			
	(5.13000)				(5.2700)			
chE		0.08010***				0.0757***		
		(3.39000)				(5.5000)		
Operpm			0.02370***				0.0260***	
			(2.71000)				(2.9500)	
ROE				0.06730***				0.0272***
				(4.47000)				(4.2600)
AstTvr	0.04530	0.22600	0.53300**	0.06230	0.3650***	0.5020***	0.8160***	0.4400***
	(0.24000)	(1.21000)	(2.47000)	(0.31000)	(2.8200)	(3.7500)	(5.3700)	(3.3500)
Lev%	0.01280**	-0.00241	-0.00121	-0.00315	-0.0049	-0.0120***	-0.0104**	-0.0154***
	(1.97000)	(-0.40000)	(-0.21000)	(-0.53000)	(-1.1700)	(-2.8000)	(-2.5200)	(-3.7600)
Size	-0.05470	-0.02690	-0.05890	-0.05220	0.05280	0.0649	0.0538	0.0547
	(-0.84000)	(-0.40000)	(-0.93000)	(-0.81000)	(1.2100)	(1.4400)	(1.2100)	(1.2600)
Liq	-0.00687	-0.01920	-0.02820	-0.02290	-0.0175	-0.0307	-0.0133	-0.0289
	(-0.22000)	(-0.63000)	(-0.95000)	(-0.76000)	(-0.7000)	(-1.1600)	(-0.5200)	(-1.1700)
MktBk	0.05320	-0.27400*	-0.14000	0.00248	0.1140*	-0.0210	0.0645	0.0741
	(0.44000)	(-1.86000)	(-1.15000)	(0.02000)	(1.9200)	(-0.3100)	(1.1300)	(1.3200)
Constant	0.69200	1.92000	1.80500	1.36300	-1.6890	-0.2990	-1.6670	-1.1770
	(0.44000)	(1.25000)	(1.18000)	(0.89000)	(-1.3100)	(-0.1600)	(-1.2900)	(-0.9400)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	819.00000	819.00000	819.00000	819.00000	1303.0000	1303.0000	1303.0000	1303.0000
PseudoR2	0.17200	0.16900	0.13700	0.17100	0.1260	0.1700	0.1200	0.1160
chi2	123.80000	96.31000	93.53000	116.70000	162.4000	159.8000	146.7000	161.3000
P-value	0.00000	0.00000	0.00000	0.00000	0.0000	0.0000	0.0000	0.0000
Variables	**Panel C: DOMD vs. DNCD**				**Panel D: DOMD vs. DDCD**			
	Model 9	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**	**Model 15**	**Model 16**
ROA	-0.14800***				-0.1720***			
	(-5.53000)				(-6.7200)			
chE		-0.0569***				-0.0251***		
		(-2.7500)				(-3.5400)		
Operpm			-0.0349***				-0.0388***	
			(-3.5400)				(-4.5600)	
ROE				-0.0611***				-0.0688***
				(-2.9800)				(-5.5300)

	Panel C: DOMD vs. DNCD				Panel D: DOMD vs. DDCD			
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
AstTvr	-0.44600**	-0.5180**	-0.6020***	-0.4510**	-0.1320	-0.4490**	-0.4350**	-0.0968
	(-2.10000)	(-2.4500)	(-2.8200)	(-2.2000)	(-0.7600)	(-2.4000)	(-2.3700)	(-0.5500)
Lev%	0.02330***	0.0294***	0.0312***	0.0310***	0.0129**	0.0203***	0.0205***	0.0207***
	(2.96000)	(3.9100)	(4.1500)	(4.0000)	(2.4700)	(3.9400)	(4.0000)	(3.8100)
Size	-0.44400***	-0.4720***	-0.4460***	-0.4400***	-0.2620***	-0.2980***	-0.2650***	-0.2630***
	(-5.15000)	(-5.5600)	(-5.4900)	(-5.3500)	(-4.4600)	(-5.0700)	(-4.7200)	(-4.2700)
Liq	0.00579	0.0195	0.0050	0.0197	0.0197	0.0238	0.0017	0.0332
	(0.19000)	(0.7000)	(0.1500)	(0.7100)	(0.7800)	(1.0200)	(0.0500)	(1.4100)
MktBk	0.00840	0.2840**	0.1310	0.0563	0.0851	0.2570***	0.1680**	0.1010
	(0.07000)	(2.1400)	(1.0500)	(0.4000)	(1.2800)	(3.3900)	(2.5100)	(1.4600)
Constant	7.31100***	6.8880***	6.3830***	7.0830***	6.3950***	5.5720***	5.6540***	5.9140***
	(3.32000)	(3.5100)	(2.7700)	(3.6700)	(4.1200)	(3.9400)	(3.9300)	(3.7900)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	518.00000	518.0000	518.0000	518.0000	951.0000	951.0000	951.0000	951.0000
PseudoR2	0.28300	0.2520	0.2480	0.2620	0.2390	0.1480	0.1910	0.2310
chi2	123.60000	99.4500	121.5000	101.7000	144.6000	124.6000	139.7000	137.7000
P-value	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's own work.

Table 7 (B): Dividend Changes during COVID-19: Sample Sensitivity

Variables	Panel E: DDCD vs. DNCD			
	Model 17	Model 18	Model 19	Model 20
ROA	0.00845			
	(0.47000)			
chE		-0.03980**		
		(-2.29000)		
Operpm			0.01190*	
			(1.85000)	
ROE				0.000199
				(0.030000)
AstTvr	-0.24500	-0.25300	-0.29300	-0.223000
	(-1.23000)	(-1.24000)	(-1.48000)	(-1.130000)
Lev%	0.01060*	0.00703	0.01000*	0.009840*
	(1.84000)	(1.22000)	(1.83000)	(1.770000)
Size	-0.06630	-0.06790	-0.07340	-0.064800
	(-1.03000)	(-1.04000)	(-1.14000)	(-1.010000)
Liq	-0.00905	-0.01230	-0.00991	-0.009840
	(-0.32000)	(-0.44000)	(-0.35000)	(-0.340000)
MktBk	-0.17200	-0.17600	-0.14100	-0.194000
	(-1.35000)	(-1.51000)	(-1.16000)	(-1.560000)
Constant	1.76400	1.76900	1.88400	1.791000
	(1.16000)	(1.13000)	(1.24000)	(1.180000)
Industry & Country Dummies	Yes	Yes	Yes	Yes
N	951.00000	951.00000	951.00000	951.000000
PseudoR2	0.10800	0.12400	0.11100	0.108000
chi2	78.96000	78.61000	81.06000	79.100000
P-value	0.00000	0.00000	0.00000	0.000000

Source: Author's own work.

Table 8: Dividend Increases vs. No-change dividends

Variables	Panel A: (25% > DICD) vs. DNCD				Panel B: (25% ≤ DICD < 50%) vs. DNCD			
ROA	0.1350***				0.1540***			
	(8.2500)				(7.7500)			
chE		0.0604***				0.1250***		
		(4.3900)				(5.4600)		
Operpm			0.0414***				0.05710***	
			(6.0400)				(6.50000)	
ROE				0.0708***				0.08600***
				(7.4300)				(7.36000)
AstTvr	0.0845	0.3560***	0.6580***	0.1000	0.1160	0.3830***	0.75400***	0.13700
	(0.6900)	(2.9300)	(5.0500)	(0.8000)	(0.7100)	(2.6100)	(5.04000)	(0.83000)
Lev%	0.0095**	-0.0064	-0.0015	-0.0066*	0.0104**	-0.0104**	-0.00080	-0.00890*
	(2.2600)	(-1.6300)	(-0.3800)	(-1.6600)	(1.9900)	(-2.1100)	(-0.17000)	(-1.84000)
Size	0.1250***	0.1980***	0.1460***	0.1340***	-0.0060	0.0584	0.00121	-0.00202
	(2.8300)	(4.5300)	(3.3400)	(3.0300)	(-0.1100)	(1.0400)	(0.02000)	(-0.04000)
Liq	-0.0064	-0.0110	-0.0348	-0.0151	-0.0555*	-0.0705**	-0.10500***	-0.06600**
	(-0.2500)	(-0.4800)	(-1.2100)	(-0.6300)	(-1.7500)	(-2.3200)	(-3.13000)	(-2.11000)
MktBk	0.0722	-0.2120**	-0.0702	0.0568	0.1090	-0.1700	-0.01400	0.11700
	(0.7100)	(-2.1400)	(-0.7600)	(0.5800)	(0.9300)	(-1.5800)	(-0.14000)	(1.03000)
Constant	-4.2800***	-4.2410***	-4.0570***	-3.8980***	-2.7870**	-2.1180*	-1.97000	-1.96100
	(-3.2600)	(-3.5400)	(-3.2200)	(-2.8800)	(-2.0700)	(-1.6600)	(-1.56000)	(-1.46000)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1544.0000	1544.0000	1544.0000	1544.0000	1230.0000	1230.0000	1230.00000	1230.00000
PseudoR2	0.1300	0.1020	0.1120	0.1270	0.1620	0.1680	0.14100	0.16100
chi2	209.0000	166.7000	180.4000	202.1000	178.1000	147.4000	168.90000	173.70000
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000	0.00000
Variables	**Panel C: (50% ≤ DICD < 75%) vs. DNCD**				**Panel D: (75% ≤ DICD <100%) vs. DNCD**			
ROA	0.1300***				0.1650***			
	(6.7900)				(5.3900)			
chE		0.138***				0.1470***		
		(5.200)				(3.3500)		
Operpm			0.032***				0.0446***	
			(3.700)				(3.6300)	
ROE				0.0739***				0.0983***
				(6.6400)				(5.5900)
AstTvr	-0.0209	0.228	0.463***	-0.0065	0.4740*	0.7320***	0.9760***	0.5010*
	(-0.1200)	(1.310)	(2.790)	(-0.0400)	(1.7600)	(2.9000)	(4.2700)	(1.8100)

Variables	Panel C: (50% ≤ DICD < 75%) vs. DNCD				Panel D: (75% ≤ DICD <100%) vs. DNCD			
Lev%	0.0039	-0.017***	-0.007	-0.0121**	0.0113	-0.0158	-0.0012	-0.0107
	(0.6700)	(-3.050)	(-1.340)	(-2.2400)	(1.0900)	(-1.5100)	(-0.1200)	(-1.0700)
Size	0.0178	0.111	0.042	0.0194	0.0828	0.1800	0.0639	0.0725
	(0.2600)	(1.620)	(0.620)	(0.2900)	(0.6100)	(1.2000)	(0.4500)	(0.5200)
Liq	-0.0044	-0.025	-0.032	-0.0124	0.0088	-0.0215	-0.0207	-0.0167
	(-0.1400)	(-0.870)	(-0.910)	(-0.4200)	(0.1900)	(-0.4000)	(-0.3300)	(-0.3400)
MktBk	0.0524	-0.189	-0.132	0.0510	0.3600	0.2000	0.2290	0.3620*
	(0.4800)	(-1.400)	(-1.030)	(0.4700)	(1.5800)	(0.6200)	(0.8300)	(1.7300)
Constant	-2.2850	-2.000	-2.150	-1.6980	-6.0130**	-6.1080**	-4.8670*	-4.8860*
	(-1.2800)	(-1.060)	(-1.160)	(-0.9500)	(-2.4100)	(-2.2700)	(-1.9500)	(-1.9100)
Industry & Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1093.0000	1093.000	1093.000	1093.0000	848.0000	848.0000	848.0000	848.0000
PseudoR2	0.1230	0.155	0.097	0.1220	0.2000	0.2300	0.1630	0.2060
chi2	125.1000	106.000	100.700	122.1000	95.1200	82.8800	91.2900	99.7700
P-value	0.0000	0.000	0.000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's own work.

Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 49-62
10.2478/fiqf-2023-0026

COLOUR SYMBOLISM IN FINANCE

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Abstract

Colour symbolism plays an important role in everyday life and science. The subject is interdisciplinary and receives significant attention in the literature. It is increasingly entering the field of economics and finance. The authors are the first to research the connotations and symbolism of colours in finance. The following research aims to: identify and determine the meaning of colours in connection with the word "finance", determine the popularity of the use of particular colours in relation to the word "finance", and identify the most popular subject areas in the literature related to the most commonly used colour in finance. Bibliometric and textual analyses were adopted as research methods. The main research conclusions are as follows. Of the 14 colours examined, only green, blue, brown, black and white showed connotations accurately portrayed in the text. Apart from the colour black, the symbolism is universal and unambiguous. For black, the symbolism is twofold, with one of the meanings going back to historical times. The dominant colour is green. The main research areas pursued under "green finance" include investing in and financing environmentally friendly projects (including various types of technology), developing financial instruments to support environmentally friendly activities and supporting clean energy projects.

JEL classification: G00, Q01
Keywords: Finance, Colours, Green, Blue, Black, White

Received: 01.06.2023 Accepted: 08.09.2023

Cite this:
Prusak B. & Mushafiq M. (2023) Colour Symbolism in Finance. Financial Internet Quarterly 19(4), pp. 49-62.

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Introduction

Research on colours is interdisciplinary and concerns such scientific fields and disciplines as physics, biology, chemistry, psychology, philosophy, art, anthropology and linguistics. However, it should be noted that it is not a finite set, as the colour symbolism covers many more areas, including management sciences, economics, finance, etc. The human perception of colours is subjective and depends on the interpretation of electromagnetic waves in the human brain. Light-sensitive cells called cones and rods transmit signals to the brain when light enters the eyes. The rods interpret brightness and darkness, while the cones are responsible for interpreting different electromagnetic waves, which translates into the brain's perception of specific colours (Cugelman, 2020, p. 3). Each colour has specific attributes such as hue, saturation and brightness. At the same time, it is worth noting that colour sensations are influenced by many factors, such as various diseases, human development and age, cultural or linguistic factors and gender (Elliot et al., 2015). Research on colour categorisation dates back to ancient Greece and shows that different colour systems formed within communities, which also changed (Crone, 1999; Feisner & Reed, 2014; Maclaury et al., 2007). However, in the late 1960s, thanks to Berlin and Kay (1969), work began on a universalist approach to colour naming. Since then, two approaches have clashed in the literature, i.e. universalist and relativist approaches to colour naming (Dedrick, 1998). According to the former, there is a limited number of universal colours. In relation to them, it is possible to develop a certain consistency and accuracy in the use of vocabulary referring to given colours (Gonigroszek, 2008, p. 95). On the other hand, the relativist approach assumes that cultural and linguistic differences strongly influence the naming of colours, making it difficult to develop their generally recognised names. Some authors believe that the truth lies somewhere in the middle and deny the extremes of both theories (Gonigroszek, 2008, p. 99; Kay & Regier, 2007).

Colours can take on different connotations in given societies, change over time and differentially influence human behaviour and cognitive processes (Elliot & Maier, 2014). Moreover, in different cultures, the same colour can have positive or negative meanings (Yu, 2014). Therefore, research into colour symbolism is such an important issue. This article focuses on analysing the meaning of colours in finance. The interest in such a topic stems from the fact that it is becoming fashionable in economic, management or financial science research to use colours to describe an important area of exploration. Such combinations include, for example, the silver economy (Marcucci et al., 2021), green entrepreneurship (Ebrahimi & Mirbargkar, 2017) and green marketing (Papadas et al., 2017). Analogously, colours refer to the concept of "finance". This research aims to: 1) identify and determine the meaning of colours in connection with the word "finance", 2) determine the popularity of the use of particular colours in relation to the word "finance", 3) identify the most popular subject areas in the literature related to the most commonly used colour in finance. Bibliometric and textual analyses were adopted as research methods. This is the first study of its kind in finance, and its results made it possible to determine the symbolic character of colours in this scientific discipline.

Besides the introduction, the article structure is as follows. The second part outlines the theoretical background that introduces the research. It concerns issues related to colour symbolism. The next section presents the methodology. The research results can be found in Section 4. The last part discusses the study's findings and limitations.

Theoretical background

Colour has accompanied human beings since the dawn of time and is not only associated with aesthetics but also represents a particular message and meaning. In some instances, colour is a source of information for the audience and can also influence their behaviour (Elliot & Maier, 2012). Therefore, a research area called colour symbolism has developed in the literature. It deals with the representation of colour meanings in the context of certain things, beliefs and values (Gasparyan & Asatryan, 2019). Initially, colour symbolism was rooted in nature; in this view, it is timeless. Over time, it began to apply to more and more areas, including culture (Turganbayeva et al., 2014; Park, 2000), religion (Benz, 2005), history (Eagan, 2011), literature (Skard, 1946; Kibalka, 2013; Cong & Chistyakov, 2021), folklore (Raclavská, 2006; Nusratova, 2020), film (Kwon & Cho, 2008; Mcholland, 2019), art (Wheelock, 2005; Gholamreza, 2016), music (Leuders, 1958), theatre (Shahin, 2004), myths, legends (Yu, 2014), fashion (Wi & Choy, 2008), geography (Freant, 2013). Colours can convey sensibilities, values and ideas. The use of appropriate colours can influence, for example, emotions and feelings (Kaya & Epps, 2004) and, at the same time, people's behaviour, e.g. they can irritate, increase blood pressure, decrease or increase aggression (Schauss, 1979; https://www.colormatters.com/). Memory, experience, intelligence and cultural background influence how colours affect individuals (Feisner & Reed, 2014, p. 7). Colours can be employed in the creative education process (Markovic, 2014). It also turns out that individuals' perception and naming of colours is not identical and differs, among other things, according to gender (Webster 2015). When it comes to colour symbolism, it can be universal in certain areas and circles of people (Hovers et al., 2003; Tham et al., 2020). On the other hand, considering the meaning of colours in the world without giving a specific limiting framework is difficult, as it is not identical, changes over time and is culturally conditioned (Gage, 2000). For example, Pastoureau (2018) shows how the meaning of the colour blue has changed over time. In ancient Greece, it was associated with evil, later with Virgin Mary, then considered the colour of royalty, and next acquired political and military meaning during the French Revolution. In the modern era, this colour is also associated with romance. Similar analyses were carried out for other colours, e.g. red (Wreschner et al., 1980). A very comprehensive presentation of the symbolism of the primary colours is shown by Heller (2014) in her book Wie Farben wirken. Farbpsychologie. Farbsymbolik. Kreative Farbgestaltung. Depending on cultural backgrounds, the same colours can have both positive and negative connotations (Yu, 2014). After completing a questionnaire on the perception of the meaning of colours, the project entitled "Global Color Survey" (https://www.colorcom.com/global-color-survey) provides research results on the symbolism of colours and the differences in this area.

In economics, finance and management, there are many terms where a colour combined with another word represents a certain meaning or idea. This issue was discussed in a 2016 article by Rosyanova (2016), "Color-Symbolism in English Terminology". For example, blue chips refer to recognisable, financially sound and highly capitalised companies; the black market is a market where illegal products and services are traded; the black knight is an investor who plans a hostile takeover of a company. Within this research area, colours are also used in connection with specific disciplines or sub-disciplines, e.g. green marketing means marketing towards environmentally friendly and beneficial products and services; silver economy "covers economic opportunities arising from the public and consumer expenditure related to population ageing and the specific needs of the population over 50" (The Silver Economy. Opportunities from Ageing, 2015); green entrepreneurship is conscious entrepreneurial action taking into account social and environmental aspects; turquoise management is a concept proposed by F. Laloux or, most generally, a management style based on three pillars: self-management, wholeness and evolutionary purpose (Laloux, 2015). At the same time, it is worth adding that when it comes to management styles, many more colours are ascribed to them in the literature, e.g. red, amber, orange, green (Rutkowska, 2015). Similar connotations of colour with finance are found in the literature. However, no research has been done in this area yet. The authors, therefore, are the first to attempt to fill this research gap.

Methodology

The research was conducted in multiple stages. Firstly, a strategy was developed to search for publications on connotations of colours with the word finance or those derived from it (e.g. financial, financially). The colours analysed were considered the most popular and, based on the authors' knowledge, had connotations with other academic disciplines related to finance. A total of 14 colours were identified; they are included in Table 1. Next, the publication search strategy involved entering the phrase "colour Financ*" in the "Article title, Abstract, Keywords" field. These queries were searched on 15 October 2022. Scopus was used as the source of publications, as it is considered one of the most reliable databases in the scientific world. Stage I yielded the results shown in Table 1, from which it can be concluded that no publications with connotations were obtained for as many as six colours. In four cases, the number of records was 1 or 2, while 8 or 11 records were found for three colours. The dominant colour in this area is green.

Table 1: Scopus search outcomes

Colour	Search	Results from Scopus
Green	"Green Financ*"	941
Blue	"Blue Financ*"	11
White	"White Financ*"	8
Black	"Black Financ*"	8
Grey	"Grey Financ*"	2
Red	"Red Financ*"	1
Brown	"Brown Financ*"	1
Silver	"Silver Financ*"	1
Orange	"Orange Financ*"	0
Gold	"Golden Financ*"	0
Purple	"Purple Financ*"	0
Turquoise	"Turquoise Financ*"	0
Pink	"Pink Financ*"	0
Yellow	"Yellow Financ*"	0

Source: Author's own work.

Following the initial results, further research proceeded as follows.
Stage II – identification of the importance of colour connotations in finance; the texts containing white, black, blue, brown, red, silver and grey were examined in detail. In the case of the colour green, its importance in finance is well-established; therefore, Stages III and IV include extended analyses due to its popularity.
Stage III – a textual analysis of the ten most influential publications in terms of citability showing connotations of the colour green with finance. It aimed to identify research findings among the key green finance publications and determine their publication period, the type of publisher and the number of citations.
Stage IV – a citation bibliometric analysis to identify the main areas of interest in green finance.

Results

Meaning of colours

In the second stage, 31 records were analysed. The textual analyses for green were not included here, as these are in stages III and IV. Of the records identified, two overlapped for black and grey. This means that a total of 30 publications were assessed, of which only some contained colour connotations with finance. The literature sources and the meanings of these connotations are shown in Table 2.

Table 2: Meanings of colours in connotations with finance

Colour	Meaning	Source
White	White financial institutions – financial institutions that offer products to white people and discriminate against non-whites. Some publications focus on financial behaviour regarding borrowing, saving, investing and financial security issues between different races of people (e.g. white and black).	Wiese (1999) Rucks-Ahidiana (2017); Cho (2011)
Black	Black financial market – a market in which financial transactions are carried out illegally. Black finance – a term referring to illegal financial flows, e.g. money laundering. Black financial institutions – financial institutions that support African-Americans, e.g. banks where the majority of deposits come from African-Americans, the majority of loans are made to black individuals or entrepreneurs and are owned by black people.	Ivanova (2007) Masciandaro (2007) Hunter (2018); Black (1979)
Green	Green finance refers to actions in finance for eco-friendly initiatives and environmental sustainability.	Many publications
Blue	Activities designed to finance sustainable development and conservation projects in the ocean and coastal areas. Addresses the topic of finance in the marine industry. Blue finance is a subset of green finance that focuses on marine sustainability and clean water protection.	Thompson (2022); Nagisa et al. (2022); Tirumala & Tiwari (2022); Kuwae et al. (2022); Xu et al. (2021); Wabnitz and Blasiak (2019); Tian et al. (2019); Pascal et al. (2018) Turner and Rios (2022)
Brown	Opposite of green finance – financial measures to support projects with highly negative environmental impacts, e.g. high CO2 emissions.	Neisen et al. (2022)
Red	Lack of direct connotation Only: *To be in the red financially* means to sustain losses.	Makeenko (2013)
Silver	Lack of connotation	-
Grey	Lack of connotation	-

Source: Author's own work.

In addition to the colour green, direct connotations were found for blue, black, white and brown. In finance, blue denotes the application of various financial operations in the ocean and coastal areas. One author sees it as an element of green finance. The opposite of green finance is brown finance, which denotes the involvement of financial resources in environmentally damaging projects. Black finance has a twofold meaning, i.e. it is regarded as all kinds of financial operations carried out illegally or through the prism of racial differences, e.g. the provision of financial services only to black people. The opposite of the latter is white finance, i.e. offering financial products only to white people. One publication notes the combination of the colour red with the word financially. However, it does not provide meaning in the context of finance, as the previously mentioned colours do. It represents a common idiom used in the English financial language, i.e. to be in the red, which means to be in debt, to incur losses. The opposite of this phrase is to be in the black, which means to have money in the bank or to generate profits.

Textual Analysis of Top 10 "Green Finance" Articles

The search query "Green Financ*" returned a total of 941 articles. The textual analysis covered the top 10 articles by citation (following Chung et al., 2004; Fahimnia et al., 2015; Xu et al., 2018) from the most to the less cited as presented in Table 3. Speaking from an investment perspective, Taghizadeh-Hesary and Yoshino (2019) provided a framework for inducing private participation in green finance. Taghizadeh-Hesary and Yoshino (2020) argued that using the tax spillover to boost the rate of return on green initiatives, creating green loan guarantee strategies to reduce default risk, establishing society-based trust funds and acknowledging green portfolio risk through fiscal and policy de-risking are ways to mitigate green investment risks. Lam and Law (2016) stated that crowdfunding could be a significant part of green financing for renewable energy projects. He et al. (2019) found green financial development has an adverse influence on bank loan issuing and, to some extent, hampers the improvement of renewable energy investment efficiency. Yu et al. (2021) reasoned that green credits are less likely to be made available to privately owned businesses, even though green finance regulations can effectively reduce the overall financial constraints for green innovation. However, despite their financial restrictions, these firms exhibit relatively high levels of innovation.

According to Zhang et al. (2021), in green finance from an energy perspective, government investment in human resources and green energy technology R&D stimulates the growth of a sustainable green financial system. Wang and Zhi (2016) showed how active financial instruments might be used to promote sustainable energy to accomplish environmental conservation.

From another perceptive of total factor productivity, (2022) show that the growth of green financing greatly raises theLee and Lee level of green productivity. From the environmental entrepreneurship perceptive, Sun et al. (2020) indicate that green entrepreneurship reduces environmental damage, whereas money per capita greatly increases it, implying that policymakers should enforce green financing. Finally, Zhang et al. (2019) performed a bibliometric analysis on green finance and found that climate change and climate finance are dominant in green finance research.

Table 3: Top 10 articles from search "Green Financ*"

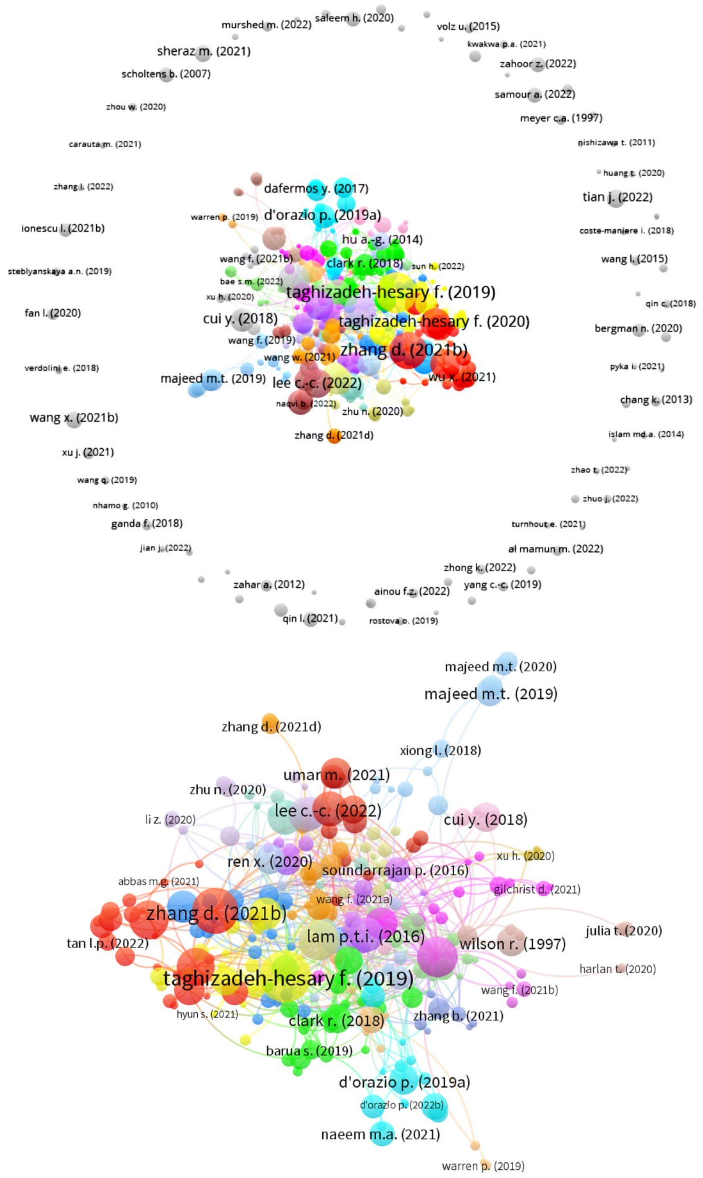
Author	Year	Journal	Citations
(Taghizadeh-Hesary & Yoshino, 2019)	2019	Finance Research Letters	225
(Zhang et al., 2021)	2021	Energy Policy	177
(Zhang et al., 2019)	2019	Finance Research Letters	145
(Wang & Zhi, 2016)	2016	Energy Procedia	137
(Sun et al., 2020)	2020	Science of the Total Environment	129
(Taghizadeh-Hesary & Yoshino, 2020)	2020	Energies	125
(Lee & Lee, 2022)	2022	Energy Economics	110
(Lam & Law, 2016)	2016	Renewable and Sustainable Energy Reviews	110
(He et al., 2019)	2019	Renewable Energy	109
(Yu et al., 2021)	2021	Energy Policy	103

Source: Author's own work.

Citation analysis

Based on the search results of Scopus, we performed a citation bibliometric analysis. It is a bibliometric research type that examines how frequently an article is cited. The threshold for minimum citations of 5 was set using VOSviewer. A total of 334 articles met the criteria; they are depicted in Figure 1 (a). However, 253 papers out of 334 were network-connected. Figure 1 (b) shows 21 clusters based on those 253 articles.

Figure 1: Results of citation analysis

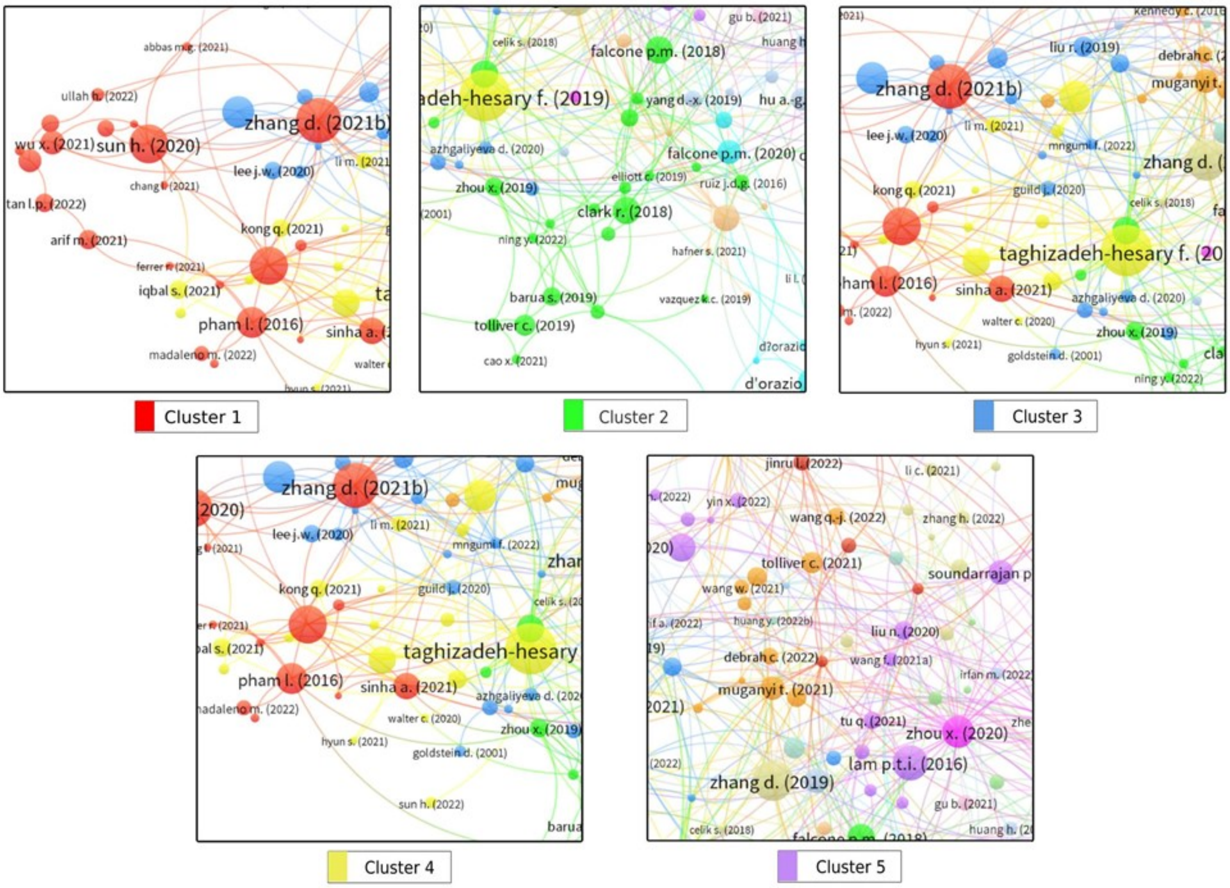


Source: Author's own work.

The top 5 clusters, as presented in Figure 2, were analysed to identify themes in the literature (see: Table 4). Cluster 1 includes 23 articles, mainly dominated by Pham, 2016; Sun et al., 2020; Taghizadeh-Hesary and Yoshino, 2020; Dongyang Zhang et al., 2021. The general theme of Cluster 1 concerns investments in green finance, including public and private spending (Chien et al., 2021; Pham, 2016; Taghizadeh-Hesary & Yoshino, 2020; Dongyang Zhang et al., 2021). Its secondary theme is the implementation of sustainable entrepreneurship to reduce environmental pollution (Iqbal et al., 2020; Sadiq et al., 2022; Sun et al., 2020).

Cluster 2 has 22 articles. It is dominated by Clark et al., 2018; Falcone et al., 2018; Ng, 2018; Tolliver et al., 2019. The common theme of this cluster is green bonds as an investment tool to promote sustainability (Cao et al., 2021; Clark et al., 2018; Mathews & Kidney, 2012; Ning et al., 2022; Tolliver et al., 2019; X. Zhou & Cui, 2019). The secondary theme is how the overall financial system needs to be "Green" (Batrancea et al., 2020; Falcone et al., 2018; Ng, 2018). Cluster 3 has 19 articles, mainly dominated by Hsu et al. (2021), focusing on green innovation. The themes included in Jin et al., 2021; Liu et al., 2019; Rasoulinezhad & Taghizadeh-Hesary, 2022 focus on efficiency, which concerns energy and green financing.

Figure 2: Top 5 clusters formed through citation analysis



Source: Author's own work.

Cluster 4 has 16 articles, and the works by Nawaz et al., 2021; Taghizadeh-Hesary & Yoshino, 2019; Yoshino et al., 2019 are prominent. The theme of the cluster can be identified as green financing for energy sources (Hyun et al., 2021; Li et al., 2021; Li et al., 2022). Cluster 5 is dominated by Lam and Law, (2016); As well as Soundarrajan and Vivek, (2016). Two themes can be noted in this cluster: the first one is green finance for sustainable development (Xu et al., 2022; Yin & Xu, 2022; Zhang et al., 2021; Zhou & Xu, 2022), and the second is green finance for green technology (Fang & Shao, 2022; Gong et al., 2020).

Table 4: Themes identified in the top 5 clusters

Cluster	Theme	Author(s)
Cluster 1	Investments in Green Finance	(Chien et al., 2021; Pham, 2016; Taghizadeh-Hesary & Yoshino, 2020; Zhang et al., 2021)
	Green Finance and Entrepreneurship	(Iqbal et al., 2020; Sadiq et al., 2022; Sun et al., 2020)
Cluster 2	Green Bonds as Investment Tool	(Cao et al., 2021; Clark et al., 2018; Mathews & Kidney, 2012; Ning et al., 2022; Tolliver et al., 2019; Zhou & Cui, 2019)
	Greening of Financial Systems	(Batrancea et al., 2020; Falcone et al., 2018; Ng, 2018)
Cluster 3	Green Finance and Green Efficiency	(Jin et al., 2021; Liu et al., 2019; Rasoulinezhad & Taghizadeh-Hesary, 2022)
Cluster 4	Green Finance for Energy	(Hyun et al., 2021; Li et al., 2021; Li et al., 2022)
Cluster 5	Green Finance for Green Sustainable Development	(Xu et al., 2022; Yin & Xu, 2022; Zhang et al., 2021; Zhou & Xu, 2022)
	Green Finance and Green Technology	(Fang & Shao, 2022; Gong et al., 2020)

Source: Author's own work.

Conclusions

The research carried out led to achieving the objectives set out in the introduction. The colours that show connotations with finance include green, blue, black, white and brown. Their meaning is presented in Table 2. Of these colours, green is dominant. This shows that the issues related to the financial aspects of environmental measures are critical and fit in with current trends in finance research. Among the other colours, blue and black were also significant. Regarding white and brown, only one publication each was identified that directly showed connotations. Most connotations were universal, i.e. they had similar meanings in the context of finance. However, in the case of the colour black, two meanings were identified, i.e. one related to illegal financial transactions and the other to the provision of financial services exclusively to black individuals. While the former can be seen as a universal meaning, the latter connotation relates to a specific territory (the United States) and time frame. A similar situation occurred with the colour white, and these connotations appeared in historical publications. In addition, it can be noted that most publications referring to the colours green, blue and brown have been published very recently, i.e. no later than 2018. This confirms that financial themes and research on environmental action, including seas, oceans and coastal areas, are now gaining importance. They fit into a broader research area called sustainable finance.

Given the bibliometric analysis results for the dominant colour, green, it can be seen that among the key areas of interest are: investments in green finance, green finance and entrepreneurship, green bonds as investment tools, greening of financial systems, green finance and green efficiency, green finance for energy, green finance for green sustainable development, green finance and green technology. The main focus areas are: investing in and financing environmentally friendly projects (including various types of technology), developing financial instruments to support environmentally friendly activities and supporting clean energy projects.

Limitations of this study include the fact that it only dealt with colour connotations with finance. Future research on colour symbolism may also concern disciplines or sub-disciplines such as economics, management, marketing, and entrepreneurship.

Disclosure statement

The authors report there are no competing interests to declare.

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Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 63-79
10.2478/fiqf-2023-0027

Financial Internet Quarterly

ASSESSMENT OF PUBLIC EDUCATION EXPENDITURE EFFICIENCY ACROSS LITHUANIAN MUNICIPALITIES

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Abstract

Efficiency of education expenditure is the ability to maximize the educational achievement given the resources invested. Although public education expenditure tends to increase, yet this does not necessarily guarantee high quality of education services. This study aims to assess public education expenditure efficiency of Lithuanian municipalities and to identify the factors explaining its variations. The study used data for 2013-2019 from 60 Lithuanian municipalities. Corrected Ordinary Least Squares method was employed for public education expenditure efficiency assessment and regression analysis was used to determine its influencing factors. Inputs included financial (public expenditure for education and maintenance) and nonfinancial (composition of teachers, occupied area, etc.) variables. Passing ratio of Lithuanian (national) language and math exams were used as efficiency outputs. The context variables represented environmental factors of educational achievements, such as number of business entities, users of social housing, libraries, and culture centres as well as municipalities' overall financial autonomy. Results of the research are ambiguous. When assessed by the overall passing of the exams, the efficiency was high, scoring 86-90%. But when evaluated by passing exams with the highest scores, it did not even reach 40%. Two types of public expenditure were identified as the most influential factors - public expenditure for education with the negative trend, and municipality own financing with the positive influence on the public education expenditure efficiency. Such results support the decentralization of public education expenditure management and call for alternative output measures in the Lithuanian public education system.

JEL classification: D61, H75, I22
Keywords: Public Expenditure Efficiency; Expenditure on Education; Municipal Finances

Received: 31.08.2023 Accepted: 29.10.2023

Cite this:
Legenzova R., Gaigalienė A., Rudytė D., Skunčikienė S. & Kazlauskienė V. (2023) Assessment of public education expenditure efficiency across Lithuanian municipalities. Financial Internet Quarterly 19(4), pp. 63-79.

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Introduction

Education is one of the key areas where public resources are allocated. As a result, an efficient use of such resources is expected, which subsequently should yield sustainable outcomes, such as economic growth or wealth accumulation. Economic growth-related research (Afonso & St. Aubyn, 2005) proved a positive education impact on economic growth. In addition to the economic effects associated with education there are notable non-economic benefits (Gavurov et al., 2017), such as improved life-satisfaction and happiness, health, and life expectancy. A systematic literature review conducted by Benos and Zotou (2014) across 989 previous studies documented generally positive effect of education on gross domestic product (GDP). Interestingly, a study by Coman et al. (2023) on the effect of education on GDP across Central and Eastern European countries concluded on the lack of long-term cointegration between those two variables in Lithuania. This suggests that although Lithuania allocates relatively sufficient funding to sustain its education system, outputs of the education are lower than those of other countries. Moreover, since 2008, European countries have experienced a decrease in public education financing as a percentage of their GDP and Lithuania is among the three European Union countries with the greatest decrease, at 1.5% over the last 15 years. According to Eurostat in 2019 public education expenditure (excluding early childhood) relative to GDP in Lithuania was 3.8%, compared to 4.43% in Latvia (data for Estonia is not available), 4.67% in Poland, 4.5 % in the Czech Republic and an average of 4.76% for all European Union countries (see: Coman et al., 2023) for further analysis of public education spending in Central and Eastern Europe and its effect on gross domestic product).

In light of decreasing financing, to maintain or even increase educational attainments, such as graduation exam passing rate and scores, Lithuania must employ their limited financial resources more effectively. A study by the Organization for Economic Cooperation and Development (OECD, 2017) on the Lithuanian educational system, among other aspects, also recommended that to improve the quality of higher education and to achieve efficiency of public expenditure a comprehensive consolidation of public higher education is needed. Actions are needed not only on a national but more importantly on a municipal level. An analysis of the Lithuanian education system (Municipal Debt Restructuring, 2020) revealed that even with the same public financing policy, educational attainments differ significantly across different municipalities. For example, Lithuanian municipalities differ significantly in education expenditure per student and hourly rate of a teacher. This suggests that some local units are managing their educational funds more efficiently than others and it is likely that higher efficiency is influenced by municipality-specific variables, such size and availability of cultural and educational infrastructure, municipality economic development and financial autonomy, etc. Therefore, it is not only relevant to assess the level of public expenditure efficiency but also to identify the variables that contribute to the success of the municipalities. By recognizing the factors that lead to better educational outcomes, other municipalities can replicate their success, and ensure that the decreasing resources are allocated wisely.

The aim of the research was to assess public education expenditure efficiency of Lithuanian municipalities and to identify the factors explaining efficiency variations among the municipalities. The research used data from 60 Lithuanian municipalities and covered the period of 2013-2019. Corrected Ordinary Least Squares (COLS) method was employed to assess the efficiency of education expenditure across Lithuanian municipalities while regression analysis identified statistically significant factors explaining the efficiency variations among the municipalities.

The article is structured as follows. The first section reviews the literature on public education expenditure and its efficiency assessment. The second section firstly overviews the Lithuanian education system and then describes research methods for the evaluation of public education expenditure efficiency across Lithuanian municipalities and its influencing factors, presents the research sample and limitations. The third section provides the research results while the fourth section discusses our findings and their implications. The fifth section concludes the study.

Literature review

Efficiency of public education expenditure

There is a large number of studies analysing the efficiency of public spending with rather diverse methods, data, and scope (Arias-Ciro, 2020). However, theoretical guidance of education efficiency has been relatively limited, and the term is not uniformly defined (Kosor, 2013). Only recently have a few reviews summarizing findings of previous research been published (De Witte & Lopez-Tores, 2017, Arias-Ciro, 2020). In most of the studies education efficiency is estimated by linking inputs of the education system with its outputs aiming to assess whether the education system makes the best possible use of the resources (De Witte & Lopez-Tores, 2017). Although efficiency assessment seems to have a common approach, the complexity, and specifics of education systems across countries, differences in socio-economic, political, and other factors result in a wide variety of inputs, outputs and assumptions used. At local government level (which is still under-researched) efficiency measurement with the selection of variables is even more complex task, due to the difficulty in collecting data and measuring local services (Balaguer-Coll et al., 2013).

Education efficiency related studies commonly concentrate either on allocative or on technical efficiency evaluation. Allocative efficiency is assessed by exploring how the composition of resources should at a given expenditure level be reallocated to expand the level or quality of educational services. Technical efficiency is seen as the extent to which the education system could expand its activities without engaging additional resources, or, vice versa, how much the resources could be contracted without reducing the activities or their quality level (Blank, 2000). Gimenez et al. (2017) also emphasize the importance of social-economic conditions in each assessed country.

In this paper we concentrate on technical efficiency and define it similarly to Gavurova et al. (2017) as maximizing the educational outcomes given the resources available in the educational system and considering the social-economic conditions of the area (municipalities in our case).

Review of previous research

Education expenditure efficiency has been explored at various teaching levels (i.e., primary, high or higher education) and geographical regions. As discussed by Agasisti and Zoido (2018), most of the studies focus on OECD countries or specific country groups characterized by similar socio-economic environment and availability of comparable data. Leading researchers in across-country studies are Afonso (2005a, 2005b, 2006, 2010, 2013) and Agasisti (2014, 2018, 2019) who conducted multiple studies assessing public education efficiency in Europe, OECD countries or in international setting. Miningou (2019) explored quality of education and the efficiency of public expenditure in 130 countries, Cordero et al. (2018) in 36 countries participating in Programme for International Student Assessment (PISA), Prasetyo and Zuhdi (2013) in 81 countries, Aristovnik (2013) conducted research in Eastern Europe while Gavurova et al. (2017) used secondary data of PISA and governmental spending to assess public education efficiency across European countries. Comparative research on education expenditure efficiency differences across countries commonly relies on inputs and outcomes of education systems provided in world educational databases, which then may be used as a benchmark and provide valuable information for national education policies (Hužvar & Rigova, 2016).

The empirical literature also contains studies that assess efficiency of education expenditure of a specific country or its region (Table 1 in Appendix). For instance, Tu et al. (2018) evaluated efficiency of preschool education and its influencing factors in 31 provinces of China. Melo-Becerra et al. (2020) estimated the local efficiency of the public expenditure of education in Colombia estimating disperse variations in efficiency levels (between 26% and 98%). Wanke et al. (2021) explored the relationship between efficiency measures in the education production function and various official managerial indicators used in Brazil. Kutlar et al. (2012) conducted an analysis on the economic effectiveness of 27 municipalities in Turkey, which also included efficiency of public education. Solihin et al. (2005) analysed the efficiency and effectiveness of local government expenditure on the education sector in 28 districts of East Java. Blackburn et al. (2014) applied the public sector Data Envelopment Analysis (DEA) model to estimate the efficiency of 1650 primary and 400 secondary schools in New South Wales (Australia) estimating a moderate level (approximately 82%) expenditure efficiency, while Wanke et al. (2016) extended analysis of this region applying a two-stage network DEA model. Surprisingly, there is very little research assessing the efficiency of education expenditure of individual European countries. Vitek and Martinkova (2015) used a set of effectiveness and efficiency variables and analysed descriptive statistics of primary education in the Czech Republic. Kyriakides et al. (2019) explored efficiency of educational investments across all public schools in Cyprus. Aparicio et al. (2018) explored main drivers of productivity changes at especially vulnerable public schools in Catalonia during the period of global financial crisis (years 2009-2013), Scippacercola and Ambra (2014) analysed the situation in secondary schools of the Cambria region.

Studies based on a single country commonly use school-level or municipality-level data, employing more diverse methods beyond just DEA (e.g. multilevel regression analysis and discriminant function analysis by Kyriakides et al., 2019 or Hicks-Moorsteen index by Aparicio et al., 2018). When it comes to the inputs, educational expenditure per student stands out as the most frequently used metric (Blackburn et al., 2014; Aparicio et al., 2018; Vitek & Martinkova, 2015; Kutlar et al. 2012; Aristovnik, 2013; Arias & Torres, 2017). Among the non-financial inputs, number of teachers per student (Aparicio et al., 2018; Kutlar et al., 2012; Scippacercola & Ambra, 2014), investments in premises (Tu et al., 2018) and occupied area related measures (Scippacercola & Ambra, 2014; Kyriakides et al., 2019) are the most commonly used. Local administrative units-related research usually relies on results of national exams as output variables (see: Table 1) in contrast to standardized international tests (e.g. PISA used for across country analysis). As discussed by Wanke et al. (2016) several studies have also provided supportive evidence that efficiency of public education is affected by contextual variables, such as school type, teacher characteristics and family characteristics (e.g. Scippacercola & D'Ambra, 2014). In the assessment of the efficiency of higher education within a single country/region, studies tend to focus on understanding the drivers of higher efficiency levels in terms of costs (expenditures, funds, resources, etc.) and learning (academic achievement, etc.) (Wanke et al., 2016). Depending on the method used, the actual level of efficiency may be reported as a ratio (Melo-Becerra et al., 2020; Blackburn et al., 2014) or assessed within a contextual framework (Wanke et al., 2016; Solihin et al., 2005). Review of previous studies highlights that a lack of comparable time series data is the key constraint for single country-studies. Moreover, the variety of input and output variables and research methods used makes it challenging to compare their results directly. Nevertheless, such studies bring valuable policy implications, empowering policymakers to make supported decisions and implement targeted reforms.

Building on the findings of previous studies within the aim of this study we hypothesize that:

H_1: The efficiency level of higher education expenditure is moderate.

H_2: Financial inputs have a statistically significant and positive effect on the efficiency of public education.

H_3: Non-financial inputs have a statistically significant and positive effect on the efficiency of public education.

Research methodology

Overview of the Lithuanian education system

Lithuanian educational institutions are divided into public (state/municipal) and private schools, which could be either partially financed by the state or fully self-financed. This study covers state/municipal primary schools, secondary-education schools and gymnasiums (thereafter referred to as public high schools). Public high schools are in every municipality, and have the same financing model, constituting a comparable sample.

In Lithuania, higher education is publicly funded at all levels, achieved through state donations. Two types of funds—educational funds and maintenance funds—are available for public high school financing. Under the current system, the main part of educational funds is allocated to a class (as a teaching unit), so the amount of funding received by a school depends on the number of classes in that school, but not on the number of students in the class. Number of students in a class depends on the population density in the region (therefore it is higher in the cities) and popularity of the school. A much smaller part of educational funds referred to as expenditure for other teaching needs (educational support, management, and teaching tools) is allocated per student, so the funding received by a school is dependent on the number of students in a class. Maintenance-related expenditure must be covered by the school's owner, which in the case of public high schools is the municipality.

Method for public education efficiency assessment

Various non-parametric or parametric estimation techniques for public education expenditure efficiency measurement were used in previous research (Haelermans & Ruggiero, 2013). Data Envelopment Analysis (DEA) is the most popular non-parametric method widely used at all education levels, while Stochastic Frontier Analysis (SFA) and Corrected Ordinary Least Squares (COLS) are two the mostly used parametric methods (Baba et al., 2021). DEA method is one of the most popular methods (Blackburn et al., 2014; Prasetyo & Zuhdi, 2013; Gavurova et al., 2017; Agasisti & Zoido, 2018; Mota & Meza, 2020) because it allows analysing of multiple inputs, and outputs and does not require a specific functional form (Lampe & Hilgers, 2015). However, as it is discussed by Cook et al. (2014) using DEA may have some issues if selected variables are mixed and expressed in different ways: percentages, indexes or remaining raw. Differently from the non-parametric methods, SFA is not deterministic but a stochastic model, which is usually preferred because of its ability to differentiate between inefficiency and noise (Scippacercola & Ambra, 2014; Muvawala & Hisali, 2012; Miningou, 2019). Use of traditional SFA requires use of multiple inputs or outputs and applying a specific functional form (Lampe & Hilgers, 2015). SFA also has limitations as it requires specific assumptions about the distribution of the error term, and independence between the inefficiency and random error (Gomez-Deniz & Perez-Rodriguez, 2017). In our study we chose to use the COLS method. Similar to DEA, it is a deterministic approach, meaning that no statistical noise is allowed in the model; it is also parametric as SFA (Narbon-Perpina & De Witte, 2018), which determines the frontier based on a specific functional form using econometric techniques. COLS method is defined as a shifted average function which requires two main steps: to estimate the error term and then to shift the frontier up by the amount of the largest residual (Vasanthi et al., 2017). COLS method is more suitable for smaller datasets (Alarenan et al., 2019) which is relevant for Lithuania since the dataset is relatively small and the selected variables are expressed at different scales. The usage of the parametric methods also allows for choosing the functional form of function between the more restricted Cobb-Douglas and the most frequently used functional form in efficiency analysis – translog (Lampe & Hilgers, 2015). In our study, the more flexible log-linear function was used and equations referring to Vasanthi et al. (2017) and Alarenan et al. (2019) were applied.

The first step in COLS application involved estimation of the residuals using equation (1).

$$lnER_{i,t} = \beta_0 + \beta_1 \bullet lnME_{i,t} + \beta_2 \bullet lnEE_{i,t} + \beta_3 \bullet lnTT_{i,t} + \beta_4 \bullet YT_{i,t} + \beta_5 \bullet lnTA_{i,t} + \beta_6 \bullet lnLA_{i,t} + \beta_7 \bullet lnFP_{i,t} + \beta_8 \bullet lnSP_{i,t} + \theta_t + \varepsilon_{i,t} \quad (1)$$

where ER defines the output measure in municipality i at year t (exam results), $Me_{i,t}$ – school maintenance expenditure in thousand euros, $EE_{i,t}$ – educational expenditure in thousand euros, $TT_{i,t}$ – teachers per pupil, $YT_{i,t}$ – part of young teachers, %, $TA_{i,t}$ – total school area in square meters, $LA_{i,t}$ – learning area in square meters, $FB_{i,t}$ – part of foreign pupils, %, $SP_{i,t}$ – part of pupils with special needs, % in municipality i at year t. β_0 is an intercept, β_1 - β_8 regression coefficients, θ_t – time dummies, $\varepsilon_{i,t}$ – idiosyncratic error.

The second step estimated the maximum residual using equation (2).

$$\varepsilon_{\max} = \max(\varepsilon_{i,t}) \quad (2)$$

Then the new COLS intercept was estimated by using equation (3).

$$b_{COLS} = b_0 + \varepsilon_{\max} \quad (3)$$

Finally, the efficiency coefficients were estimated by using equation (4).

$$E_{it} = \exp(-b_{COLS}) \quad (4)$$

where E_{it} are estimated efficiency coefficients in municipality i at year t, which values lie between 0 and 1, meaning the higher value associated with higher efficiency.

Methods for identification of efficiency determinants

The second objective of the paper was to identify whether and which intrinsic variables (the inputs of efficiency model) as well as other variables (controls) affect the public education expenditure efficiency in municipalities. For that purpose, equation (5) was applied.

$$lnE_{i,t} = \beta_0 + \beta_1 \bullet lnOF_{i,t} + \beta_2 \bullet lnSH_{i,t} + \beta_3 \bullet lnBE_{i,t} + \beta_4 \bullet lnLB_{i,t} + \beta_5 \bullet lnCC_{i,t} + \theta_t + \varepsilon_{i,t} \quad (5)$$

where $E_{i,t}$ defines the efficiency in municipality i at year t, $OF_{i,t}$ – municipalities own funds measured as a part of all income, %, $SH_{i,t}$ - individuals who were on lists for social housing per 1 thousand inhabitants, $BE_{i,t}$ - the number of business entities per 1 thousand inhabitants, $LB_{i,t}$ - the number of libraries per 1 thousand inhabitants, $CC_{i,t}$ - the number of culture centres per 1 thousand inhabitant, β_0 is an intercept, β_1 - β_5 regression coefficients, θ_t – time dummies, $\varepsilon_{i,t}$ – idiosyncratic error.

To test the validity of OLS models Breusch-Pagan heteroscedasticity test and Wooldridge serial correlation test were performed for all models. The main validity testing results are presented along with the results of our models, while more detailed information can be presented upon request.

Research variables

Research variables used in this study are summarized in Table 2 along with their descriptive statistics.

Outputs. In line with the previous research, we chose to use graduation exam passing rates and scores as the output measures. In this study two exams (Mathematics and Lithuanian language) were chosen and two output measures for each exam were used – overall exam passing ratio - MEP (mathematics exam pass) and LEP (Lithuanian exam pass) and exam passing with the highest score ratio (86-100 out of 100) – namely, MEP86-100 and LEP86-100.

Inputs chosen for our analysis represent two financial and six qualitative inputs. Education expenditure (EE) is measured in euros per student and represents national transfers to the schools (through municipality budgets) for educational purposes (e.g. for teaching staff salaries). This type of funding, as explained above, is allocated to schools according to the predetermined formula based on the number of classes in a school except for schools with foreign speaking pupils and pupils with special needs (then more funds are allocated). The level of public financing differs considerably across separate municipalities ranging from 274.78 Euro per pupil to as high as 3742.9 Euro per pupil, with standard deviation of 271.52 Euro per pupil.

Table 2: Descriptive statistics of research variables

Variables		Min	Max	Mean	St. dev.
Output					
E	LEP, %	62.50	100.00	89.03	5.37
	LEP 86-100, %	0.00	60.00	9.37	4.92
	MEP, %	56.90	100.00	87.48	7.39
	MEP 86-100, %	0.00	23.33	6.27	4.09

	Variables	Min	Max	Mean	St. dev.
	Input				
ME	Maintenance expenditure per pupil, Euro	274.78	3742.9	764.14	271.52
EE	Education expenditure per pupil, Euro	1423.8	2709.9	1820.1	231.03
TT	Number of teachers per pupil	0.09	0.23	0.12	0.02
YT	Share of teachers up to 29 years old, %	0.00	50.00	3.76	6.87
TA	Total school area per pupil, sq. m.	9.66	41.88	16.34	4.30
LA	Total learning area per pupil, sq. m.	3.82	12.17	6.02	1.39
FP	Share of foreign pupils, %	0.00	3.65	0.19	0.36
SP	Share of special needs pupils, %	1.65	46.50	14.58	5.72
	Context variables				
OF	Own funds as share of all income, %	4.40	38.7	11.19	5.28
SH	Individuals listed for social housing per 1000 inhabitants	1.33	43.24	7.61	4.43
BE	Number of business entities per 1000 inhabitants	11.67	76.85	23.74	11.11
LB	Number of libraries per 1000 inhabitants	0.06	1.46	0.74	0.38
CC	Number of culture centres per 1000 inhabitants	0.01	1.21	0.38	0.27

Source: Author's own work.

Maintenance expenditure (ME) covers salaries of the maintenance staff, utility expenses, student transportation, expenditures for repairs, etc. School maintenance expenditures are covered by municipalities and are decided upon more flexibly according to the needs of separate schools within a municipality. This type of expenditure varies across municipalities less than educational expenditure, but the differences are still considerable and indicate that schools have to seek educational attainments with different financial inputs.

The teachers per pupil ratio (TT) ranges from 0.09 to 0.23 in the analysed period and is one of the qualitative indicators indicating the size of classes (according to the number of pupils) representing the level of individual attention given to a pupil which eventually may influence the pupil's educational outcomes.

The share of teachers up to 29 years old (YT) is not a very common indicator in education efficiency research, yet it is a very relevant measure for Lithuania as the aging of teaching personnel is and will remain a significant problem for many municipalities. As presented in Table 1 on average Lithuanian schools have less than 4% of teachers age 29 or younger (and some schools do not have them at all).

Part of foreign pupils (FP) and part of pupils with special needs (are variables that represent both the more difficult and complex teaching environment as well as different financing schemas. Classes with foreign or special needs pupils have access to special donations or additional teaching staff. The share of foreign pupils in Lithuanian municipalities is considerably low; however, the share of pupils with special needs is much higher and varies more considerably across municipalities (up to 46%).

Two indicators - total school area in square meters (and learning area in square meters) were included in the model to represent the infrastructure of schools which they have available for the educational process. The infrastructural variables also demonstrate big differences across municipalities.

Efficiency measures. In this study four efficiency estimates E1, E2, E3, and E4 were calculated for four distinct output measures. E1 represents public high education efficiency when output is measured by the passing rate of Lithuanian language exam. E2 – for Lithuanian exam passing with the highest score (86-100). The remaining two efficiency estimates are based on the mathematics exam results, E3 – for mathematics exam passing rate and E4 – mathematics exam passing with the highest score (86-100).

Context variables. To better understand public education expenditure efficiency, in our research we decided to use five additional context variables. These variables are not directly connected to the educational process or its financing schemas but are recognized in previous research as important environmental factors of educational achievements (e.g. Agasisti & Dal Bianco, 2006). Individuals who were on lists for social housing per 1 thousand inhabitants (SH) and the number of business entities per 1 thousand inhabitants (BE) were chosen to represent the current economic situation in the municipality region. The number of libraries per 1 thousand inhabitants (LB) and the number of culture centres per 1 thousand inhabitants (CC) indicate the possibilities for learning outside the school environment, as libraries and culture centres not only give access to books and computers, but also host a variety of cultural and educational events. The variable of municipalities' own tax income, measured as a % share of all income, (OF) reflects the level of municipalities' overall financial autonomy.

Sample and data sources

This study used unbalanced panel data of 60 municipalities in Lithuania. The data period covered a period of 2013 - 2019. Statistical data is collected from the Lithuanian Department of Statistics database (2022), except data of separate Quality of Life indicators from the control variable section. This data was obtained from the Open Lithuanian finance (2022) database.

Results

Efficiency of education expenditures across Lithuanian municipalities

The first step of efficiency calculations was to conduct regression analysis (equation 1). The results of regression analysis (with standard errors) are presented in Table 3.

Table 3: OLS model results (with standard errors)

Variables	LEP	LEP86-100	MEP	MEP86-100
Constant	6.1544 (0.5291)	19.9942*** (5.0850)	6.8872*** (0.6742)	15.4367*** (5.7310)
Maintenance expenditure per pupil	-0.0232 (0.0183)	0.3589** (0.1777)	0.0179 (0.0233)	0.3180 (0.1990)
Education expenditure per pupil	-0.2050*** (0.0719)	-2.8754*** (0.6923)	-0.3762*** (0.0915)	-1.9938** (0.7774)
Number of teachers per pupil	0.0542 (0.0384)	-0.2489 (0.3706)	-0.0447 (0.0490)	0.0543 (0.4222)
Share of young teachers < 29 years, %	-0.0080** (0.0040)	-0.0382 (0.0390)	0.0094* (0.0051)	-0.0058 (0.0438)
Total school area per pupil, sq. m.	0.0306 (0.0255)	0.2811 (0.2446)	0.0595* (0.0324)	-0.0058 (0.2759)
Total learning area per pupil, sq. m.	-0.0497* (0.0272)	-0.2402 (0.2616)	-0.0053 (0.0347)	-0.6347** (0.2947)
Share of foreign pupils, %	-0.0076** (0.0035)	-0.0502 (0.0339)	0.0172*** (0.0045)	0.1241*** (0.0380)
Share of special needs pupils, %	0.0412*** (0.0091)	0.1308 (0.0874)	0.0260** (0.0116)	0.2343** (0.0982)
R Squared	0.1929	0.1840	0.5404	0.3852
Breusch-Pagan test (Prob > chi2)	< 0.0100	< 0.0100	< 0.0100	0.1300
Wooldridge test (p-value)	0.0900	< 0.0100	< 0.0100	< 0.0100

*** Shows the statistical significance at 99%, ** shows the statistical significance at 95%, and * shows the statistical significance at 90% level. Standard errors are represented in the brackets. Statistically significant impact is highlighted in bold.

Source: Author's own work.

The validity of all OLS models was tested using Breusch-Pagan heteroscedasticity test and Wooldridge serial correlation. Data analysis showed the presence of heteroscedasticity in most of the models and the evidence of serial correlation in several models. To deal with these issues, heteroskedasticity and autocorrelation (HAC) robust standard errors were included in all the models. The results of regression analysis (with HAC robust standard errors) indicating significant input variables are presented in Table 4.

Table 4: OLS model results (with HAC robust standard errors) used to calculate efficiency

Variables	LEP	LEP86-100	MEP	MEP86-100
Constant	6.1544*** (0.5321)	19.9942*** (6.5794)	6.8872*** (0.6507)	15.4367** (6.3207)
Maintenance expenditure per pupil	-0.0232 (0.0203)	0.3589 (0.2095)	0.0179 (0.0234)	0.3180 (0.2473)
Education expenditure per pupil	-0.2050*** (0.0658)	-2.8754*** (0.8754)	-0.3762*** (0.1005)	-1.9938** (0.9174)
Number of teachers per pupil	0.0542 (0.0451)	-0.2489 (0.4987)	-0.0447 (0.0680)	0.0543 (0.4932)
Share of young teachers <29 years, %	-0.0080** (0.0038)	-0.0382 (0.0389)	0.0094 (0.0054)	-0.0058 (0.0434)
Total school area per pupil, sq. m.	0.0306 (0.0226)	0.2811 (0.2501)	0.0595 (0.0653)	-0.0058 (0.3478)
Total learning area per pupil, sq. m.	-0.0497** (0.0238)	-0.2402 (0.2885)	-0.0053 (0.0167)	-0.6347* (0.3630)
Share of foreign pupils, %	-0.0076** (0.0035)	-0.0502 (0.0366)	0.0172*** (0.0045)	0.1241*** (0.0398)
Share of special needs pupils, %	0.0412*** (0.0138)	0.1308 (0.1400)	0.0260** (0.0123)	0.2343** (0.1184)
R Squared	0.1929	0.1840	0.5404	0.3852

*** Shows the statistical significance at 99%, ** shows the statistical significance at 95%, and * shows the statistical significance at 90% level. HAC robust standard errors are represented in the brackets. Statistically significant impact is highlighted in bold.

Source: Own elaboration.

The next step of our analysis was to calculate the efficiency coefficients E1, E2, E3 and E4, using equations 2, 3, and 4. The average efficiency coefficients E1, E2, E3 and E4 and their descriptive statistics are presented in Table 5 (the histograms of the frequency distributions of all four efficiency measures showed normal distributions). The evaluation efficiency level (for testing H_1 hypothesis) was performed based on the study by Melo-Becerra et al. (2020) and Blackburn et al. (2014). Efficiency coefficients above 80% were treated as indicators of high efficiency, between 50 and 80 % – as of moderate efficiency and below 50 – as of low efficiency.

Table 5: Descriptive statistics of efficiency coefficients

	Efficiency				
Variable	Obs.	Mean	St. Dev.	Min	Max
E1 (LEP)	222	0.9043	0.0441	0.6611	1
E2 (LEP86-100)	221	0.3748	0.1613	0.0435	1
E3 (MEP)	222	0.8643	0.0544	0.6735	1
E4 (MEP86-100)	218	0.3174	0.1564	0.0318	1

Source: Author's own work.

According to our estimations, the same inputs result in different efficiency levels for different output measures. When assessed by the overall passing rate of the Lithuanian (LEP) and mathematics (MEP) exams, the efficiency scores were high averaging 90% and 86% respectively. But when evaluating efficiency by passing the exams with the highest scores (LEP86-100 and MEP86-100), the results did not even reach 40% (37% for the Lithuanian exam and 32% for mathematics). Notably, the efficiency levels for the mathematics exam are lower than for the Lithuanian language exam.

Factors explaining efficiency of public education expenditure across Lithuanian municipalities

Two sets of variables are used to identify the determinants of public education efficiency – input variables and context variables including both financial and non-financial measures. The results of regressions used for calculation of efficiency measures (equation 1) were further interpreted for identification of factors explaining efficiency of public education expenditure across Lithuanian municipalities. As presented in Table 3, all four outputs (LEP, LEP86 - 100, MEP, MEP86 - 100) used to calculate efficiencies, had negative statistically significant dependency on the educational expenditure (EE). Interestingly, LEP results were also negatively influenced by share of young teachers (YT), total learning area per pupil (LA) and share of special needs pupils (SP), and positively influenced by the share of foreign pupils (FP). Regarding mathematics, both MEP and MEP86 - 100 were positively influenced by the share of foreign pupils (FP), and the share of special need pupils (SP). None of these inputs influenced LEP86 - 100 results.

Equation 5 was used to evaluate whether context variables had any influence on the efficiency levels. Results of regression analysis for the context variables (with standard errors) are presented in Table 6, while the results of regression (with HAC robust standard errors) indicating significant context variables are presented in Table 7.

Table 6: Regression results for context variables (with standard errors)

Variables	E1	E2	E3	E4
Constant	-0.1938*** (0.0707)	-0.5065 (0.6577)	-0.4283*** (0.0892)	-2.5831*** (0.7557)
Own funds as share of all income	0.0284** (0.0114)	0.5542*** (0.1058)	-0.0028 (0.0144)	-0.0419 (0.1240)
Individuals listed for social housing per 1000 inhabitants	0.0083 (0.0077)	-0.0007 (0.0706)	0.0076 (0.0097)	0.0398 (0.0828)
Number of business entities per 1000 inhabitants	0.0493** (0.0203)	0.2595 (0.1888)	0.0955*** (0.0256)	0.3378 (0.2186)
Number of culture centres per 1000 inhabitants	0.0000 (0.0044)	0.0343 (0.0406)	0.0169*** (0.0056)	-0.0560 (0.0476)
Number of libraries per 1000 inhabitants	0.0143** (0.0072)	0.0664 (0.0670)	-0.0010 (0.0091)	-0.0013 (0.0781)
R Squared	0.0884	0.1637	0.1070	0.1053
Breusch-Pagan test (Prob > chi2)	< 0.0100	< 0.0100	< 0.0100	< 0.0100
Wooldridge test (p-value)	0.3900	0.2100	< 0.0100	< 0.0100

*** Shows the statistical significance at 99% and ** shows the statistical significance at 95% level. Standard errors are represented in the brackets. Statistically significant impact is highlighted in bold.

Source: Own elaboration.

Table 7: Regression results for context variables (with HAC robust standard errors)

Variables	E1	E2	E3	E4
Constant	-0.1938*** (0.0714)	-0.5065 (0.6063)	-0.4283*** (0.0962)	-2.5831*** (0.7525)
Own funds as share of all income	0.0284*** (0.0107)	0.5542*** (0.1032)	-0.0028 (0.0152)	-0.0419 (0.1073)
Individuals listed for social housing per 1000 inhabitants	0.0083 (0.0079)	-0.0007 (0.0656)	0.0076 (0.0089)	0.0398 (0.0781)
Number of business entities per 1000 inhabitants	0.0493** (0.0203)	0.2595 (0.1751)	0.0955*** (0.0273)	0.3378 (0.2338)
Number of culture centres per 1000 inhabitants	0.0000 (0.0037)	0.0343 (0.0345)	0.0169*** (0.0052)	-0.0560 (0.0432)
Number of libraries per 1000 inhabitants	0.0143** (0.0064)	0.0664 (0.0693)	-0.0010 (0.0099)	-0.0013 (0.0861)
R Squared	0.0884	0.1637	0.1070	0.1053

*** Shows the statistical significance at 99% and ** shows the statistical significance at 95% level. HAC robust standard errors are represented in the brackets. Statistically significant impact is highlighted in bold.

Source: Own elaboration.

The obtained results (Table 7) show that the financial autonomy of municipalities (measured as share of own funds in all income) had a positive and significant effect on efficiency measured by LEP and LEP86 - 100. The number of operating business entities in a municipality has a positive effect on the efficiency measured by LEP and MEP, the number of cultural centres –by MEP while the number of libraries - measured by LEP.

Discussion

Our study provides valuable yet ambiguous insight into the efficiency of public education expenditure of Lithuanian municipalities. Our first hypothesis that the efficiency level of higher education expenditure is moderate was rejected. In the case where educational attainments were measured by the overall passing of national exams, the scores of 86-90% suggest that public education expenditure efficiency is high if evaluated from the perspective of its main aim – i.e., to provide broad scope higher education. Comparable results were also reported by Melo-Becerra et al. (2020) for some Colombian municipalities and Blackburn et al. (2014) for Australian schools, however the results should be compared with caution due to different variables and the different object of the assessment in Blackburn et al. (2014) study. On a broader perspective, results of our study bring interesting insights. Despite decreasing and below EU average public education expenditure (Coman et al., 2023), Lithuania has demonstrated remarkable efficiency in utilizing educational funds.

The results of the efficiency assessment were discouraging and leading to the rejection of the first hypothesis when looking from the passing exams with the highest grades perspective. In this case the efficiency levels were low (32-37%). Interestingly, we also conducted additional analysis on municipality clusters (big cities, villages, resorts, and others) and the results were consistent with the entire sample. This heterogeneity in efficiency measures suggests that some municipalities may be able to improve their educational outcomes without increasing their resources. Actually, we observed variations among different municipalities in the output variables when schools in some municipalities show much higher educational attainment results than the others. Such variation among the local units is not an exception in our analysed country. They were also observed across Colombian municipalities (Melo-Becerra et al., 2020). This pattern is not unique to Lithuania. For example, it has been previously observed in Colombian municipalities (Melo-Becerra et al., 2020). From a broader perspective, our study supports OECD (2017) conclusions and recommendations that the ineffective allocation of funds, particularly when assessing efficiency based on top exam scores, impedes the correlation between educational investment and economic growth in Lithuania. This points to a critical area for improvement that directly impacts national GDP.

While analysing the data for output variables, we also observed that the passing rate as well as attaining of the highest scores is considerably lower in the exam of mathematics than the exam of Lithuanian language. Such results are not in line with previous research (e.g. Gavurova et al., 2017), where results in mathematics were higher than reading skills. In the case of Lithuania, official reports and studies have been repeatedly indicating the lack of qualified teachers in mathematics, forecasting this deficit to increase even more in the future (OECD, 2015 and 2017; Municipal Debt Restructuring, 2020).

The second hypothesis of our study, which questioned whether public education expenditure has a significant and positive impact on public education efficiency was rejected. Three variables directly representing expenditure were used in our analysis – educational expenditure and maintenance expenditure (as education-related input variables) and municipality own resources (as a content variable representing municipalities' financial independence). We found that only the financial autonomy of municipalities is a significant determinant for the efficiency measured by the scores of Lithuanian exams (both the overall and with the highest scores). Also, our study did not find significant evidence of the influence of maintenance expenses on the efficiency of public education. Similar results were observed by Wanke et al. (2016) in primary and secondary schools of Australia. Unexpectedly, in our study the educational expenditures had a significant and negative effect on the efficiency of public education in municipalities measured by all 4 types of educational attainments. This indicates shocking evidence that the more expenditure is allocated to the schools of a certain municipality the worse national exam scores in that municipality are. Such findings present new evidence on the shortcomings of Lithuanian public education expenditure allocation formulas and were not previously reported by other studies on municipality level efficiency assessment. On one hand, such results may be explained by the peculiarities of the national educational expenditure allocation system. Even though the national formula for resource allocation in Lithuania is the same across all municipalities, the level of educational expenditure varies considerably across municipalities. This is influenced by the size of schools, size of classrooms, qualification of personnel as well as other funds allocation criteria. Although more in depth analysis on the national public education expenditure allocation system is needed, our results suggest that the current resources allocation system is not the most efficient in enabling the pupils to seek the highest academic achievements. On the other hand, such a negative effect could indirectly explain why Lithuania, having public education funding per GDP lower than the European Union average, also lags behind in the long-term relationship between public education spending and economic growth (Coman et al., 2023).

Our study also involved the analysis of the influence of non-financial variables on the efficiency of public education in Lithuanian municipalities. The third hypothesis stating that non-financial inputs have a statistically significant and positive effect on the efficiency of public education brought mixed results requiring further investigation. Interestingly, three of our nonfinancial input variables (share of young teachers, total learning area per pupil, and number of foreign pupils) demonstrated a negative effect on the public education efficiency measured by the overall passing of the Lithuanian exam. The effect of the same variables on the other efficiency measures was not statistically significant, except for the variable of number of foreign pupils, which demonstrated a positive effect on the educational attainments in mathematics. A number of foreign pupils who might experience difficulties learning the Lithuanian language is a rational explanation of the lower efficiency of the overall passing of the Lithuanian exam. However, similar to our comment on financial variables, a negative effect of having young teachers and more learning space calls for immediate enquiries into the issue. On the other hand, findings related to teachers' experience are consistent with previous results. For example, it proved to be an important determinant of the efficiency of primary and secondary education in Australia (Wanke et al., 2016). As for the contextual variables, a rather robust positive effect on the efficiency of public education (measured by the overall passing of the exams) was observed for the number of business entities. Furthermore, the number of cultural objects (culture centres and libraries) were also found to influence the results of public education efficiency (but only for efficiency measured by the overall passing of the math exam). This is in line with the findings of Agasisti (2014), suggesting that economically and culturally stronger municipalities create more favourable conditions in which to seek higher educational attainments.

Our findings demonstrate several policy implications. Based on our results we advocate for the change in the national public expenditure allocation model and for greater autonomy of Lithuanian municipalities in decision-making regarding educational expenditure. Financial autonomy for municipalities in education spending can yield several benefits, including closer alignment with local needs, increased accountability and transparency, improved efficiency, and better use of resources. Such autonomy would empower municipalities to identify areas where funds are being wasted and redirect them towards more effective uses, enabling them to make higher quality decisions. Additionally, municipalities would be better positioned to utilise their resources efficiently and deliver education services more effectively (Kopańska, 2018). Ultimately, this autonomy could lead to increased public trust and support for education spending. Overall, studies on the effectiveness of education expenditure are important in both the national and Central and Eastern European contexts and holds significant practical value. In the European context, Lithuania continues to demonstrate below-average efficiency of public education expenditure (Aristovnik, 2013; Gavurova, et al., 2017), prompting immediate actions. The results of our study aim to contribute to increasing the efficiency of public spending in education. Since education costs in municipalities make up the largest part of expenditure (more than half of all costs), their more effective utilization would enhance the efficiency, competitive advantage and economic productivity of the entire country. In Central and Eastern Europe, many countries face social integration challenges related to national minorities, economic inequalities, and other social issues. Education can be a vital tool to address these challenges, while effectiveness studies can assist countries to better understand how their education spending can promote social inclusion.

Conclusions

This research provides valuable evidence of the efficiency of public education expenditure across Lithuanian municipalities and identifies financial and non-financial factors that explain the scores of overall exam results and top-tier exam results and therefore the efficiency variations among the municipalities.

The results of the research are ambiguous. When assessed by the overall passing scores of mathematics and Lithuanian (national) language exams, the efficiency of the educational system was found to be as high as 86-90%. However, when evaluated by the passing of both exams with the highest scores, the efficiency was found to be below average ranging between 32-37%. Our research has assessed the influence of financial and nonfinancial inputs, as well as contextual measures on the efficiency of public education. Two types of financial variables were found to be statistically significant. Educational expenditure, which is a state donation allocated to a school by municipality based on the number of classes, had a negative impact on the results of all assessed exams. In contrast, municipality own funding, representing municipalities' financial autonomy, had a positive influence on public education efficiency when assessed by the scores of Lithuanian exams. Regarding nonfinancial variables, the share of foreign pupils and pupils with special needs had the most significant impact on exam scores. Furthermore, the number of business entities and cultural objects (culture centres and libraries) were also found to influence the results of public education efficiency, but the influence of nonfinancial factors was evident only for the specific output measures.

Lithuanian public education expenditure, decreasing and below the EU average, demonstrates high efficiency when providing general education. However, when assessing efficiency based on top educational attainments, it shows ineffective allocation of funds and critical areas for improvement that directly impact the national GDP. Results of our study support the decentralization of public education expenditure management and call for alternative output measures in Lithuanian public education system. They can be used to make informed education and public finance policy decisions aiming to improve public education expenditure efficiency in Lithuania.

One of the limitations of this study relates to the specifics of the Lithuanian public education system and its financing model. This makes it more difficult to apply methods and variables used in other studies to the Lithuanian context. Also, it makes it more difficult to compare our findings to the other studies. Another limitation of this research is related to the availability of reliable municipality level information on the input and context variables for the entire research period. Use of other input and output variables could lead to different efficiency measurements.

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Appendix

Table 1: An overview of single country/region research

Authors (year)	Scope	Method	Inputs	Output	Results
Vitek and Martinkova (2015)	Primary schools in the Czech Republic	Descriptive statistics	Expenditure per student, salaries of teachers, numbers of pupils, use of facilities	Language, mathematics and natural science results of less successful students	Overall assessment of efficiency is difficult due to the lack of time series data. Cost efficiency is overall positive and improving.
Kyriakides et al. (2019)	Public schools in Cyprus	Multilevel regression analysis and Discriminant function analysis	Educational investment	Overall achievement in the Pancyprian examinations	Educational investment had a positive effect on the effectiveness status of a school if invested in least effective schools.
Aparicio et al. (2018)	298 Catalan public primary schools	Hicks-Moorsteen total factor productivity change index	Expenditure per student, number of teachers, maternal educational level	Average grade in the sixth grade for Catalan, Spanish and English	During 2009-2014 (the crisis period) schools improved their total factor productivity by raising academic achievement despite cutbacks in resources.
Scippacercola and Ambra (2014)	Secondary schools in Cambria	Stochastic Frontier Analysis and Tobit model	Multiple structural, financial, technological, human resources, and environmental variables	Production frontier	The production inputs (number of teachers per 100 students and the number of students per class) have a significant impact. The financial variables (extra revenue funds) and the structural variables (the total area of the classes and the presence of school libraries) are not significant.
Melo-Becerra et al. (2020)	Colombian municipalities	Stochastic Frontier Analysis	Multiple factors representing institutional environment and fiscal autonomy	Enrolment in upper secondary education, the public-school quality and the average math score	The efficiencies vary between 26% and 98%. Differing regional patterns are observed for the cases of education quality and enrolment.
Tu et al. (2018)	31 provinces of China	Two-step Data Envelopment Analysis and Tobit	Public expenditure on personnel, public funds expenditure in preschool education, capital construction expenditure in preschool education	Number of pre-school teachers and number of pre-school classes, number of teachers, education of teachers, average dormitory size.	Local differences in preschool education expenditure efficiency were observed. The efficiency on local preschool education spending in the eastern part is larger than the west and middle regions. Most of the loss of overall efficiency resulted from the scale efficiency.

Authors (year)	Scope	Method	Inputs	Output	Results
Solihin et al. (2005)	East Java	Data Envelopment Analysis	Number of teachers per student, number of classrooms per student, ratio or the number of schools per school-age population, level of government spending	Index of Education	Government spending in the education sector in most of the district and the city of East Java Province is not efficient.
Blackburn et al. (2014)	1650 primary and 400 secondary schools in New South Wales (Australia)	Data Envelopment Analysis	Total expenditure per pupil	Average test scores on reading, writing, spelling, grammar and numeracy	A moderate level of overall cost efficiency (approx. 82 %). The efficiency increases for the quintile of schools with the most favorable environment. Further, efficiency gains are realized with increasing enrollment.
Wanke et al. (2016)	New South Wales (Australia) primary and secondary schools	Two-stage network Data Envelopment Analysis	Multiple financial variables, including total cost, teacher salaries, maintenance, depreciation, utility, etc. costs, value of school land and building	Reading, writing, spelling, grammar and numeracy test scores	Australian public schools are heterogeneous. The collective efficiency of the educational units analyzed did not change during the period of study.

Source: Author's own work.

Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 80-96
10.2478/fiqf-2023-0028

Financial Internet Quarterly

THE DETERMINANTS OF GREEN FINANCE AND EFFECT ON THE BANKING SECTOR

Yusuf Gör [1], Bilgehan Tekin [2]

Abstract

This study examines the prerequisites and challenges faced by local and foreign commercial banks in Türkiye in supporting green business initiatives. This study uses backward logistic regression analysis to identify variables affecting green financing practices using annual data from Turkish deposit banks from 2012 to 2021. This study addresses the growing interest in understanding the role of commercial banks in promoting green finance and contributes to the existing literature by revealing the current efforts of Turkish commercial banks in this area. The main findings show that factors influencing green financing practices are derivative financial assets, loans, tangible assets, equity capital, company size, female representation on boards, presence of audit committees and company experience. The study highlights the relationship between these factors and green financing methods adopted by depository banks. It is worth noting that the assets of these banks were built within the framework of green financing and practices such as green buildings, green loans and green bonds were introduced. In addition, the size and experience of custodian banks help influence their green financing practices. The findings provide a framework for policy makers, practitioners and academics who wish to gain a deeper understanding of the dynamics of Turkish financial institutions and green finance.

JEL classification: G21, G23, M41

Keywords: Investment, Green finance, profitability, banking sector, logistic regression, commercial banks

Received: 01.09.2023 Accepted: 14.11.2023

Cite this:
Gör Y. & Tekin B. (2023) The determinants of green finance and effect on the banking sector. Financial Internet Quarterly 19(4), pp. 80-96.

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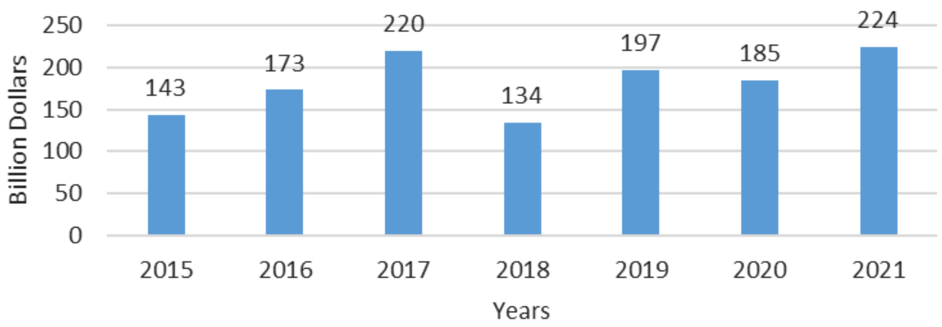
Introduction

In the 1970s, the Club of Rome identified population growth, food shortage, energy shortage, industry, and environmental problems as factors affecting the world's future in its "Growth Limits" report (Meadows et al., 1972). This led to the emergence of the concept of green finance, defined as the integration of the financial system with an environmentalist approach (Zengin & Aksoy, 2021). In simpler terms, green finance is a financial framework built on protecting the ecological environment (Whang & Zi, 2016), encompassing concepts such as green investment and green financing, collectively referred to as green finance (Chopra et al., 2005).

Green finance addresses environmental problems resulting from industrial development and is influenced by the global concern of climate change. The Paris Climate Agreement, reached after the United Nations Climate Change Conference of the Parties and endorsed by 196 countries, played a pivotal role in the widespread adoption of green finance practices (Soundarrajan & Vivek, 2021). Especially with the focus on climate change, green finance has become increasingly prevalent, catalyzing the transition of various sectors toward green practices (Ryszawska, 2016). The scope of green finance includes costs such as land and project preparation (Zadek & Flynn, 2013). It is emphasized that both the public and private sectors should implement green finance, as it not only updates infrastructure but also brings economic advantages, adds value, and creates sectoral benefits (Komşuoğlu, 2019; Soundarrajan & Vivek, 2016).

Figure 1 shows that the global size of green finance increased from $143 billion in 2015 to $224 billion in 2021, reflecting notable growth even after accounting for the impact of the pandemic. In 2021, Western Europe emerged as the dominant region in the distribution of green finance, comprising 77% of the total with $63.1 billion. South Asia followed with $5.5 billion. A study initiated by the European Union in March 2018 focused on creating green finance product labels and determining which products qualify as green finance. The aim of the study was to differentiate green finance practices from traditional financing methods, emphasizing standards and incentives (European Commission Initiative on Sustainable Finance, 2018). In Brazil, a guide law on the environment of financial institutions was published in 2014. This legislation aimed to define environmental risks by financial institutions and establish corporate governance structures to address these risks (Stuber, 2014).

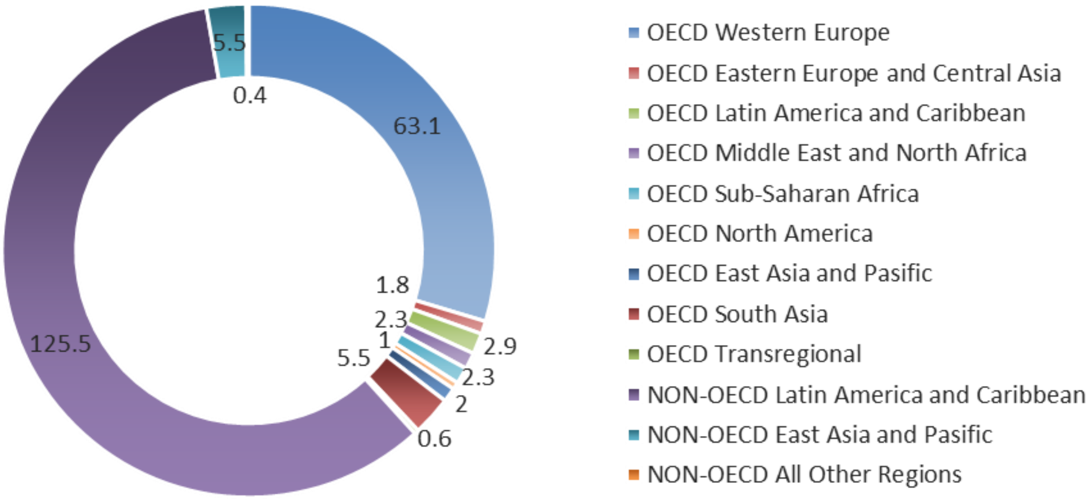
Figure 1: Green Finance



Source: https://idfc.org (Accessed: 16.11.2023).

Figure 2 shows climate finance commitments for the year 2021. While non-OECD countries had commitments of $102 billion in 2020, this increased to $131 billion in 2021. In OECD countries, commitments rose from $76 billion to $81 billion. The East Asia and Pacific region accounts for 60% of the 2021 commitments, totaling $125.5 billion, while Western Europe holds approximately 30% with $63.1 billion.

Figure 2: Climate Finance Commitments in 2021



Source: idfc.org (Accessed: 16.11.2023).

The utilization of green finance products not only heightens environmental awareness but also amplifies environmental benefits (Cochu et al., 2013). These products serve as a source of prestige for both users and service providers, fostering a positive working environment for employees engaged in green finance services, leading to increased job satisfaction and efficiency (Cochu et al., 2013). Investors exhibit a preference for green finance due to ethical considerations and the desire to cultivate a positive image and reputation (Della Croce et al., 2011). Various financial instruments fall under the umbrella of green financial products, including green loans, green deposits, green bonds, green funds, green insurance products, green securities, and green infrastructure investments (Lindenberg, 2014; Soundarrajan & Vivek, 2016). Green loans specifically cater to financing projects aimed at resolving environmental issues (Güler & Tufan, 2015). Moreover, projects dedicated to environmental protection secure funding through instruments such as green sukuk or green bonds, along with similar financial tools like green funds (Kandır & Yakar, 2017; Ela, 2019; Sevim et al., 2018).

Green loans, recognized as a solution to environmental challenges by international financial institutions such as the World Bank (Volz et al., 2015), involve considering environmental impact in various investments. Users of green loans are obligated to allocate funds to projects addressing environmental issues (Gündoğan & Bitlis, 2018). Governments encourage financial institutions to adopt green finance practices, making green loans a pivotal financial tool for developing green economies (Xu & Li, 2020; Yan et al., 2016). In Figure 3, the components of green finance are illustrated, comprising green investments, green public policies, and the green financial system. Green bonds, which are utilized in financing environmentally friendly projects, are a key element. These bonds, initially issued by the World Bank in 2007 and later in Türkiye in 2016, are subject to the essential condition that the proceeds be used for green project purposes, monitored through evaluations by rating and audit companies (Jun et al., 2016; TSKB, 2016).

Figure 3: Green Finance

Source: Lindenberg, N. (2014). Definition of green finance. In Definition of Green Finance, Lindenberg, Nannette.

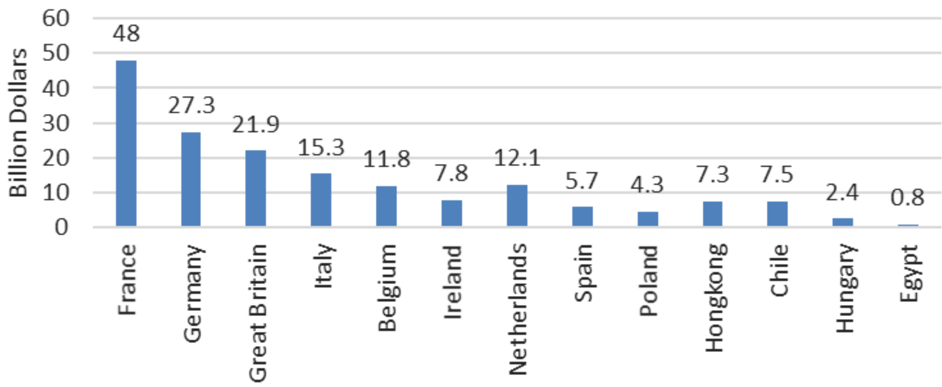
Transparency principles outlined in the Voluntary Process Guide of 2014 guide the issuance of green bonds, attracting institutional investors' attention (Zerbib, 2018). The Green Bond Principles, established by ICMA in 2017, encompass principles related to income use, project valuation, income management, and reporting (ICMA, 2017). China's Central Bank Green Bond Guide (2015) and the National Development and Reform Commission Green Bond Guide (2017) regulate green bond issuances in China, while the Association of Southeast Asian Nations introduced the Green Bond Principles in 2017 (Gündoğan & Bitlis, 2018; ASEAN GBS, 2017). In 2017, the Indian Securities and Exchanges Board issued a green bond guide, and Malaysia's Securities Commission set standards for green sukuk (Turguttopbaş, 2020). Hong Kong established the Green Certification System and Green Bond Grant System in 2018, ensuring compliance with the purpose of green finance pre- and post-issuance (GreenBond Grant Scheme, 2018). Factors such as green infrastructure costs, low green bond yields, and issuance costs impact the demand for green bonds, with these bonds exhibiting a negative issuance premium compared to traditional bonds in the market (Bakshi, 2015; Gianfrate & Pati, 2018). Although green bonds have higher spreads in secondary markets, their secondary market returns are also higher (Hirtenstein, 2017; Karpf & Mandel, 2017).

We see that the use of green bonds has increased, especially in 2021. It is understood from the figure that there has been a 4-fold increase in terms of both proportion and amount, especially in 2021, when more developed countries use green bonds compared to other years (Sakai et al., 2022).

Figure 4 shows that France preferred the green bond the most in the six-year period. In the period above, France was the country that made the most issuance with 48 billion dollars in the use of green bonds in the world. Germany followed France with 27.3 billion dollars and England with 21.9 billion dollars.

Between 2016 and 2021, the total usage of green bonds was as follows: Europe reached 161 billion dollars, Asia Pacific nine billion dollars, Western Hemisphere countries 8 billion dollars, the Middle East and Central Asia were below one billion dollars, and Africa was also below one billion dollars.

Figure 4: Distribution of Green Bond Usage in the World



Source: Sakai, A., Fu, C., Roch, F. & Wiriadinata, U. (2022). "Sovereign Climate Debt Instruments: An Overview of the Green and Catastrophe Bond Markets." IMF Staff Climate Note 2022/004, International Monetary Fund, Washington.

The emission volumes between 2017 and 2022 show that the European continent has the greenest bond issuance, followed by the Asia-Pacific continent (Wass et al., 2023).

Moreover, green loans serve as a means to transform industries (Hu et al., 2020), with commercial banks playing a crucial role as intermediaries in facilitating green loans to address environmental problems (Xing et al., 2020). In Türkiye, a private company extended the first green loan of $260 million for a wind power plant, with German investment banks providing funding, and four Turkish banks acting as guarantors and collateral representatives (Turguttopbaş, 2019). China extensively employs green credit as a green finance product (Zhou et al., 2020). Green Project Finance loans adhere to international standards, and loan pricing is evaluated by international credit rating agencies throughout the maturity period (Turseff1000, 2018). Green securitization, exemplified by the Hawaii Green Energy Market Securitization Program, allows investors to gain returns from environmentally sensitive assets and finance green technology through green bonds (Sakuda, 2015).

Management prioritizing environmental concerns serves as a catalyst, fostering investor confidence and encouraging investments in environmentally conscious stocks. This commitment to sustainable practices is frequently mirrored in indices that showcase eco-friendly businesses, such as the Luxembourg Green Index (LGX) (Turguttopbaş, 2020). Since the 2016 G-20 summit, green finance has gained prominence among central banks, financial system actors, and managers (Falcone, 2020). Banks, central banks, and governments have become integral to green financial systems, with the inclusion of green investment banks (OECD, 2016). The banking sector, acting as a financing source and implementing innovative green finance practices, plays a vital role in spreading green finance (Barbieri et al., 2016; Soundarrajan & Vivek, 2016). Green finance practices have been found to impact financial performance positively (Falcone et al., 2020) and contribute to the improvement of financial systems (Ghisetti & Quatraro, 2013). Nevertheless, the banking sector faces risks in allocating resources to green finance systems (Berensmann & Lindenberg, 2016).

Examining the relationship between green finance practices, financial ratios, profitability, and efficiency is considered beneficial (Komşuoğlu, 2019).

The banking sector plays a pivotal role in driving sustainable practices, and the increasing global emphasis on environmentally responsible financial initiatives has prompted a closer examination of green finance practices within the industry. In this context, our study seeks to investigate the factors influencing green finance practices among deposit banks operating in Türkiye from 2012 to 2021. The overarching goal is to discern whether these practices have a discernible impact on the profitability of the banks involved.

Our research question is "To what extent do various factors influence the adoption and implementation of green finance practices by deposit banks in Türkiye, and what is the nature of the relationship between green finance practices and the profitability of these banks?" The hypotheses of this study are:

H_1: There is a significant relationship between corporate governance indicators (YKBO, YKKO, YKDO, and YKKY) and the implementation of green finance practices in deposit banks.

H_2: Profitability indicators, namely Return on Assets (ROA) and Return on Equity (ROE), are positively associated with the adoption of green finance practices by deposit banks.

H_3: Banks with established green finance practices exhibit a higher degree of institutionalization compared to those without such practices, as indicated by corporate governance variables.

H_4: Control variables (FNKO and BYUK) do not significantly impact the relationship between green finance practices and bank profitability, serving as stable benchmarks in the analysis.

These hypotheses guide our exploration, aiming to provide insights into the determinants and consequences of green finance practices in the Turkish deposit banking sector. Through empirical analysis, we seek to contribute valuable knowledge to the ongoing discourse on sustainable financial practices in the global banking industry.

Conceptional framework and literature

Due to environmental degradation, the earth is facing the problem of accelerated melting of glaciers and polar ice caps. Therefore, natural phenomena such as wind, floods and heat waves have increased significantly (Zheng et al., 2021). These environmental problems, including ecological imbalances, biodiversity loss, land degradation, and ecological damage, are increasingly affecting the global economy and international politics (Liu et al., 2020). Developing countries are more vulnerable to the effects of climate change and depend heavily on global climate finance funding to protect and mitigate climate change. However, access to financial support is difficult for many countries due to limited institutional capacity in project design and planning (Ngwenya & Simatele, 2020). Every part of the world's economy deals with environmental problems and their impacts every day. Due to the growing dangers of climate change, the idea of green banking has recently received much attention in the green finance literature

(Chen et al., 2022). Given the growing international efforts to combat climate change, green finance (GF) has received much attention in the recent literature.

Its conceptual ambiguity prevents researchers from reaching a consensus on its significance (Zheng et al., 2021). Whang and Zi (2016) looked at the position that the general public should adopt regarding green finance under the current market circumstances. Gülcan (2017) used the financial ratios of the BIST 50 companies in his research to investigate the connection between green financial management and financial indicators. Güler and Tufan (2015) looked at the connection between financial ratios and the use of green credit. They noted the benefits of green finance. Bangladesh was the focus of Lalon's (2015) research on green financial products. Gizep (2019) similarly looked at green financial assets. Based on Türkiye and the rest of the globe, Kandır and Yakar (2017) discussed green bonds. Green finance was described and its connection to the banking industry was outlined in a study performed in India by Soundarrajan and Vivek (2016). According to Antonietti and Marzucchi's (2014) research, green fixed-asset investments made by Italian businesses positively impact business performance. The research by Falcone (2020) looked at how green finance can help with investments in and changes to the environment. The research done by Mahalleolu (2019) provides details on green finance methods. The research done by Turguttopbaş (2020) explains how green finance developed and how it is used. On the other hand, Zengin and Aksoy's research from 2021 explains the connection between green marketing and green finance. The paper by Soundarrajan and Vivek (2016) explains the development of green finance in India. Green credit policies and green finance practices were examined in China by Zhang et al. (2021) using the difference in differences (DID) analysis approach. The analysis's findings revealed the advantages of green finance applications but found no change in green credit policies. Ning and She (2014) discovered that green loans harm economic development in their study. Zhang (2021) found that this financing strategy was expensive despite mentioning the necessity of green credit arrangements for environmentally friendly output. Afridi et al. (2021) claim that green loans are a less risky investment due to their examination of 24 Pakistani banks functioning from 2009 to 2015. Managers seeking to increase their business loans and lower the risk of default will also find the results helpful. According to their results, banks should invest more in green initiatives. Zheng et al. (2021) examined the major obstacles to green finance's implementation in Bangladesh and looked into how bankers perceived various aspects of green finance. When compared to other financial institutions, both banks and non-bank entities, the findings of the study reveal that private commercial banks play the most significant role in advancing green finance in Bangladesh. They account for a substantial 74.2% share of the total green finance in the country. Green finance applications are mentioned and their applicability in Türkiye is looked at in the research by Kuloğlu and Öncel (2015). In the study conducted by Najaf and Najaf (2021), it was determined that green finance practices in Malaysia have positive and negative effects on financial performance. In Yu et al. (2021), the incentives for green finance, the green finance practices of businesses in China between 2001 and 2017, and the regulatory bodies' perspectives on green finance are all included. Şimşek and Tunal (2022) looked at the evolution of green finance, the products that fall under it, and their current state. The study by Du et al. (2022) emphasized the relationship between China's green finance policies and green companies. It was determined that China should offer more supportive policies. In addition, it has been determined that there is a relationship between green finance and financial performance. Chen et al. (2022) looked into how Bangladeshi private commercial banks' green banking practices affected their environmental performance and found sources of green funding. The investigation discovered that green banking practices significantly enhance green finance. Additionally, the environmental performance of banks is strongly and favorably impacted by banks' green initiative financing.

This paper addresses a significant gap in the existing literature by examining the factors that influenced the green financing practices of Turkish depository banks between 2012 and 2021 and investigating the potential impact of these practices on profitability. Despite the growing literature on sustainable finance and corporate practices, there is little research specifically focused on the Turkish banking sector. This study adds to the literature by using annual data from Turkish deposit banks and applying backward logistic regression analysis to identify variables that influence green financing practices. This approach allows for a nuanced understanding of the ideal model and provides insight into the institutionalization of banks' adoption of green financial applications by incorporating variables related to corporate governance. In addition, the inclusion of control variables increases the robustness of the study. By filling this gap, this paper not only enriches the knowledge of sustainable finance, but also provides practical insights for policymakers, practitioners and academics interested in moving towards greener and more profitable practices in the Turkish banking sector. The results of this study provide a valuable contribution to the ongoing discussion on green finance and sustainability in the banking sector.

Data and methodology

The study conducted an analysis on the annual data of deposit banks in Türkiye from 2012 to 2021, utilizing information obtained from the Public Disclosure Platform via the banks' websites. The selection of variables was guided by existing literature, and the research, encompassing deposit banks listed by the Turkish Banking Regulation and Supervision Agency, aimed to discern the factors influencing green finance practices of these banks during the specified period, as well as exploring the potential impact of such practices on their profitability. To identify the variables affecting green finance practices, the research employed backward logistic regression analysis. This analytical approach involves including all variables in the analysis and systematically eliminating them step by step, ultimately facilitating the identification of an ideal model.

Backward logistic regression analysis was chosen for several reasons. First, our study includes an investigation of several possible variables that may affect the green financing practices of Turkish depository banks over a period of time. Backward logistic regression analysis provides an efficient mechanism for handling a large number of variables and helps us identify the most relevant factors by systematically eliminating those variables that do not have a significant effect in the model. Furthermore, given the exploratory nature of our research question and the lack of a predetermined set of variables, backward logistic regression analysis met our goal of stepwise model refinement. This approach allows us to uncover key determinants of green financing practices that may not be apparent in the initial analysis stages.

Table 1 outlines the variables used in the analysis, encompassing profitability rates (ROA and ROE) and green finance applications as both dependent and independent variables in the YEFN analysis. Additionally, corporate governance-related variables (YKBO, YKKO, YKDO, and YKKY) were included to examine the hypothesis that banks implementing green finance practices might be more institutionalized. Other financial ratios (FGTV, KRTV, MDTV, MVTV, NATV, NTKR, OZTV, and TFTV) are included in the analysis as performance indicators believed to potentially impact green finance. Control variables, FNKO and BYUK, were also integrated into the study. The data and methodology employed in this research contribute to a comprehensive exploration of the factors influencing green finance practices in Türkiye's deposit banks, shedding light on their potential impact on profitability.

Table 1: Variable List

Variable Type	Abbreviations	Definition
Independent Variable	BYUK	Company Size
Independent Variable	FGTV	The ratio of Interest Income to Total Assets
Independent Variable	FNKO	Financial Leverage Ratio
Independent Variable	KRTV	The ratio of Loans and Receivables to Total Assets
Independent Variable	MDTV	The ratio of Tangible Fixed Assets to Total Assets
Independent Variable	MVTV	The ratio of Deposit to Total Assets
Independent Variable	NATV	Ratio of Cash and Equivalents to Total Assets
Independent Variable	NTKR	Net Profit for the Period
Independent Variable	OZTV	The ratio of Equity to Total Assets
Dependent Variable	ROA	Return on Assets Ratio
Dependent Variable	ROE	Return on Equity Ratio
Independent Variable	TECR	Company Age
Independent Variable	TFTV	Ratio of Derivative Financial Assets to Total Assets
Dependent Variable	YEFN	Status of Using Green Finance Applications
Independent Variable	YKBO	Board of Directors Independence Rate
Independent Variable	YKDO	The ratio of the Number of Audit Committee Members to the Number of Board Members
Independent Variable	YKKO	Ratio of Female Members of the Board of Directors

Source: Author's own work.

Table 2 contains the descriptive statistics of the variables included in the analysis. In the period covering the years 2012-2021, it is observed that the cash and equivalents of 26 deposit banks was around 18% on average. In addition, it is understood that the ratio of derivative financial assets is around 1%. It is understood from the table that loans and receivables were realized as approximately 55% in the said process. In the same period, the ratio of tangible fixed assets is around 10%.

On the other hand, the average deposit was 58%, and the shareholders' equity was approximately 15%. In this process, banks have profited approximately 1.5 billion TL. Return on assets was 1.3% and return on equity was around 7%. The interest income ratio to assets had an average value of around 9%. In line with this information, it is understood that the asset sizes of deposit banks have developed at a greater rate than their profitability. On the other hand, it is understood from the findings that the conversion ratio of deposits to loans is almost one.

Table 2 shows that between 2012-2021, the independence rate of the board of directors of deposit banks was around 8%, and the rate of female members in the board of directors was around 17%. In light of this information, it is understood that deposit banks have developed in terms of the independence of the board of directors, which is one of the dimensions of corporate governance.

Table 2: Descriptive Statistics

Variables	Observation	Smallest	Largest	Mean	Standard Deviation
NATV	260	0.0000	0.9160	0.179307	0.1525971
TFTV	260	0.0000	0.0758	0.011259	0.0154977
KRTV	260	0.0000	0.8258	0.549531	0.2002117
MDVT	260	0.0000	0.0594	0.010244	0.0088324
MVTV	260	0.0009	0.8220	0.580546	0.1605204
OZTV	260	0.0288	0.9281	0.151508	0.1649435
NTKR	260	-767847.0000	13541060.0000	1537478.290000	2459748.4040000
ROE	260	-3.9858	0.3101	0.072508	0.2709392
ROA	260	-0.1282	0.1609	0.013145	0.0262095
BYUK	260	5.0193	9.1742	7.442458	0.9507261
FGTV	260	0.0001	0.4562	0.086314	0.0482112
YKBO	260	0.0000	0.4286	0.080189	0.1334671
YKKO	260	0.0000	1.0000	0.170995	0.1544014
YKDO	260	0.1429	1.0000	0.268501	0.0856402
YKKY	260	0.0000	1.0000	0.390297	0.2493297
TECR	260	1.0000	0.1580	43.080000	34.8540000
FNKO	260	0.0719	0.9712	0.848488	0.1649423
YEFN	260	0.0000	1.0000	0.240000	0.4270000

Source: Author's own work.

When logistic regression is expressed mathematically, the probability is based on odds and logarithms of odds. The odds concept is the ratio of the probability of occurrence of an event to the probability of it not happening (Mertler & Vannatta, 2005).

$$Odds = \frac{p(x)}{1-p(x)} \tag{1}$$

Logistic regression aims to maximize the probability of an event occurring (Hair et al., 2006). While the odds ratio is usually denoted by β, the logit is calculated by taking the natural logarithm of the odds ratio (Mertler & Vannatta, 2005).

$$Yi = \frac{e^u}{1+e^u} \tag{2}$$

Yi: The probability that the ith variable is included in one of the dependent variable categories.

e: is a constant number equal to the value 2.718.

u: is the regression equation u = B0 + B1 X1 + …..+ Bi Xi.

As a result, logistic regression analysis takes the following form with linear regression analysis creating the logit of odds ratio (Tabachnick & Fidell, 1996):

$$\ln(\frac{Y}{1-Y}) = \beta_0 + \beta_1 X_1 + \ldots + \beta_i X_i \tag{3}$$

The study's primary aim is to determine the financial statement information and corporate governance factors that affect green finance practices. For this reason, a function was created that shows the relationship between the prepared variables and green finance.

The function created to determine the variables affecting green finance practices is given below:

$$\begin{aligned} YEFN &= \beta_0 + \beta_1 NATV + \beta_2 TFTV + \beta_3 KRTV \\ &+ \beta_4 MDVT + \beta_5 MVTV + \beta_6 OZTV + \beta_7 NTKR \\ &+ \beta_8 ROE + \beta_9 ROA + \beta_{10} BYUK + \beta_{11} FGTV \\ &+ \beta_{12} YKBO + \beta_{13} YKKO + \beta_{14} YKKY + \beta_{15} TECR \\ &+ \beta_{16} FNKO + \varepsilon \end{aligned} \tag{4}$$

In order to determine the variables affecting green finance applications, the analysis was carried out with the backward stepwise logistic regression model. Since the dependent variable, YEFN, was a categorical variable, performing a logistic regression analysis was deemed appropriate. The backward stepwise logistic regression model was preferred to include all the variables in the analysis and eliminate those that did not contribute significantly to the model. According to the classification table in Table 3, it is understood that the variables in the model are classified correctly at a rate of 86%.

Table 3: Classification Table

Observed			Estimated		
			YEFN		Total Percentage
			0	1	
Step	YEFN	0	198	0	100.0
		1	62	0	0.0
	Verification Percentage				86.2

Source: Author's own work.

Table 4 includes the Omnibus Test, which calculates the significance level of the chi-square statistic for step, block, and model. This test shows the improvement in the model as the variables are removed at each step. According to Table 4, the significance value of the model was less than 0.05 in each step and the seventh step, which is the last step, and it is seen that the extracted variables contributed significantly to the model.

Table 4: Omnibus Test

		chi-square	Difference	p - value
Step 1	Step	168.844	16	0.000
	Blok	168.844	16	0.000
	Model	168.844	16	0.000
Step 2[a]	Step	0.000	1	0.992
	Blok	168.843	15	0.000
	Model	168.843	15	0.000
Step 3[a]	Step	-0.271	1	0.603
	Blok	168.573	14	0.000
	Model	168.573	14	0.000
Step 4[a]	Step	-0.994	1	0.319
	Blok	167.579	13	0.000
	Model	167.579	13	0.000
Step 5[a]	Step	-0.967	1	0.326
	Blok	166.612	12	0.000
	Model	166.612	12	0.000
Step 6[a]	Step	-0.905	1	0.341
	Blok	165.707	11	0.000
	Model	165.707	11	0.000
Step 7[a]	Step	-1.887	1	0.170
	Blok	163.820	10	0.000
	Model	163.820	10	0.000

Source: Author's own work.

Table 5 includes the model summary table. -2LL in this table is a model fit index (Hair et al., 2006); In the backward stepwise model it shows that a near-perfect fit is obtained as we move away from zero. According to Table 5, the -2 Loglikelihood number is constantly increasing and reaches -2LL 121,816 in the last step, showing that the variables in the model significantly contribute to the model. In addition, the Nagelkerke R2 and Cox & Snell R2 values in Table 5 show the amount of variance explained by the logistic model (Field, 2005), and 1.00 corresponds to a perfect model fit. Since the Cox & Snell R2 value never reaches 1.00, Nagelkerke R2 models, the modified form of Cox & Snell R2, are preferable to explain (Mulluk, 1386). In the seventh step, Nagelkerke R2 was 0.701, and Cox & Snell R2 was 0.467. Accordingly, in the last step, it is understood that the compatibility of the variables in the model with the model is 70.1%.

Table 5: Model Summary

Step	-2 Log likelihood	Cox & Snell R2	Nagelkerke R2
1	116.793[a]	0.478	0.716
2	116.793[b]	0.478	0.716
3	117.063[a]	0.477	0.716
4	118.057[a]	0.475	0.713
5	119.024[a]	0.473	0.710
6	119.929[b]	0.471	0.707
7	121.816[a]	0.467	0.701

Source: Author's own work.

The Hosmer and Lemeshow test in Table 6 is a chi-square goodness-of-fit test and shows the fit of the logistic regression model as a whole. For the result of the Hosmer and Lemeshow test to be meaningful, the required significance value must be greater than 0.05. According to Table 6, it is understood that the significance value of the Hosmer and Lemeshow test is more significant than 0.05 at each step and the last step, and therefore the model is compatible.

Table 6: Hosmer and Lemeshow Test

Step	chi-square	Difference	p - value
1	5.600	8	0.692
2	5.592	8	0.693
3	5.593	8	0.693
4	3.179	8	0.923
5	2.401	8	0.966
6	1.966	8	0.982
7	1.701	8	0.989

Source: Author's own work.

Table 7 shows the variables in the last step of the logistic regression analysis. Accordingly, the coefficients, standard errors, significance status, and Exp(B) (odds) numbers of the variables in the final version of the model are given. In the last step, it is understood that TFTV, KRTV, MDVT, OZTV, BYUK, YKKO, YKDO, YKKY, and TECR variables significantly affect the model. If the Exp(B) coefficient is greater than 1, it indicates a positive relationship, and if it is less than 1, it indicates a negative relationship (Hair et al., 2006). In line with this information, the variables TFTV, KRTV, OZTV, YKDO, YKKY, and TECR are in a negative relationship with green financing, while the variables MDVT, OZTV, BYUK, and YKKO are in a positive relationship. The model formed in this case is given below.

$$\begin{aligned} YEFN &= \beta_0 + \beta_1 TFTV + \beta_2 KRTV + \beta_3 MDVT \\ &+ \beta_4 OZTV + \beta_5 BYUK + \beta_6 YKKO + \beta_7 YKDO \\ &+ \beta_8 YKKY + \beta_9 TECR + \varepsilon \end{aligned} \tag{5}$$

Table 7: Last step Table of Variables

		Coefficient	Standard Error	Wald (odds)	Difference	p - value	Exp(B)
Step 7[a]	TFTV	-63.634	19.743	10.388	1	0.001	0.000
	KRTV	-17.284	4.394	15.475	1	0.000	0.000
	MDVT	302.033	59.394	25.860	1	0.000	1.484E+131
	MVTV	5.949	3.064	3.771	1	0.052	383.421
	OZTV	-43.386	11.991	13.091	1	0.000	0.000
	BYUK	6.244	1.096	32.463	1	0.000	514.851
	YKKO	7.474	2.354	10.080	1	0.001	1761.468
	YKDO	-12.088	4.327	7.806	1	0.005	0.000

		Coefficient	Standard Error	Wald (odds)	Difference	p - value	Exp(B)
Step 7[a]	YKKY	-4.460	1.790	6.209	1	0.013	0.012
	TECR	-0.053	0.013	17.662	1	0.000	0.949
	c	-35.724	7.135	25.066	1	0.000	0.000

Source: Author's own work.

The objective of this study is to investigate the potential impact of green finance practices on financial performance. To assess this relationship, panel data regression analysis was employed to examine the association between green finance applications and both return on assets (ROA) and return on equity (ROE) ratios. Initially, the analysis focused on determining the correlation between the return on assets ratio and green finance applications. To determine the most suitable model for panel data analysis, the Hausman test was conducted as an efficiency test. The Hausman test aids in choosing between the fixed effects model and the random effects model, guiding researchers toward the more efficient model (Çelik & Kıral, 2020). In this study, the random effects model was selected, as indicated by the Hausman test results in Table 8, where the test value of 0.3558 exceeded the critical value of 0.05.

Table 8: Return on Assets Ratio Panel Data Regression Analysis Hausman Test

Variables	Fixed Effects	Random Effects	Difference
YEFN	-0.0002673	-0.0023611	0.0020938
NATV	0.0388021	0.0231551	0.0156470
TFTV	-0.0915722	-0.1797585	0.0881764
KRTV	-0.0093465	-0.0080659	-0.0012806
MDVT	-0.0768573	-0.1437685	0.0669111
MVTV	0.0252167	0.0248859	0.0003309
OZTV	-5.5146270	-9.4555260	3.9408980
NTKR	3.3700000	3.0800000	3.0600000
ROE	0.0409555	0.0423158	-0.0013603
BYUK	0.0084333	0.0086215	-0.0001882
FGTV	0.1406073	0.1385026	0.0021047
YKBO	-0.0084618	-0.0082451	-0.0002167
YKKO	0.0078788	0.0067746	0.0011042
YKDO	0.0298353	0.0245563	0.0052789
YKKY	0.0138097	0.0129832	0.0008265
TECR	-0.0000600	-0.0000620	2.0000000
FNKO	-5.5930050	-9.5415290	3.9485240
Prob > chi2		0.3558	

Source: Author's own work.

The panel data regression analysis random effects model is mathematically illustrated below (Hedges, 1983):

$$Y_{it} = \alpha_1 + \beta_{1it} X_{1it} + \beta_{2it} X_{2it} + \ldots + \beta_{mit} X_{mit} + w_{it} \quad (6)$$

Y_{it}: Combination of the predictor variable with the time series
i: section unit
t: time unit
α_1: average constant
w_{it}: Combination of the time series and the standard error term of the cross-section

Table 9 shows the random effects model of the panel data regression analysis, which was carried out to determine whether the return on assets ratio is affected by green finance applications. According to the Hausman test result, according to the preferred random effects model, a statistically significant relationship could not be determined between the return on assets and green finance applications. As a result of the analysis, it was determined that there is a statistically significant relationship between return on assets and NATV, TFTV, MVTV, ROE, BYUK, FGTV, YKKY.

Table 9: Return on Assets Ratio Panel Data Regression Analysis Random Effects Model

ROA	Coefficient	Standard Error	p - value
YEFN	-0.0023611	0.0023988	0.325
NATV	0.0231551	0.0066162	0.000
TFTV	-0.1797585	0.0648391	0.006
KRTV	-0.0080659	0.0082182	0.326
MDVT	-0.1437685	0.1087787	0.186
MVTV	0.0248859	0.0072309	0.001
OZTV	-9.4555260	20.1289000	0.639
NTKR	3.0800000	6.0800000	0.960
ROE	0.0423158	0.0030915	0.000
BYUK	0.0086215	0.0021605	0.000
FGTV	0.1385026	0.0204591	0.000
YKBO	-0.0082451	0.0064506	0.201
YKKO	0.0067746	0.0074280	0.362
YKDO	0.0245563	0.0109520	0.025
YKKY	0.0129832	0.0448460	0.004
TECR	-0.0000620	0.0000393	0.115
FNKO	-9.5415290	20.1289600	0.635
Sabit	9.4427730	20.1278900	0.639
Prob > chi2		0.000	

Source: Author's own work.

The return on equity ratio panel data regression analysis Hausman Test is included in Table 10. Since the Hausman test value was more significant than 0.05, applying the random effects model was preferred.

Table 10: Return on Equity Ratio Panel Data Regression Analysis Hausman Test

Variables	Fixed Effects	Random Effects	Difference
YEFN	-0.0172323	-0.0058856	-0.0113467
NATV	-0.2275448	-0.1696584	-0.0578864
TFTV	1.8489770	2.3669410	-0.5179643
KRTV	0.1010179	0.0988148	0.0022032
MDVT	0.7867675	0.3841349	0.4026326
MVTV	-0.2763002	-0.2882652	0.0119650
OZTV	161.3474000	160.8918000	0.4556449
NTKR	-5.5600000	-2.9000000	-2.6600000
ROA	10.3792900	10.3122300	0.0670597
BYUK	-0.0096898	-0.0177593	0.0080695
FGTV	-1.8273360	-1.7992170	-0.0281194
YKBO	0.0849575	0.0924365	-0.0074790
YKKO	-0.0835071	-0.0836111	0.0001039
YKDO	-0.6356395	-0.6205971	-0.0150425
YKKY	-144.7010000	-0.1298381	-0.0148629
TECR	0.0002022	0.0002471	-0.0000449
FNKO	161.8523000	161.4399000	0.4124228
Prob > chi2		0.8671	

Source: Author's own work.

Table 11 shows the return on equity ratio panel data regression analysis random effects model. The analysis found no statistically significant relationship between the return on equity ratio and green finance practices. On the other hand, a statistically significant relationship was found between return on equity and TFTV, MVTV, ROA, FGTV and YKNR.

Table 11: Return on Equity Ratio Panel Data Regression Analysis Random Effects Model

ROE	Coefficient	Standard Error	p - value
YEFN	-0.0058856	0.0375207	0.875
NATV	-0.1696584	0.1053024	0.107
TFTV	2.3669410	1.0168170	0.020
KRTV	0.0988148	0.1283907	0.442
MDVT	0.3841349	1.7040610	0.822
MVTV	-0.2882652	0.1141150	0.012
OZTV	160.8918000	314.2013000	0.609
NTKR	-2.9000000	9.4800000	0.760
ROA	10.3122300	0.7533801	0.000
BYUK	-0.0177593	0.0348002	0.610
FGTV	-1.7992170	0.3285516	0.000
YKBO	0.0924365	0.1008633	0.359
YKKO	-0.0836111	0.1160321	0.471
YKDO	-0.6205971	0.1680670	0.000
YKKY	-0.1298381	0.0707186	0.066
TECR	0.0002471	0.0006166	0.689
FNKO	161.4399000	314.2037000	0.607
C	-160.7995000	314.1853000	0.609
Prob > chi2		0.000	

Source: Author's own work.

Conclusions

In December 2015, nations globally committed to formulating national climate targets at the Paris Climate Summit (COP21), emphasizing the need for urgent and substantial investment projects to achieve these goals (COP21). Despite this, many national climate action plans lack explicit emission reduction targets for financial institutions such as banks and trusts, which play a crucial role in mobilizing private capital and managing carbon risk (Schaefer, 2017). International bodies, including G7 and G20 working groups, often leverage the concept of "green finance" for these purposes (Schaefer, 2017). The term "green finance" has gained scholarly attention due to the increasing global focus on addressing climate change, although a consensus definition remains elusive (Zheng, 2021). Central banks and financial regulators engage with green finance to maintain macroeconomic and financial stability, considering the risks posed to households, businesses, and financial intermediaries by climate change (Zheng, 2021). However, modeling these risks on the financial system is challenging due to their complex and interconnected nature, surpassing the historical data's scope. Conversely, the global move towards economic decarbonization offers numerous investment opportunities, prompting central banks and supervisors to redirect financial support from traditional, environmentally harmful industries to the emerging green economy (Breitenfellner et al., 2019). While the public sector holds primary responsibility for climate action, private commercial banks have a unique position to either support or divert funding towards green investments. This study, focusing on six commercial banks, explores their practices in fostering green business ventures, emphasizing the prerequisites and challenges faced by domestic and foreign commercial banks in Türkiye (Breitenfellner et al., 2019). The research contributes to the literature by addressing the role of commercial banks in facilitating green finance and highlighting ongoing efforts of Turkish commercial banks in this area. Green finance practices involve financial policies prioritizing environmentally-oriented solutions, with factors affecting these practices including derivative financial assets, loans, tangible assets, equity, company size, gender diversity on the board of directors, audit committee, and company experience. Deposit banks' assets can be shaped within the framework of green finance, incorporating practices such as green buildings, loans, and bonds, while corporate governance, particularly the independence of the board of directors, influences these practices (Soundarrajan & Vivek, 2016; Zheng et al., 2021). However, no statistically significant relationship was found between return on assets and return on equity ratios, commonly used to measure company performance, and green finance practices. This suggests that there is no direct link between company performance and green finance practices, contrary to some findings in the literature (Gülcan, 2017; Güler & Tufan, 2015; Du et al., 2022; Xiliang et al., 2022). In conclusion, this study indicates that green finance practices in deposit banks are influenced by financial statements and corporate governance, but not necessarly ments and corporate governance, but not necessarily linked to profitability. It suggests that deposit banks implementing green finance practices prioritize environmental concerns in their financial policies, and further research across different sectors may yield different results.

In Türkiye, the emergence of concepts such as climate change and green finance on the agenda of regulatory authorities after 2021, the absence of legal obligations such as a climate law, and the lack of direct sanctions for carbon-zero practices in industry and individual consumption contribute to banks playing a more prominent role in green energy financing. The fact that there are no direct sanctions for carbon-zero practices in industry and among individual consumers also hinders the diversification of banking products in the field of green finance. Therefore, the results obtained from the study currently meet the expectations for Türkiye. It is believed that the widespread adoption of green finance and the consequent transformation of banking products will occur in the banking sector, positively impacting its profitability, either after the enforcement of legal obligations like the climate law or as a result of the continuation of the current trend in the coming years.

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Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 97-114
10.2478/fiqf-2023-0029

sciendo

Financial Internet Quarterly

ESG VOLATILITY PREDICTION USING GARCH AND LSTM MODELS

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Abstract

This study aims to predict the ESG (environmental, social, and governance) return volatility based on ESG index data from 26 October 2017 and 31 March 2023 in the case of India. In this study, we utilized GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and LSTM (Long Short-Term Memory) models for forecasting the return of ESG volatility and to evaluate the model's suitability for prediction. The study's findings demonstrate the GARCH effect inside the ESG return volatility data, indicating the occurrence of volatility in response to market fluctuations. This study provides insight concerning the suitability of models for volatility predictions. Moreover, based on the analysis of the return volatility of the ESG index, the GARCH model is more appropriate than the LSTM model.

JEL classification: C53, D53, G34, O13
Keywords: ESG Volatility, GARCH, LSTM model

Received: 22.08.2023 Accepted: 20.09.2023

Cite this:
Mishra, A.K., Kumar, R. & Bal D.P. (2023) ESG Volatility Prediction Using GARCH and LSTM Models. Financial Internet Quarterly 19(4), pp. 97-114.

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Introduction

The inherent uncertainty of the financial market is among the most significant characteristics within this sector. A significant association exists between the level of risk associated with the underlying assets, and market volatility which can further serve as a valuable indicator for assessing both (Lim & Sek, 2013). Investors take on perilous risks due to the unpredictability of their holdings, making market volatility crucial (Bata & Molnár, 2018). A security's price is more likely to fluctuate widely if its volatility is high, while it may vary more slowly if its volatility is low (Nijs, 2013). As a result, investors' actions are influenced by volatility because of its connection to the uncertainty of the financial market (Dixit & Agrawal, 2019). Investors and scholars are usually inquisitive about which securities did well and how they could be protected from loss in the stock market. Investors evaluate a firm's financial and non-financial data to understand the processes through which the company makes profits for its stakeholders. Further, this evaluation facilitates more informed choices about investments in the stock market.

Although market uncertainty is a significant factor in making investment decisions, picking the right stocks remains paramount. Notably, Kaiser & Welters (2019) found that the practical application of ESG aspects is a critical part of ESG investments for momentum investors; by embracing ESG, they may lower portfolio risk. Given this newfound importance, researchers and professionals in the financial sector have increasingly focused on quantifying volatility (Bhowmik & Wang, 2020). Although several studies have been undertaken pertaining to forecasting volatility of the stock market (Alberg et al., 2008; Lin, 2018; Su et al., 2019; Fang et al., 2020; Salisu & Gupta, 2021), there has been relatively little work done on modelling volatility concerning ESG indices. For instance, Sabbaghi (2022) investigated the consequence of the news on the market volatility of ESG enterprises and discovered that bad news had a more profound effect on volatility than good news. The effective handling of ESG issues by a firm is commonly associated with positive outcomes in key performance indicators such as return on equity (ROE), return on assets (ROA), and share price (Whelan et al., 2022).

Therefore, we attempt to determine whether ESG stocks are characterized by a high degree of volatility, to enable all stakeholders to make informed decisions regarding the appropriate course of action to take when such stocks are included in their portfolios. The objective of this study is to evaluate the return volatility of the ESG index, with the purpose of investigating the existence and predictability of volatility within this sector. We have used the ESG index of the Bombay Stock Exchange (BSE) in India, which has been specifically developed to assess the level of exposure exhibited by securities that align with sustainable investment criteria for analysis. This study uses the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and LSTM (Long Short-Term Memory) models for the prediction of return ESG Volatility and evaluates the model's applicability for prediction. Both models are employed on the notion that one may use past data to make accurate forecasts. We have used BSE'S ESG Index data from October 26, 2017 to March 31, 2023. The duration for the data has been chosen for its (data) availability. This study makes several contributions to the existing body of literature. Firstly, the study's findings imply that the GARCH effect is present in the data for the ESG index, which further indicates that fluctuations in market volatility respond to changes in market conditions. Furthermore, we employed the RNN technique for our machine-learning models. Our analysis revealed that the GARCH (1,1) regression model was the most effective in predicting volatility. Based on the comparison of predicted values, the analysis shows that the GARCH model's predictions closely match the actual values. Our findings are novel and credible since we compared the two models we used.

This paper has been structured into different sections beginning with an introduction, the remaining portion includes the following, section two investigates the relevant literature on the research topic, section three provides a discussion of the method selected for the study. Results and subsequent discussion are described in section four, followed by the conclusion in section five.

Review of literature

ESG (Environmental, Social, and Governance), comprises elements linked to the "environment", "social responsibility", and "governance" and encompasses the non-financial aspects of a company's performance (Yu & Xiao, 2022). Moreover, ESG's core tenet entails the recognition and measurement of aspects by corporations that demonstrate social responsibility, prioritize environmental sustainability, and maintain robust governance practices (Dalal & Thaker, 2019). Investor interest has increased in the incorporation of ESG factors within investment decision-making (Gangi et al., 2022).

Trade-off theory implies that corporations expect to make profits and maximize wealth, whereas legitimacy theories value ESG investments and disclosures as a way to make a profit (Behl et al., 2021). The global financial crisis raised business ethics, risk management, responsibility, and strategic stakeholder management concerns. This drew shareholder attention to ESG issues of the firms involved (Sultana et al., 2018). The availability of ESG information has increased and investors expect greater ESG disclosures (Espahbodi et al., 2019), notably

Li et al. (2018) found a positive association between the level of disclosure of ESG factors and the value of a firm. Investors worldwide are increasingly interested in the potential link connecting a company's ESG accomplishment, governance strength, and stock returns (Khan, 2019). According to Khalil & Nimmanunta (2021), investors now identify ESG measures as key considerations in managing risks, valuation, and adherence to legal requirements by companies. ESG factors have caught the attention of investors for two main reasons: ethical investment practices and managed portfolio performance (Broadstock et al., 2021). The importance of ESG stocks in an investor's portfolio is indisputable, owing to several factors, including risk, valuation, and portfolio performance. Moreover, ESG investment during situations of economic uncertainty is important since it represents an avenue for investments that are safer and carry less risk (Mousa et al., 2021). These studies indicate that the ESG factors, including disclosure, management, and performance, are vital for investors when selecting portfolio stocks. However, the area of ESG research is in a nascent stage; for example, ESG as a field of study is still in its early stages, owing to improved disclosure and availability of information (Zhou & Zhou, 2021). In addition, the review has enabled us to posit that investor interest in ESG companies is on the rise. Because of this, it is useful to investigate the volatility of the ESG index to discover more about the performance of these stocks over time. Significantly, Moalla and Dammak (2023) suggested that while investors consider ESG practices when investing, businesses should adopt a proactive standpoint to ESG to develop an ESG reputation and keep stock prices stable.

Several studies have utilized the time series model in forecasting the uncertainty of returns. Yong et al. (2021), investigated stock market return volatility in Malaysia and Singapore. Endri et al. (2021) explored stock price volatility in Indonesia during the pandemic using GARCH models. These models are developed to explain the variability patterns of time series data and are extremely effective at characterizing the volatility of financial data (Lin, 2018). Furthermore, advanced technology like artificial intelligence and deep learning procedures that have been widely utilized in wide domains have fewer constraints and superior feature extraction than conventional econometric models (Lin et al., 2022). Similarly, neural networks enhance error indicators of the best GARCH forecasts and further improve the projections and, thus the significance of the results (Kristjanpoller & Hernández, 2017). Moreover, Kim & Won (2018) utilized a hybrid model integrating LSTM (long short-term memory) and multiple GARCH and found that the former demonstrates competencies in learning complex temporal patterns from time-series data, and as data volume expands, the model can learn the features to predict realized volatility, improving prediction accuracy. Similarly, Koo and Kim (2022) suggested a model that blends LSTM and GARCH networks to forecast market volatility and mitigate the volatility distribution's extreme bias. Since the semi-strong form of market efficiency and high noise make it challenging to predict financial time series, the LSTM network can get useful details out of noisy data (Zhou et al., 2018). Notably, because ESG features are prevalent in financial markets, researchers investigate the link connecting ESG characteristics to firm financial performance; nevertheless, investors' responses to information concerning ESG are less clear (Chen & Yang, 2020). However, the studies have explored the volatility of stock prices and stock indexes using GARCH and a deep learning model on ESG volatility, specifically with respect to an Indian perspective, has been little explored. Therefore, we propose a model to evaluate ESG volatility based on BSE's ESG index using deep learning methods (LSTM) and GARCH.

Data sources and methodology

This paper is based on daily data of ESG between 26th October 2017 and 31 March 2023. In total, we have 1347 observations. The data was collected from the www.bseindia.com website. We have used the logarithm of ESG (LESG) then we calculated the return of LESG (Ratio of the LESG at present period and one period lag of LESG multiplied by 100). In the next step, we have taken the volatility of return LESG (RVLESG) by using GARCH (1,1) model. The reason for measuring the return volatility of ESG is to predict it by using two methods using GARCH (1, 1) and the long short-term memory (LSTM) framework so that our results are robust and reliable. More specifically, we have the choice between machine learning and traditional regression models. The prima facie reason is the observed better performance of machine learning models regarding accuracy, precision, and recall compared to traditional regression models. The regression models require a priori specification of the functional form and variables included. Unless specified, regression models assume linear relationships. In this respect, the machine learning models are more flexible as they do not require any prior model specification. They can automatically detect complex linear and non-linear patterns to make predictions. Machine learning models also overcome the assumptions embedded in the regression models. Specifically, if the error terms are heteroskedastic and autocorrelated, then certain adjustments are required in the case of regression but the machine learning models are less sensitive to error structures and focus more on prediction accuracy. In the next step, we conducted the LSTM, a Recurrent Neural Network (RNN) type, and the GARCH model.

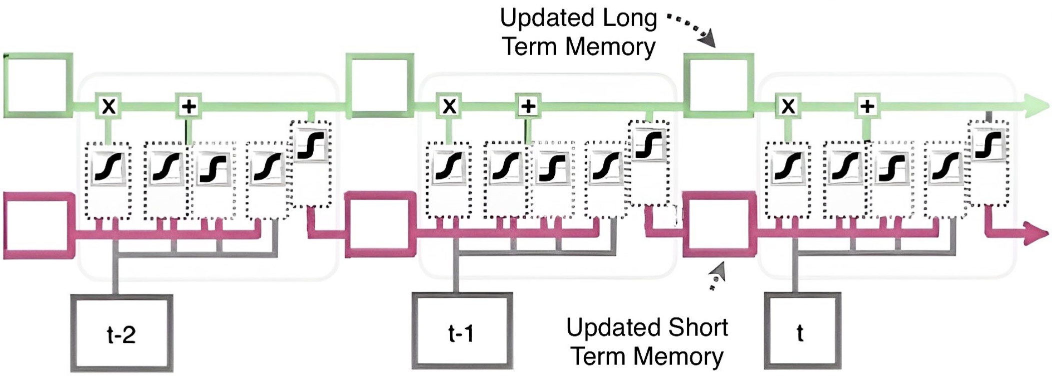
LSTM was devised to address the "exploding" and "vanishing" gradient concerns in the original RNN (Yu & Li, 2018) This is required since ESG volatility data includes long-term dependencies in the historical data. The RNN predicts future values by sequentially unrolling a unit network over past values using weights, biases, and feedback loop connections. It solves the vanishing gradient problem and has several other desirable qualities, which is why it was chosen for this study. For example, an LSTM network can account for temporal changes across time by keeping its state constant from iteration to iteration. Capturing temporal variations is essential for predicting future values for time series data. LSTM also accepts non-linear relationships, common in financial data, such as ESG volatility. To address non-linearity in time series data, LSTM employs non-linear activation functions such as tangent, sigmoid, hyperbolic, etc. Because of the variability in the factors influencing it, ESG data may suffer from variable length input sequences. As a result, LSTM is advantageous for another reason: it can accommodate variable length input. Aside from such technical reasons, we chose LSTM because of its proven accuracy in predicting factors in the financial market. And since ESG is a closely connected topic, we also want to assess LSTM's effectiveness in this case. The literature review also does not provide research that forecasts ESG volatility explicitly using the LSTM network model. The quality of prediction from LSTM is affected by data preprocessing, network architecture, and hyperparameter tuning. Tuning hyperparameters alone requires multiple combinations (theoretically, there can be infinite combinations); therefore, including all of them is beyond the scope of this study. As a result, the objective of this piece is not to be exhaustive but rather to establish a foundation for identifying the most effective approach to forecasting ESG volatility. We will predict the return ESG volatility over the test data set using the LSTM and the GARCH model and judge the accuracy based on the root mean square value. Below we have depicted the working of the LSTM model.

The elongated green line situated at the uppermost part of the unit is referred to as the "cell state" and indicates "long-term memory". Contrary to basic RNN, no weights and biases can directly modify the long-term memory in LSTM and thus avoid gradient vanishing/explosion. The pink line is referred to as the "hidden state", and it is carrying "short-term memory" across the unrolled units in the series. However, the hidden state is directly connected to weights and biases; hence, the short-term memories can be modified directly. Long and short-term memory interacts in three stages to generate predictions, these three stages include "Forget gate", "Input gate", and "Output gate". The forget gate is a crucial component that plays a role in determining the proportion of long-term memory that is to be retained. The next stage is comprised of two blocks. The block situated on the right side of the diagram integrates the short-term memory and the input in order to generate the potential for long-term memory formation. The left block is responsible for determining the proportion of possible long-term memory that ought to be retained. This retained information is then added to the long-term memory that is exiting the forget gate. Consequently, the aggregate of memory that passes through the forget gate and the input gate becomes the newly formed long-term memory. Since the second stage updates the existing long-term memory, it is usually called the input gate. The final stage also consists of two blocks. The one situated on the right side generates a novel potential short-term memory by utilizing the recently acquired long-term memory. Conversely, the block situated on the left side determines the proportion of the potential short-term memory that will be retained. The output produced by the third stage is the new short-term memory, and since this stage represents the final output generated by the complete unit network, it is referred to as the output gate. At all three gates, the RNN uses an activation function to generate output. In simple words, the activation function is a mathematical function that converts x-axis coordinates into y-axis coordinates. Traditional LSTM uses sigmoid and tanh activation functions as gating functions and output functions respectively. Efforts have been made to search for novel activation functions which can replace the sigmoid and tanh activation functions to give more accurate results. One such example is the Combined hyperbolic sine function ($y = \sinh(x) + \sinh{-1}(x)$), which was explored using a differential evolution algorithm (DEA).

The basic RNN uses a single path for short-term and long-term memories, which is why the vanishing/exploding gradient occurs. If the gradient explodes, the predicted value is highly over-estimated, and if the gradient vanishes, then the predicted value is highly under-estimated. Hence it is tough to train the basic RNN to learn long-range dependencies. LSTM is different from basic RNN in the sense that it uses two different feedback loop connections for long and short-term memories to make predictions of future values. Compared to traditional RNN, the unit structure of LSTM is much more complicated as shown in Figure 1.

Figure 4 shows the unroll of unit LSTM to predict the value for variable Y in period t + 1 using its values from periods t, t - 1, and t - 2. The input at the first unit of LSTM is $Y_t - 2$. The forget gate updates the initial long-term memory to generate the new long-term memory, which in turn acts as the initial long-term memory for the second unit. Similarly, the input and output gate generates the new short-term memory, which in turn acts as the initial short-term memory for the second unit. The same process is repeated in the second unit and the third unit. The output generated out of the third unit is the predicted value for period t + 1.

Figure 1: Unroll of unit LSTM



Source: Author's own work.

Results and discussions

We predict the return volatility of LESG using two techniques: regression and machine learning. We employ GARCH methodology in regression, and in machine learning, we have used RNN's LSTM model. In the initial step, we provided the descriptive statistics, and the results are presented in Table 1. The result shows that the RVLESG index has very high variance compared to its transformation i.e. LESG, Return, and Return Volatility. However, the transformed variable like Return Volatility is highly asymmetrical as measured by the skewness. ESG has a skewness of 0.38, whereas Return Volatility has a skewness of 7.46. Both ESG and Return Volatility have kurtosis values far from that of normal distribution. The skewness and kurtosis values suggest that none of the variables are normally distributed. And this is the reason why we have used the GARCH regression model to predict the Return Volatility. In the next stage, we have presented the results of the GARCH model in Table 2. The results from Table 2 show the output from LSTM, using different combinations of hyper-parameters.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
ESG	1,347	218.672200	54.488320	119.630000	315.840000	0.38	1.50
LESG	1,347	2.326597	0.106496	2.077840	2.499467	0.24	1.51
Return	1,346	0.018420	0.524037	-5.910230	3.598482	-1.44	22.04
RVLESG	1,345	0.268383	0.535019	0.071007	6.701008	7.46	66.83

Notes:
ESG is 'Environment social and governance' index.
LESG is Natural logarithm of ESG.
RVLESG is the volatility of Return.

Source: Author's own work.

The results in Table 2 suggest that one percentage change of one period lag in return volatility of LESG significantly influences the present period of return volatility of LESG at about 0.05 percentage level. It implies that the previous period's change positively responds to the current period. We have checked all other residual diagnostic tests such as correlogram, heteroscedasticity, and autocorrelation test. It satisfies all the properties of a classical regression model. Once we had stabilized the mean equation, we conducted the GARCH model. The equation for the GARCH (1,1) variance model indicates a constant value of 0.00646. The ARCH coefficient of 0.108, which represents the volatility response to market movements, indicates a good correlation between market movement and volatility. The coefficient GARCH of 0.865 shows more intensive variance.

The estimated GARCH equation is:

$$RVLESG = 0.00646 + 0.107961 * \left(u_{t-1}\right)^2 + 0.864839 * RVLESG_{t-1} \quad (1)$$

Where RVLESG is the predicted value of the dependent variable, u_{t-1} is displaying the first lag of the error term from the AR(1) equation and $RVLESG_{t-1}$ is the first lag of the dependent variable. The error term is estimated using the AR(1) estimates from Table 1. The AR(1) equation is:

$$Return_t = 0.033015 + 0.56237 * Return_{t-1} \quad (2)$$

Table 2: Estimated coefficient for RVLESG using GARCH

Mean Equation		
Variables	**Coefficient**	**p-value**
C	0.033015	0.0037
AR(1)	0.056237	0.0568
Variance Equation		
C	0.006460	0.0002
Resid(-1)^2	0.107961	0.0000
GARCH(-1)	0.864839	0.0000
R-squared	-0.007760	
Adjusted R-squared	-0.008510	
S.E. of regression	0.526450	
Akaike info criterion	1.131637	
Schwarz criterion	1.150983	
Hannan-Quinn criterion	1.138883	

Source: Author's own work.

Table 3: RMSE for the different combinations of hyperparameters in LSTM

	Activation function	
epochs	**ReLU**	**Default**
10	0.0280	0.098
20	0.0230	11.370
30	0.2190	0.385
40	0.0316	0.040
50	0.4520	0.106
60	0.0980	0.141

Source: Author's own work.

Using equation 2, we estimate the predicted values for Return, and then using equation 3, we calculate the value for the error term ut which is equal to the actual return minus the estimated return.

$$U_t = actual\ return - Return_t \quad (3)$$

Further, using equation 3 we calculate the square of the error term, whose first lag is to be used as the independent variable in the GARCH equation. Based on the RMSE criterion, we should choose the GARCH model over the LSTM models for predicting volatility. The RMSE of GARCH is equal to 0.011355, which is much less than the RMSE of all the LSTM variants shown in Table 2. In Figures 2 to 14 (Appendix) the predicted values of RVLESG volatility from both models are compared with the actual values in the test set of the data. Predicted values in Figures 3 to 14 were estimated using the LSTM model and differ only in terms of the type of activation function. In Figures 3 to 8 ReLU activation function is used whereas in Figures 9 to 14 the default activation function is used. The values from the LSTM vary widely from the actual values in the test set whereas, on the other hand, the GARCH predicted values move very close to the actual observed values. So, for variables like volatility, where the dependency can't be traced back to a very long past, we should refrain from using LSTM and instead apply the appropriate traditional regression models.

The aforementioned results are obviously at odds with those discovered in the related field of financial markets. This investigation will need to be more comprehensive, as was previously stated. Only a small subset of possible parameter tuning combinations has been investigated. Since ESG has such profound practical ramifications, we defer to future research in determining which alternative combinations of parameters yield the most accurate prognostic model. The practical implication of predicting return ESG volatility can be understood with the help of two examples stated below.

ESG return volatility can indicate the shift in the company's environmental profile and signal potential future risk. Take the case of BP's water Deepwater Horizon oil spill (Pallardy, 2023). This catastrophic event (2010) implied environmental risk management failure. The intensity of the failure can be seen from the fact that approximately 65 billion dollars were spent for cleanup and settlement purposes. The reputational damage was such that the company lost 50% of its share price value within a few months of the incident. This implies that investors lost 50% of their money in BP Deepwater horizon stocks/shares. Here, tracking the ESG volatility or the ESG itself could have helped investors anticipate the environmental risks, potentially helping them mitigate some of their financial losses.

Accurately predicting ESG volatility can guide companies in strategic planning to gain a competitive advantage over their competitors and peers in the light of constantly evolving regulations, societal expectations, and environmental constraints. As a real-world example, take the case of Orsted (Scott, 2021), a Danish energy company that once was a coal-intensive public utility company. This company strategically went under radical transformation to become the world's most sustainable energy company (Corporate Knights' 2020 Global 100 index). The strategic planning was in anticipation of stricter environmental regulation and increasing biasedness of public sentiments towards renewable energy.

The foregoing two real-world examples emphasize the significance of precise ESG volatility forecasting. We observe that LSTM, which showed promise in the financial market domain, may be different from the silver bullet in the related domain. This article may be considered the first mile on the road to search for more sophisticated models with better predictive power.

Conclusions

A policy paradigm change towards ESG is vital in light of the current environmental crisis and the pervasive social and economic disparities in the Indian economy. This change is not just about doing the right thing ethically. It's also an essential aspect of sound financial strategy that can lead to more opportunities and less long-term danger. The future can be made more secure through ESG-focused investing. Therefore, it is essential to determine ESG and ESG return volatility values and methods that help attract global investment to India. In this study, we compared results from machine learning to those from regression and found that the latter produced more reliable outcomes. In this study, we used the RNN technique for our machine-learning models and the GARCH (1,1) model, which exhibited the highest efficacy as a regression model. RNNs are characterized by their various configuration options. Parameters were adjusted in several iterations. Furthermore, this study offers the following significant contributions to the current body of literature. First, an assessment was made to determine the appropriateness of the model for forecasting volatility utilizing the ESG index data procured from the Bombay Stock Exchange (BSE). Previous research has indicated that the utilization of machine learning methodologies, particularly long-short-term memory (LSTM), has the potential to improve the accuracy of outcomes. However, different results have been observed. Considering this, we recommend it should not be used for shorter periods of time. Second, the applicability of the GARCH (1,1) model is considered to be best-suitable for predicting volatility in this connection. The fact that the GARCH model can be applied for shorter time periods was emphasized, as shown by the analysis. This finding was supported by the evidence. Considering this, we recommend using appropriate classical regression models rather than LSTM for the purpose of predicting volatility. Finally, the findings of the GARCH (1,1) model indicate the existence of an ARCH effect in the dataset. Consequently, the response of volatility to market fluctuations exhibits positive reactions with the intensity of market movements. Additionally, the study reveals that a one per cent change in the lagged return volatility of ESG significantly impacts the current period of return volatility of ESG, with a magnitude of approximately 0.05 percentage level.

This study offers implications for investors, policymakers and researchers concerning the presence of volatility in ESG investing particularly in shares. The findings of this study can be used by investors making investment decisions in selecting ESG or other stocks in their portfolios. The present study exclusively relies on data from the ESG index, skipping the assessment of additional criteria like expenditure, disclosure, behavioral aspects, and other microeconomic factors. Furthermore, the study provides a preliminary investigation and does not incorporate additional methodologies in machine learning. Consequently, this composition enables scholars to explore diverse methodologies and environments. The formulation of such methodologies would assist policymakers in cultivating an environment where economic actors perceive ESG not solely as a regulatory impediment but as a tactical tool capable of producing benefits for them.

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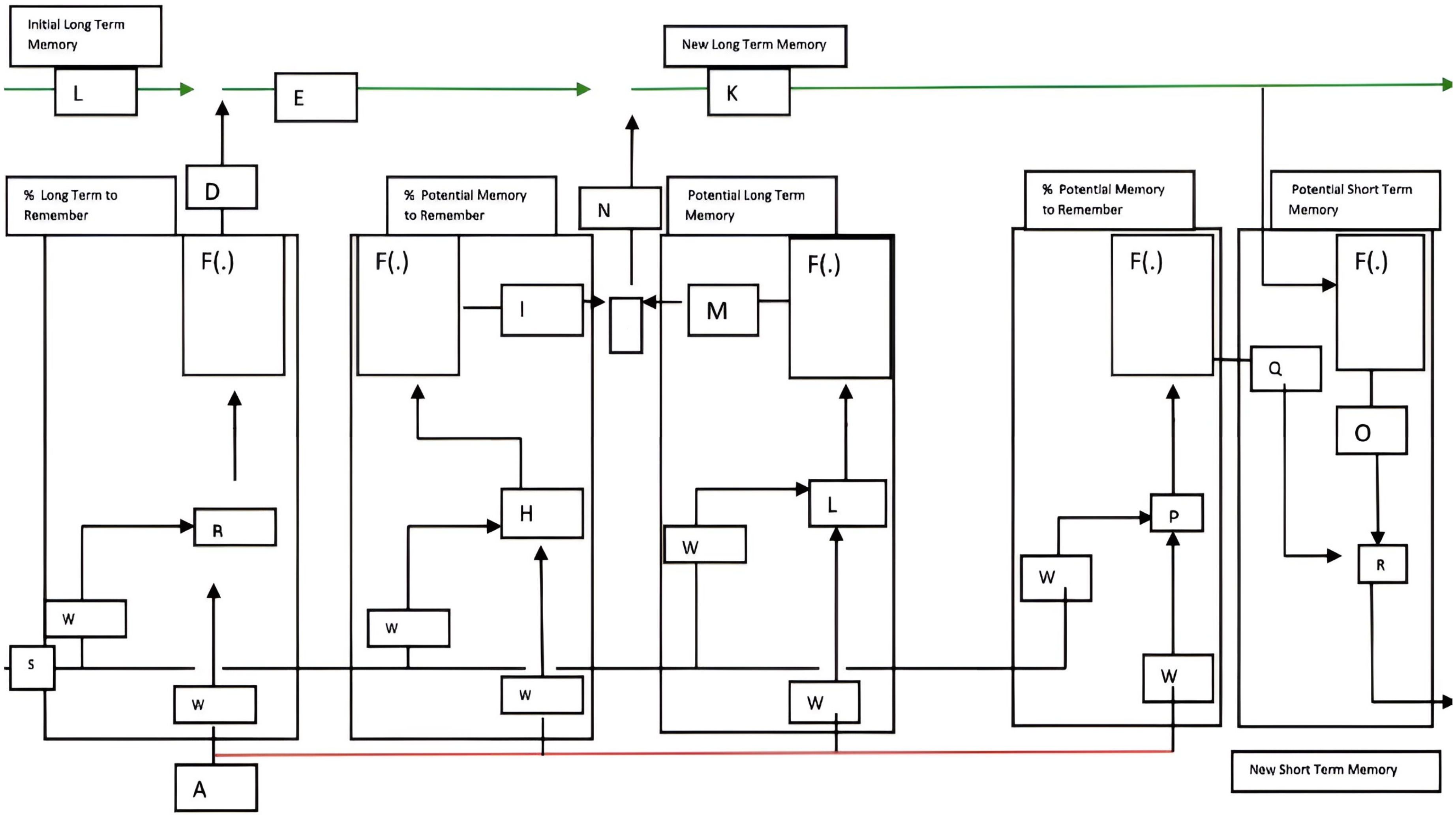
Appendinx

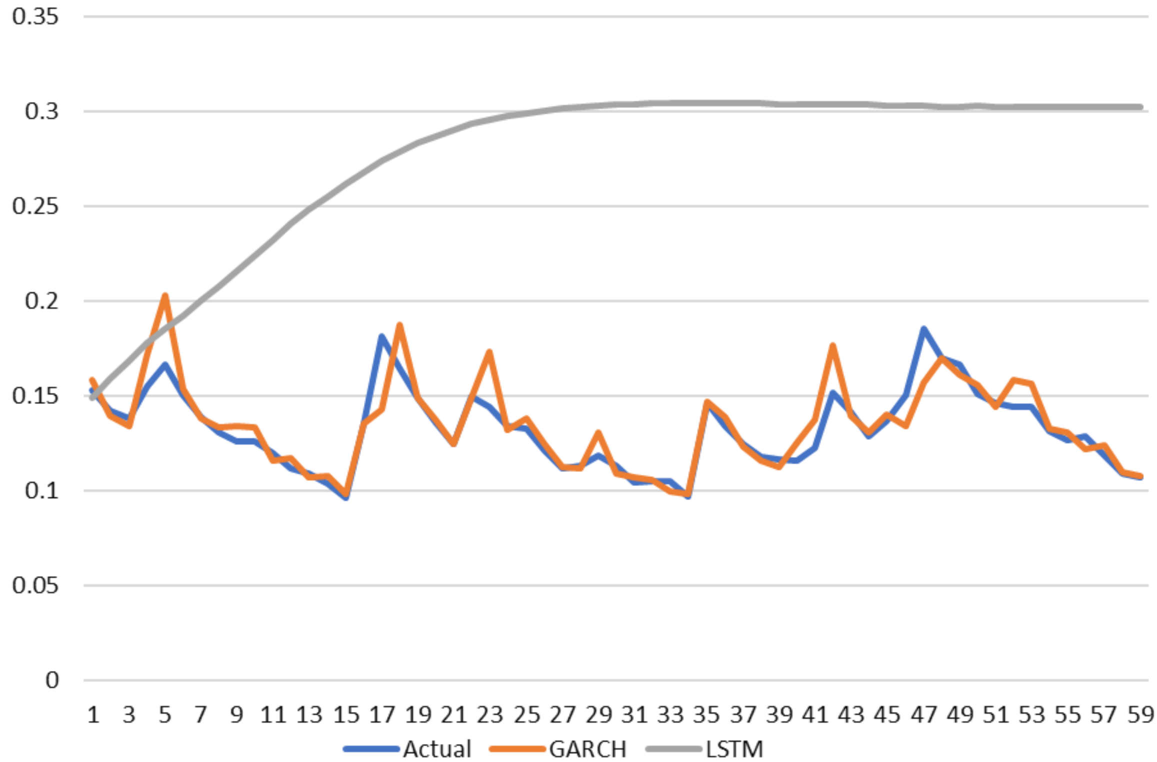
Figure 1: Structure of LSTM



w = weights. F(.) = Activation function. S = initial short-term memory. A = input at time period t-k. R = w (S +A) D = F (R): % of the initial long-term memory to remember. E = D * L. H = w (S + A. I = F(H): % of potential long-term memory to remember. L = w (S+ A). M = F(L): Potential long-term memory. N = I * M. K = E + N: New long-term memory. P = w (S + A). Q = F(P): % of potential short-term memory to be retained. O = F(K): The potential short-term memory. R = Q * O The new short-term memory, which now acts as the initial short-term memory for the next unit, or it is the final predicted value if this current unit is last in the unrolling process.

Source: Author's own work.

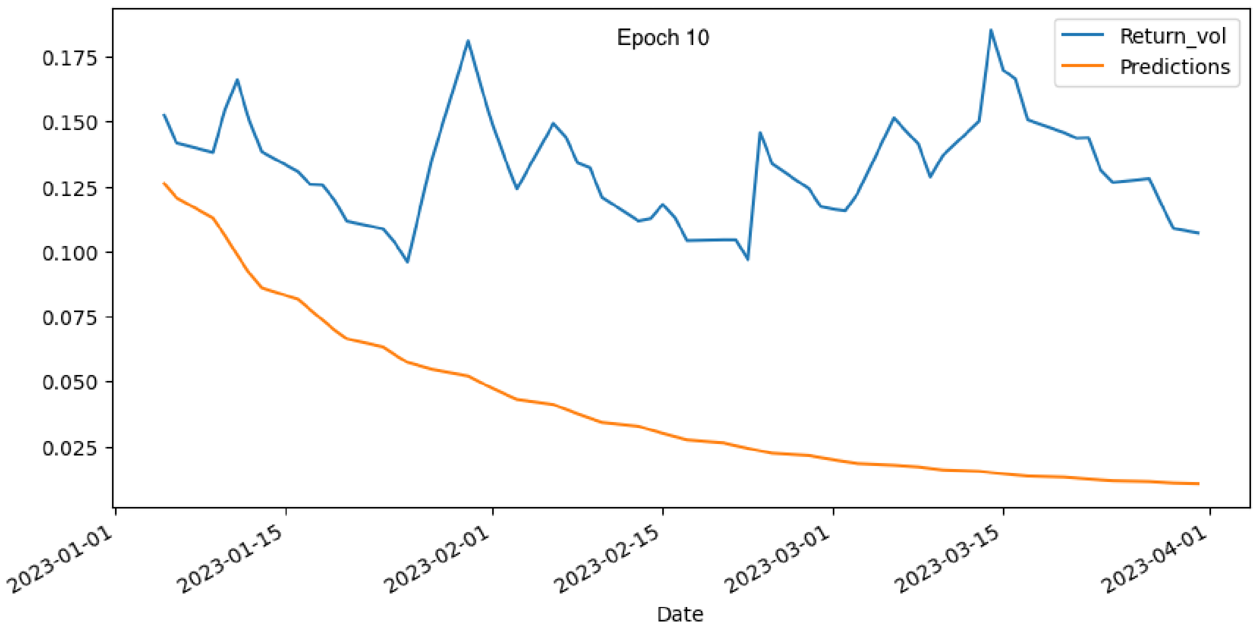
Figure 2: Comparing predicted values with the actual values over the test set of data*



* The testing data set ranges from 5th January 2023 to 31st March 2023 (frequency = daily)

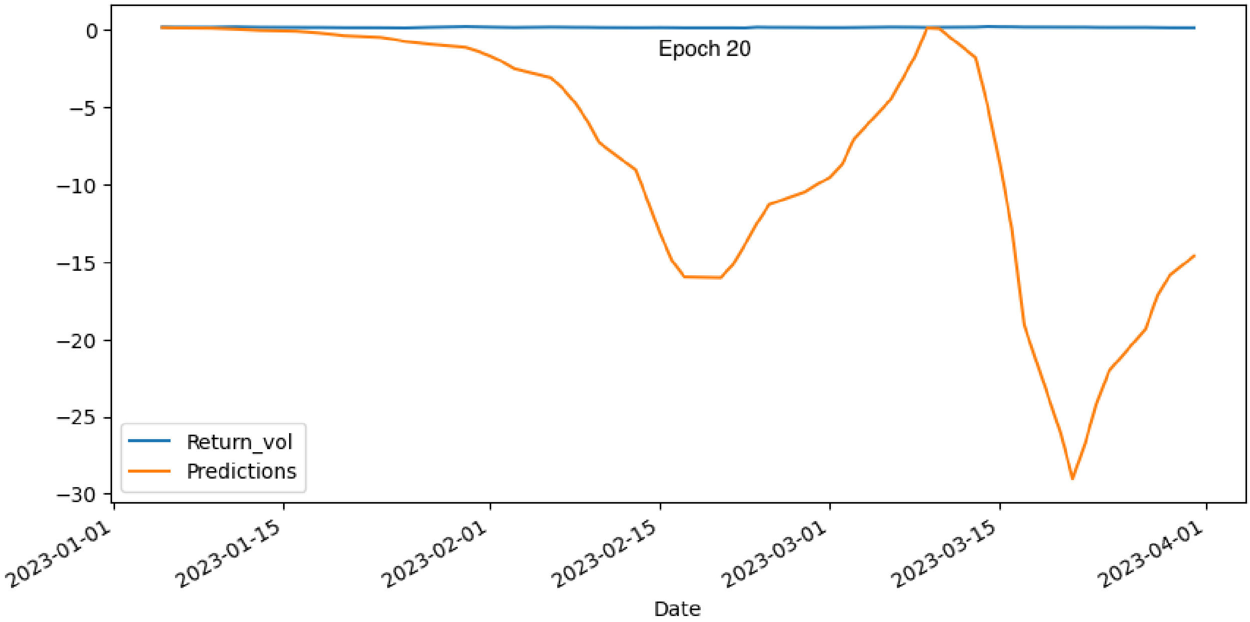
Source: Author's own work.

Figure 3: Comparing the predicted values generated from LSTM using default activation function at epoch level 10 with the actual values over the test set of data



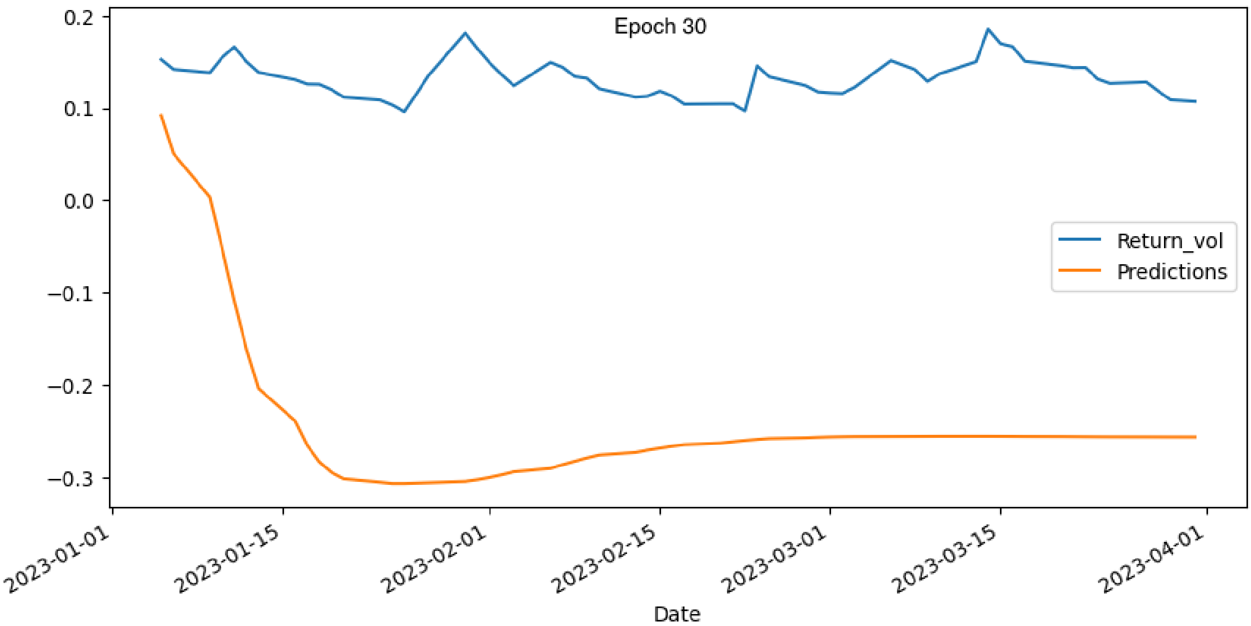
Source: Author's own calculations.

Figure 4: Comparing the predicted values generated from LSTM using default activation function at epoch level 20 with the actual values over the test set of data



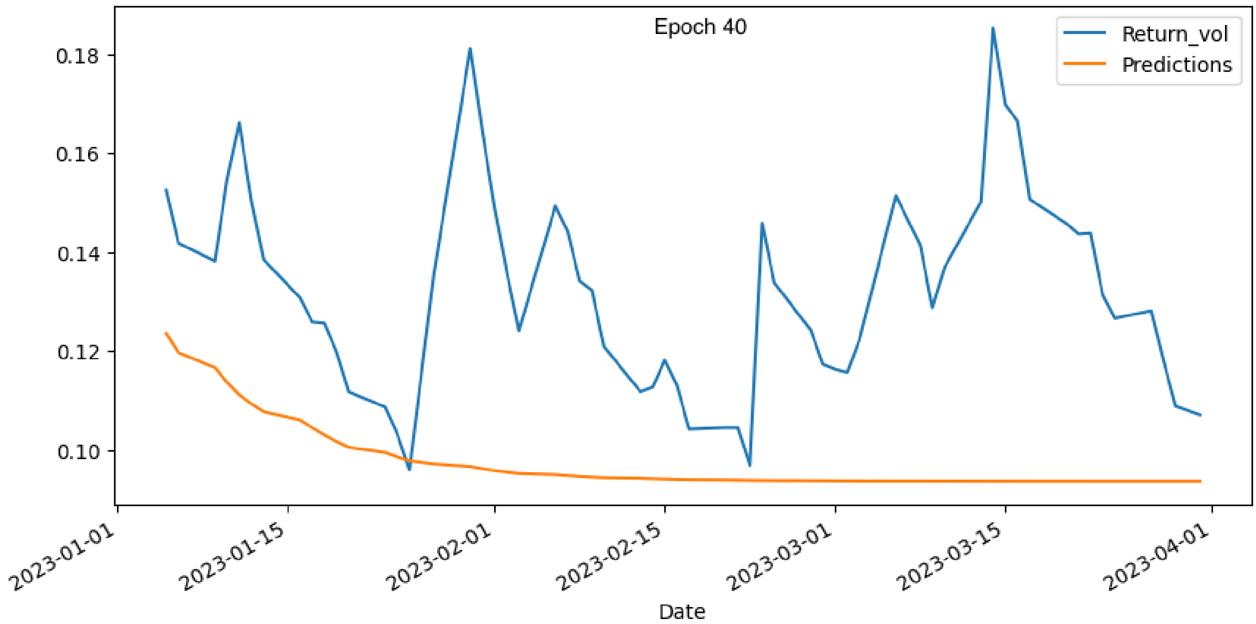
Source: Author's own calculations.

Figure 5: Comparing the predicted values generated from LSTM using default activation function at epoch level 30 with the actual values over the test set of data



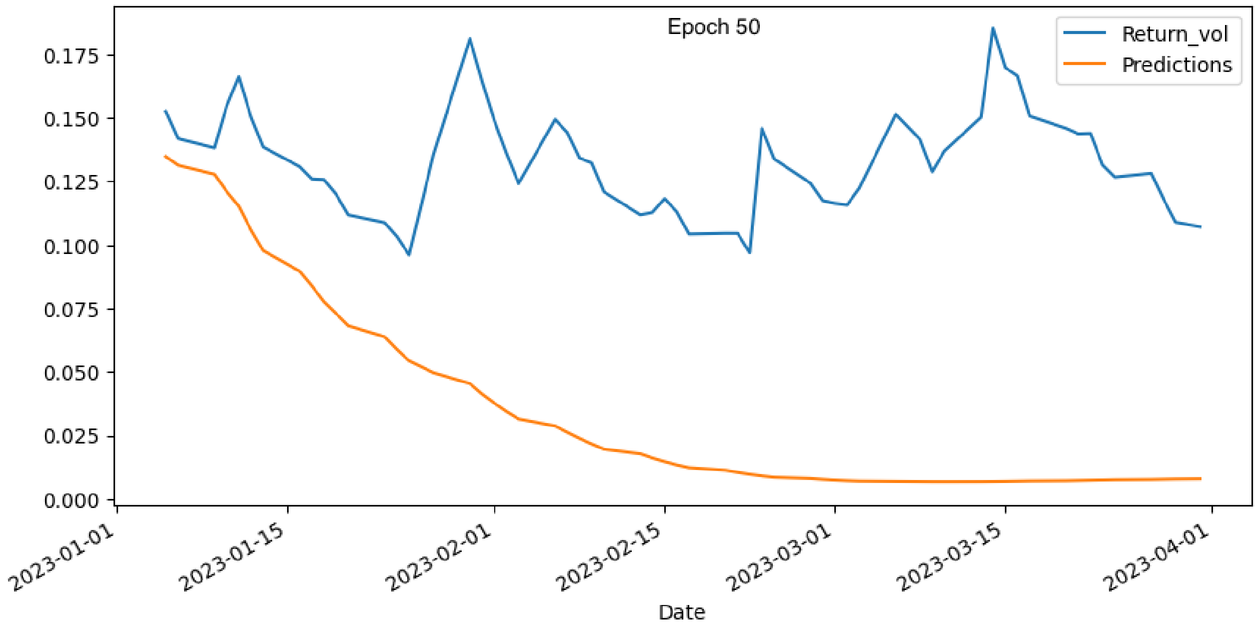
Source: Author's own calculations.

Figure 6: Comparing the predicted values generated from LSTM using default activation function at epoch level 40 with the actual values over the test set of data



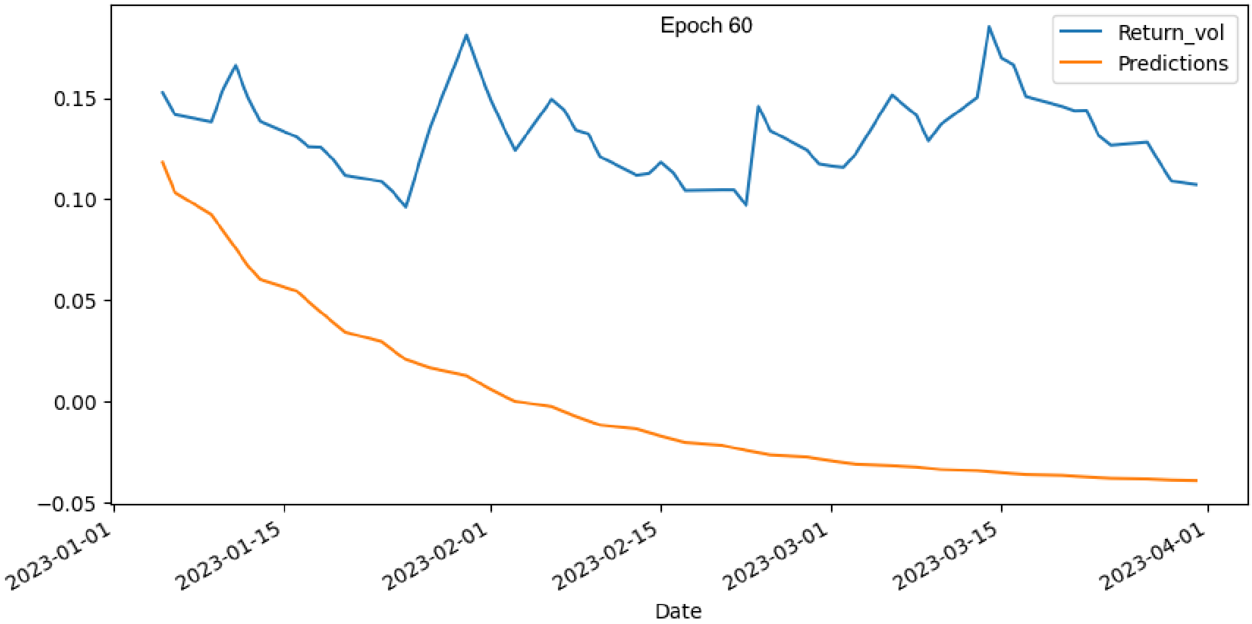
Source: Author's own calculations.

Figure 7: Comparing the predicted values generated from LSTM using default activation function at epoch level 50 with the actual values over the test set of data



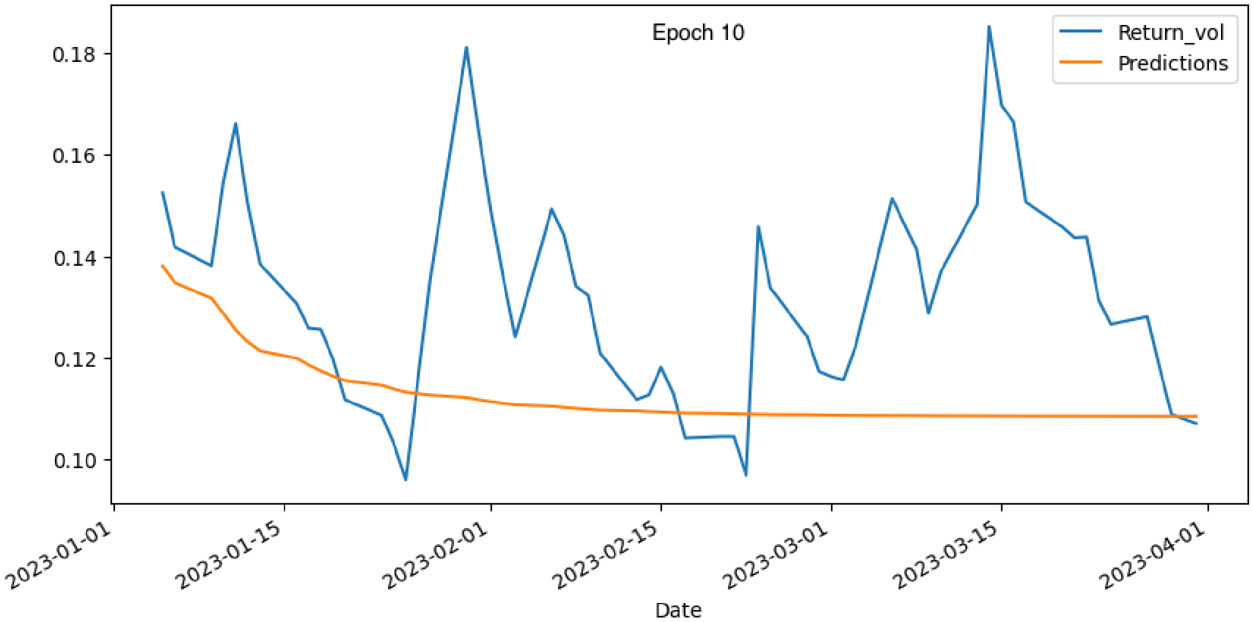
Source: Author's own calculations.

Figure 8: Comparing the predicted values generated from LSTM using default activation function at epoch level 60 with the actual values over the test set of data



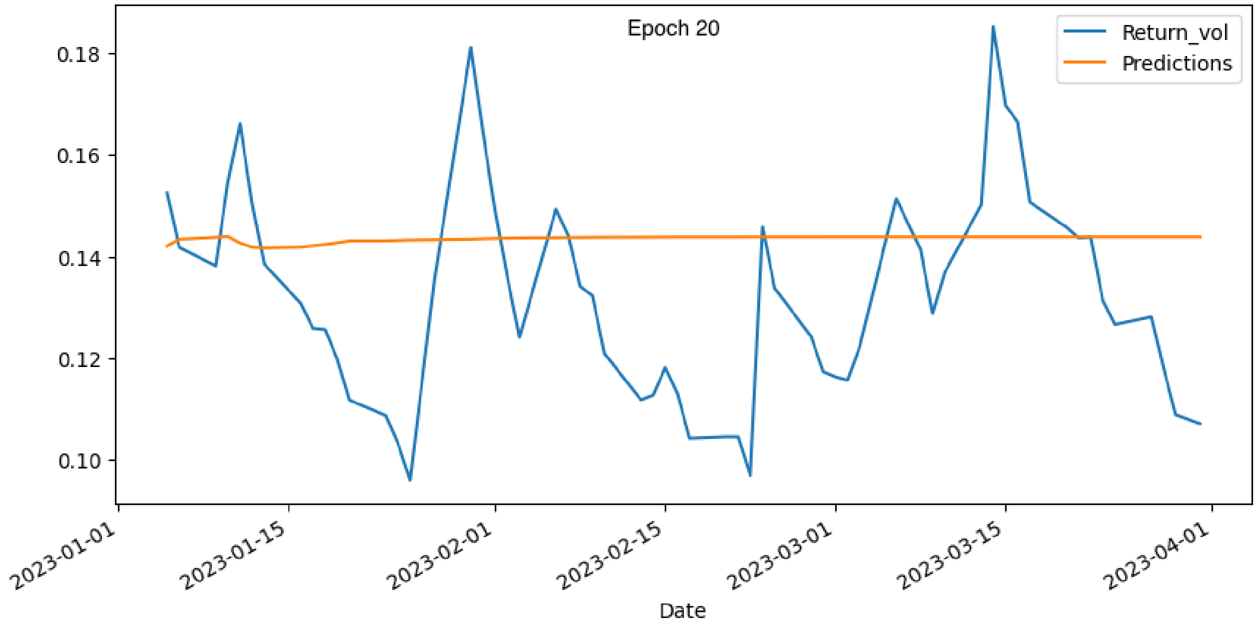
Source: Author's own calculations.

Figure 9: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 10 with the actual values over the test set of data



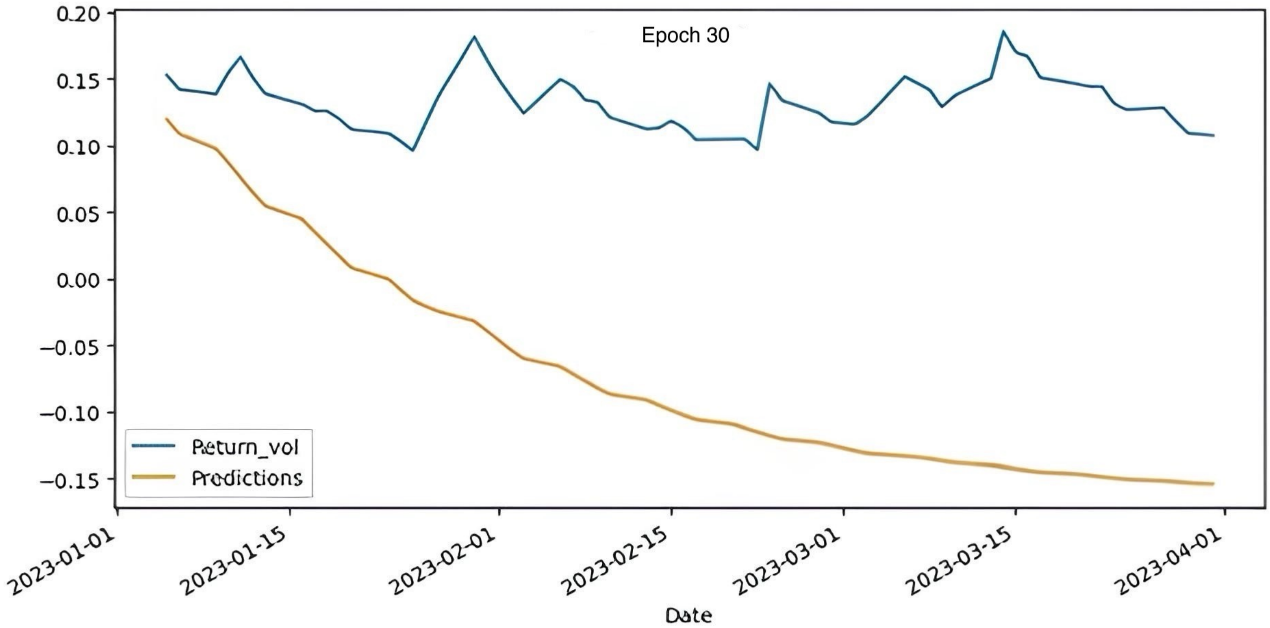
Source: Author's own calculations.

Figure 10: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 20 with the actual values over the test set of data



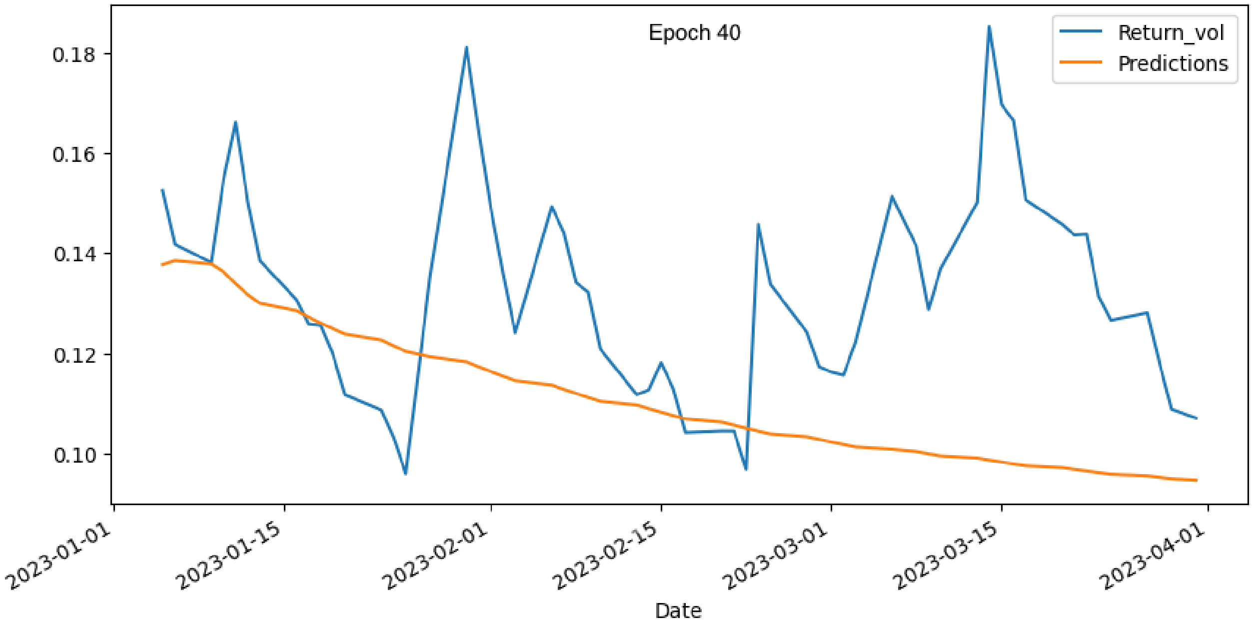
Source: Author's own calculations.

Figure 11: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 30 with the actual values over the test set of data



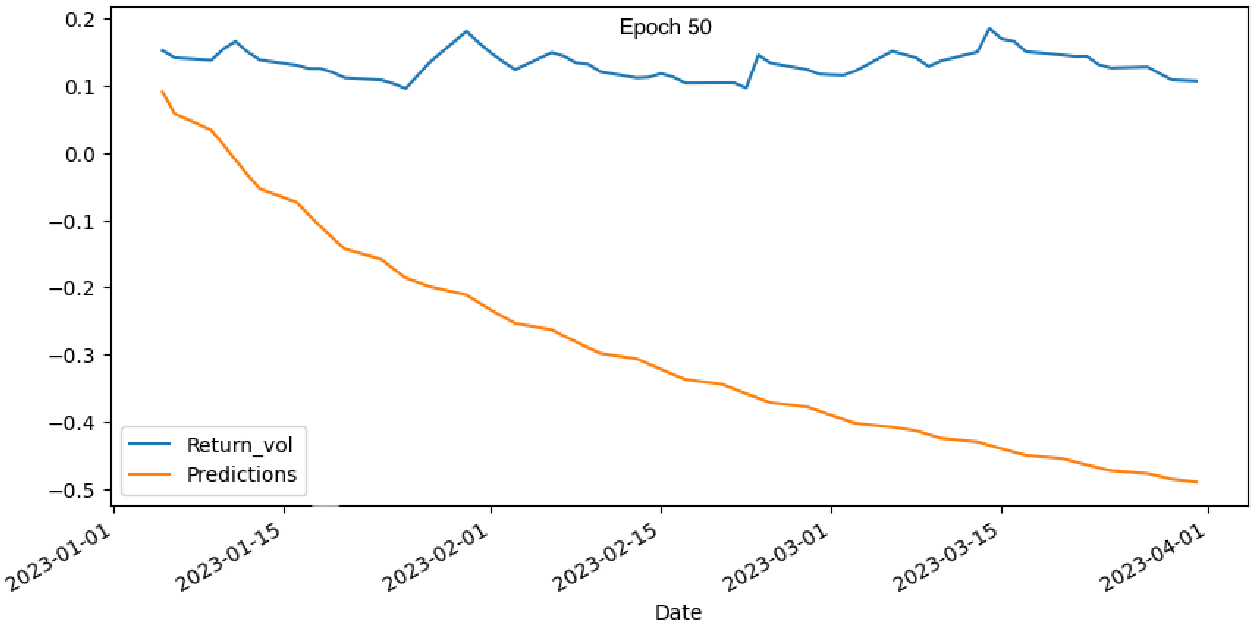
Source: Author's own calculations.

Figure 12: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 40 with the actual values over the test set of data



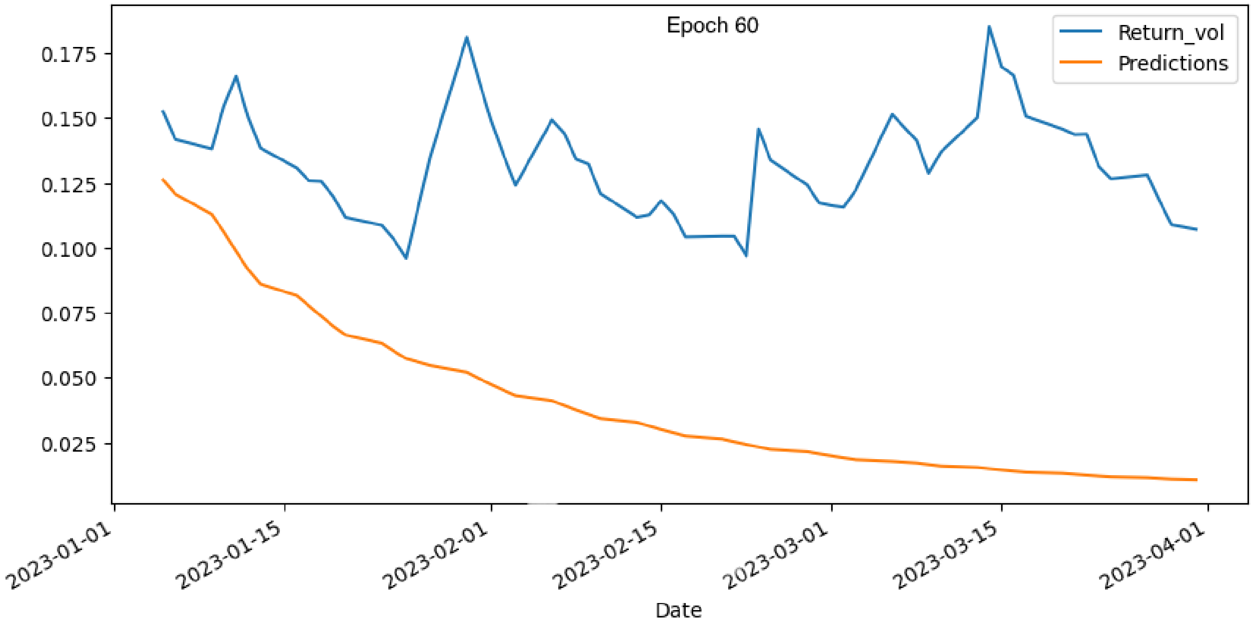
Source: Author's own calculations.

Figure 13: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 50 with the actual values over the test set of data



Source: Author's own calculations.

Figure 14: Comparing the predicted values generated from LSTM using ReLU activation function at epoch level 60 with the actual values over the test set of data



Source: Author's own calculations.

Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 115-128
10.2478/fiqf-2023-0030

Financial Internet Quarterly

THE DYNAMIC RELATIONSHIP BETWEEN BTC WITH BIST AND NASDAQ INDICES

Cagri ULU [1]

Abstract

The significance of digital investment has grown substantially, enabled by advancing technology, which provides digital monitoring of investment instruments. Consequently, analyzing these instruments has become imperative. In particular, investors are inclined to compare new investment opportunities with well-established global stock markets, seeking to capitalize on their advanced financial literacy. This study aims to employ econometric analysis to explore the dynamic relationship between Bitcoin and the BIST100 and NASDAQ 100 indices. The time frame for this investigation spans from January 1, 2017, to March 10, 2022. Stationarity was confirmed through unit root tests (ADF, PP, KPSS, ZA, FADF, and FFFFF ADF) for the subsequent utilization of Autoregressive Conditional Variance Models. Additionally, Generalized Autoregressive Conditional Variance and Dynamic Conditional Correlation Tests were conducted. Results from the Dynamic Conditional Correlation Test model revealed no statistically significant dynamic conditional correlation between Bitcoin and BIST 100. Conversely, a negative and significant dynamic conditional correlation emerged between Bitcoin and NASDAQ 100. Investors should not only monitor the market but also review academic studies before making investment decisions. In this regard, this study holds significant importance. The study is limited to the BTC, BIST, and NASDAQ indices. Researchers interested in the topic can increase the dataset to further enrich the study.

JEL classification: E00, F3, C58
Keywords: Dynamic Relations, DCC GARCH, Bitcoin, Finance, Stock Market

Received: 19.07.2023 Accepted: 07.09.2023

Cite this:
Cagri U. (2023) The dynamic relationship between BTC with BIST and NASDAQ indices. Financial Internet Quarterly 19(4), pp. 113-126.

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Introduction

Over the years, investment instruments have undergone diversification, and stock exchanges have established a mutually advantageous relationship between consumers and companies. Companies secure short-term financial resources from consumers, in return for which consumers are entitled to a share of the profits from these firms, a practice commonly encountered in traditional trading methodologies. Traditionally, the provision of resources has relied on liquid assets such as bank loans and foreign currency accounts. However, the advent of technology has ushered in a new era of investment tools, among which Bitcoin (BTC) emerges as a prominent contemporary option.

BTC made its first appearance in 2009 through a 9-page manifesto published on bitcoin.org by an individual named Satoshi Nakamoto. This introduction integrated BTC into a "Peer to Peer" system and explained the utilization of blockchain technology for secure transactions (Nakamoto, 2022). Subsequently, BTC has become a subject of discussions and comparisons with other financial investment instruments.

This study analyzes the dynamic relationship between BTC and BIST 100, an index of Borsa Istanbul, and NASDAQ 100, an index of an American stock exchange. As global financial assets are interconnected, investors need to monitor the global market and adjust their investments accordingly.

The time interval for this analysis spans from January 1, 2017, to March 10, 2022. To ensure stationarity, unit root tests (ADF, PP, KPSS, ZA, FADF, and FFFFF ADF) were conducted in the initial stage of analysis. Based on the results of these tests, Autoregressive Conditional Variance Models (ARCH) were employed. Following that, the Generalized Autoregressive Conditional Variance (GARCH-EGARCH) and Dynamic Conditional Correlation Test (DCC GARCH) were performed.

The Literature Review section provides an overview of prior research pertaining to the subject, offering insights into their respective findings. The subsequent section explains the econometric models used in this study. The results derived from these models are comprehensively examined, culminating in the Conclusion section, where the ultimate findings of the study are summarized.

Literature review

Jin and Masih (2017), gathered daily closing price data for five indices, including the FTSE Bursa Malaysia Emas Shari'ah Index, spanning from January 1, 2013, to January 2, 2017. The Bitcoin price index was sourced from Coindesk, recognized as one of the most active Bitcoin exchanges. During this period, the study applied three distinct methodologies: M-GARCH-DCC, Continuous Wavelet Transforms (CWT), and Maximum Overlap Discrete Wavelet Transform (MODWT) - to assess the correlation between Bitcoin and Shari'ah stock indices. The study's findings reveal a notably low and negative correlation between Bitcoin and Shari'ah stock indices, suggesting that Islamic stock investors could gain from diversifying their portfolios with Bitcoin. Furthermore, these results emphasize the potential benefits of further exploration into the fundamentals of cryptocurrencies within Islamic capital markets.

Conrad et al. (2018) conducted a study focusing on the relationship between volatility and stock market movements in cryptocurrencies, specifically Bitcoin (BTC). The research analyzed long-term and short-term volatility using the GARCH-MIDAS model, which extracts the components of long- and short-term fluctuations in cryptocurrencies. The study covered data from May 2013 to November 2017. Results indicated that the volatility of the S&P 500 had a negative and highly significant impact on long-term BTC volatility. Additionally, the S&P 500 volatility risk premium had a significantly positive influence on long-term BTC volatility. Moreover, a strong positive relationship was found between the Baltic exchange rate index and long-term BTC volatility, indicating a close link between BTC volatility and global economic activity.

Naimy and Hayek (2018) conducted a study aiming to predict volatility in BTC. The analysis focused on the BTC/USD exchange rate between April 1, 2013, and March 31, 2016. Different models, including GARCH (1,1), EWMA, and EGARCH (1,1), were compared to determine the most effective in explaining BTC volatility. The study identified EGARCH (1,1) as the most effective model. However, it was noted that early BTC behavior should be closely monitored, as future results may vary.

Gyamerah (2019) analyzed the volatility of BTC returns using sGARCH, iGARCH, and tGARCH models, covering the period from January 01, 2014, to August 16, 2019. The study revealed that the TGARCH-NIG model was the most effective in predicting BTC return series volatility.

Ardia et al. (2019) tested the presence of regime changes in the GARCH volatility dynamics of Bitcoin daily returns using MSGARCH models. They used a dataset of 2355 observations of BTC prices in USD, spanning from August 18, 2011, to March 3, 2018. The study found strong evidence for regime changes in the GARCH process, and MSGARCH models outperformed single regime specifications when estimating VAR.

Segnon and Bekiros (2020) proposed approaches to model the dynamics governing the mean and variance processes of BTC markets. The study used price observations between January 1, 2013, and November 28, 2018. Markov variation multifractal and FIGARCH models were found to outperform other GARCH-type models in estimating BTC return volatility. Combined estimates were observed to improve individual model estimates.

Venter and Maré (2020) used the GARCH model to analyze the pricing performance of BTC. They also evaluated implied volatility indices of BTCUSD and Cryptocurrency Index (CRIX) datasets. Daily data from January 1, 2016, to January 3, 2019, were considered. The study showed that BTCUSD and CRIX volatility indices exhibited a similar course when tested with the GARCH model. Short-term volatility (30 days) was generally lower compared to longer maturities.

Wang (2021) studied the volatility of BTC returns using the GARCH (1,1) model and other asymmetric models, such as TARCH and EGARCH. The analysis covered the period from October 2013 to July 31, 2020. The study revealed that the GARCH (1,1) model exhibited clustering characteristics in BTC volatility and return, with the volatility being a permanent process but decreasing over time. BTC was found to have a revised asymmetric effect between positive and negative shocks, making it suitable for investors to add to their portfolios as a safe-haven asset during economic depressions.

Sui and Elliott (2021) examined the pricing of BTC options, incorporating both conditional varying variance and regime switching in BTC returns. The study employed a nonlinear time series model combining the SETAR model and the GARCH model to model Bitcoin return dynamics. Daily data between July 18, 2010, and May 31, 2018, were used. The GARCH model showed implied volatility skewness for short-term options.

Abar (2020) aimed to make successful predictions in cryptocurrencies, particularly BTC, using the GARCH model and SVM-EKK regression. The study used BTC price series data from January 1, 2017, to February 29, 2020. Both models provided healthy predictions for the cryptocurrency price series.

Ciaian et al. (2021) estimated BTC's transaction demand and speculative demand equations with a GARCH model using high-frequency data covering hourly data from 2013 to 2018. The results showed that both transaction demand and speculative demand had a statistically significant effect on BTC price formation. Additionally, the BTC price reacted negatively to the BTC velocity but positively to the size of the BTC economy.

Akin et al. (2023), conducted data collection from CoinMarketCap on the three largest cryptocurrencies (Bitcoin, Ethereum, and Binance Coin) on a weekly basis, spanning from August 1, 2017, to April 1, 2022. This period constituted the data collection window for the study. Employing the dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model, the study analyzed the CoinMarketCap dataset. The results of the investigation indicated a noteworthy impact of news and events concerning central bank digital currencies (CBDCs) on Bitcoin returns. Both the CBDC uncertainty index and CBDC attention index exhibited a considerable influence on Bitcoin returns, signifying that positive news in this context could yield substantial returns. These findings underscore the notion that investors' future expectations regarding cryptocurrencies are significantly molded by CBDC-related news and events.

Methodology

While working on a time series, it is of great importance that the series be stationary. Depending on the stationarity, the method is selected by which the series will be advanced. Different stationarity tests are used to understand the reliability of the series (Petrica et al., 2017). In this study, first of all, ADF, PP and KPSS tests, which are traditional and do not allow structural break, were performed. Then, ZA, FADF and FFFF ADF unit root tests were carried out, which allow for modern and structural breaks. After the test results, VAR analysis was performed, and ARCH effects were investigated in the series. The study was terminated with the DCC GARCH test to analyze the dynamic relationship between the series.

Unit root test results not considering structural breaks

Stationarity tests were conducted to check the significance of the series. Augmented Dickey-Fuller (ADF), Phillips Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root tests, which do not take into account the structural break, were applied. Stationarity is of great importance in determining the analyses to be made on the time series.

Table 1: ADF, PP and KPSS Unit Root Test Results in Level

Characteristics		ADF		PP		KPSS	
		Intercept	Interceptand Trend	Intercept	Interceptand Trend	Intercept	Interceptand Trend
BTC	Test Statistics	-1.667067	-1.914840	-1.670458	-1.993322	3.269261	0.340945
	1%	-3.435161	-3.965109	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863552	-3.413266	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567891	-3.128657	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.447900	0.646100	0.446100	0.603900		
BIST100	Test Statistics	-0.619607	-1.617013	-0.488347	-1.539903	2.824638	0.704447
	1%	-3.435169	-3.965120	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863556	-3.413271	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567893	-3.128660	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.863700	0.786100	0.890900	0.815500		
NASDAQ 100	Test Statistics	-1.032457	-2.234098	-1.112875	-2.367322	4.045332	0.721599
	1%	-3.435196	-3.965159	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863568	-3.413290	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567899	-3.128671	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.743500	0.469600	0.712700	0.396600		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels.

Source: Author's own work.

ADF, PP and tests, which are unit root tests that do not consider structural break, were applied. All tests were examined at the level and it is understood that stationarity could not be achieved because the probability values are greater than 0.05. When the KPSS test results are examined, it is seen that the series are not stationary.

Table 2: ADF, PP and KPSS Unit Root Test Results in 1st Difference

Characteristics		ADF		PP		KPSS	
		Intercept	Interceptand Trend	Intercept	Interceptand Trend	Intercept	Interceptand Trend
BTC	Test Statistics	-36.94505	-36.949500	-36.97179	-36.972170	0.13498	0.103774
	1%	-3.43517	-3.965115	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86355	-3.413269	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56789	-3.128659	-2.56789	-3.128659	0.34700	0.146000
	Prob.	0.00000	0.000000	0.00000	0.000000		
BIST100	Test Statistics	-22.97963	-22.980120	-36.46394	-36.460150	0.13504	0.080503
	1%	-3.43517	-3.965120	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86356	-3.413271	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56789	-3.128660	-2.56789	-3.128659	0.34700	0.119000
	Prob.	0.00000	0.000000	0.00000	0.000000		
NASDAQ 100	Test Statistics	-11.80934	-11.813670	-44.35551	-44.350220	0.07610	0.073464
	1%	-3.43520	-3.965159	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86357	-3.413290	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56790	-3.128671	-2.56789	-3.128659	0.34700	0.119000
	Prob.	0.00000	0.000000	0.00010	0.000000		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels.

Source: Author's own work.

The same tests were applied again by taking the first differences of the series. Since the probability values for ADF and PP are less than 0.05 in all series, it can be said that stationarity is achieved. When the KPSS test results are examined, it is seen that stationarity is provided. At the 1% significance level, all tests are significant.

Unit root test results considering structural breaks

Unit root tests are essential in increasing reliability. After the traditional models, modern unit root tests started to be applied to the series.

For this study, Zivot Andrews (ZA), Fractional Augmented Dickey Fuller (FADF) and Fractional Frequency Flexible Fourier Form Augmented Dickey-Fuller (FFFFADF) tests, which allow structural break, were applied.

Table 3: ZA Unit Root Test Results

Characteristics		Model A (Intercept)	Model B (Trend)	Model C (Intercept and Trend)
BTC	Test Statistics	-2.870013	-2.206822	-3.431682
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	10.19.2020	11.19.2019	01.08.2018
BIST100	Test Statistics	-3.720117	-3.864384	-3.953157
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	4.20.2018	3.11.2020	2.18.2020
NASDAQ100	Test Statistics	-4.388460	-2.872674	-3.644380
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	4.03.2020	12.17.2018	10.04.2018

Source: Author's own work.

According to Table 3 when the statistical values of the series and the critical values are compared, it is understood that stability cannot be achieved for the BTC, BIST and NASDAQ indices. The absolute values of the test statistics are greater than the critical value.

Table 4: FADF and FFFF ADF Unit Root Test Results

Series	Min. KKT	k	FADF
BTC	3.270491	1.0	3.198692 (10)
BIST 100	0.276864	1.0	3.290393 (12)
NASDAQ 100	0.273501	1.0	3.357170 (12)
			Fractional FADF
BTC	3.268545	1.4	2.892659 (10)
BIST 100	0.275422	0.1	7.044294 (12)
NASDAQ 100	0.272455	0.5	4.595373 (12)

Source: Author's own work.

Based on the results of the FADF Unit Root Test, the application of the FADF for analysis is rejected because the F constraint value was lower than the F table value in all series. To increase the reliability of the stationarity analysis, the FFFFF ADF test was conducted.

The FFFFF ADF test results indicate that the F table value is greater than the actual fractional FADF values in all series. Therefore, the appropriate unit root analysis for the series is the ADF Unit Root Test, which takes into account the structural break.

Upon analyzing the results of the ADF unit root test, it is observed that the series become I(1) stationary when the first difference is taken. In I(1) stationary series, ARCH and GARCH effects are chosen as suitable modeling approaches for capturing volatility and dynamics in the data.

Autoregressive conditional variable variance models

After unit root tests for the variables, appropriate ARMA models should be determined. The ARMA models for the series and the number of alternative GARCH models after the ARCH effect were estimated as follows.

BTC – ARMA (3,3) and GARCH (1,1)
BIST100 – ARMA (3,3) and GARCH (1,1)
NASDAQ100 – ARMA (4,4) and EGARCH (1,1)

BTC Index

According to the significance of the coefficients and the minimum Akaike and Schwarz information criteria, which are the model selection criteria, the ARMA(3,3) model was determined as the appropriate model for the BTC return variable. The results are given in Table 5.

Table 5: ARMA(3,3) Model Result on BTC Index Return

Variable	Coefficient (Std. Error)	t-Statistics	Prob.
Constant Term	0.00276000 (0.00192700)	1,431.969	0.1524
AR(1)	0.81941800 (0.14335000)	5,716.197	0.0000***
AR(2)	-0.69738700 (0.15441200)	-4,516.406	0.0000***
AR(3)	0.79733400 (0.11020600)	7,234.958	0.0000***
MA(1)	-0.85103100 (0.14375600)	-5,919.970	0.0000***
MA(2)	0.74547700 (0.15730600)	4,739.035	0.0000***
MA(3)	-0.79002000 (0.11588500)	-6,817.280	0.0000***
SIGMASQ	0.00250700 (0.00000517)	4,850.710	0.0000***
Akaike	-3.13855900		
Schwarz	-3.10678200		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the table is examined, the AR(1) coefficient (0.819418) expresses the value of BTC index return one period ago. The coefficient AR(2) (-0.697387) represents its value two periods ago, and the coefficient AR (3) (0.797334) represents its value three periods ago. In other words, an increase in the BTC return that occurred a period ago has an increasing effect on the current return of BTC. An increase in the return of two periods ago affects the current return negatively. An increase in the return of three periods ago affects the return positively in the current period. The MA coefficient represents the shocks to the system. In other words, it shows the error term. Looking at the MA(1) (-0.851031) coefficient, it is seen that a shock that occurred a period ago has a decreasing effect on the BTC return in the current period. Looking at the MA(2) (0.745477) coefficient, it was observed that a shock that occurred two periods ago increased the BTC return in the current period, and looking at the MA(3) (-0.790020) coefficient, it is possible to say that a shock that occurred three periods ago reduced the return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

Table 6: ARCH Effect in ARMA(3,3) Model of BTC Index

Q Statistics		Prob.
ARCH(5)	13.83629	0.0167
Q(10)	3.67910	0.4510
Q2(10)	17.41300	0.0660

Source: Author's own work.

When analyzing the results in the table, it was determined that there is no autocorrelation problem in the ARMA(3,3) model according to the Q(10) statistic for the 10^{th} delay. However, the Q2(10) statistic is significant, indicating that the model has a different variance, implying an ARCH effect.

The ARCH(5) value of 13.83629 with a corresponding probability value of 0.0167 shows the presence of an ARCH effect in the ARMA(3,3) model at the 5% significance level.

Due to the presence of the ARCH effect in the ARMA(3,3) model, the modeling continued with autoregressive conditional heteroskedasticity (ARCH) models. Different GARCH-type models were tried for BTC, and the most suitable (minimum) model for BTC was determined to be ARMA(3,3) - GARCH(1,1) based on assumptions, significance of coefficients, and minimum Akaike and Schwarz information criteria.

Upon examining the results in the last table for the ARMA(3,3) - GARCH(1,1) model, the coefficients α (0.148011) and β (0.598011) were found to be positive and statistically significant at the 1% significance level. The non-negativity condition for variance coefficients was satisfied.

In the GARCH model, α indicates the initial effect of the shock, and β indicates the persistence of the shock in the system. With a β coefficient of 0.598011, it can be interpreted that the shock to the system is not permanent, as the coefficient is close to 1. The half-life shock value was calculated to determine the duration of the shock in the system. However, the specific formulation for calculating the half-life shock value is not provided in the given text.

Half-life Shock

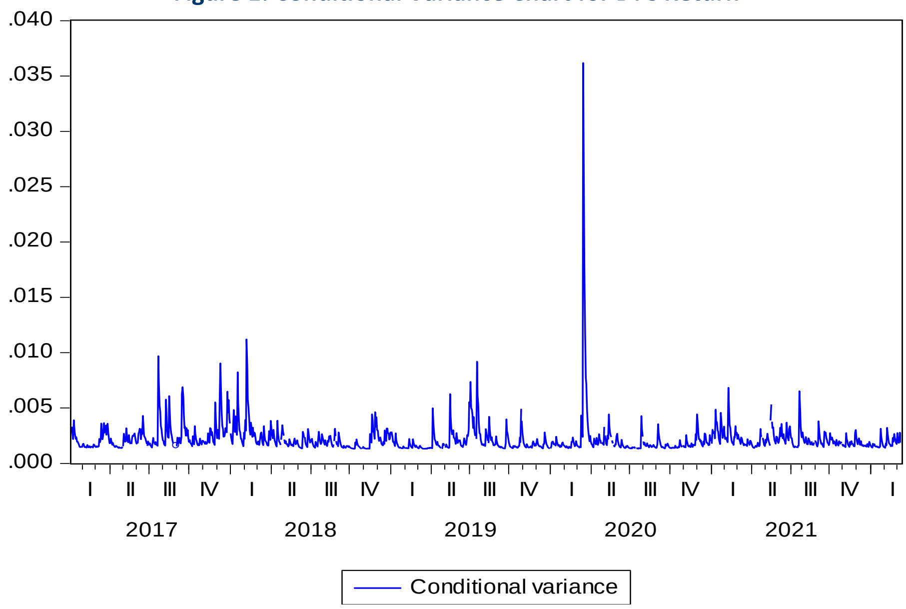
$$-\frac{\ln(0.5)}{\ln(a+b)} = -\frac{\ln(0.5)}{\ln(0.1480+0.5998)} = 2.86 \quad (1)$$

According to the value obtained, the shock to the system regarding the BTC index return stays in the system for an average of 3 days. From this point of view, it is seen that the shock to the system is not permanent.

To determine whether there is an ARCH effect in the residues obtained from ARMA(3,3) - GARCH(1,1) model, ARCH(5) statistics were examined and the obtained value was found as 5.493894 and the probability value as 0.3586. Therefore, the ARCH effect is eliminated in the model. In addition, looking at the Q(10) statistics, it is seen that there is no autocorrelation problem in the model.

The following figure shows the conditional variance graph obtained from the ARMA(3,3) - GARCH(1,1) model.

Figure 1: Conditional Variance Chart for BTC Return



Source: Own elaboration with using the EViews package program.

BIST 100 index

Alternative ARMA(p,q) models have been tried for the BIST 100 index return. The significance of the coefficients was determined as the ARMA(3,3) model as the appropriate model for the BIST 100 return variable according to the minimum Akaike and Schwarz information criteria, which are the model selection criteria. The results are as in the table below:

Table 7: ARMA(3,3) Model Result on BIST100 Index Return

Variable	Coefficient	T-Statistics	Prob.
Constant Term	0.00074000 (0.00046200)	1.600027	0.1098
AR(1)	-0.31207000 (0.10665500)	-2.925940	0.0035***
AR(2)	-0.25749000 (0.07437900)	-3.461840	0.0006***
AR(3)	-0.76769000 (0.07899300)	-9.718440	0.0000***
MA(1)	0.30009800 (0.10457300)	2.869748	0.0042***
MA(2)	0.33213000 (0.06745900)	4.923416	0.0000***
MA(3)	0.80202800 (0.07991300)	10.036280	0.0000***
SIGMASQ	0.00021100 (0.00000446)	47.260720	0.0000***
Akaike	-5.61514600		
Schwartz	-5.58336900		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the table is examined, the AR(1) coefficient (-0.31207) represents the value of the BIST 100 index return a period ago. The coefficient AR(2) (-0.25749) represents its value two periods ago, and the coefficient AR(3) (-0.76769) represents its value three periods ago. In other words, an increase in the BIST 100 return that occurred a period ago has a reducing effect on the current return of BIST 100. An increase in the return from two periods ago affects the current return negatively. It can be said that an increase in the return of three periods ago affects the return negatively in the current period. The MA coefficient represents the shocks to the system. Looking at the MA(1) (0.300098) coefficient, it is seen that a shock that occurred a period ago has an increasing effect on the BIST 100 return in the current period. Looking at the MA(2) (0.33213) coefficient, it is observed that a shock that occurred two periods ago increased the BIST 100 return in the current period, and looking at the MA(3) (0.802028) coefficient, it is possible to say that a shock that occurred three periods ago increased the return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

The Q and Q2 statistics of the ARMA(3,3) model and ARCH statistics were examined to determine whether the model has an ARCH effect.

Table 8: ARCH Effect on the ARMA(3,3) Model of the BIST 100 Index

Q Statistics		Prob.
ARCH(5)	78.30416	0.000
Q(10)	5.49580	0.240
$Q^2(10)$	129.71000	0.000

Source: Author's own work.

Upon examining the results in the table, it is evident that there is no autocorrelation problem in the ARMA(3,3) model based on the Q(10) statistic for the 10th delay. However, the Q2(10) statistic is significant, indicating a different variance in the model. Additionally, the ARCH(5) value is 78.30416 with a corresponding probability value of 0.000, confirming the presence of an ARCH effect in the ARMA(3,3) model at the 1% significance level.

Due to the identified ARCH effect in the ARMA(3,3) model, the modeling process proceeds with autoregressive conditional variance (GARCH) models. Various GARCH-type models were tested for BIST 100, and the most suitable (minimum) model was determined to be ARMA(3,3) - GARCH(1,1) based on the assumptions, significance of coefficients, and minimum Akaike and Schwarz information criteria. The results for this model are presented in the last table.

Examining the last table, we find that the α (0.149861) and β (0.599861) coefficients are positive and statistically significant at the 1% significance level, satisfying the non-negativity condition for variance coefficients. In the GARCH model, α represents the initial effect of the shock, while β indicates the persistence of the shock in the system. With a β coefficient of 0.5998, we can conclude that the shock to the system is not permanent.

The half-life shock value, which measures how long the shock to the system lasts, is calculated using a specific formulation. However, the formulation is not provided in the given text.

Half Life Shock

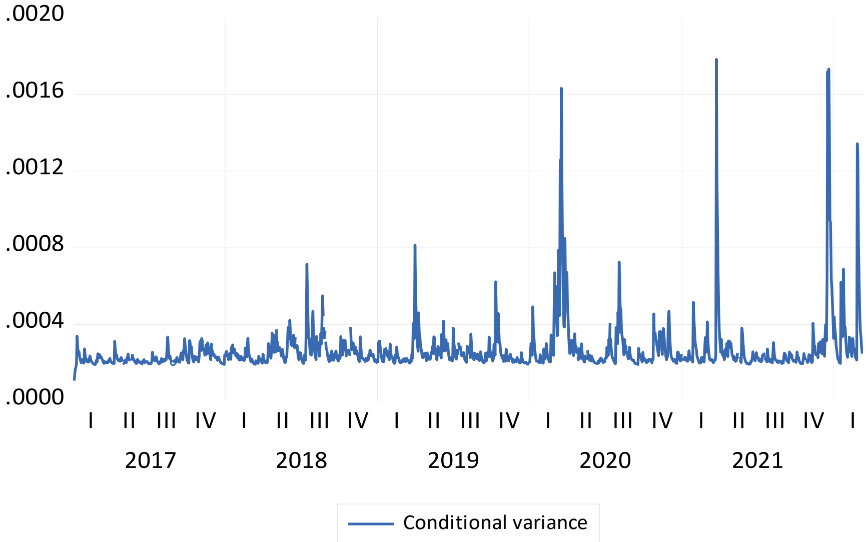
$$\frac{\ln(0.5)}{\ln(a+b)} = -\frac{\ln(0.5)}{\ln(0.1491+0.5998)} = 2.39 \qquad (2)$$

According to the value obtained, the shock to the system regarding the BIST 100 index return stays in the system for an average of 2.5 days. If the GARCH parameter was close to 1, it could be said to have a permanent effect on the system, but the β coefficient was 0.59 and was less than 1. Therefore, it is not possible to talk about its permanent effect on the system.

To determine whether there is an ARCH effect in the residues obtained from ARMA(3,3) - GARCH(1,1) model, ARCH(5) statistics were examined and the obtained value was found as 3.517340 and the probability value as 0.6208. Therefore, the ARCH effect is eliminated in the model. In addition, looking at the Q(10) statistics, it is seen that there is no autocorrelation problem in the model.

The following figure shows the conditional variance graph obtained from the ARMA(3,3) - GARCH(1,1) model.

Figure 2: Conditional Variance Chart for BIST 100 Return



Source: Own elaboration with using the EViews package program.

NASDAQ 100 Index

According to the significance of the coefficients and the minimum Akaike and Schwarz information criteria, which are the model selection criteria, the ARMA(4.4) model was determined as the appropriate model for the NASDAQ 100 return variable. The results are shown in the table below.

Table 9: ARMA(4.4) Model Result for NASDAQ 100 Index Return

Variable	Coefficient	T-Statistics	Prob.
Constant term	0.00076700 (0.00037000)	2.074435	0.0382***
AR(1)	-2.70751800 (0.04919100)	-55.040960	0.0000***
AR(2)	-3.47726500 (0.11334200)	-30.679350	0.0000***
AR(3)	-2.41629600 (0.11152800)	-21.665330	0.0000***
AR(4)	-0.79038900 (0.04514900)	-17.506090	0.0000***
MA(1)	2.55696100 (0.05866200)	43.587910	0.0000***
MA(2)	3.12193500 (0.13125500)	23.785210	0.0000***
MA(3)	2.03757400 (0.12722800)	16.015130	0.0000***
MA(4)	0.60099300 (0.05145700)	11.679520	0.0000***
SIGMASQ	0.00018900 (0.00000045)	42.057840	0.0000***
Akaike	-5.71957500		
Schwarz	-5.67985400		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the results are analyzed, the coefficients AR (1) (-2.707518), AR(2) (-3.477265), AR(3) (-2.416296) and AR(4) (-0.790389) show the NASDAQ 100 index returns as one, two, three and four, respectively. represent their previous values. In other words, an increase in the NASDAQ 100 return that occurred one, two, three and four periods ago has a decreasing effect on the current return of the NASDAQ 100. The MA coefficients represent the shocks to the system. According to in the system in four periods increased the NASDAQ 100 return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

In the table below, the Q and Q2 statistics of the ARMA(4.4) model and ARCH statistics are examined to determine whether there is an ARCH effect in the model.

Table 10: ARCH Effect in ARMA(4.4) Model for NASDAQ 100 Index

Q Statistics		Prob.
ARCH(5)	304.0880	0.000
Q(10)	1.7172	0.424
$Q^2(10)$	873.8600	0.000

Source: Author's own work.

When the table is examined, the presence of the ARCH effect was determined according to the 1% significance level according to the ARMA(4.4) model. The ARCH (5) coefficient was 304.0880 and the probability value was 0.000. When Q and Q2 are examined, it is understood that there is no autocorrelation problem in the ARMA(4.4) model. With the ARCH effect, the modeling should be continued with autoregressive conditional variance models. Alternative GARCH type models have been tried. The EGARCH (1,1) model from these models has been estimated since it meets the necessary conditions (minimum Akaike and Schwarz criteria) and the results are shown in the last table.

The last table shows the ARMA(4.4) - EGARCH(1.1) model estimation result for the NASDAQ100 return. The α, β and γ coefficients are statistically significant at the 1% significance level. In the EGARCH model, the asymmetry coefficient γ is negative and statistically significant at the 1% significance level. There is an asymmetry (γ) effect in the model. Therefore, it can be said that the effect of negative shocks on the conditional variance of the NASDAQ100 index is greater than that of positive shocks. In other words, negative shocks have an increasing effect on the volatility of the NASDAQ100 index compared to positive shocks. In the model, the beta coefficient was obtained as 0.9666. Since this value is close to 1, the shock to the system is permanent. In the EGARCH model, the half-life shock is calculated according to the following formulation.

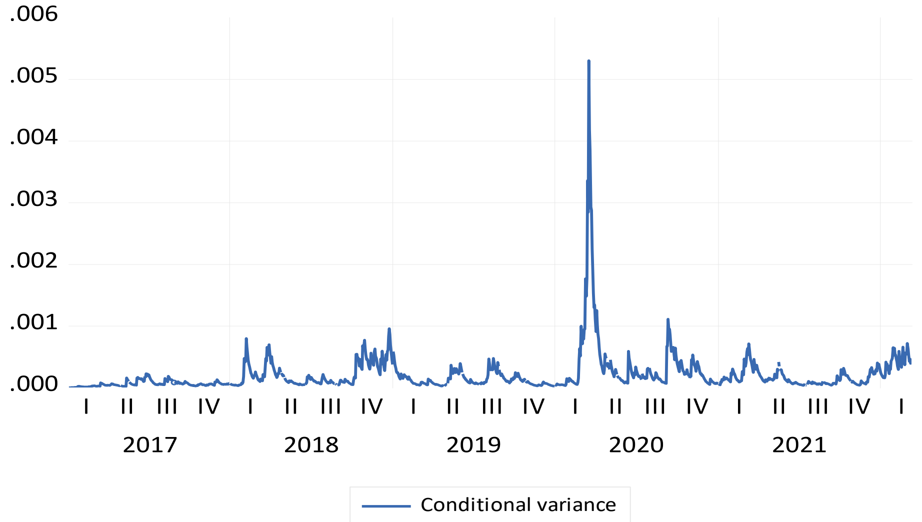
Half-Life Shock

$$-\frac{\ln(0.5)}{\ln(b)} = -\frac{\ln(0.5)}{\ln(0.9669)} = 20,592 \tag{3}$$

According to the result above, a shock to the NASDAQ index remains in the system for an average of 21 days.

The following figure shows the conditional variance graph obtained from the ARMA(4.4) - EGACRH(1,1) model for the NASDAQ 100 index.

Figure 3: Conditional Variance Chart for NASDAQ 100 Return



Source: Own elaboration with using the EViews package program.

Table 11: GARCH and EGARCH Results According to Appropriate ARMA Models for Data

Variable	BTC	BIST100	NASDAQ100
ARMA Equation			
Constant term	0.003102 (0.001456)	0.0013170 (0.0005430)	0.001290 (0.000194)
AR(1)	-0.010225 (0.148000)	-0.3826500 (0.0650799)	-1.887870 (0.332712)
AR(2)	-0.147530 (0.133689)	-0.3121400 (0.0712070)	-0.912530 (0.766489)
AR(3)	0.847426 (0.142471)	-0.8812300 (0.0660550)	0.419741 (0.724689)
AR(4)			0.340404 (0.282115)
MA(1)	0.049025 (0.159618)	0.3657310 (0.0577020)	1.847940 (0.326041)
MA(2)	0.147159 (0.148325)	0.3523590 (0.0564910)	0.825444 (0.740675)
MA(3)	-0.838227 (0.154863)	0.9089430 (0.0565310)	-0.507270 (0.698372)
MA(4)			-0.380390 (0.273415)

Variable	BTC	BIST100	NASDAQ100
Variance Equation			
Constant term	0.000524 (0.000108)	7.53E-05 (1.93E-05)	-0.461020 (0.077349)
α	0.148011 (0.032488)	0.1498610 (0.0385490)	0.219221 (0.036503)
β	0.598011 (0.069650)	0.5998610 (0.0880850)	0.966978 (0.007262)
γ			-0.150020 (0.024969)
ARCH(5)	5.493894 (0.358600)	3.5173400 (0.6208000)	1.064345 (0.957200)
Q(10)	6.114000 (0.191000)	5.8253000 (0.2130000)	4.744900 (0.093000)
$Q^2(10)$	7.311000 (0.696000)	6.2817000 (0.7910000)	4.939900 (0.895000)
Akaike	-3.271966	-5.7329000	-6.234410
Schwarz	-3.228192	-5.6891000	-6.178663

Note: The numbers in parentheses in the GARCH (1,1) model indicate standard errors. The numbers in parentheses for ARCH, Q and Q2 Statistics represent probability values.

Source: Own elaboration.

Analysis of dynamic relationship between variables

While the GARCH models look at the volatility, the DCC GARCH model looks at the volatility spread of the dynamic relationship between two variables. The table below shows the results of variance causality among the variables used in the study.

Table 12: DCC GARCH Model Estimation Results Between Variables

Variables	BTC - BIST	BTC - NASDAQ
γ_{12}	0.025618 (0.046637)	-0.974280*** (0.021882)
α	0.006015 (0.003773)	0.039558*** (0.014669)
β	0.986373*** (0.011058)	0.960432*** (0.015052)
dƑ	4.346441*** (0.264170)	3.626931*** (0.158930)
Diagnostic Tests		
Hosking (20)	39.372700 [0.241200]	59.617900 [0.967600]
Hosking(50)	39.372700 [0.408200]	195.143000 [0.544000]
Li-McLeod (20)	21.791600 [0.241300]	59.746400 [0.938100]
Li-McLeod(50)	219.401000 [0.141800]	194.794000 [0.551000]

Note: The numbers in round brackets show the standard error values, and the numbers in square brackets show the probabilities. ***, **, * indicate significance at 1%, 5% and 10% significance levels, respectively.

Source: Own elaboration.

In the table, the γ12 coefficient represents the dynamic conditional correlation between Bitcoin and the selected indices. The α coefficient indicates the effect of lagged quadratic shocks on conditional volatility, while the β coefficient represents the persistence of shocks, where a value approaching 1 indicates that incoming shocks are permanent.

The DCC-GARCH model proposed by Engle (2002) was utilized to examine the volatility spread between Bitcoin and the chosen indices. This model offers the advantage of determining possible changes in conditional correlations and the variation of conditional correlations over time for time-varying volatility.

The estimation of the model was initially performed between Bitcoin and BIST 100. According to the table, there is no statistically significant volatility spread at the 5% significance level between Bitcoin and the BIST 100 index, as the γ12 coefficient is statistically insignificant. Additionally, the probability values (shown in square brackets) for the Hosking and Li-McLeod values are greater than 0.05, indicating no issue with the model. The β coefficient suggests that the shock to the system is permanent, and when there is a volatility spread between Bitcoin and BIST 100, a shock to the system permanently affects the volatility spread.

Next, the model was estimated between Bitcoin and NASDAQ 100. The γ12 coefficient indicates a strong correlation, being close to 1 with a negative correlation. A statistically significant volatility spillover at the 1% significance level is observed between Bitcoin and the NASDAQ market. This implies that an increase in Bitcoin volatility has negatively affected the NASDAQ market. The α coefficient is significant and positive, indicating that an increase in lagged quadratic shocks increases the current value of conditional volatility. The β coefficient is close to 1, indicating a permanent volatility spread between Bitcoin and NASDAQ.

When examining the Hosking and Li-McLeod coefficients, it is evident that the model is estimated correctly, and there is no ARCH effect in the squares anymore. This means that the residuals of the established model have no ARCH effect, making the model accurate and meaningful.

Conclusion

The study discusses the dynamic relationship between Bitcoin and selected indices (BIST 100, NASDAQ 100) and analyzes the impact of shocks on the financial market, especially during the Covid-19 outbreak.

When examining the conditional variance graphs of the returns of the studied series, it is observed that significant shocks have occurred, and the Covid-19 epidemic has had a major impact on all variables. Besides Covid-19, the Central Bank's interest rate decisions have also caused significant shocks in the BIST 100 return. Similar results are observed in the conditional variance graphs of NASDAQ 100 and Bitcoin returns, indicating the financial impact of the Covid-19 outbreak on both indices.

Furthermore, the permanence of the shocks in the system is crucial. The shocks regarding the Bitcoin index return last for an average of 3 days, suggesting that the shock is not permanent. The shocks for the BIST 100 index return last for an average of 2.5 days, indicating a non-permanent effect. However, the shocks for the NASDAQ 100 return persist on average for 21 days, suggesting a more permanent impact.

In conclusion, domestic policy decisions in Turkey are effective in the formation of shocks compared to the selected global stock market indices. However, the Covid-19 epidemic has significant effects on all series. The dynamic relationship analysis reveals that there is no dynamic conditional correlation between Bitcoin and BIST 100, but there is a dynamic conditional correlation between Bitcoin and NASDAQ 100, with a negative relationship between them. This suggests that Bitcoin's impact on the Turkish stock market as a developing country and on NASDAQ indices from developed countries can be understood.

In light of the findings presented in this study, it becomes evident that our research builds upon and extends the existing body of knowledge in the field of cryptocurrency-market interactions. Previous research, as exemplified by the works of Jin and Masih (2017) and Conrad et al. (2018), has explored the correlation between Bitcoin and various stock market indices, shedding light on potential diversification opportunities for investors. Moreover, studies like that of Sui and Elliott (2021) have delved into the pricing dynamics of Bitcoin options, offering insights into derivative markets. Our study, which examines the relationship between Bitcoin and select indices (BIST 100 and NASDAQ 100) during the Covid-19 pandemic, contributes by revealing the differential impact and persistence of shocks on these variables.

In particular, our analysis echoes the earlier findings of Gyamerah (2019) and Ardia et al. (2019), highlighting the presence of regime changes and the importance of dynamic conditional correlations. While we concur with the observation that domestic policy decisions in Turkey significantly influence shocks in the BIST 100 index, we extend the narrative by demonstrating the remarkable impact of the Covid-19 pandemic on both domestic and international financial markets. Moreover, our study reaffirms the dynamic relationship between Bitcoin and global indices, especially the NASDAQ 100, with a negative dynamic conditional correlation, in line with the findings of Naimy and Hayek (2018), and Segnon and Bekiros (2020).

In summary, our research not only underscores the continued relevance of cryptocurrency analysis in the context of global financial markets, but it also underscores the evolving nature of these relationships, particularly during times of significant economic disruption such as the Covid-19 pandemic. By delving into the dynamics of Bitcoin's interaction with both emerging and developed market indices, we provide a nuanced perspective on the evolving role of cryptocurrencies in the modern financial landscape.

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