STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **number**, Month 2026, pp 1–22.
Published online in International Academic Press (www.IAPress.org)

Using the First Difference, Forward Orthogonal Deviations, and System GMM Techniques to Measure the Impact of Environmental, Social and Governance Performance on Financial Risks for Companies listed on the S & P EGX/ESG index

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Abstract This paper proposes the use of the first difference generalized method of moments (FD-GMM), forward orthogonal deviations generalized method of moments (FOD-GMM), and system generalized method of moments (Sys-GMM) techniques to measure the impact of environmental, social, and governance (ESG) performance criteria as independent variables and return on total assets (ROA), leverage (LEV), liquidity (LIQ), firm growth rate (FGR), and size of enterprise (SIZE) as control variables on the financial risks as dependent variables, which can be measured by Altman's Z-score index. This study applied to seventeen companies of non-financial institutions which comply with sustainability standards and there are in S & P EGX / ESG index in Egypt that include various sectors in the period from 2020 to 2024. The study used consistent, valid instruments and coefficient bounds tests to select the best model. The results showed that the two step FOD-GMM model was the most effective model to estimate the relationship between ESG-score, G-score, and control variables on financial risks compared to the FD-GMM and System-GMM models .It was more suitable and safer for small sample that used in this study, in addition they have valid instruments and consistent estimators. It has also a higher predictability compared to other models.

Keywords Environmental, social and governance (ESG) index; Financial risks; Pooled least squares (POLS) ; Fixed Effects Model (FEM); First difference-Generalized method of moments (FD-GMM) ; Forward orthogonal deviations - Generalized method of moments (FOD-GMM); System - Generalized method of moments (Sys-GMM).

AMS 2010 subject classification: 62P20, 62P12, 62P25, 78M05, 91B05, 62H12, 39A13.

DOI:10.19139/soic-2310-5070-3636.

1. Introduction

Risk is one of the main factors used in evaluating the financial performance of companies and can be defined as the degree of fluctuation in return or the inability to predict future return as a result of the difference between the expected return and the actual return. According to corporate governance theory, companies cannot ignore risks or change their levels randomly, but must understand how to deal with them effectively. It is certain that companies face different levels of risk in different areas of their activity. In this context, the capital asset pricing model. Sharpe [28] indicated that there are two types of risks to which companies are exposed. The first is systematic risk, which refers to external factors that fall outside the scope of control such as political, economic, legal, social, and financial market factors. These risks are also known as non-verifiable risks or market risks, and are measured using the beta coefficient (β). The second type is non-systematic risk (Idiosyncratic Risk), which is the risk specific to each company individually, and falls within the scope of the company's control, and is called diversified risk

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

such as technological, financial, and marketing changes. In order to achieve the Sustainable Development Goals, companies should analyze private risks by incorporating non-financial performance indicators as well as financial performance. The most prominent of these indicators are: environmental and social performance and governance (ESG). Standards (ESG) are one of the main determinants that affect the magnitude of companies' risks Alkaraan et al[3]and Bilyay-Erdogan et al[9].From the perspective of agency theory and risk interests theory, evidence suggests that companies that achieve high results in environmental, social, and governance performance have a greater chance of reducing the risks they face by improving their relationships with stakeholders, which leads to improved financial performance. The Environmental, Social and Governance Practices Report (ESG) is a comprehensive tool that reflects the ability of corporate management to apply sustainable development principles and achieve its goals, and provides actionable reports to decision-makers and stakeholders. The report covers three main practices related to environmental performance in operations, control, carbon emissions, energy use, and water consumption. Social performance practices include gender diversity, worker turnover, combating discrimination, applying global health and safety standards, protecting children's rights, and ensuring workers' rights. While governance performance practices include board diversity, combating bribery and corruption, adhering to ethical behavior, principles of honor, protecting data privacy, and reporting sustainability privacy. In this context, the Egyptian Stock Exchange cooperated with the Institute of Egyptian Directors (E Foundation to launch the S&P EGX/ESG index), which is the second index at the level of emerging markets after the successful launch of the index in India S&P India/ESG. In this initiative, the Egyptian Stock Exchange shows its interest in modern global trends in financial markets, which increasingly emphasis sustainable development standards. This led to the integration of environmental and social performance and governance practices from a sustainability perspective into the corporate reports of publicly listed companies.Therefore, the motivation and main contributions of this paper are represented as follows:(1) Analyzing the impact of environmental, social, and governance performance on the financial risks of companies listed on the Egyptian stock market. (2) Predicting financial risks in companies with high ratings and low ratings included in the ESG index. As for the practical importance of the study, environmental and social performance and governance (ESG) issues are among the important challenges facing companies in applying the practices of these areas within the framework of sustainable development in line with the Sustainable Development Goals (SDGs). These practices help restore investor confidence and motivate them to make informed investment decisions by identifying investment risks and opportunities. The paper can be utilized to connect financial and non-financial performance as part of the company's strategy. As for the scientific importance, it is represented in shedding light on the financial risks of companies listed on the ESG Stock Exchange Index, which is a fundamental pillar of the country's economic performance and social development, in addition to the scarcity of researches that introduced the impact of ESG scores on the risks of these companies in Egyptian society.

2. Literature review

Feng et al[15]; Luo et al [20] studied the effects of environmental, social, and governance (ESG) ratings on the risk of stock price collapse among listed Chinese companies using the fixed effects model (FEM) and robustness test. They found that there is a negative significant correlation between ESG ratings and the risk of stock price collapse for Chinese companies. The results proved that higher ESG ratings reduce the likelihood of stock price collapse risk in these companies. It has also been shown that the environmental, social, and governance dimensions and the risk of stock price collapse have an increasingly important correlation in emerging stock markets. From 2002 to 2018. Neitzert and Petras[22] examined a sample of 582 banks around the world using multivariate linear constant effects (FE) regression models to measure the impact of corporate social responsibility and environmental activities on banks' risk management. The results also showed that there is an impact of corporate social responsibility activity in reducing risks at the overall level; Then environmental activities and governance did not achieve the same results. Medane [21] applied panel data models to S&P 500 companies from 2012 to 2023, and found a statistically significant negative relationship between ESG performance and stock returns of these companies, as well as a positive relationship between ESG scores and asset return/equity return. Cerqueti et al[12] used a network analysis to illustrate how funds at different levels interact with environmental, social, and governance dimensions with the risk of contagion resulting from rapid sales of cross-fund assets. This is the first attempt to analyze environmental, social, and governance investment from a systemic point of view. According to this analysis, funds with a higher ESG rating experience a less significant loss in the relative market value than their counterparts with a lower ESG rating. Octavian and Utama [23] applied a multiple regression model using the ordinary least squares (OLS) method and found that there is no effect of ESG on the risk of stock collapse in Indonesian energy companies. Silva[27] reached the same result; she stated that ESG is less effective in developing countries such as Indonesia; this led to weak investor protection and enforcement of regulations. Gupta et al[16]also used the ordinary least squares method to measure the impact of ESG on risk in Indian consumer goods companies. The Mann - Whitney U test was used to compare the risks of companies with high ESG scores and low ESG scores and showed that highly rated companies had lower overall and unsystematic risks. Regression results showed that systematic, unsystematic, and aggregate risks were negatively associated with the composite ESG score. Saidane and Abdallah[26] used the panel vector auto-regressive model (PVAR) to find out whether there is a causal relationship between the risk of a company defaulting and corporate social responsibility in addition to the environmental dimension in African companies or not. Their findings revealed a one-way relationship between them. They also found that there is a positive and significant impact of corporate stability on corporate social responsibility, and that environmental performance has a negative and significant impact on corporate stability. Eratalay and Cortés [14] also analyzed the systemic risks of the S&P Europe 350 component inventories for the period January 2016-September 2020 and applied the VAR-MGARCH model and the principal components analysis (PCA) to estimate the volatility and correlations between the yield shocks of these inventories. The impact of environmental, social, and governance classifications on systemic risk indicators was measured using fixed effects models (FEM) and pooled least squares (POLS). The results showed that companies with higher ESG ratings reduce systemic risk compared to companies with lower ratings. Taskin et al[29] used machine learning-based algorithms: decision tree (DT), random forest (RF), K-nearest neighbor (KNN), and logistic regression (LR) to predict future ESG scores as a determinant of future ESG performance based on current ESG scores in Turkish companies. The results have proved that previous ESG scores are reliable predictors of future ESG performance. Wang et al [30] proposed a stacked generalization model that employs random forest (RF), gradient Boosting decision tree (GBDT), extreme gradient boosting (XGBoost), and light gradient boosting machine (LightGBM) as base learners, with Bayesian ridge regression (BRR) as the meta-model for integrating the predictions of these diverse models to develop an ESG scores prediction model for Chinese companies. According to the findings, SGM-BRR is the most effective model for predicting ESG scores. Bhandari et al[8] proposed a framework to implement architectures of deep learning (DL) machines, specifically long-short term memory (LSTM), gated recurrent unit (GRU), and convolutional neural network (CNN) models to predict the volatility of the ESG index. Furthermore, a series of statistical analyses was conducted to validate the robustness and reliability of the model. Experimental results showed that the LSTM model is the best model to fit high prediction accuracy relative to comparing it with more complex models. Chen[13] also compared the auto-regressive integrated moving averages (ARIMA) model with the long-short term memory (LSTM) model for predicting ESG factors. The results indicated a clear superiority of the LSTM model over ARIMA. This paper also provides practical insights for investors and policymakers interested in integrating environmental, social, and governance considerations into investment strategies and economic planning. Handoyo[17]investigated whether (ESG) performance statistically meaningful effects on corporate outcomes .The study used 2156 publicly listed firms (2016–2023) across North America, South America, Europe, Asia, and Oceania. The paper has applied fixed-effects instrumental-variables (IV) model (FEM-IV) and system generalized method of Moments (Sys-GMM) models The static IV estimates indicate that environmental and social performance are positively associated with both accounting profitability (ROA) and market valuation (Tobin's Q), whereas governance performance is not statistically significant in contemporaneous specifications. HansenandXie[18] investigated the impact of Overall ESG and individual Disclosure scores on the financial performance of publicly traded companies in Post-Soviet EU states, specifically focusing on Return on Assets (ROA), Return on Equity (ROE), and Return on Investment (ROI) using multiple linear regression model and a sample of 245 firms . The findings reveal that neither overall ESG nor individual Disclosure scores significantly affect ROA, ROE, or ROI. Notably, the Environmental Disclosure Score shows a negative but non-significant relationship with financial performance, while the Social and Governance Disclosure Scores also lack statistically significant effects.Alabi[1] It aimed to study the contribution of ESG disclosure to creating company value. The study was based on secondary data from the annual and sustainability reports of 94 sample companies listed on the Nigerian Stock Exchange (NGX) Group from 2016 to 2022. The results of the generalized momentarily differential method (GMM) regression revealed a significant positive relationship between ESG disclosure and firm value creation. The results of the dynamic threshold model indicate positive nonlinear effects of ESG disclosure on firm value in firms with low governance practices. However, the effect is significantly magnified in firms that exhibit higher governance effectiveness. Adardour et al[2]aimed to provide an updated systematic review on the relationship between Environmental, Social, and Governance (ESG) performance and firm risk. Our results reveal that most studies report a negative association between ESG practices and financial and market risks. However, results vary according to ESG dimensions, risk types, and contextual factors such as company size, region, macroeconomic factors, and industry sector. Parveen[24]examined how to integrate (ESG) factors to improve financial decision-making, and emphasized how (ESG) considerations affect business transparency, long-term corporate value development, and risk management. The study found that issues related to standardization, data quality, and green washing risks are among the difficulties that come with integrating ESG standards. This paper concludes with brief recommendations for policymakers and financial institutions to enhance the integration of environmental, social, and governance factors, with a focus on improving regulatory frameworks, increasing transparency, and consistent reporting standards. Asmiand Wong[6]found that sustainability is a main topic in the ESG and risk literature, especially with the recent shift towards governance structure and performance evaluation. It emphasized the role of environmental, social and governance (ESG) in resilience, risk management and value creation. These results demonstrate the importance of integrating sustainability into the decision-making process in companies.

Table 1.The non-financial companies that are listed on the S&P EGX/ESG index of the Egyptian Stock Exchange (1)

ISIN	Reuters Code	Company Name
EGS305I1C011	EFID.CA	Edita Food Industries S.A.E
EGS30901C010	JUFO.CA	Juhayna Food Industries
EGS33041C012	ORWE.CA	Oriental Weavers
EGS33321C018	DSCW.CA	Dice Sport & Casual Wear
EGS380S1C017	SKPC.CA	SidiKerir Petrochemicals - SIDPEC
EGS38191C010	ABUK.CA	AbouKir Fertilizers
EGS381B1C015	RMDA.CA	Tenth Of Ramadan Pharmaceutical Industries & Diagnostic-Rameda
EGS38211C016	MICH.CA	Misr Chemical Industries
EGS39061C014	MFPC.CA	Misr Fretilizers Production Company - Mopco
EGS3C161C014	LCSW.CA	Lecico Egypt
EGS3E181C010	EGAL.CA	Egypt Aluminum
EGS42051C010	ETRS.CA	Egyptian Transport (EGYTRANS)
EGS490S1C014	TAQA.CA	Taqa Arabia
EGS512O1C012	ISPH.CA	Ibnsina Pharma
EGS65851C015	OCDI.CA	Six of October Development & Investment (SODIC)
EGS673T1C012	GBCO.CA	GB Corp
EGS673Y1C015	EMFD.CA	Emaar Misr for Development
EGS690C1C010	RAYA.CA	Raya Holding For Financial Investments
EGS69101C011	HRHO.CA	EFG Holding
EGS691G1C015	BTFH.CA	Beltone Holding
EGS73541C012	CCAP.CA	QALA For Financial Investments
EGS74191C015	RACC.CA	Raya Contact Center
EGS95001C011	ORAS.CA	Orascom Construction PLC

(*) Egypt for information Dissemination- EGID, https://www.egidegypt.com.

The limits of the current paper are represented by non-banking companies listed on the stock market that submitted detailed reports on their annual practice of environmental and social performance and ESG governance, and companies affiliated with banks and financial services were excluded due to the difference in the nature of the activity of these companies and the legal requirements to which they are subjects. The number of companies of the sample in this paper reached seventeen out of twenty-three non-financial companies for which data were available. The total number of financial and non-financial companies that follow the S&P EGX / ESG index is thirty companies. The time period data of these companies from practice reports is the period from 2020 to 2024.

Table 1. Shows these non-financial companies and the study variables in Table 2. They are the company's financial risks (FR_{it}) which are measured using Altman's Z-score model, which was developed by the American scientist Edward Altman in 1968 as a measure of the company's probability of bankruptcy. The company's Z-score model combines five financial prediction ratios, and this variable can be calculated using the following equation:

$$Z- \text{ score } = 1.2 \text{ A} + 1.4 \text{ B} + 3.3\text{C} + 0.6\text{D} + 1.0\text{E} \quad (1)$$

Where (Z-score) represents a financial measure that assesses the company's bankruptcy risk. The components of Z-score index as follow: (A) represents working capital divided by total assets. A higher ratio indicates that the company has sufficient liquidity to cover its short-term obligations, which is a positive indicator of continuity and the ability to invest to achieve growth. (B) represents retained earnings divided by total assets. A higher ratio indicates that the company is profitable over time. (C) represents EBIT divided by total assets, which indicates more operating profit per dollar of total assets. (D) represents the market value of shares divided by total liabilities, which indicates that the company has more shares to absorb losses. (E) represents a measure of the company's ability to convert assets into sales, which is represented by total sales divided by total assets. The independent variables are environmental, social, and governance score ($ESG - score_{it}$), environmental and social score ($ES-$ score $_{it}$), and social score ($G-$ score $_{it}$). As for the control variables, they are: company size(Size $_{it}$), financial leverage (LEV_{it}), firm growth rate (FGR_{it}), rate of return on assets (ROA_{it}), and liquidity (LIQ_{it}).

Table 2. The study variables and their measurement methods [(*)]

Type	Variable name and symbol	Measurement
Dependent variables	Financial Risks (FR)	Z - score $= 1.2 \text{ A} + 1.4 \text{ B} + 3.3\text{C} + 0.6\text{D} + 1.0\text{E}$ A = Working Capital ÷ Total Assets B = Retained Earning ÷ Total Assests C = Profits before interest and tax ÷ Total assets D = Market Value of Equity ÷ Total Liabilities E = Total Sales ÷ Total assets
Independent variables	ESG performance (ESGscore) Environmental and social Scores (ES-score) Governance score (G-score)	According to Hua Zheng ESG rating, the assignment is 1-9 from low to high Environmental and social disclosure scores Governance disclosure score
Control variables	Return on assets (ROA) Leverage (LEV) Liquidity(LIQ) Firm growth rate (FGR) Size of enterprise (Size)	ROA = Corporate net profit ÷ total assets LEV = Total liabilities + total assets LIQ = Current assets ÷ current assets Growth = ((Current Profit - Past Profit) ÷ Past Profit)) *100 Natural logarithm of total assets of the enterprise

(*)Source: Egypt for information Dissemination-EGID, https://www. egidegypt.com & https://www.mubasher.info/countries/sa.

The equation (2) shows the relationship between Z-score, ESG-score, and control variables as follows:

Z-score $_{it}=\alpha_0+\alpha_1$ Z-score $(-1)_{1i}+\alpha_2$ ESG-score $_{it}+\alpha_3$ ROA $_{it}+\alpha_4 LEV_{it}+\alpha_5 LIQ_{it}+\alpha_6 FGR_{it}$ $+\alpha_7$ Size $_{it}+\varepsilon_{1it}$ ..... (2)

The equation (3) shows the relationship between Z-score, ES-score, and control variables as follows:
Z-score $_{it}=\beta_0+\beta_1$ Z-score $(-1)_{1it}+\beta_2$ ES-score $_{it}+\beta_3 ROA_{it}+\beta_4 LEV_{it}+\alpha_5 LIQ_{it}+\beta_6 FGR_{it}$ $+\beta_7$ Size $_{it}+\varepsilon_{2it}$ ..... (3)

The equation (4) shows the relationship between Z -score, G-score, and control variables as follows:
Z-score $_{it}=\mu_0+\mu_1$ Z-score $(-1)_{1it}+\mu_2$ G-score $_{it}+\mu_3$ ROA $_{it}+\mu_4 LEV_{it}+\mu_5 LIQ_{it}+\mu_6 FGR_{it}$ $+\mu_7$ Size $_{it}+\varepsilon_{3it}$ ..... (4)
The study assumed a set of hypotheses which are empirical expectations, not theoretical certainties as follows:
$\mathbf{H}_1$: There is a significant relationship between total environmental, social, and governance (ESG-score) performance and Z-score.
$\mathbf{H}_2$: There is a significant relationship between total environmental and social performance (ES-score) and Z-score.
$\mathbf{H}_3$: There is a significant relationship between governance performance (G -score) and Z-score.
$\mathbf{H}_4$:There is a significant relationship between ROA, LEV, LIQ, FGR and SIZE and Z-score.
$\mathbf{H}_5$:It is expected that the FOD-GMM has a better efficiency than FD-GMM and System-GMM.
$\mathbf{H}_6$:It is expected that the FOD-GMM has a higher predictability than FD-GMM and System-GMM.

3. Materials and methods

3.1. Generalized method of moments (GMM)

3.1.1. First-difference GMM (FD-GMM) transformation.

Dynamic panel data regression is a regression method that adds lag to dependent variables and makes independent variables. Hendayanti et al[19]. The model's equation can be written in equation (5):

$$y_{i,t}=\delta y_{i,t-1}+x'_{i,t}\beta+\varepsilon_{i,t} \tag{5}$$

Where i represents the values $1,2,3,\ldots n$ and t values $1,2,3,\ldots T$, the index i displays the cross-sectional dimensions, while the t index shows the time series dimensions. If $y_{i,t}$ is a function of $\varepsilon_{i,t}$, then $y_{i,t-1}$ is also a function of $\varepsilon_{i,t}$. The regressor on the right side (explanatory endogenous) $y_{i,t-1}$ correlates with $u_{i,t}$. Static panel estimation models such as OLS in dynamic panel equation models will be biased and inconsistent. Baltagi [7]. First, the difference can overcome the correlation problem between the lag of bound variables and the error component. This aims to eliminate the individual effects of μ_i on the model. By making the first difference in the dynamic panel model above, it can be written as equation (6):

$$y_{i,t}-y_{i,t-1}=\delta\left(y_{i,t-1}-y_{i,t-2}\right)+\left(\varepsilon_{i,t}-\varepsilon_{i,t-1}\right) \tag{6}$$

With i values $1,2,3,\ldots n$ and t values $1,2,3,\ldots T$. Therefore, the variable instrument matrix for the first differencing model is defined in equation (7):

$$Z_{\text{diff}}=\begin{pmatrix} [\Delta y_{i,2}] & 0 & \cdots & 0 \\ 0 & [\Delta y_{i,3}] & \vdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & [\Delta y_{i,T-2}] \end{pmatrix} \tag{7}$$

Parameter estimation by Arellano and Bond[5] uses the GMM principle to obtain a consistent estimate. GMM estimator for δ to be obtained by minimizing the square function.

$$\widehat{\delta}=\left[\left(N^{-1}\sum_{i=1}^{N}Z_i\Delta y'_{i,t-1}\right)\widehat{W}\left(N^{-1}\sum_{i=1}^{N}Z'_i\Delta y_{i,t-1}\right)\right]^{-1}\left[\left(N^{-1}\sum_{i=1}^{N}Z_i\Delta y'_{i,t-1}\right)\widehat{W}\left(N^{-1}\sum_{i=1}^{N}Z'_i\Delta y_i\right)\right] \tag{8}$$

So, based on the moment of condition and the variable instrument matrix of the first differencing model above, an estimate is obtained, namely:

$$\widehat{\delta}_{\text{diff}}=\left[\left(N^{-1}\sum_{i=1}^{N}\Delta y'_{i,t-1}Z_{\text{diff}}\right)\widehat{W}\left(N^{-1}\sum_{i=1}^{N}Z'_{\text{diff}}\Delta y_{i,t-1}\right)\right]^{-1}\left[\left(N^{-1}\sum_{i=1}^{N}\Delta y'_{i,t-1}Z_{\text{diff}}\right)\widehat{W}\left(N^{-1}\sum_{i=1}^{N}Z'_{\text{diff}}\Delta y_{i,t}\right)\right] \tag{9}$$

δ is a consistent estimate for any weight matrix (W). This estimate was obtained by conducting the GMM Arellano-Bond one-step consistent estimator estimation method. So, to get a consistent estimate for δ (a two-step efficient estimator), substitute the weight W with Λ^{-1}, so that the results of the GMM Arellano-Bond estimate are as follows:

$$\widehat{\delta}_{\text{diff}}=\left[\left(N^{-1}\sum_{i=1}^{N}\Delta y'_{i,t-1}Z_{\text{diff}}\right)\widehat{\Lambda}^{-1}\left(N^{-1}\sum_{i=1}^{N}Z'_{\text{diff}}\Delta y_{i,t-1}\right)\right]^{-1}\left[\left(N^{-1}\sum_{i=1}^{N}\Delta y'_{i,t-1}Z_{\text{diff}}\right)\widehat{\Lambda}^{-1}\left(N^{-1}\sum_{i=1}^{N}Z'_{\text{diff}}\Delta y_{i,t}\right)\right] \tag{10}$$

The equation above is an unbiased, consistent, and efficient estimate of the Arellano-Bond GMM.

3.1.2. Forward orthogonal deviations generalized method of moments (FOD-GMM) transformation.

In order to estimate β, the first step is to remove the fixed effect η_i by transforming the dependent and explanatory variables. This paper studies transforming the variables using FOD transformation. Phillips [25].

The FOD transformation subtracts from each variable its within-group average over future periods. For example, the FOD transformed explanatory variables for the i th individual in the For example, the FOD transformed explanatory variables for the i th individual in the t th period are , $\ddot{x}_{i,t} := c_t\,(x_{i,t}-\bar{x}_{i,t})$, where $\bar{x}_{i,t} := 1/(T-t))\sum_{\delta=1}^{T-t} x_{i,t+s}$ and $c_t^2 := (T-t)/(T-t+1)$. Similarly, the transformed value of the $(i,t)th$ observation on the dependent variable is $\ddot{y}_{i,t} := c_t\,(y_{i,t}-\bar{y}_{i,t})$, where $\bar{y}_{i,t} := (1/(T-t))\sum_{b-1}^{T-t} y_{i,t+s}$, The constant c_t ensures the transformed errors (the $v_{i,ts}$) are conditionally homoscedastic and uncorrelated. Arellano [2]. Now let $z_{i,t}$ denote a $q_t \times 1$ vector of instrumental variables for the ith individual in the tth period $(t=1,\ldots,T-1)$ Also, set $Z'_t := (z_{1,t,\ldots,}z_{n,t})\,, \ddot{x}'_t := (\ddot{x}_{1,t},\ldots,\ddot{x}_{n,t})\,, \ddot{y}'_t := (\ddot{y}_{1,t},\ldots,\ddot{y}_{n,t})$ and finally $P_t := Z_t\,(Z'_tZ_t)\,Z'_t$. Then, the FOD GMM estimator can be written as :(see, e.g., Arellano [4].

$$\beta := \left(\sum_{t=1}^{T-1}\ddot{x}_tP_t\ddot{x}_t\right)^{-1}\sum_{t-1}^{T-1}\ddot{x}_tP_t\ddot{y}_t \tag{11}$$

As an alternative to Eq. (11), the FOD-GMM estimator can also be expressed as a two-stage least squares (TSLS) estimator after removing fixed effects with the FOD transformation. To see this, let $Z_{d,i}$ be the block-diagonal matrix given by:

$$Z_{d,i} := \begin{pmatrix} z_{i,1} & 0 & \cdots & 0 \\ 0 & z_{i,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & z_{i,T-1} \end{pmatrix} \tag{12}$$

Also, define $\dot{x}_t := (\ddot{x}_{i,1},\ldots,\ddot{x}_{i,T-1})$ and $\dot{y}_t := (\ddot{y}_{i,1},\ldots,\ddot{y}_{i,T-1})$.Then, note that:

$$\sum_{k=1}^{T-t} \ddot{x}_t P_t \ddot{x}_t = \sum_{k=1}^{n} \dot{x}_t z_{d,i} \left(\sum_{k=1}^{n} z_{d,i} z_{d,i} \right)^{-1} \sum_{k=1}^{n} z_{d,i} \dot{x}_t \tag{13}$$

Similarly,

$$\sum_{=1}^{T-t} \ddot{x}_t P_t \ddot{y}_t = \sum_{=1}^{n} \dot{x}_t z_{d,i} \left(\sum_{=1}^{n} z_{d,i} z_{d,i} \right)^{-1} \sum_{=1}^{n} z_{d,i} \dot{y}_t \tag{14}$$

From Eq.(14) and Eq.(11),we see that the FOD- GMM estimator can be expressed as a TSLS estimator after applying the FOD transformation to the dependent and explanatory variables and upon using block-diagonal instrument matrices:

$$\widehat{\beta} = \left[\sum_{i=1}^{n} \dot{x}_t z_{d,i} \left(\sum_{i=1}^{n} z_{d,i} z_{d,i} \right)^{-1} \sum_{i=1}^{n} z_{d,i} \dot{x}_t \right]^{-1} \times \sum_{i=1}^{n} \dot{x}_t z_{d,i} \left(\sum_{i=1}^{n} z_{d,i} z_{d,i} \right)^{-1} \sum_{i=1}^{n} z_{d,i} \dot{y}_t \tag{15}$$

It is well-known that TSLS is efficient GMM when the errors are conditionally homoscedastic and uncorrelated. Moreover, as already noted, if $v_{i,ts}$ is conditionally homoscedastic and uncorrelated, then the transformed errors ($\ddot{v}_{i,ts}$) are conditionally homoscedastic and uncorrelated. Hence, if $v_{i,ts}$ is conditionally homoscedastic and uncorrelated, the FOD-GMM estimator is the asymptotically efficient GMM estimator given the moment restrictions. This is a total of $E\left(z_{i,t} \ddot{v}_{i,ts}\right) = 0, (t = 1, \ldots, T-1)$. This is a total of $\sum_{t-1}^{T} q_t$ moment restrictions, which can be a large number when T is large, especially if $q_T^* := \max 1 \leq t \leq T - 1 q_t$-i.e. maximum per-period number of instrumental variables increases with T. Therefore, although the FOD-GMM estimator is efficient when the errors are conditionally homoscedastic and uncorrelated, we might anticipate it to be biased when T is not small.

3.1.3 System generalized method of moments (Sys-GMM) transformation.

The system generalized method of moments estimation method from Blundell and Bond(Sys-GMM) estimates the equation system using a combination of the first difference moment and the level condition moment. The GMM estimator δ was obtained by minimizing the squared function weighted J(δ) as in equation (11). Arellano & Bond [5].

$$\frac{\partial J(\widehat{\delta})}{\partial \widehat{\delta}} = 2 \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{\text{sys}} \right) \widehat{W} \left(N^{-1} \sum_{i=1}^{N} Z'_{\text{sys}} \varphi_i \right) \right] + 2 \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{\text{sys}} \right) \widehat{W} \left(N^{-1} \sum_{i=1}^{N} Z'_{\text{sys}} \varphi_i \widehat{\delta} \right) \right] = 0 \tag{16}$$

Then, a one-step consistent estimator is obtained for the system, namely:

$$\widehat{\delta} = \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{\text{sys}} \right) \widehat{W} \left(N^{-1} \sum_{i=1}^{N} Z'_{\text{sys}} \varphi_i \right) \right]^{-1} \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{\text{sys}} \right) \widehat{W} \left(N^{-1} \sum_{i=1}^{N} Z'_{\text{sys}} \varphi_i \right) \right] \tag{17}$$

So, a two-step efficient Blundell and Bond GMM System estimator is produced, which is as follows: Blundell and Bond [10].

$$\widehat{\delta} = \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{sys} \right) \widehat{\Psi}^{-1} \left(N^{-1} \sum_{i=1}^{N} Z'_{sys} \varphi_i, -1 \right) \right]^{-1} \left[\left(N^{-1} \sum_{i=1}^{N} \varphi'_{i,-1} Z_{sys} \right) \widehat{\Psi}^{-1} \left(N^{-1} \sum_{i=1}^{N} Z'_{sys} q_i \right) \right] \tag{18}$$

The two-step efficient Blundell and Bond GMM System Estimator estimation results in equation (18) above are more efficient than the one-step efficient Arellano and Bond Estimator. The following figure shows the analysis stages of the first-difference generalized method of moments (FD-GMM) and the system generalized method of moments (Sys-GMM). Hendayanti et al [19]. The analysis steps that will be carried out in this study are as follows: (1) Conduct descriptive statistics and a correlation matrix from financial risks data and the factors that influence it. (2) Evaluate dynamic panel data models with FD-GMM and FOD-GMM. (a) Conduct a parameter consistency test of the FD-GMM model with the Arellano-Bond test. (b) Conducting a valid instrument test using the Sargan test. (c) Perform an unbiased test by calculating the parameters of the pooled least squares and fixed effect models and comparing them with the estimator values obtained from the FD-GMM and FOD-GMM models. (3) Evaluate dynamic panel data models with Sys-GMM. (a) Conducting a Sys-GMM model parameter consistency test with the Arellano-Bond test. (b) Conducting a valid instrument test using the Sargan test. (c) Carry out an unbiased test by calculating the parameters of the pooled least square and fixed effect models and comparing them with the estimator values obtained from the FD-GMM, FOD-GMM and Sys-GMM models. (4) Determine the best panel model between FD-GMM, FOD-GMM and Sys-GMM models based on the criteria of parameter consistency, valid instruments, and unbiased parameters. (5) Performing parameter significance testing as well as the best model interpretation. (6) Making conclusions based on the best model obtained.

4. Results and discussion

4.1. Descriptive statistics for Z-score and ESG ratings and control variables

The following table shows the descriptive statistics for all the study variables, as the arithmetic mean of the Z -score index was equal to 1.8, which assesses the financial risks and the extent of exposure of non-financial companies to the S&P EGX/ESG index at bankruptcy risks, which is a value close to 3, indicating that most companies are in a strong financial position, and the maximum value of these risks reached 11 and the lowest value was -0.70 .

Table 3. Descriptive statistics for Z-score, ESG ratings and control variables

	Bankruptcy Rating		ESG Ratings		Control Variables				
	Z-score	ESG-score	ES-score	G-score	ROA	LEV	LIQ	FGR	SIZE
Mean	1.80	92.70	64.8	27.90	0.00	0.60	2.40	-98.5	22.8
Median	1.40	90.0	65.0	25.0	0.00	0.60	1.60	30.5	22.9
Maximum	11.0	100.0	68.0	35.0	0.00	1.60	15.2	1962	25.7
Minimum	-0.70	86.0	61.0	23.0	0.00	0.00	0.70	-14092	18.6
Std. Dev.	1.90	4.60	1.0	4.5	0.00	0.30	2.30	1558.1	1.60
Skewness	2.70	0.70	-1.7	0.7	6.30	1.10	3.70	-8.6	-0.4
Kurtosis	12.6	1.80	11.7	1.7	40.9	5.00	19.3	78.4	2.70
Jarque-Bera	428	11.9	308	13.1	5661	32.4	1138	21200	2.60
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30
Sum	150	7883	5510	2374	0.1	52.7	202.4	-8369	1937
Observations	85	85	85	85	85	85	85	85	85

It is also clear that the ESG-Score average reached 92.7,The lowest value was 86 and the highest value was 100. The high minimum and maximum ESG-score sustainability index also reflects strong performance for companies. The ES-Score average reached 64.8, which indicates that the performance standards of companies in these cases will be good. It also turns out that the highest value is 68 and the lowest value is 61. It was found that the arithmetic mean of the performance index scores for the governance criterion is 27.9 ; its lowest value was 23 and its highest value was 35 . We note that the average return on assets (ROA) was 0.00 and the highest and lowest value were approximately the same value. The average of leverage (LEV) was approximately 0.6; the highest value was 1.6 and the lowest value was 0.00 . While the arithmetic mean of the liquidity (LIQ) index was 2.4 , the highest value was 15.2, and the lowest value was 0.7. We note that the arithmetic mean of the company's growth rate index (FGR) deviates greatly from its highest and lowest value, and this is explained by the high standard deviation of this index. Finally, it becomes clear to us that the arithmetic mean of the SIZE company size index was 22.8, its lowest value was 18.9 , and its highest value was 25.7 .The high standard deviation in the Z-score may be due to many factors such as economic and global events that occurred in the period from 2020 to 2024, such as the Covid-19 crisis, the change in global currency rates, and fluctuations in interest rates, in addition to the Russian - Ukrainian war, which affected the Egyptian economy as a whole. As for the normal distribution of time series, all variables do not follow the normal distribution, as is clear from the probability value of the Jarque-Bera test statistics, except for the company size which follows the normal distribution. We note that the condition of normality is not a basic condition or requirement in comparing the capabilities of the FD-GMM, FOD-GMM, and Sys-GMM models, and its performance is poor with small samples.

4.2. Correlations matrix between Z-score, ESG ratings, and control variables

In table (4), before discussing the statistical model's estimation of FD-GMM, FOD-GMM, and Sys-GMM estimators, it is necessary to conduct a correlation matrix between the study parameters, especially the explanatory variables, to avoid the emergence of autocorrelation problems between the residuals of the estimation, so that the

Table 4. Correlations Matrix between Z-score and ESG Ratings and Control Variables

Variable	Z-score	ESG-score	ES-score	G-score	ROA	LEV	LIQ	FGR	SIZE
Z-score	1.00	-0.06	0.00	-0.06	-0.10	-0.56	0.11	-0.17	-0.13
ESG-score	-0.06	1.00	0.19	0.97	-0.10	0.08	-0.12	0.10	-0.18
ES-score	0.00	0.19	1.00	0.04	0.03	-0.01	-0.04	-0.03	-0.16
G-score	-0.06	0.97	0.04	1.00	-0.11	0.09	-0.10	0.10	-0.16
ROA	-0.10	-0.10	0.03	-0.11	1.00	0.07	-0.07	0.02	-0.39
LEV	-0.56	0.08	-0.01	0.09	0.07	1.00	-0.31	-0.01	-0.02
LIQ	0.11	-0.12	-0.04	-0.10	-0.07	-0.31	1.00	-0.08	-0.11
FGR	-0.17	0.10	-0.03	0.10	0.02	-0.01	-0.08	1.00	0.03
SIZE	-0.13	-0.18	-0.16	-0.16	-0.39	-0.02	-0.11	0.03	1.00

obtained model is not false and does not reflect the true relationship between the study variables, and also to avoid the problem of double steps of the estimated models. The results of the following table show that there is no multicollinearity between the regression variables due to the lack of a strong correlation between the interpreted variables. This is considered good for estimating the model.

4.3. Estimation of FD-GMM, FOD-GMM and Sys-GMM transformations

4.3.1 Estimation of FD-GMM transformation for Z-score and ESG-score

In table (5), the pooled least squares (POLS) model shows that there is a significant relationship between the Z-score index. Which measures the financial risks of companies, and Z-score (-1), LEV, and FGR. The other variables, such as ESG-score, ROA, LIQ, and SIZE were insignificant, In addition to the constant. The explanatory ability of this model was also high as the adjusted coefficient of determination is equal to 0.76 and the all-model was significant where the prob(F-statistic) was equal to (0.000). The model also showed almost no serial correlation between the residuals, as the Durbin-Watson statistic test value appeared close to two. In the fixed effects model (FEM), it was found that there is a significant relationship between the Z-score index and Z-score (-1), ROA, FGR, and SIZE, In addition to the constant. The other variables, such as ESG-score, LEV, and LIQ, were insignificant. The explanatory ability of this model was also high as the adjusted coefficient of determination is equal to 0.82 and the all- model was significant where the prob(F-statistic) was equal to (0.000). Almost no serial correlation between the residuals that found in the model, where the Durbin-Watson stat test value was 2.182 . The one-step FD-GMM model found that there is a significant relationship between the Z-score index and FGR only. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 5 indicate that the p-value is $0.836 > 0.05$, which means that the instruments are valid. The Arellano-Bond test was used to determine the association between residuals in the one-step FD-GMM model. The autocorrelation test result in table 5 showed the value of AR (1) test results had a probability value of $0.5993 > 0.05$, and the AR (2) test result had a probability value of $0.971 > 0.05$. This means that estimation using the one-step FD-GMM approach is consistent. Based on table 5, the Z-score (-1) variable in the one-step FD-GMM model was 0.372. In the fixed effect model was 0.360 , but it was 0.572 in the pooled least squares model, which means that $0.360 < 0.372 < 0.572$ and this means that the estimator lies within plausible bounds. This is a necessary condition but not sufficient condition for reduced bias. Bond[11]The two-step FD-GMM model was found to show that there is a significant relationship between the Z-score index and Z-score(-1),LEV and FGR. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 5 indicate that the p-value is $0.168 > 0.05$, which means that the instruments are valid. The Arellano-Bond test was used to determine the association between residuals in the two-step FD-GMM model. The autocorrelation test results in table 5 showed that the value of AR (1) test results had a probability value of $0.2485 > 0.05$, but the value of AR(2) test is equal to N/A. The reason for this result is that the sample is small and insufficient, so we can consider that two-step FD-GMM model is inconsistent. Based on table 5, the Z-score(-1) variable in the two step FD-GMM model was 0.372 , in the fixed effect model was 0.360 , but it was 0.572 in the pooled least squares model, which means that $0.360 < 0.372 < 0.572$ and this means that the estimator lies within plausible bounds.

Table 5. Estimation of FD-GMM transformation for Z-score and ESG-score.

Environmental and Social (ESG-Score)								
	POLS		FEM		One-step FD-GMM		Two-step FD-GMM	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Z-score(-1)	0.572	0.000**	0.360	0.000**	0.372	0.204	0.372	0.001**
ESG	-0.009	0.712	-0.051	0.066	0.054	0.387	0.021	0.552
ROA	-28.71	0.340	-211	0.014**	109.3	0.653	46.39	0.518
LEV	-0.914	0.028**	-2.101	0.066	-4.897	0.155	-5.463	0.023**
LIQ	-0.054	0.287	0.005	0.931	-0.013	0.875	0.011	0.356
FGR	0.000	0.000**	0.000	0.000**	0.000	0.038**	0.000	0.001**
SIZE	-0.078	0.271	-0.674	0.008**	-0.343	0.248	-0.285	0.268
C	3.881	0.219	22.491	0.005**				
R-squared	0.785		0.878					
Adjusted R-squared	0.759		0.815					
F-statistic	31.218		13.825					
Prob(F-statistic)	0.000		0.000					
Durbin-Watson stat	1.879		2.182					
J-statistic					2.092		7.799	
Prob(J-statistic)					0.836		0.168	
Instrument rank					12		12	

Arellano-Bond Serial Correlation Test				
	One-step FD-GMM		Two-step FD- GMM	
Test order	m-Statistic	Prob.	m-Statistic	Prob.
AR(1)	-0.525337	0.5993	-1.154095	0.2485
AR(2)	0.036521	0.9709	NA	NA

Source: data introduced by E-views v.13, note that *,**and *** are the significant levels of $1\%, 5\%$ and 10%.

4.3.2 Estimation of FD-GMM transformation for Z-score and ES-score.

In table (6), the pooled least squares (POLS) model shows that there is a significant relationship between the Z-score index, which measures the financial risks of companies, and Z-score (-1), LEV, and FGR. The relationship between Z-score index and remaining variables was insignificant.

Table 6. Estimation of FD-GMM transformation for Z-score and ES-score.

Environmental and Social (ES-Score)								
	POLS		FEM		One-step FD-GMM		Two-step FD-GMM	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Z-score(-1)	0.575	0.000**	0.364	0.000**	0.378	0.355	0.410	0.002**
ES-score	0.032	0.737	0.007	0.959	2.671	0.492	3.294	0.193
ROA	-26.097	0.378	-122.7	0.106	33.567	0.907	-92.29	0.349
LEV	-0.892	0.033**	-1.476	0.203	-8.601	0.288	-8.313	0.043**
LIQ	-0.047	0.340	0.010	0.865	0.023	0.686	0.034	0.226
FGR	0.000	0.000**	0.000	0.000**	0.000	0.686	0.000	0.865
SIZE	-0.068	0.334	-0.420	0.067	0.387	0.632	0.541	0.294
C	0.736	0.913	11.103	0.330				
R-squared	0.784			0.869				
Adjusted R-squared	0.759			0.800				
F-statistic	31.202			12.648				
Prob(F-statistic)	0.000			0.000				
Durbin-Watson stat	1.874			2.019				
J-statistic						0.332		5.871
Prob(J-statistic)						0.997		0.319
Instrument rank						12		12
Arellano-Bond Serial Correlation Test								
One-step First difference GMM					Two -step First difference GMM			
Test order	m-Statistic			Prob.		m-Statistic	Prob.	
AR(1)	0.600			0.549		0.985		0.325
AR(2)	-0.215			0.830		-2.635		0.008

Source: data introduced by E-views v.13, note that *,**and *** are the significant levels of $1\%, 5\%$ and 10%.

The explanatory ability of this model was also high as the adjusted coefficient of determination is approximately equal to 0.76 , and the all-model was significant where the prob (F-statistic) was equal to (0.000). The model also showed almost no serial correlation between the residuals, as the Durbin-Watson statistic test value appeared close to two. In the fixed effects model(FEM), it was found that there is a significant relationship between the Z-score index and Z-score (-1) and FGR. The other variables were an insignificant. The explanatory ability of this model was also high as the adjusted coefficient of determination is equal to 0.80 , and the all-model was a significant where the prob(F-statistic) was equal to (0.000). Almost no serial correlation between the variables was found in the model, as the Durbin-Watson stat test value was 2.019. The one-step FD-GMM model found that there was an insignificant relationship between the Z-score index and all variables. The Sargan test results in table 6 indicate that the p-value is $0.997 > 0.05$, which means that the instruments are valid. The Arellano-Bond test was used to determine the association between residuals in the one-step FD-GMM model. The autocorrelation test result in table 6 showed that the value of AR (1) test result had a probability value of $0.549 > 0.05$, and the value of AR (2) test had a probability value of $0.830 > 0.05$. This means that estimation using the one-step FD-GMM approach is consistent. Based on table 6, the Z-score (-1) variable in the one-step FD-GMM model was 0.378 , in the fixed effect model was 0.364 , but it was 0.575 in the pooled least squares model, which means that $0.364 < 0.378 < 0.575$ and this means that the estimator is good and it lies within plausible bounds. The two-step FD-GMM model found that there is a significant relationship between the Z-score index and Z-score(-1) and LEV. The relationship between

Z-score index and the other variables were insignificant. The Sargan test results in table 6 indicate that the p-value is $0.319 > 0.05$, which means that the necessary criteria for the valid instrument have been met. The Arellano-Bond test was used to determine the association between residuals in the two-step FD-GMM model.The autocorrelation test results in table 6 showed that the AR (1) test result had a probability value of $0.325 > 0.05$,but the value of AR(2) test is $0.008 < 0.05$. This means that estimation using the two-step FD-GMM approach is inconsistent. Based on table 6, the Z-score (-1) variable in the two-step FD-GMM model was 0.410 , in the fixed effect model was 0.360 , but it was 0.572 in the pooled least squares model, which means that $0.360 < 0.410 < 0.572$ and and this means that the estimator lies within plausible bounds.

4.3.3 Estimation of FD-GMM transformation for Z-score and G-score.

In table (7), the pooled least squares (POLS) model shows that there is a significant relationship between the Z-score index and Z-score (-1), LEV, and FGR. The relationship between Z-score index and remaining variables was insignificant. The explanatory ability of this model was also high as the adjusted coefficient of determination is approximately equal to 0.76 , and the all-model was a significant where the prob (F-statistic) was equal to (0.000).

Table 7. Estimation of FD-GMM transformation for Z-score and G-score.

Governance (G-Score)								
	POLS		FEM		One-step FD-GMM		Two-step FD-GMM	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Z -score(-1)	0.572	0.000**	0.361	0.000**	0.378	0.220	0.383	0.001**
G-score	-0.008	0.743	-0.053	0.068	0.063	0.419	0.029	0.436
ROA	-28.431	0.345	-211.34	0.014**	147.999	0.607	33.59	0.731
LEV	-0.906	0.030**	-2.122	0.065	-4.876	0.170	-5.345	0.028**
LIQ	-0.053	0.294	0.007	0.904	-0.014	0.858	0.010	0.428
FGR	0.000	0.000**	0.000	0.000**	0.000	0.057	0.000	0.001**
SIZE	-0.076	0.276	-0.674	0.008**	-0.314	0.292	-0.289	0.258
C	3.234	0.105	19.221	0.004**	0.378	0.220	0.383	0.001**
R-squared	0.785		0.878					
Adjusted R-squared	0.759		0.815					
F-statistic	31.198		13.810					
Prob(F-statistic)	0.000		0.000					
Durbin-Watson stat	1.879		2.195					
J-statistic					1.774		7.622	
Prob(J-statistic)					0.879		0.178	
Instrument rank					12		12	

Arellano-Bond Serial Correlation Test				
One-step First difference GMM			Two-step First difference GMM	
Test order	m-Statistic	Prob.	m-Statistic	Prob.
AR(1)	-0.448	0.655	-1.489	0.137
AR(2)	0.021	0.983	NA	NA

Source: data introduced by E-views v. 13 , note that *,**and *** are the significant levels of $1\%, 5\%$ and 10%.

The model also showed almost no serial correlation between the residuals, as the Durbin-Watson statistic test value was 1.879. In the fixed effects model (FEM). It was found that there is a significant relationship between the Z-score index and Z-score (-1), ROA, FGR, SIZE, and the constant. The other variables were not significant. The explanatory ability of this model was also high as the adjusted coefficient of determination is equal to 0.82 , and the all-model was significant where the prob(F-statistic) was equal to (0.000).There was no auto-correlation between the variables was found in the model, as the Durbin-Watson stat test value was 2.195.The one-step FD-GMM model found that there was an insignificant relationship between the Z-score index and all variables. The Sargan test results in table 7 indicate that the p-value is $0.879 > 0.05$, which means that the instruments are valid. The Arellano-Bond test was used to determine the association between residuals in the one-step FD-GMM model. The autocorrelation test results in table 7 showed that the AR (1) test results had a probability value of $0.655 > 0.05$, and AR (2) test results had a probability value of $0.983 > 0.05$. This means that estimation using the one-step FD-GMM approach is consistent. Based on Table 7, the Z-score (-1) variable in the one-step FD-GMM model was 0.378 , in the fixed effect model was 0.361 , but it was 0.572 in the pooled least squares model, which means that $0.361 < 0.378 < 0.572$ and this means that the estimator lies within th bounds. The two-step FD-GMM model was found to show that there is a significant relationship between the Z-score index and Z-score (-1), LEV, FGR, and the constant. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 7 indicate that the p-value is $0.178 > 0.05$, which means that the instruments are valid. The Arellano and Bond test used to determine the association between residuals in the two-step FD-GMM model. The autocorrelation test results in table 7 showed that the AR(1) test results had a probability value of $0.137 > 0.05$, but the value of AR(2) test is equal N/A, the reason of this result due to the sample is insufficient,so we can consider that two-step FD-GMM model is inconsistent. Based on table 7,the Z-score (-1) variable in the two-step FD-GMM model was 0.383, in the fixed effect model was 0.361, but it was 0.572 in the pooled least squares model, which means that $0.361 < 0.383 < 0.572$ and this means that the estimator lies within bounds.

4.3.4 Estimation of FOD-GMM transformation for Z-score and ESG, ES, and G scores.

In table 8 the ESG-score model use the one-step FOD-GMM transformation. There is a significant relationship between the Z-score and ROA, and SIZE, but the other variables were insignificant. According to the Sargan test results, the p-value of $0.43 > 0.05$ indicates that the instruments are valid. The Z-score(-1) variable in the one-step FOD-GMM model was 0.33 ; in the fixed effect model, it was 0.360 but it was 0.572 in the pooled least squares model, which means that it does not lie between the fixed effect estimator and the pooled least squares estimator. The two-step FOD-GMM model showed that there is a significant relationship between the Z-score index and Z-score(-1), ESG-score, ROA, and SIZE. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 7 indicate that the p-value is $0.41 > 0.05$, which means that the instruments are valid. Based on table 8,the Z-score(-1) variable in the two-step FOD-GMM model was 0.29 ; in the fixed effect model, it was 0.360 but it was 0.572 in the pooled least squares model, which means that it does not lie between the fixed effect estimator, and pooled least squares estimator. FOD-GMM in G-score model removes the individuals fixed effects and it solves the problem of autocorrelation by subtracting the average of all future values from the current value. This transformation helps decouple the current error term from the variable's historical values, thereby ensuring the absence of historical interaction within the error terms, so the estimator is consistent.

In table 8 the ES-score model uses the one-step FOD-GMM transformation.There was an insignificant relationship between the Z-score and all variables. According to the Sargan test results, the p-value of $0.68 > 0.05$ indicates that there is a valid instruments. Based on table 8, the Z -score (-1) variable in the one-step FOD-GMM model was 0.37, and in the fixed effect model was 0.364 , but it was 0.575 in the pooled least squares model, which means that $0.364 < 0.37 < 0.575$ and this means that the estimator is good and the estimator lies within plausible bounds. The two-step FOD-GMM model was found to show that there is a significant relationship between the Z-score index and Z-score(-1) only. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 8 indicate that the p-value is $0.19 > 0.05$, which means that there is a valid instruments. Based on table 8, the Z-score (-1) variable in the two-step FOD-GMM model was 0.35 ; in the fixed effect model, it was 0.364 but it was 0.575 in the pooled least squares model, which means that it does not lie within the bounds. FOD-GMM in G-score model removes fixed effects by subtracting the average of all future values from the current values,this avoids creating serial correlation in transformed errors, so the estimator is consistent. In the G-score model in table 8 used the one-step FOD-GMM transformation. There was a significant relationship between the Z-score and ROA and SIZE, but the other variables were not significant.

Table 8. Estimation of FOD-GMM transformation for Z-score and ESG,ES and G scores.

	ESG-Score				ES-Score				G-Score			
	1-Step		2-Step		1-Step		2-Step		1-Step		2-Step	
	FOD-GMM		FOD-GMM		FOD-GMM		FOD-GMM		FOD-GMM		FOD-GMM	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Z-score(-1)	0.33	0.14	0.29	0.0**	0.37	0.16	0.35	0.0**	0.33	0.18	0.28	0.0**
ESG-score	-0.08	0.09	-0.06	0.05**								
ES-score					0.37	0.53	0.36	0.33				
G-score									-0.07	0.20	-0.07	0.0**
ROA	-280	0.0**	-238	0.0**	-95.9	0.46	-112	0.25	-250	0.03	-225	0.0**
LEV	-0.92	0.74	-1.63	0.23	-5.17	0.34	-3.929	0.09	-0.333	0.91	-1.27	0.4
LIQ	-0.05	0.71	-0.05	0.49	-0.07	0.55	-0.02	0.61	-0.08	0.58	-0.10	0.3
FGR	0.00	0.93	0.000	0.55	-0.00	0.20	0.00	0.08	0.00	0.92	0.00	0.6
SIZE	-1.1	0.0**	-0.9	0.0**	-0.38	0.44	-0.43	0.26	-0.98	0.0	-0.82	0.0**
Sum Squ. Res.	38.9		25.9		33.6		27.6		40.3		28	
J-statistic	4.85		5.08		3.11		7.41		5.09		5.4	
Prob(J-stat.)	0.43		0.41		0.68		0.19		0.41		0.40	
Instr.rank	12		12		12		12		12		12	

Source: data introduced by E-views v.13, note that *,**and *** are the significant levels of $1\%, 5\%$ and 10%.

According to the Sargan test results,the p-value of $0.41 > 0.05$ indicates that the valid instrument has met. The Z-score(-1)variable in the one-step FOD-GMM model was 0.33 ; in the fixed effect model, it was 0.360 but it was 0.572 in the pooled least squares model, which means that it does not lie between the fixed effect estimator, and pooled least squares estimator. The two-step FOD-GMM model was found to show that there is a significant relationship between the Z-score index and Z-score(-1),G-score, ROA and SIZE. The relationship between Z-score index and other variables was insignificant. The Sargan test results in table 8 indicate that the p-value is $0.40 > 0.05$, which means that the instruments are valid. Based on table 8, the Z-score (-1) variable in the two-step FOD-GMM model was 0.28 ; in the fixed effect model, it was 0.361 but it was 0.572 in the pooled least squares model, which means that it does not fall between the fixed effect estimator, and pooled least squares estimator, which means that the model estimator is biased. FOD-GMM in G-score model removes fixed effects by subtracting the average of all future available observations, this avoids creating serial correlation in transformed errors, so the estimator is consistent.

4.3.5 System generalized method of moments (Sys-GMM) transformation.

In table 9 the ESG-score model uses the two-step Sys-GMM transformation. There was an insignificant relationship between the Z-score and all variables. According to the Sargan test results, the value of its J-statistic is equal to $1.47\text{E} - 36$ by using GMM-Cross Section (White cov.) estimation method, which means that the value of p is less than 0.05. It also means that the instruments are invalid. The Z-score(-1) variable in the two-step Sys-GMM model was 1.415; in the fixed effect model, it was 0.360 but it was 0.572 in the pooled least squares model, which means that it does not lie between the fixed effect estimator and the pooled least squares estimator, which means that the model estimator is out of bounds. Based on table 10, it has been shown that there is no autocorrelation, where P-values appeared greater than 0.05 in the Portmanteau Tests for Auto-correlations, which means that the estimator is consistent.

In table 9 the ES-score and G-score models use the two-step Sys-GMM transformation. They have an insignificant relationship between the Z-score and all variables. According to the Sargan test results,the values of their J-statistic is equal to $1.23\text{E} - 32$ and $-6.50\text{E} - 34$ respectively. For Sys-GMM model the instruments also are invalid; therefore results are not reliable. To apply the Sys-GMM model it needs a large sample. In the ES-score and G-score models the values of Z-score (-1) variable in the two-step Sys-GMM model also were 1.152 and 1.354;in the fixed effect model,it was 0.361 but it was 0.572 in the pooled least squares model, which means that it does not lie between the fixed effect estimator and the pooled least squares estimator, which means that

Table 9. Estimation of two-step Sys-GMM model for ESG-score, ES-score and G-score models

ESG-Score			ES-Score			G-Score		
First-Equation Sys-GMM			First-Equation Sys-GMM			First-Equation Sys-GMM		
Variable	Coeff.	Prob.	Variable	Coeff.	Prob	Variable	Coeff.	Prob
C(1)	-15.536	0.878	C(1)	53.828	0.371	C(1)	13.355	0.696
Z -soreE(-1)	1.4152	0.669	Z-score(-1)	1.152	0.294	Z-score(-1)	1.354	0.584
ESG-score(-1)	0.4707	0.830	ES-score(-1)	-0.692	0.413	G-score(-1)	0.389	0.783
ROA(-1)	-223.846	0.807	ROA(-1)	-0.275	0.998	ROA(-1)	-145.615	0.745
LEV(-1)	3.0991	0.875	LEV(-1)	0.939	0.870	LEV(-1)	2.357	0.861
LIQ(-1)	-0.076	0.736	LIQ(-1)	-0.148	0.319	LIQ(-1)	-0.138	0.721
FGR(-1)	0.000	0.563	FGR(-1)	0.000	0.528	FGR(-1)	0.000	0.3303
SIZE(-1)	-1.281	0.804	SIZE(-1)	-0.411	0.426	SIZE(-1)	-1.087	0.744
Second-Equation Sys-GMM			Second-Equation Sys-GMM			Second -Equation Sys-GMM		
C(9)	-0.8056	0.779	C(9)	-0.051	0.930	C(9)	-0.955	0.807
D(Z-score(-1))	0.791	0.2001	D(Z-score(-1))	0.629	0.167	D(Z-score(-1))	0.819	0.247
D(ESG-score)	-0.058	0.773	D(ES-score)	-0.265	0.539	D(G-score)	-0.059	0.817
D(ROA)	473.70	0.824	D(ROA)	-271	0.662	D(ROA)	613.6	0.837
D(LEV)	-9.942	0.617	D(LEV)	-2.404	0.721	D(LEV)	-10.88	0.677
D(LIQ)	0.116	0.778	D(LIQ)	0.148	0.746	D(LIQ)	-0.048	0.801
D(FGR)	-0.001	0.503	D(FGR)	-0.001	0.213	D(FGR)	-0.001	0.594
D(SIZE)	2.407	0.735	D(SIZE)	-0.193	0.930	D(SIZE)	2.892	0.769
Determinant residual covariance	29.527		Determinant residual covariance	2.668		Determinant residual covariance	25.27	
J-statistic	$1.47\text{E}-36$		J-statistic	$1.23\text{E}-32$		J-statistic	$6.50\text{E}-34$	
Prob(J-statistic)	0.000		Prob(J-statistic)	0.000		Prob(J-statistic)	0.000	

Source: data introduced by E-views v.13, note that *, **and *** are the significant levels of $1\%, 5\%$ and 10%.

Table 10. System residual portmanteau tests for auto-correlations in two-step Sys-GMM

Null Hypothesis: no residual auto-correlations up to lag h							
	Sys-GMM-ESG-score		Sys-GMM- ES-score		Sys-GMM- G-score		
Lags	Adj Q-Stat	Prob.	Adj Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.9282	0.7382	1.5107	0.8166	2.1132	0.7032	4
2	1.9282	0.9814	1.5107	0.9917	2.1132	0.9751	8
3	1.9282	0.9994	1.5107	0.9998	2.1132	0.9991	12
4	2.3054	1.0000	1.8989	1.000	2.5018	0.9999	16
5	4.5992	0.9997	3.7392	0.9999	4.6443	0.9997	20
6	4.6957	1.000	5.2726	0.9999	4.6885	1.000	24
7	4.6957	1.000	5.2726	1.000	4.6885	1.000	28
8	4.6957	1.000	5.2726	1.000	4.6885	1.000	32
9	5.1185	1.0000	5.6529	1.000	5.1273	1.000	36
10	5.7093	1.0000	9.3049	1.000	6.0209	1.000	40
11	7.5648	1.0000	14.9344	0.9993	6.7346	1.000	44
12	7.5648	1.000	14.9344	0.9999	6.73612	1.000	48

the model estimators do not lie within plausible bounds. Based on table 10, it has been shown that there is no auto-correlation, where P-values appeared greater than 0.05 in the Portmanteau tests for auto-correlations, which means that the estimator is consistent.

Table 11 shows the comparison between FD-GMM, FOD-GMM and Sys-GMM models using the tests of consistent, valid instruments, bounds and the significance of Z-score with ESG-score, ES-score and G-score.

Table 8 and table 11 show that the two-step FOD-GMM-ESG and two-step FOD-GMM-G models are better than the others models because they have a valid instruments, and consistent estimators.
There are also a significant relationship between Z-score and ESG-score, G-score, Z-score(-1), ROA and SIZE.

Table 11. Comparison between FD-GMM, FOD-GMM, and Sys-GMM models using the tests of consistent valid instruments and coefficient bounds and the significance for ESG-score, ES-score, and G-score.

The model	Valid Instruments Test	Consistent Test	Bounds Test	T- Test
	Sergan Test	Autocorrelation Tests		Sig.
Enviromental, Social and Governance (ESG) Score				
One-step FD-GMM	Valid	Consistent	Within bounds	Insignificant
Two-step FD-GMM	Valid	Inconsistent	Within bounds	Insignificant
One-step FOD-GMM	Valid	Consistent	Out of bounds	Insignificant
Two-step FOD-GMM	Valid	Consistent	Out of bounds	Significant
Two-step Sys-GMM	Invalid	Consistent	Out of bounds	Insignificant
Enviromental and Social (ES) Score				
One-step FD-GMM	Valid	Consistent	Within bounds	Insignificant
Two-step FD-GMM	Valid	Inconsistent	Within bounds	Insignificant
One- step FOD-GMM	Valid	Consistent	Within bounds	Insignificant
Two-step FOD-GMM	Valid	Consistent	Out of bounds	Insignificant
Two-step Sys-GMM	Invalid	Consistent	Out of bounds	Insignificant
Governance (G) Score				
One-step FD-GMM	Valid	Consistent	Within bounds	Insignificant
Two-step FD-GMM	Valid	Inconsistent	Within bounds	Insignificant
One-step FOD-GMM	Valid	Consistent	Out of bounds	Insignificant
Two-step FOD-GMM	Valid	Consistent	Out of bounds	Significant
Two-step Sys-GMM	Invalid	Consistent	Out of bounds	Insignificant

4.4 The actual, fitted values, and residuals for Z-score in ESG-score, ES-score, and G-score models.

This paper aims to measure the relationship between Z-score and ESG-score, ES-score and G-score and control variables. It also aimed to predict the financial risks in seventeen companies included in the ESG index. The predictability of the following models that appeared their significant in this paper such as FD-GMM and FOD-GMM. The following criteria are used: RMSE, MAE and MAPE to select the best model . The Two-step FOD-GMM-ESG model is the best model in terms of predictability. It achieved the lowest values of RMSE, MAE and MAPE that reached to (0.844, 0.009 and 3.906) respectively compared with one-step FD-GMM-ESG, two-step FOD-GMM-ESG and one-step FOD-GMM-ESG models. The figures (1),(2),(3)and (4) show the actual, fitted and residuals values of Z-score for these models.

Table 12. The comparison of predictability criteria of FD-GMM and FOD-GMM models

Model	RMSE	MAE	MAPE
ESG-score			
One-step FD-GMM	1.156	0.713	8.026
Two-step FD-GMM	1.032	0.633	6.260
One-step FOD-GMM	0.874	0.593	4.584
Two-step FOD-GMM	0.844	0.009	3.906
ES-Score			
Two-step FD-GMM	2.752	1.508	16.914
Two-step FOD-GMM	0.735	0.487	5.120
G-score			
Two-step FD-GMM	1.019	0.609	6.245
One-step FOD-GMM	0.961	0.646	4.385
Two-step FOD-GMM	0.994	0.691	1.590

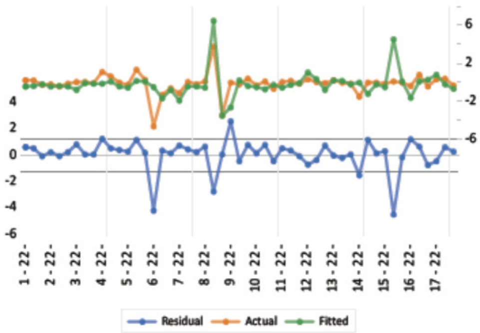

Figure 1. Residuals of One-step FD-GMM-ESG

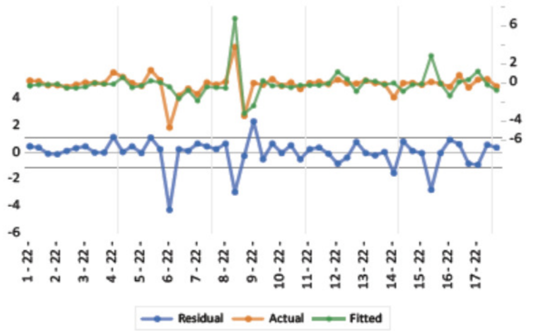

Figure 2. Residuals of Two-step FD-GMM-ESG

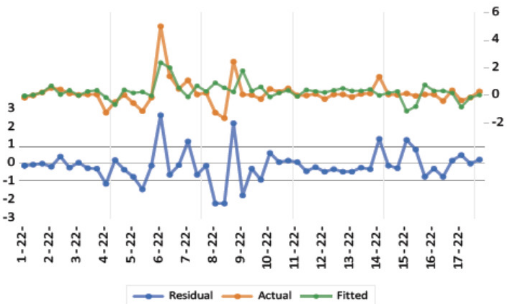

Figure 3. Residuals of One-step FOD-GMM-ESG

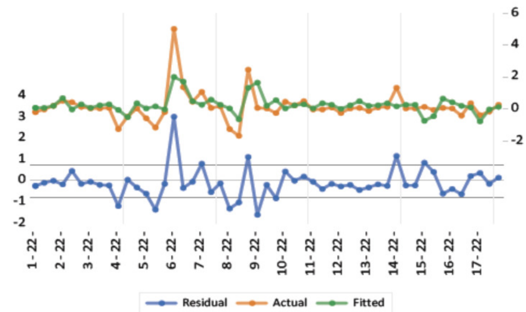

Figure 4. Residuals of Two-step FOD-GMM-ESG

In ES-score the Two-step FOD-GMM-ES model is the best model in terms of predictability. It achieved the lowest values of RMSE, MAE and MAPE that reached to (0.735, 0.487 and 5.120) respectively compared with two-step FOD-GMM-ES model. The figures (5) and (6) show the actual, fitted and residuals values of Z-score for two models.

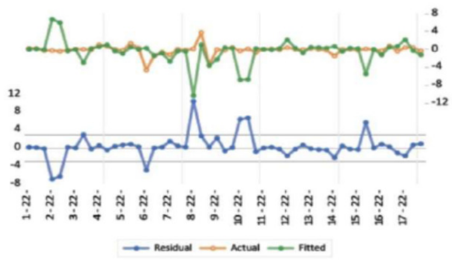

Figure 5. Residuals of Two-step FD-GMM-ES

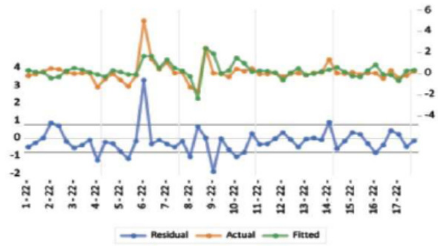

Figure 6. Residuals of Two-step FOD-GMM-ES

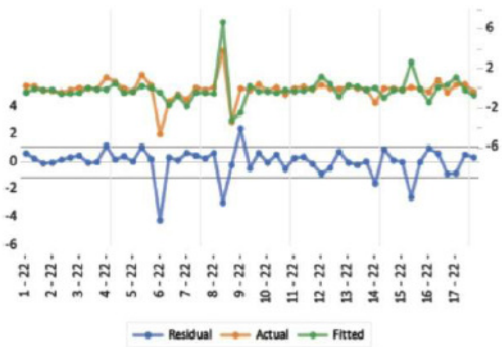

Figure 7. Residuals of Two-step FD-GMM-G

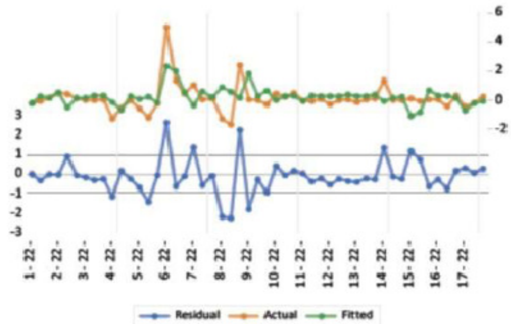

Figure 8. Residuals of One-step FOD-GMM-G

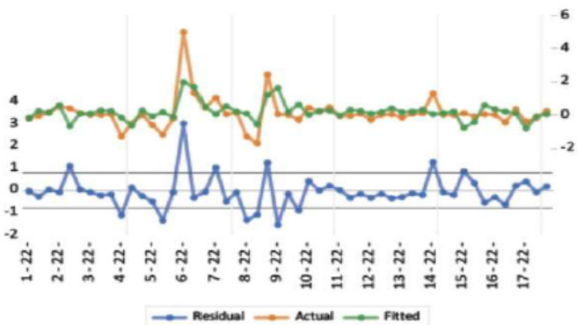

Figure 9. Residuals of Two-step FOD-GMM-G

In G-score the one-step FOD-GMM-G model is the best model in terms of predictability. It achieved the lowest values of RMSE and MAE that reached to (0.961 and 0.646) respectively compared with two-step FD-GMM-G and two-step FOD-GMM-G models. The figures (7), (8) and (9) show the actual, fitted and residuals values of Z-score for the three models.

5. Conclusion

This paper is an attempt at a scientific contribution to increase awareness and interest in one of the most important topics that has received great interest in the international business environment, which is the issue of environmental, social, and governance performance and its role in reducing financial risks, which enhances the competitive advantage of these companies listed in the S& P EGX/ESG index and ensures their sustainable survival. The researcher also recommends that all companies in emerging financial markets and stakeholders benefit from his results in financial forecasting and achieving what is called financial stability. This study aimed to measure the impact of environmental, social, and governance performance (ESG scores) as the independent variables and return on total assets (ROA), leverage (LEV), liquidity (LIQ), firm growth rate (FGR), and size of enterprise (SIZE) as control variables on financial risks as a dependent variable, which can be measured by the Z-score index using the first difference generalized method of moments (FD-GMM) , forward orthogonal deviations generalized method of moments (FOD-GMM) and system generalized method of moments (Sys-GMM) transformations. This study applied to seventeen companies of non-financial institutions that are in S & P EGX / ESG index that include various sectors in the period from 2020 to 2024.

• The study assumed hypotheses and the results were as follows:There is a significant relationship between the ESG-score and ES-score and the financial risks only in the two-step FOD-GMM model compared to other models, so we can accept the first and third hypotheses.

• There is an insignificant relationship between environmental and social (ES-score) and the Z-score index in all models, so we will reject the second hypothesis.

• The results of control variables were as follows: (1) There is a significant relationship between return on assets (ROA) and Z-score index in the following models: FEM-ESG-score, FEM-G-score, one-step FOD-GMM-ESG, two-step FOD-GMM-ESG and two-step FOD-GMM-G (2) There is a significant relationship between financial leverage (LEV) and Z-score index in the following models: POLS, two-step FD-GMM-ESG, two-step FD-GMM-ES and two-step FD-GMM-G. (3) There is no significant relationship between liquidity (LIQ) and Z-score in all estimated models. (4) There is a significant relationship between firm's growth rate (FGR) and Z-score in the following models: POLS and FEM for ESG-score, ES-score and G-score, one-step FD-GMM-ESG, two-step FD GMM for ESG-score and G-score models. (5) For the company size (SIZE), there is a significant relationship between it and the Z-score index in the following models: FEM for ESG-score and G-score, one-step FOD-GMM-ESG and two-step FOD-GMM for ESG-score and G-score. From the previous results we conclude that the following variables such as ROA, LEV,FGR and SIZE will reduce the financial risks in non-financial companies listed in S & P EGX/ESG index, so we can accept the fourth hypothesis.

• For the fifth hypothesis, the results showed that the efficiency of two-step FOD-GMM-ESG and two-step FOD-GMM-G models have a better efficiency than other models because they have a valid instruments , no auto-correlation between residuals and significant relationships between Z-score and ESG-score and G-score although the lagged dependent variable for two models lies out of bounds, so we will accept the fifth hypothesis. In general, the researcher attributes the efficiency and suitability of some of the FOD-GMM models compared to FD-GMM and SYS-GMM models because they are applicable to the small sample.

• For the sixth hypothesis, the results showed that the two-step FOD-GMM-ESG, two-step FOD-GMM-ES, and two-step FOD-GMM-G models have a higher predictability than FD-GMM and System-GMM models, so we will accept the sixth hypothesis.

Finally, based on the previous results, we recommend that investors take into account environmental, social, and governance practices when making their investment decisions, as focusing on companies that apply environmental, social, and governance practices may lead to achieving more stable returns in the long term. Company managers must also increase disclosure of these practices due to their role in improving reputation and enhancing creditworthiness, which reduces financing costs and corporate risks and enhances competitiveness. At the policy level, we recommend that decision makers use FOD-GMM models, that their significance appeared in the current study, and use them to predict future financial risks. We also recommend that they develop legislation that supports these environmental, social, and governance practices and provide incentives for companies that adhere to them, such as soft loans and tax benefits, to ensure the integration of these principles into financial markets more effectively.

Future works

From the results of the current study, the researcher proposes some of the following future studies: (1) Using GARCH and LSTM models to study the ESG volatility prediction. (2) Using a hybrid SGM-BRR model that employs random forest (RF), gradient boosting decision tree (GBDT), extreme gradient boosting (XGBoost), and light gradient boosting machine (LightGBM) as base learners, with bayesian ridge regression (BRR) as the meta-model for integrating to predict ESG scores. (3) Using a deep learning (DL) machine as long shorter memory (LSTM), gated recurrent unit (GRU), and convolutional neural network (CNN) models to predict the volatility of the ESG index and financial risks.(4) Applying the methods of the current study to estimate the ESG index to other institutions that differ in nature from the nature of the current study's non-financial companies, such as banks and non-banking financial institutions.

Acknowledgement

I would like to thank my mother, my father, my brother an Engineer Hany Hussein, my sister Dr. Hanan Hussein, Assistant Professor of Business Administration at Ain Shams University, and Professor Hayam Wahba, Professor of Finance and Investment and the Dean of the School of Business Administration at Nile University for their continuous support. I would also like to thank the editor and the referees for their suggestions and corrections to improve the quality of this paper.

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