Grey Systems: Theory and Application

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Audit report forecast: an application of nonlinear grey Bernoulli model

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Abstract

Purpose – The widespread application of traditional grey model (GM) in different academic fields such as electrical engineering, education, mechanical engineering and agriculture provided the authors with an incentive to conduct the present empirical research in an accounting field, in particular, auditing practice. In this regard, the purpose of this paper is to employ the nonlinear type of the original GM to forecast the drastically changed data on audit reports, primarily due to the fact that the linear nature of GM is unable to forecast nonlinear data precisely. In essence, this paper adds value to the strand of audit report literature by examining the impact of different financial ratios on auditors' opinion and then forecasting audit reports by employing GMs.

Design/methodology/approach – The grey forecasting model is known as a system containing uncertain information presented by grey numbers, equations and matrices. The grey forecasting model is employed by using a differential equation in an uncertain system with limited data set which is suitable for smoothing discrete data. In addition, the analyses are conducted by applying a sample of top 50 listed companies on the Tehran Stock Exchange during 2011-2016.

Findings – The findings suggest that audit reports are most influenced by the current ratio and conversely, least influenced by the ratio of working capital turnover. Moreover, the authors argue that the Nash nonlinear grey Bernoulli model is more precise than the nonlinear grey Bernoulli model and GM in forecasting audit reports.

Originality/value – The current study may give more strength to stakeholders in order to analyse and forecast audit report.

Keywords Nonlinear grey Bernoulli model, Audit report, Financial ratio

Paper type Research paper

1. Introduction

Auditing practice is considered as one of the fundamental parts of corporate liability regime. In this regard, the fulfilment of corporate liability function is primarily dependent on authentic and reliable information examined by an external and independent auditor. Indeed, auditors incorporate "value added" to the accounting information provided by the firms and validate their financial statements. Further, auditing is performed and the audit report is prepared with due professional care, suggesting that a considerable number of audit-related issues and uncertainties are addressed solely on the basis of auditors' professional judgment. In general, auditors are appointed to provide reasonable assurance that financial statements are free from material misstatements, whether due to fraud or error. A long range of corporate stockholders including bankers, vendors, creditors, employees, customers and the government rely and base their economic decisions to different degrees on the information reflected in audited financial statements. From stockholders' viewpoint, the usefulness of an audit lies in the fact that how well the auditors conduct the auditing practice to find and detect material errors, fraud, illegal actions and going concern issues in financial statements and express their opinions on the

level of compliance of these items with the statutory requirements and standards. Therefore, audit reports play a dominant role in stockholders' decision-making process and the present study, accordingly, attempts to address this issue by forecasting the reports using grey models (GMs) in practice (Hayes *et al.*, 2014). An audit report is the final product of an audit process, serving as a major vehicle of communication between the auditor and interested users. This report occupies no more than a few standard lines and paragraphs and consequently those not knowledgeable in auditing and/or accounting may regard this brevity as rather inadequate for expressing a professional opinion and believe that the reports somehow lack the required substance. However, audit reports are the outcome of great care and the consummation of a rigorous and lengthy audit process and therefore the preceding argument is just a paradox. In addition, the incremental demand for reliable information in today's economy underlines a growing need for independent and capable bodies to ensure the reliability of such information and reports (Hayes *et al.*, 2014). Altogether, the information content of different types of audit reports may directly enhance or moderate the perceptions of financial statement users. In other words, the standard unqualified audit reports contain the highest level of assurance and reliability of financial statements and any deviation from the standard report appears to convey a less favourable message about the financial position and health of a given business to interested users.

In the light of current information overload or explosion era and also the incremental growth of business transactions as well as advances in information technology, some limitations have been placed upon the optimum and efficient usage of financial information. To our knowledge, to date, more than 300 prediction models, including both qualitative and quantitative methods, have been developed to predict financial data more efficiently and precisely (Huang *et al.*, 2014). In this regard, prior literature argues that among all forecasting methods, whether qualitative (e.g. trend prediction method, the Delphi methods, the expert system, etc.) or quantitative (e.g. time series analysis, neural networks, exponential smoothing, linear multiple regression analysis, generic algorithm, grey forecasting models, etc.) forecasting methods, neural networks exhibit signs of better forecasting performance and precision as compared to traditional models (Januskevicius, 2003; McMillan, 2007; Chuang *et al.*, 2009). Although use of artificial neural networks in practice is much more difficult and time-consuming than regression models, the likelihood of higher performance efficiency justifies employing this forecasting method. Accordingly, it is recommended that future studies determine a performance efficiency threshold between the neural networks and traditional models. In addition to preceding discussion, it is also argued that the novelty, easiness of calculation and satisfactory results of grey theory have attracted much academic attention in recent years (Chen *et al.*, 2009; Huang *et al.*, 2014). More specifically, a significant strand of empirical research studies has widely employed grey modelling in different research areas such as engineering, accounting, finance, agriculture and education (Chen *et al.*, 2009).

Our empirical research contributes to the existing accounting literature in several ways. First, our paper is one of the few studies which investigate the impact of financial ratios as explanatory variables on audit reporting. Specifically, we attempt to prioritise the audit reports of each firm based on the calculated weights of financial ratios by using grey relational analysis (GRA), while previous papers concentrate only on the effect of audit reports on the elements of financial statement. Second, we employ the nonlinear type of the original GM (nonlinear grey Bernoulli model (NGBM)) to forecast the drastically changed data on audit reports for companies listed on the Tehran Stock Exchange (TSE). To our knowledge, to date, there is no empirical study having employed grey theory in practice to forecast audit reports. Third, we conduct our study in

an immature audit market and a developing stock market, i.e. the TSE, with novel characteristics, leading to unexpected and interesting results. Furthermore, not only the benefits of the grey group modelling contain the ability of forecasting but also the characteristics of easy calculating and few observations are further advantages of this modelling. The grey group model has also liberated the users from the procedures of the model-based selection and the sample data assumptions in statistics analysis. Therefore, in this paper a prospective analysis is contributed which head managers, financial analysers, auditors and other information users can apply them in their future investigation and decisions. Beside that other investigation on this field of study mostly applied a retrospective view which implies to analysing financial data of recognised financial events.

The present study proceeds as follows. Section 2 reviews the related literature, offers an underpinning theoretical framework and presents our hypotheses. Section 3 discusses our empirical methodology. Section 4 presents descriptive statistics and the main empirical results. Finally, Section 5 concludes the paper.

2. Theoretical framework, literature review and hypothesis development

The well-known grey system theory with its multi-subject, intersection and abstraction nature primarily deals with uncertain systems in which partial information is known and the samples are of small size. Devised and proposed first by Professor Deng in 1982 (Deng, 1989), grey theory has been developing for more than 30 years and has become more and more mature and perfect in recent years. The theory is applied in different academic areas and many empirical research studies have considered grey prediction model as their research hotspots, leading to a booming subject of plot structure (Li, 2006). The grey theory is known for its novel characteristics. To illustrate, the calculation process in its prediction models is rather easy as compared to other forecasting methods, primarily because these models only need as few as four raw data for forecasting. Furthermore, the lack of regularity among these four raw data eliminates the need for normality and the level of significance tests in grey modelling (Huang *et al.*, 2014). The grey modelling is also the bridge between the grey system theory and practice. In addition, the grey modelling is applied on the basis of grey relational theory (Xiao, 2002). In this regard, Li (2006) introduces the stability problem of grey prediction model. Specifically, the author argues that the establishment of the grey prediction model on the basis of accumulated generating operation and the least square method produces errors frequently, particularly when the grey prediction modelling is used to fit the pure exponential sequence. The author's findings suggest that choosing an appropriate multiple of data transformation can be effective both in increasing the model precision and eliminating the stability problem of the model.

In general, adequate information is a prerequisite for appropriate decision making. However, it is rare to find a system with all its information known, mainly because the determination process of most systems components and their interrelationships is either impossible or uneconomical. Moreover, the output information of these systems is also imperfect and/or incomplete. Consequently, uncertainty is an indispensable part of the systems, which *per se* brings about major problems in dealing with these systems (David, 1994). Since the incompleteness of information is the essential feature of a grey system, the starting point for the investigation of these systems is the situations with deficiency or lack of information (David, 1994). In other words, the primary objective of grey theory and its applications is to establish a bridge connecting the social and natural sciences, in which the grey concept is indicative of deficiency of information as well as uncertainty (Liu and Lin, 2006). The term "grey" in the grey system theory is typically derived from the specific concept of information used to apply the theory in practice. More specifically, the situations

with no information (i.e. the part of information that is unknown) and the situations with perfect information (i.e. the part of information that is known) in GRA are defined as "black" and "white", respectively. Further, the situations (uncertainties) between these extremes are called "grey", "hazy" or "fuzzy" (Liu and Lin, 2006; Chan and Tong, 2007). Based on the preceding definition, the qualitative and quantitative information are set on a continuum, from a total lack of information (black area) through middle (grey area) to complete information (white area). Using highly noisy data of US dollar to Euro parity, Kayacan *et al.* (2010) compare the performances of different GMs such as GM (1, 1), Grey Verhulst model and modified GMs using Fourier series. The authors argue that the modified GMs, in particular the modified GM (1, 1) using Fourier series, exhibit better performance both in model fitting and forecasting. Using data mining techniques, Ravisankar *et al.* (2011) indicate that the debt levels of companies with financial statements fraud are higher than their counterparts, suggesting that the management of fraudulent companies has a greater incentive to manipulate financial statements and achieve certain debt levels. As a result of this phenomenon, the likelihood of the issuance of qualified audit report increases as well. Likewise, Martens *et al.* (2008) provide some empirical evidence that there is a significant and positive relationship between firms' debt levels and the likelihood of qualified going concern reports.

Some recent empirical studies have used the optimised NGBM for more precise forecasting. Wang (2013), for instance, employs a method based on Nash balance theory to optimise the initial condition used in the Nash NGBM (1, 1) and forecast the five chief economic indices of high technology enterprises in China. The author's findings suggest that the data are fitted well by using the optimised Nash nonlinear grey Bernoulli model (NNGBM). That is, the NNGBM gives a superior modelling performance. Proposing an effective power optimisation algorithm for the NGBM, Pao *et al.* (2013) forecast three different types of energy consumption (i.e. renewable, nuclear and total primary energy consumption) in the growing market of Russia. The authors contend that the NGBM with optimal power model is remarkably more efficient than the GM. Hsin and Chen (2014) successfully apply grey forecasting to the prediction of stock price and suggest that the achievement of higher and better forecasting performance is subject to three points: the unchanged stock price; the uncontrolled price fluctuation; and the discontinuous feature of stock price increments. Some recent studies conducted in the field of biology and medical indicate the applications of grey system theory to predict some special illnesses. For instance, Zhang *et al.* (2014) employ an optimised solution of NNGBM, called PSO-NNGBM (1, 1) to predict the incidence of Hepatitis B in Chinese setting. The authors argue that the optimised model significantly improves the precision and forecasting performance of the original NGBM (1, 1). Chang *et al.* (2015) provide some evidence regarding the problems of small data set forecasting, particularly in manufacturing system, and indicate that the forecasting errors and results with limited data set could be improved by using a multi-model procedure (grey incidence analysis and hybrid forecasting model).

Chen and Hsin (2016) adopt NGBM and NNGBM to predict the currency exchange rate of Taiwan's two top trading partners, America and China. The results of the study show that Taiwan's currency will appreciate against USD and CNY from the fourth quarter of 2015 to the second quarter of 2016. They conclude that this method is highly acceptable for international traders and investors. Dong *et al.* (2017) introduce a new prediction model, namely discrete grey model (DGM), to forecast the changing trend of quality cost. Their paper demonstrates that DGM can be used to forecast quality cost based on Juran's cost characteristic curve, especially when the authors do not have much information or the sample capacity is rather small. When operated by practical weakening buffer operator, the randomness of time series can be obviously weakened and the prediction accuracy can

be significantly improved. He and Jiang (2017) investigate the comparative performances of grey prediction models (GM) and Markov chain integrated GMs in a production demand prediction problem. Their numerical results reveal that the Grey-Markov model based on GM (2,1) achieves better prediction performance than the other models. Chen *et al.* (2009) also investigate the efficiency of GM (1,1) group model on forecasting the earnings per share (EPS). Their empirical study indicates that improper amount of observations is not helpful to reduce the forecasting errors and at the same time increases the cost of model construction. Furthermore, they find that the in-sample and post-sample forecast performances also show that the grey group model with the proper amount of observations is a competitive and competent method for the non-stationary seasonal time series analysis, forecast and control. Not only do the advantages of the grey group model inhere the ability of forecasting but also the characteristics of easy calculating and few necessary observations.

Overall, we posit our hypotheses in the null form as follows:

H1. The GM delivers a suitable performance for forecasting audit reports.

H2. The NGBM delivers a suitable performance for forecasting audit reports.

H3. The NNGBM delivers a suitable performance for forecasting audit reports.

3. Research methodology

3.1 The GM implementation procedures

Grey forecasting models are applied by using a differential equation in an uncertain system with limited data set. These models are suitable for smoothing discrete data. Indeed, a grey system is defined as a system containing uncertain information presented by grey numbers, equations and matrices. In this sense, the grey numbers act as the system cells or atoms. Furthermore, a grey number may be defined as a number with uncertain information. For instance, the ratings of attributes are described by the linguistic variables and can be expressed by numerical intervals. These intervals contain uncertain information. Overall, it can be stated that a grey number is regarded as a number whose exact value is uncertain, but the numerical intervals containing its value is known (Li *et al.*, 2007). Technically, an equation is called a differential equation when it meets the following criteria: the information density is high and the intervals contain the level of grey differences. The GM is formed by using the following first degree differential equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{1}$$

The whitening equation is therefore as follows:

$$x^{(0)}(i) + az^{(1)}(i) = b \tag{2}$$

where:

$$z^{(1)}(i) = \frac{1}{2}\big(x^{(1)}(i) + x^{(1)}(i+1)\big) \tag{3}$$

This method is called whitening and there is no mathematical proof for it. In the preceding equations, i represents the time and the parameters a and b stand for development

GS

coefficient and the grey factor, respectively. These coefficients are calculated by using the following least square method:

$$A = \begin{bmatrix} -z^{(1)}(1) & 1 \\ -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{4}$$

$$\dot{x}_n = \begin{bmatrix} x^{(0)} & (2) \\ x^{(0)} & (3) \\ \vdots & \vdots \\ x^{(0)} & (n) \end{bmatrix} \tag{5}$$

$$\beta = \begin{bmatrix} a \\ b \end{bmatrix} \tag{6}$$

Therefore:

$$X_n = A\beta \tag{7}$$

Using least square method, the following is obtained:

$$\sum_{i=1}^{n} e_i^2 = e'e = (X_n - A\beta)'(A_n - A\beta) = X_n'X_n - X_n'A\beta - \beta'A'X_n + \beta'A'A\beta$$

$$= X_n'X' - 2\beta'A'X_N + \beta'A'A\beta \tag{8}$$

$$\frac{\partial(e'e)}{\partial\beta} = -2A'X_N + 2A'A\beta = 0 \tag{9}$$

$$\beta = \begin{bmatrix} a \\ b \end{bmatrix} = (A'A)^{-1}A'X_n \tag{10}$$

The following equation will be obtained by using the Laplace transform for the above-cited grey forecasting equation:

$$sx^{(1)}(s) - u(0) + ax^{(1)}(s) = \frac{b}{s} \tag{11}$$

Therefore:

$$x^{(1)}(s) = \frac{x^{(0)}(1) - (b/a)}{s+b} + \frac{(b/a)}{s} \tag{12}$$

If the inverse Laplace transform is used, then:

$$\hat{x}^{(1)}(i+1) = \left(\hat{x}^{(0)}(1) - \frac{b}{a}\right)e^{-ai} + \frac{b}{s} \tag{13}$$

Therefore, the following equation will be obtained:

$$\hat{x}^{(0)}(i+1) = \hat{x}^{(1)}(i+1) - \hat{x}^{(1)}(i) = \left(\hat{x}^{(0)}(1) - \frac{b}{a}\right)(1 - e^a)e^{-ai} \quad i = 1, 2, 3, \ldots \quad (14)$$

Finally, the following equations represent smoothing series and forecasting series for GM, respectively:

$$\left\{ x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \right\} \quad (15)$$

$$\left\{ \hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \ldots, \hat{x}^{(0)}(n+k) \right\} \quad (16)$$

The NGBM and NNGBM are also defined as following equations:

$$\hat{x}^{(0)}(i+1) = \left[\left(\hat{x}^{(0)}(1) - \frac{b}{a}\right)e^{-a(1-n)i} + \frac{b}{s} \right]^{1/(1-n)} \quad n \neq 1, \ k = 1, 2, 3, \ldots \quad (17)$$

$$\text{Min } \varepsilon\left(\text{avg}(n, p \mid x^{(0)})\right) \quad p \in [0, 1], \ n \in R^2 \quad (18)$$

3.2 The GM error analysis
The relative percentage error (RPE) is defined as the difference between the real and forecast values. It is used to evaluate the precision at a specific time instant k as follows:

$$\text{RPE} = \varepsilon(K) = \frac{X^{(0)}(K) - \hat{X}^{(0)}(K)}{X^{(0)}(K)} \times 100\%, \ K = 2, 3, \ldots, m \quad (19)$$

The following average relative percentage error (ARPE) is also used to evaluate the total model precision:

$$\text{ARPE} = \varepsilon(\text{avg}) = \frac{1}{K-1} \sum_{i=2}^{k} |\varepsilon(i)|, \ i = 2, 3, \ldots, m-3 \quad (20)$$

3.3 Regression models and setting audit report priorities using GRA
The present study examines three independent regression models to determine the most appropriate forecasting model. Indeed, the model yielding the least deviation from real values (the least RPE) is chosen as the best model. The approach of choosing one model from different forecasting models is primarily based on the idea that there can be only one model which can explain and predict a series of data. Our regression models are presented as follows (Table I):

$$\begin{aligned} \text{GM}_{i,t} = {} & a_0 + \beta_1\,\text{CR}_{i,t} + \beta_2\text{QR}_{i,t} + \beta_3\text{AT}_{i,t} + \beta_4\,\text{WCT}_{i,t} + \beta_5\,\text{DR}_{i,t} \\ & + \beta_6\,\text{DER}_{i,t} + \beta_7\text{GPR}_{i,t} + \beta_8\text{ROSR}_{i,t} + \beta_9\,\text{EPS}_{i,t} + \beta_{10}\text{PDR}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (21)$$

$$\begin{aligned} \text{NGBM}_{i,t} = {} & a_0 + \beta_1\,\text{CR}_{i,t} + \beta_2\text{QR}_{i,t} + \beta_3\text{AT}_{i,t} + \beta_4\,\text{WCT}_{i,t} + \beta_5\,\text{DR}_{i,t} \\ & + \beta_6\,\text{DER}_{i,t} + \beta_7\text{GPR}_{i,t} + \beta_8\text{ROSR}_{i,t} + \beta_9\,\text{EPS}_{i,t} + \beta_{10}\text{PDR}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (22)$$

Symbol	Variable	Calculation	Description
CR	Current ratio	Current assets/Currrent liabilities	Liquidity ratio
QR	Quick ratio	(Current assets−(Inventories+Prepayments))/Currrent liabilities	Liquidity ratio
AT	Asset turnover	Net sales/Total sssets	Activity ratio
DR	Debt ratio	Total liabilities/Total assets	Leveraging ratio
DER	Debt to equity ratio	Long term debt+Value of leases/Average shareholders equity	Leveraging ratio
GPR	Gross profit rate	Gross profit/Net sales	Profitability ratio
EPS	Earnings per share	Net earnings/Number of shares	Market ratio
WCT	Working capital turnover	Net sales/Working capital	Activity ratio
ROSP	Profit margin	Net profit/Net sales	Profitability ratio
PDR	Payout ratio	Devidends/Earnings	Market ratio

Table I.
Calculation method
of variables

$$\text{NNGBM}_{i,t} = a_0 + \beta_1\,\text{CR}_{i,t} + \beta_2\text{QR}_{i,t} + \beta_3\text{AT}_{i,t} + \beta_4\,\text{WCT}_{i,t} + \beta_5\,\text{DR}_{i,t}$$
$$+ \beta_6\,\text{DER}_{i,t} + \beta_7\text{GPR}_{i,t} + \beta_8\text{ROSR}_{i,t} + \beta_9\,\text{EPS}_{i,t} + \beta_{10}\text{PDR}_{i,t} + \varepsilon_{i,t} \tag{23}$$

3.4 Decision matrix

We collected the data on financial indices (i.e. liquidity ratios, activity ratios, leveraging ratios, market ratios and profitability ratios) from hardcopy financial information stored in the TSE library during 2011-2016 in order to set priorities for variables affecting audit reports. In this regard, we first utilise a matrix with respect to indices scoring based on the criterion, i.e. decision matrix. In general, the starting point of the GRA is the decision matrix (just like other multi-criteria decision techniques). A decision matrix is defined as a matrix with $M \times N$ elements, M alternative options (M columns) and N criteria (N rows). The decision matrix is shown by Y and the term Y_{ij} represents its elements. The following matrix represents a decision matrix with M options and N criteria:

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{24}$$

Next, we use a weighted decision matrix as a tool to compare alternatives regarding multiple criteria of different levels of significance. In other words, this matrix enables us to rank the entire alternative relative to a "fixed" reference and thus create a partial order for the alternatives.

3.5 Target reference series

Once the grey relations were formed, all performance values are located in the range [0, 1]. In this case, the closer the value of x_{ij}, the better performance of the index i in the alternative j.

The reference series typically looks for an alternative whose comparative series is closer to this target series. We define reference series as follows:

$$X_o = (x_{o1}, x_{o2}, \ldots, x_{oj}, \ldots, x_{on}) = (1, 1, \ldots, 1, \ldots, 1) \tag{25}$$

3.6 Grey relational coefficient and grey relational grade

Technically, a grey relational coefficient is calculated to express the relationship between ideal and actual normalised results and presented as follows:

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta \text{Min} + \zeta \Delta \text{Max}}{\Delta_{ij} + \zeta \Delta \text{Max}} \quad i = 1, 2, \ldots m, \ j = 1, 2, \ldots, n \tag{26}$$

where ζ is distinguishing or identification coefficient and used to limit or extend the range of grey relational coefficient. Therefore, ΔMin and ΔMax are the minimum and maximum values of Δ_{ij}, respectively. After calculating all the grey relational coefficients, we calculate the grey relational grades using the entropy technique. The grey relational grade indicates the correlation between target reference series and comparative series. In the following calculations, w stands for the weight of financial indices per year calculated by entropy technique.

First, we normalise the decision matrix data by using linear method in an entropy technique. A matrix is defined as a normal matrix when the sum of elements located in each column is equal to 1. The following formula has been used to normalise the decision matrix:

$$n_{ij} = \frac{x_{ij}}{\sum x_{ij}} \tag{27}$$

where n_{ij} indicate each elements of normal matrix. In the next step, we determine the weight of each index (E_j) using the following equation:

$$E_j = -k \sum \left[n_{ij} LN(n_{ij}) \right] \tag{28}$$

$$D_j = 1 - E_j \tag{29}$$

where "k" is calculated as follows:

$$K = \frac{1}{\ln(A)} = \frac{1}{\ln(31)} = 3.434 \tag{30}$$

To calculate the normal weight, the following equation is used:

$$W_j = \frac{d_j}{\sum d_j} \tag{31}$$

Table II presents the final calculated weight of financial indices by using Shannon entropy technique.

	ROSP	GPR	CR	QR	WCT	AT	DR	DER
E_j	10.684	10.726	11.240	10.846	9.640	10.732	11.601	11.319
D_j	−9.684	−9.726	−10.240	−9.846	−8.640	−9.723	−10.601	−10.319
W_i	0.123	0.123	0.130	0.125	0.110	0.124	0.135	0.131

Table II.
The weight of financial indices calculated by Shannon entropy technique

4. Research findings

4.1 Descriptive statistics

Table III details the descriptive statistics of the variables used in regression models. As it is obvious, the gross profit ratio (GPR) and EPS indicate the highest and lowest average values, respectively. In addition, while DR variable shows the highest maximum value, the QR, GPR and market ratios exhibit the lowest values. Since the skewness or kurtosis coefficients of some variables are lower or higher than the range [0, 3], it is concluded that the sample data are not normal.

4.2 The assumptions of standard linear regression models

There are several assumptions with respect to standard linear regression models in that the violation of these assumptions brings about some errors in the estimation of regression parameters and also hypotheses examination. Using different extensions, we examine the assumptions of standard linear regression models in order to relax the effects of their violation (e.g. biased or misleading forecasts or confidence intervals yielded by a regression model). What follows is a succinct review of the assumptions tested for our regression models.

4.2.1 Normality of the error distribution. We use Jarque-Bera (JB) test in order to examine whether model coefficients are significantly different from zero (i.e. the error distribution is normal and is not influenced by the presence of a few large outliers). In statistics, the JB test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The null hypothesis of this test is the normality of the error distribution. After conducting the test, the obtained test statistics and their probability values indicated that the distribution of errors at 0.05 margin of error is not normal. Table IV summarises the results of JB test both before and after the normalising process. Besides, the results of the normality test for each regression model are presented in Table VI. The results indicate that the normality of the residuals of all estimated regression models is confirmed at 0.05 significance level ($P1$: 0.7935; $P2$: 0.2947; $P3$: 0.6345).

Variable	Mean	SD	Min.	Max.	Skewness	Kurtosis
CR	0.6625	0.3977	0.0003	3.2815	0.249	1.196
QR	0.1273	0.1396	0	0.9135	1.614	5.173
AT	0.6839	0.3128	0.0011	1.7952	−0.242	−0.387
WCT	0.0129	0.5731	0.0013	3.7163	1.128	2.763
DR	0.2414	0.2192	0.0042	4.1894	4.181	63.826
DER	0.4961	0.3286	0.0018	2.8953	1.329	5.193
GPR	1.6953	0.3997	0	2.2748	−1.328	2.386
ROSR	0.3516	0.2521	0.0015	1.3458	−1.519	1.836
EPS	0.0061	0.0124	0	1.8743	1.807	4.845
PDR	0.0141	0.0017	0	2.1147	3.782	8.215

Table III.
Descriptive statistics of regression models variables

Variable	Prior to normalising process Jarque-Bera statistic	*p*-value	Subsequent to normalising process Jarque-Bera statistic	*p*-value
The forecasting performance of the GM	5.593	< 0.001	0.622	0.697
The forecasting performance of the NGBM	4.186	< 0.001	0.719	0.621
The forecasting performance of the NNGBM	4.001	< 0.001	0.526	0.197

Table IV.
The results of JB test before and after the normalising process

4.2.2 Correlations. The matrix of Pearson correlation coefficients among research variables is shown in Table V. As it is evident, the forecasting performance of the GM is positively and significantly correlated with the forecasting performance of the NGBM, the forecasting performance of the NNGBM, liquidity ratios, working capital turnover (WCT), debt to equity ratio (DER), GPR and profit margin (ROSP). By contrast, it is negatively and significantly correlated with asset turnover (AT) and debt ratio (DR). Moreover, based on the results of Pearson statistic, the forecasting performance of the NGBM is significantly and negatively correlated with WCT and profitability ratios; conversely, its performance is positively and significantly correlated with the forecasting performance of the NNGBM, current ratio (CR), AT, DER and payout ratio (PDR). Finally, the forecasting performance of the NNGBM is positively and significantly correlated with CR, DR, DER and PDR. It is also significantly and negatively correlated with quick ratio (QR) and profitability ratios.

4.2.3 Multicollinearity. The multicollinearity is regarded as a phenomenon in which two or more independent variables in the regression model are highly correlated. That is, one variable can be predicted accurately from others. Indeed, high correlation among independent variables relaxes the multicollinearity problem. As it is evident in Table VII, the degree of correlation among independent variables is low, meaning that the simultaneous entry of variables into research model do not bring multicollinearity. The present study utilises the Ramsey test to evaluate the multicollinearity assumption. As it is shown in Table V, the probability value of Ramsey statistic for all three estimated models is more than the significance level of 0.05 and consequently the appropriateness of estimated models is confirmed under the null hypothesis.

4.2.4 Homoscedasticity (constant variance) of the errors. To test serial correlation of (the idiosyncratic component of) the errors in models, we conduct Breusch-Pagan test on the residuals of the (quasi-) demeaned model, which should be serially uncorrelated under the null of no serial correlation in idiosyncratic errors. The results in Table V indicate that the errors of all estimated regression models are not serially correlated ($P1$: 0.0003; $P2$: < 0.001; $P3$: < 0.001). Accordingly, we use the generalised least squares estimation method to handle this problem.

4.2.5 Independence of errors. Based on this assumption, the residual or errors of a regression model must be uncorrelated with each other. Therefore, we employ Durbin-Watson test in order to examine the correlation among models residuals. As it is evident in Table V, the Durbin-Watson statistic of all estimated models is located in the range [1.5, 2.5], suggesting that the independence of errors is confirmed for all models (i.e. the errors are uncorrelated) ($D1$: 2.15; $D2$: 2.19; $D3$: 2.29).

4.3 Specification tests (diagnostics) in panel data models

The present study employs panel data technique to estimate the regression models. In statistics and econometrics, the term "panel data" refers to multi-dimensional data frequently involving measurements over time. Panel data contain observations of multiple phenomena obtained over multiple time periods for the same firms or individuals. Thus, we

Model	Jarque-Bra statistic χ^2	p-value	Breusch-Pagan statistic F	p-value	Durbin-Watson statistic D	Ramsey statistic F	p-value
1	1.8536	0.7935	4.6839	0.0003	2.15	4.2741	0.0746
2	1.3975	0.2947	13.6549	< 0.001	2.19	14.1748	0.2863
3	1.5984	0.6345	65.2761	< 0.001	2.29	0.5831	0.5027

Table V.
The test results of
regression models
assumptions

GS

conduct F-Limer specification test using Eviews statistical software to specify the appropriate model between panel data model and ordinary least square (OLS) model. The null hypothesis of this test is the preference of OLS model. As shown in Table V, the obtained probability values for all models are less than the margin of error (0.05), thus the panel data model is chosen. The next step is to choose the appropriate model between fixed effects model and random effects model. In this regard, we conduct Hausman test. The results of this test are also shown in Table VI. The obtained p-values for all models imply the appropriateness of fixed effects model, again, because it is less than the margin error of 0.05. Overall, all regression models in the present research are fitted using the panel data and fixed effects models (Table VII).

4.4 Estimation results

4.4.1 The GM. Table VIII reports the results obtained from estimating the GM model by using fixed effects model. According to probability value of F-statistics, it can be concluded that the overall model is significant at 95 per cent confidence interval (P: < 0.001). Further, the coefficient of determination (R^2) also implies that 40.75 per cent of forecasting performance of the GM is explained by the variables included in the model. The results of coefficients shown in Table VIII suggest that the variables CR, DR, GPR, ROSR, EPS and PDR are significantly associated with the GM forecasting performance. Therefore, *H1* is supported. In other words, it is conclude that the GM delivers a suitable performance for forecasting audit reports. The positive coefficients of CR, DR, and profitability ratios are also indicative of a positive and significant relationship with the GM.

4.4.2 The NGBM. The second regression model (the NGBM) is also estimated by using fixed effects model. Again, the overall model is significant based on the results shown in Table IX (P: < 0.001) and 65.21 per cent of the NGBM forecasting performance is explained by the variables included in the model (R^2: 65.21). The results for second regression model also indicate that the liquidity ratios, DR, profitability ratios and market ratios are significantly associated with the NGBM forecasting performance. In this case, the positive coefficients of CR, DR and profitability ratios indicate the positive impact of the variables on the NGBM. Taken together, the results provide empirical support for *H2* and thus the NGBM delivers a suitable performance for forecasting audit reports.

4.4.3 The NNGBM. The estimation results of the NNGBM are shown in Table X. As it is evident, the overall significance of the model is confirmed (P: < 0.001) and also 71.31 per cent of the NNGBM forecasting performance is explained by the variables included in the model. The variables CR, DR, GPR as well as market ratios exhibit significant relationships with the NNGBM forecasting performance. Moreover, the variables CR, DR, GPR, ROSR and PDR are positively associated with the NNGBM. Finally, our findings for the NNGBM provide supporting evidence for *H3*. More specifically, the NNGBM delivers a suitable performance for forecasting audit reports.

Model	n	Test	Statistic type	Statistic value	df	p-value
1	186	F Chow	F	9.1836	−69.194	0.0002
		Hausman	χ^2	20.4893	10	0.0001
2	186	F Chow	F	1.596	−69.194	<0.001
		Hausman	χ^2	30.618	10	0.0029
3	186	F Chow	F	3.0825	−69.194	<0.001
		Hausman	χ^2	12.4381	10	<0.001

Table VI.
The results of specification tests in panel data models

Table VII.
The matrix of Pearson correlation coefficients among research variables

p-value	$GM_{i,t}$	$NGBM_{i,t}$	$NNGBM_{i,t}$	CR	QR	AT	WCT	DR	DER	GPR	ROSR	EPS	PDR
$GM_{i,t}$	1												
$NGBM_{i,t}$	0.055 (−0.001)	1											
$NNGBM_{i,t}$	0.055 (−0.002)	0.064 (−0.000)	1										
CR	0.598 (−0.000)	0.309 (−0.000)	0.499 (−0.000)	1									
QR	0.041 (−0.000)	−0.056 (−0.145)	−0.042 (−0.000)	−0.015 (−0.630)	1								
AT	−0.000 (−0.001)	0.068 (−0.007)	0.162 (−0.082)	0.415 (−0.000)	−0.043 (−0.272)	1							
WCT	0.012 (−0.005)	−0.023 (−0.000)	0.147 (−0.066)	0.126 (−0.208)	0.074 (−0.060)	−0.068 (−0.081)	1						
DR	−0.135 (−0.000)	0.009 (−0.180)	0.097 (−0.013)	0.056 (−0.154)	0.075 (−0.054)	0.018 (−0.630)	−0.018 (−0.630)	1					
DER	0.013 (−0.001)	0.022 (−0.027)	0.521 (−0.001)	0.057 (−0.142)	−0.234 (−0.000)	−0.185 (−0.000)	0.185 (−0.000)	−0.159 (−0.000)	1				
GPR	0.032 (−0.209)	−0.125 (−0.000)	−0.125 (−0.000)	0.019 (−0.569)	0.126 (−0.001)	0.074 (−0.060)	−0.068 (−0.081)	0.068 (−0.081)	0.158 (−0.000)	1			
ROSR	0.117 (−0.001)	−0.062 (−0.033)	−0.062 (−0.033)	0.069 (−0.028)	−0.003 (−0.907)	0.021 (−0.107)	0.574 (−0.000)	0.052 (−0.007)	−0.022 (−0.018)	0.063 (−0.817)	1		
EPS	−0.046 (−0.173)	0.015 (−0.699)	0.015 (−0.699)	0.006 (−0.801)	0.111 (−0.001)	0.019 (−0.603)	0.142 (−0.021)	0.578 (−0.182)	0.001 (−0.001)	0.439 (−0.002)	−0.101 (−0.005)	1	
PDR	0.214 (−0.000)	0.234 (−0.000)	0.014 (−0.010)	0.014 (−0.000)	0.014 (−0.000)	0.004 (−0.054)	0.014 (−0.000)	0.414 (−0.080)	0.218 (−0.095)	0.214 (−0.000)	0.013 (−0.000)	−0.004 (−0.005)	1

Note: In the original, the $NGBM_{i,t}$ and $NNGBM_{i,t}$ columns each show a leading value "0" above the diagonal "1".

Variable	Coefficient	t-statistic	p-value	Result
a_0	4.9952	19.5328	<0.001	Significant; positively
CR	0.3205	0.5317	0.0001	Significant; positively
QR	−0.2297	−3.1023	0.0602	Non-significant
AT	−0.3957	−4.8649	0.0785	Non-significant
WCT	0.0125	0.3974	1.1402	Non-significant
DR	0.0011	0.8963	0.0002	Significant; positively
DER	1.0793	3.2817	0.0824	Non-significant
GPR	0.0135	2.2184	0.0001	Significant; positively
ROSR	0.0113	0.5313	<0.001	Significant; positively
EP	−0.6890	−7.1181	0.0001	Significant; negatively
PDR	−0.00001	−0.6363	0.0002	Significant; negatively
Model R^2			40.75	
Model F-statistic			13.2485	
F-statistic p-value			<0.001	

Table VIII.
The results of the estimation of the GM model parameters using fixed effects model

Variable	Coefficient	t-statistic	p-value	Result
a_0	0.3855	10.5008	<0.001	Significant; positively
CR	0.3205	0.1725	<0.001	Significant; positively
QR	−0.1916	−2.1517	0.0002	Significant; negatively
AT	−0.1740	−33.001	0.0605	Non-significant
WCT	0.0286	0.4969	0.2500	Non-significant
DR	0.8603	0.7853	0.0002	Significant; positively
DER	−0.4484	3.0025	0.0524	Non-significant
GPR	0.9105	1.2105	0.0005	Significant; positively
ROSR	0.0123	0.5523	<0.001	Significant; positively
EPS	−0.0090	−5.1254	<0.001	Significant; negatively
PDR	−0.0025	−0.3296	0.0003	Significant; negatively
Model R^2			65.21	
Model F-statistic			8.1013	
F-statistic p-value			<0.001	

Table IX.
The results of the estimation of the NGBM parameters using fixed effects model

Variable	Coefficient	t-statistic	p-value	Result
a_0	6.1088	10.3005	0.0022	Significant; positively
CR	0.5022	1.7423	<0.001	Significant; positively
QR	−0.00011	−1.0015	0.1802	Non-significant
AT	−0.1214	−7.4686	0.0005	Significant; negatively
WCT	2.0005	0.3974	2.0002	Non-significant
DR	1.0515	2.4142	<0.001	Significant; positively
DER	2.3980	3.2817	0.9253	Non-significant
GPR	0.0015	5.1818	0.0002	Significant; positively
ROSR	0.0215	0.1845	1.0315	Significant; positively
EPS	−0.5202	−5.1042	<0.001	Significant; negatively
PDR	0.00025	0.7524	<0.001	Significant; positively
Model R^2			71.31	
Model F-statistic			9.2809	
F-statistic p-value			<0.001	

Table X.
The results of the estimation of the NNGBM parameters using fixed effects model

4.5 The inputs ranking
There are several ways to measure the level of influence that each input has on the output, known as "inputs ranking". In this regard, the present study employs the mean squared errors (MSE). Based on this technique, any given variable with higher level of MSE indicates greater impact on audit report. The results are shown in Table XI. As it is evident, audit reports are most influenced by the CR. Conversely, they are least influenced by the ratio of WCT.

4.6 The best estimated model
A model with the least possible MSE value is regarded as the best forecasting model. Accordingly, we rank our estimated regression models in an ascending order to determine the best forecasting model. The results indicated in Table XII suggest that the NNGBM delivers the best forecasting performance as compared to other models.

5. Concluding remarks
The present study aims to employ the GM in an accounting field and forecast audit reports for top 50 companies listed on the TSE during 2011-2016. In this regard, the information of financial statements is analysed by using the GRA. Specifically, we used some financial ratios (liquidity, leverage, market, activity and profitability ratios) for this purpose and indicated and calculated their weights by using the Shannon entropy technique. After examining the assumptions of standard linear regression models and conducting the specification tests in panel data models, our findings provide empirical support for our hypotheses. In other words, the GM, the NGBM and the NNGBM deliver a suitable performance for forecasting audit reports. However, we rank the estimated regression models by using the MSE. The paper's findings provide some evidence indicating that the NNGBM delivers the best forecasting performance as compared to the other models including the GM and the NGBM. This finding is consistent with Chun *et al.* (2010), Wang (2013) and Zhang *et al.* (2014). Furthermore, our results are consistent with Wang and Hsu (2008), Huang and Jane (2009) and Mohammadi and ZeinodinZade (2011) in terms of forecasting precision of GMs in comparison with other methods. Using the MSE, we also examine the level of influence that each financial ratio has on audit report. In this case, the

Variable	MSE	Rank
CR	0.134	1
PDR	0.132	2
AT	0.131	3
QR	0.127	4
DR	0.125	5
ROSP	0.125	6
DER	0.124	7
GPR	0.123	8
EPS	0.122	9
WCT	0.109	10

Table XI.
Variables ranking
based on the MSE

Regression Model	Score	Rank
NNGBM	1.3299	1
NGBM	1.2983	2
GM	1.2811	3

Table XII.
Regression models
ranking based on
the MSE scores

CR yields the highest possible impact on audit report whereas the WCT indicates the lowest influence. Consistent with Spathis (2003), Gaganis *et al.* (2005, 2007), Sajjadi *et al.* (2007), Amini *et al.* (2011) and Jamei *et al.* (2013), audit reports are most influenced by the CR, DER and EPS, respectively.

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