UNIVERSITY OF NAIROBI

Panel Data Modelling: Application to Financial Performance of Non-Financial Firms Listed at Nairobi Securities Exchange

BY

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Abstract

Background: Financial performance has always been estimated using cross-sectional data. However, because typical firm heterogeneity is not effectively controlled, biased results have been reported. Both specific and general group behaviors can be designed using panel data. They provide useful information, are more efficient, and have larger fluctuations than cross-sectional data. Data that is cross-sectional or time series in nature, as opposed to data that is a panel in form, is incapable of detecting and quantifying the statistical effect. With the most appropriate panel data model to predict and monitor the factors associated with the financial performance of non-financial firms as listed on the Nairobi Securities Exchange, researchers will get to find the relevant elements using panel data rather than cross-sectional data, especially in finance. It will also make it easier for investors to spot trends among the NSE's listed companies. This study thus sought to bring into light the most appropriate panel model in analysing the different factors that affect the financial performance of non-financial firms listed on the Nairobi Securities Exchange.

Objective This study's primary objective was to determine the most appropriate panel data model to predict and monitor the factors associated with the financial performance of non-financial firms as listed on the Nairobi Securities Exchange. The findings will thus add to the existing body of knowledge and enlighten potential investors on how to evaluate performance over time. Other stakeholders who will find the findings useful include the Kenyan government and Capital Markets Authority and will use the results in formulating regulations and policies for publicly listed companies.

Methods: This study adopted a panel data approach in the attempt to investigate the factors influencing the financial performance of non-financial institutions listed at the Nairobi Securities Exchange, Kenya. The study used the data obtained from the Nairobi securities exchange on the financial performance of non-listed firms. Descriptive statistics was also used to understand the nature of the data in relation to the research interest.

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Declaration and Approval

I the undersigned declare that this dissertation is my original work and to the best of my knowledge, it has not been submitted in support of an award of a degree in any other university or institution of learning.

16th November 2022

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In my capacity as a supervisor of the candidate's dissertation, I certify that this dissertation has my approval for submission.

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Dedication

I dedicate this research to my family, my loving dad Patrick Mburu and mom, Rebecca Mwangi for their encouragement and support, and for giving me a chance to further my studies, my siblings Collins Mburu, Michael Mwangi and Isabella Mwihaki for their motivation, support and understanding throughout this laborious journey. I am grateful

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ESTHER NYAMBURA IRUNGU

Nairobi, 2022.

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Abbreviations and Notations

Abbreviations and notations for specific chapters can be found in those chapters,and those that are generally used are listed below:

AIMS	Alternate Investment Market Segment
CMA	Capital Markets Authority
CS	Capital Structure
EDA	Exploratory Data Analysis
EPS	Earnings per Share
FE	Fixed Effects
FISMS	Fixed Income Securities Market Segment
FL	Financial Leverage
FS	Firm Size
LEV	Leverage
LM	Lagrange Multiplier test
LTD	Long Term Debt
NSE	Nairobi Securities Exchange
OLS	Ordinary Least Squares
POLS	Pooled Ordinary Least Square
PROF	Profitability
RE	Random Effects
ROA	Return on Assets
ROE	Return on Equity
ROI	Return on Investments
US	United States
STD	Short Term Debt
SC	Share Capital

Definition of Terms

Heterogeneity: Is defined as a dissimilarity between elements that comprise a whole. When heterogeneity is present, there is diversity in the characteristic under study.

Homogeneity: In a panel data model setting implies that panel data model parameters both the slope coefficients and the constant are constant across individuals.

Endogeneity: It occurs when a predictor variable x in a regression model is correlated with the error term e in the model. Endogeneity can arise as a result of measurement error,autoregression with autocorrelated errors, and omitted variables.

Exogeneity: Refers to when there is no correlation between the independent variable and the error term in the regression model, a variable is said to be exogenous.

Time series data: A time series data is a sequence of numerical data points in successive order, measured typically at successive points in time spaced at uniform time intervals. It is a collection of observations of well-defined data items obtained through repeated measurements over time.

Cross-sectional data: Cross-sectional data refers to data collected by observing many subjects such as individuals, firms or countries/regions at the same point of time, or without regard to differences in time.

Financial Performance: Financial performance is a subjective evaluation of a company's ability to employ assets from its principal method of operation to create revenue. The phrase is also used to describe a firm's overall financial health during a certain time period.

Listed Firms: Refers to firms trading in a stock market (NSE)

Share Capital: Refers to the total amount of capital raised by the company issuing shares

Short Term Debt: Short-term debt, also known as current liabilities, refers to a company's financial obligations that are due to be paid off within a year. Short-term bank loans, accounts payable, wages, lease payments, and income taxes payable are all examples of common types of short-term debt.

Long Term Debt; Long-term debt has a maturity date of more than a year and is generally regarded differently than short-term debt. Long-term debt is a liability that must be repaid for the issuer, whereas debt owners account for it as an asset.

Retained Earnings: Retained earnings are a company's total net earnings or profit after deducting dividends. They are also known as the profits surplus.

Non-Financial Firms: This refers to firms quoted at stock market other than those in the banking, insurance, some investment firms and some commercial and service firms (NSE, 2016).

1 GENERAL INTRODUCTION

1.1 Background Information

According to Roach (2021), the term performance originates from "parfournir," a French word that implies to bring through, to beget, or carry out. Performance is the action of fulfilling, achieving, administering, and performing tasks assigned and that can only be tested against measured and calculated sets of timing, fullness, money, and precision (Galar and Kumar, 2019). Performance, according to Schaltegger and Wagner (2017), in the field of finance, refers to the evaluation of the operational business, performance outcomes, and guidelines. Performance is necessary for assessing the adherence, financial standing, and success of a company. The capital employed, the profitability, equity, and assets as well as the firm's return on investment mirror the results (Naz et al., 2016).

Several indicators such as capital adequacy ratio, cash flow, leverage, financial stability, and revenue growth measure the use and collection of funds over a specific period which are all defined as the Company's financial performance (Fatihudin, 2018). Financial performance primarily reflects business sector results that demonstrate the sector's financial condition and performance over a particular period. It demonstrates how well a company uses its resources to maximize shareholder value and return on assets (Nguyen and Nguyen, 2020). A company's financial performance is very critical for its' survival and health. Its' performance financially is attributed to its monitoring and controlling abilities for its resources (Jain et al., 2017). According to De Massis et al. (2018), the effectiveness and efficiency with which a firm manages its resources for operational, investment, and financing activities is reflected in its high performance.

While there is a burgeoning body of theoretical and empirical literature on listed firms' financial performance, it is uncertain on both the unit of measure and predictors of firm financial performance (Saridakis et al., 2017). According to ", Intellectual Capital and Financial Performance: A Meta-Analysis and Research Agenda," (2019), past studies have proxied ROE, ROI, Tobin's Q, and ROA to estimate a firm's financial performance. Some have employed all or some of these proxies for the performance of a firm's finances. These studies have yet to ascertain which of these proxies is the most accurate theoretically and/or empirically measure of a firm's financial performance. To benchmark financial performance, leverage ratios, solvency, liquidity, and profitability efficiency can be used (Fatihudin et al. 2018).

When making a purchasing or selling decision of investment instruments/portfolios in the financial markets, investors use technical and fundamental analysis (Fatihudin, 2018). Fundamental analysis is centered on the company's financial statements. The image/graph statistics are used for technical analysis. Both are equally essential in making an investment portfolio/instrument decision and have both advantages and disadvantages. In practice, however, because of its practical ability, most investors rely on technical analysis (Palepu et al., 2020).

1.1.1 Firm's Performance and EPS

For a long time, financial pundits and other non-expert users of financial statements have proclaimed EPS to be the pinnacle of financial performance (Johnson, 2017). The ratio of profit a company allocates towards each outstanding share of common stock is known as EPS. Managers have enormous pressure to achieve satisfactory EPS results. This originates from the necessity for companies to make a report of their revenues after every three months which has been dubbed "quarteritis."There appears to be a gradually rising emphasis on short-term EPS performance emerging from global supervisors who appear to be aware of the implications of EPS variations on share prices (Ball and Brown, 2019). Managers use a range of EPS management methods rather than focusing their time and effort on projects that maximise long-term shareholder wealth. The consequences of EPS falling short of expectations for manager is assessed in terms of EPS (Ball and Brown, 2019).

Public companies can increase their per-share earnings by purchasing their stock on the open market. As a result of the acquisition, earnings per share rise, this in return reduces the number of the shares but keeps the earnings constant. While the overall operational and profitability efficiency remains unchanged, the earnings per share rise with the same earnings amount and with fewer shares (McEnroe and Sullivan, 2018). In the determination of the price of the stock market, most financial analysts trust that EPS is the most significant factor. By rising or by having higher earnings per share, a stock's price can be driven up. In contrast, falling earnings per share can cause a stock's market price to fall. Also, through EPS, one can calculate the ratio of price-to-earnings. It is achieved by dividing the price of the stock market by its' per-share earnings. Many investors regard this as an excellent company's stock value predictor (Musallam, 2018).

Diluted EPS considers all securities, such as stocks and bonds, which have the potential to cancel out or reduce basic EPS. Common stock shares are typically purchased by investors to generate income through dividends or to resell at a higher profit (Robbetze et al., 2016). Investors understand that low EPS can result in insufficient or inconsistent dividend payments and fluctuating stock prices. As a result, businesses strive to generate EPS figures that rise over time. An increase in EPS, however, does not always indicate improved performance because EPS can rise for a myriad of purposes. EPS can rise significantly resulting from increased net income. It can, however, rise when a company repurchases its amount of inventory. Similarly, even if a company's net income increases, earnings per share (EPS) may fall if the amount of shares increases faster than net income (Pennacchi and Santos, 2021).

Companies are fundamentally restructuring their operational methods and business performance. Using the sustainable business development concept companies are experimenting with social responsibility for generations both current and future. They often combine with their promise of protecting the environment and the quest for development that is cost-effective (D'Aveni, 2018). Many businesses are attempting to implement significant changes in their commitments, policies, short and long-term strategic frameworks, and business structures based on the new phenomenon. Financial factors considered are such as the company's size, the companys ability to make profit, its ability to govern and pay debts, its capital turnover, and so on (Fatihudin, 2018). Companies are classified as major, medium, or micro. Small businesses include family businesses, individual firms, conglomerates, and joint ventures (Fatihudin, 2018).

A cross-sectional analysis is a study of an entire group within a larger group of entities over a particular time period. In terms of financial application, such an analysis is typically focused on a subset of connected firms and industries (Löher, 2016). A cross-sectional analysis, according to Pollard (2018), is a type of analysis in which a shareholder, consultant, or financial consultant compares a specific company to its industry peers. A portfolio manager or an investor uses statistical information from financial statements when conducting a cross-sectional analysis to evaluate and make comparisons that are useful for separate companies (Pollard, 2018). Traditionally, financial performance has been estimated using cross-section data. However, because typical firm heterogeneity is not adequately controlled, this has produced biased results (Bruns et al., 2017). Panel data can be used to design both specific and general group behaviors. They give important information, are more effective, have larger variations than cross-sectional data. Cross-sectional or time series data, as opposed to panel data, are incapable of detecting and quantifying effects that are statistical. Estimation biases emerge when groups are merged into a single time series. Panel data can assist in minimizing these biases. These are some of the benefits of panel data over cross-sectional data (Porter et al., 2018).

Using panel data rather than cross-sectional data will allow researchers to identify the associated factors, particularly in finance. It will also make it easier for investors to identify patterns for various firms listed on the NSE. Longitudinal temporal changes assessment is critical for learning the specific time firms' factors that might otherwise be missed. The use of a panel data approach to analyzing a firm's performance will also assist researchers in understanding how panel data approaches can be used to predict and monitor the factors associated with the financial performance of firms listed on Nairobi Securities Exchange.

1.1.2 The Nairobi Securities Exchange

The NSE remains as the main securities exchange of Kenya and also the leading securities exchange within the East African countries; this makes it able to offer platforms for the issuance and trading of debt and equity securities (Kioko,2015).The NSE is a body corporate established under the Companies act (CAP 486) of the Kenyan law and comprise of all licensed stock brokers as the shareholders (Muigai,2016).The capital markets authority of Kenya regulates the exchange and its main function is to provide a stock market where shares are bought and sold (Olang,2017).The NSE focusses on helping the trade clearance arrangement of equities, debt derivatives and other related financial tools. Notably all companies in the securities exchange are mandated to be listed as this enables the investors to buy and sell securities of a company therefore it is connected to the soundness of Securities Exchange (Maniagiet al.,2013).

NSE began as an association of stockbrokers and shaped the development of securities market in Kenya through regulating trading activities. The market is organized into three main segments; the MIMS, FISMS and AIMS.MIMS is the central market quotations are made. Firms seeking short term sources of capital trade in MIMS, while trading involving treasury and corporate bonds, preference shares and debenture stocks take place at FISMS. Therefore, NSE has a mandate to encourage savings and investments as well as providing easy access to capital for both international investors and borrowers together.There are sixty-two firms listed on the NSE and are divided into thirteen division i.e., Agricultural, Automobiles and Accessories, Banking, Commercial and Services, Construction and Allied, Energy and Petroleum, Insurance, Investment, Investment Services, Manufacturing and Allied, Telecommunication and Technology, Real Estate Investment Trust and Exchange Traded Funds. There are 44 non-financial companies' highlighted in NSE.

1.2 Research Problem

It is reported in the literature that firms' financing decisions are essential in determining investment decisions. It is also evidenced that the presence of frictions in unlocking external sources of finance, such as imperfect information, has a significant impact on management's ability to capitalize on opportunities for productive investment (Agénor and Canuto, 2017). The Kenyan government has made concerted efforts, in collaboration with corporations and individuals in the private sector, to create an enabling environment for carrying out business in the country. As a result, while the organizations listed on the NSE have expanded their effectiveness, others have seen their fortunes deteriorate, and some have even been delisted from the NSE's list in recent years. Significant efforts to turn these companies around, or even reduce them, have primarily centred on restructuring their finances. Managers and practitioners, on the other hand, continue to struggle with inadequate direction for making appropriate financial decisions (Cascio et al., 2016). According to Pham et al. (2020), many of the hurdles facing the industries placed under governmental supervisors, which resulted in stakeholders' wealth loss and overall confidence of investors in the NSE, were chalked up to financing, although there was no objective and systematic proof to substantiate this claim. On this basis, the aim of this research will be to examine the factors that affected the performance of non-financial companies listed on the NSE from 2008 to 2017. Traditionally, financial performance has already been approximated using cross-section data. However, because typical firm heterogeneity is not appropriately controlled, this has produced biased results. In terms of performance, researchers continue to believe that non-financial firms have untapped potential. Furthermore, studies have not determined why one firm outperforms the other. Many financial analysts, on the other hand, believe that EPS is the single greatest factor in understanding a stock's market price. The resulting number is a sign of a company's profitability, and thus its outcomes. Other non-financial indicators are overlooked by most investors but have an impact on a company's performance. The problems are not listed, most likely due to a lack of knowledge about the precise factors or limited data. Using a panel data approach, this study attempted to fill this conceptual gap. The study attempted to address the issue by allowing for more broad areas of heterogeneity. Despite explicitly modeling unobservable firm-specific fixed effects, it was predicted that they will be incorporated into the model. A panel data analysis was conducted in this study to determine the factors that affect the performance of non-financial firms listed on Kenya's NSE.

1.2.1 Research Hypotheses

1. H_{01}: There is no significant effect of short-term and long-term debt on the financial performance of non-financial firms listed on the Nairobi Securities Exchange.
   H_{11}: There is a significant effect of short-term and long-term debt on the financial performance of non-financial firms listed on the Nairobi Securities Exchange.

2. H_{02}:There is no significant effect of retained earnings and share capital on the financial performance of non-financial firms listed on the Nairobi Securities Exchange.
   H_{12}:There is a significant effect of retained earnings and share capital on the financial performance of non-financial firms listed on the Nairobi Securities Exchange.

1.3 Objectives

1.3.1 General objective

The main objective of this study was to identify the best panel data model for predicting and monitoring the factors associated with the financial performance of non-financial entities listed on the Nairobi Securities Exchange.

1.3.2 Specific Objectives

This study aimed at the following specific objectives:

1. To identify the factors associated with the financial performance of non-financial firms listed on the Nairobi Securities Exchange.

2. To determine the effect of short-term and long-term debt on the financial performance of non-financial firms listed on the Nairobi Securities Exchange.

3. To analyze the influence of retained earnings and share capital on the financial performance of non-financial companies listed on the Nairobi Securities Exchange.

1.4 Significance of the study

Panel studies are a type of research method that analyzes data on individuals, households, and, increasingly, firms, countries, or other entities over time. The information can come from survey data, national statistics, or other sources. F. Lazarsfeld pioneered the use of panel data in a study of public opinion in the 1940s, using market research collected over time. Panel studies are now commonly used in social and life sciences research. Panel data studies can sometimes be made based on data from countries, organizations, or just about any social unit. While the methods of collecting data may differ for both panel data sets, the description of the panel remains consistent in that it defines a specific type of method for collecting that gauge the same unit repeatedly over time (Andreb, 2017). Panel studies are an indispensable research tool in the social and economic sciences. Panels can respond to most research questions that cross-sectional data would not normally answer. They even overcome some of the limitations and potential biases of cross-sectional data when testing theories and designing policies.

This study aimed to understand how EPS is an important determinant in evaluating a firm's performance. The study was designed to add to corporate finance as well as literature. Moreover, it adds to our understanding of the NSE and especially the application of the panel data approach in analyzing the performance of non-financial firms. Unfortunately, managers recognize how well the number of outstanding shares affects EPS and are frequently in a position to try to influence EPS by executing transactions that target a specific EPS number. The findings will thus add to the existing body of knowledge and enlighten potential investors on how to evaluate performance over time. Other stakeholders who will find the findings useful include the Kenyan government and Capital Markets Authority and will use the results in formulating regulations and policies for publicly listed companies.

1.5 Scope of the Study

The study used annual secondary data available for all non-financial firms from 2008 to 2017. The data was sourced from NSE and specifically from the firms audited financial statements and reports, as well as from NSE handbooks and online materials. The study intended to have panels for all listed non-financial firms but some had to be dropped due to unavailability of data.

1.6 Limitation of the Study

Each panel study is a long-term investment that necessitates significant financial and human resources. Unfortunately, not even all institutions listed have the resources to document and disseminate their data in a reliable and user-friendly manner. Also, since variables are often measured at multiple time points for each subject over a relatively long period; a common challenge is that data on some of these variables may be missing at critical times. In this case, some of the non-financial institutions had been delisted over the years from the NSE. Also, there was a recurring issue of missing data for some of the non-financial institutions.

2 LITERATURE REVIEW

2.1 Introduction

2.1.1 Financial Performance

Financial performance is defined as a measure of a company's ability to generate revenue using its available resources. It serves as a road map for future company decisions, asset purchases, and managerial oversight (Anik et al., 2021). It indicates what the management has accomplished in monetary terms over a certain time period and can be used to compare similar organizations in the same industry. Financial performance, according to Ongore and Kusa (2014), provides a means of evaluating corporate activity in objective monetary terms. The firm's primary goal is to maximize shareholder value, therefore performance measurement aids in determining how much richer a shareholder becomes as a result of investment decisions made over time (Anik et al., 2021).

Firms frequently finance a portion of their assets with equity such as ordinary, preference, and retained earnings capital, while the remainder is financed with other resources such as long-term financial debts or liabilities such as bonds, bank loans, and other loans and other short-term liabilities such as trade payables (Gambacorta et al., 2014). Companies can pick from a variety of different financial arrangements. Short-term loan financing, long-term debt financing, share capital, and retained earnings are only a few examples. Lease financing, the usage of warrants, the issuance of convertible bonds, the signing of forward contracts, and the trading of bond swaps are all options available to a company according to Ghazouani (2013). To optimize overall market value, companies can also issue thousands of different securities in limitless combinations (Dare and Sola, 2010). As a result, financial structure is vital and fundamental in the business life cycle, not only to maximize shareholder value but also to influence financial growth (Ishaya and Abduljeleel, 2014).

According to Odongo (2013), financial performance can be measured by return on investment (ROI), return on equity (ROE), and return on assets (ROA) as the dependent variable. A firm's financial performance is measured by how better off the shareholders are at the end of a period, than the investors were at the beginning of the period. This is determined using financial ratios, which are obtained from financial statements such as income statements, cash flow statements, and balance sheet or by using data on stock market prices (Altan, Yusufazari and Beduk, 2014). The financial ratios provide an indication of whether the firm is achieving the owners' objectives of improving their financial welfare.

Cooper and Schindler (2014) observed a significant positive association between debt ratio and measures of profitability, while Adesina (2012) discovered a significantly positive relationship between debt ratio and measures of profitability.Because the major purpose of shareholders investing in a business is to increase their wealth, evaluating a firm's success should show how much wealthier the shareholder has become as a result of the investment over a specified time period.An appropriate performance metric is designed to compensate for all effects of investments on shareholder wealth (Dietrich and Wanzenried, 2014). Financial leverage boosts a company's return on equity when the earnings power of its assets exceeds the average interest expense of its debt.

2.1.2 EPS and Financial Performance

EPS is an essential business indicator used to assess a company's risk, organizational performance, and profitability. To compute diluted EPS, the Total basic profits are adjusted for any after-tax savings that would occur from the exchange of convertible instruments for ordinary shares before being divided by the increased number of ordinary shares while the basic EPS is calculated by dividing the actual earnings after preference shares by the weighted average number of ordinary shares (Kennon, 2014). Since EPS is frequently reflected in share price behaviour changes, they are used to forecast future share prices (BDO, 2014).

Robbetze et al. (2016) explored whether the type of profit per share (basic, diluted, or headline EPS) is most closely associated to share prices. The top 40 JSE-listed companies were included in the sample. The time period spanned from 2005 through 2013. The study findings were that headline profits per share had lower association coefficients than other categories of earnings per share. Overall and according to the findings, basic EPS was the most important driver of the fluctuations of prices of the shares. However, it was suggested that investors analyze the economic climate when making investments. This is because diluted EPS appears to have substantial correlations with share prices during times of economic difficulty Vaidya (2014).

Total basic profits are adjusted for any after-tax savings that would occur from the exchange of convertible instruments for ordinary shares before being divided by the increased number of ordinary shares to calculate diluted EPS (BDO, 2014). Increases in the number of ordinary shares frequently result in lower, and thus diluted, earnings per share (Kennon, 2014). Furthermore, an entity's basic and diluted EPS must be declared on the face of the Statement of Profit or Loss and Other Comprehensive Income (BDO, 2014).According to Vaidya (2014), the most fundamental sort of EPS is basic EPS. When calculating basic EPS, profit or loss attributable to the owning corporation must be adjusted for after-tax amounts of preference dividends (IFRS, 2014). To calculate basic EPS, we divide the weighted average number of ordinary shares by the actual earnings after preference shares. Diluted EPS is more difficult to understand than pure EPS (Kennon, 2014). Diluted EPS is the amount of earnings per share that a company would earn if all warrants, convertibles, and options were exercised, resulting in an increase in total ordinary share capacity (Koppeschaar et al., 2013).

According to Robbetze et al. (2016), even today, EPS is considered to be the single most popular, widely used financial performance benchmark of all. Financial executives in the USA had reported that the majority were of the opinion that earnings were the most important performance measure they report to outsiders. EPS is also the linchpin undergirding strategic decision making like share valuations, management performance incentive schemes and merger and acquisition negotiations. EPS is simple to calculate and easily understood and management is congratulated when there is positive EPS growth. It is no surprise that managers take a special interest in EPS when their compensation is linked to the EPS performance of the company. Most investors are familiar with the valuation multiple, the P/E ratio, which has EPS as the denominator (Robbetze et al., 2016).

Adkins, Matchett and Toy (2010), attribute the obsession with EPS to the fact that EPS neatly summarizes the earnings generated for shareholders and the shareholder's view appeals to investors and management alike. Short term EPS performance is especially important for younger companies for which future growth expectations are more sensitive to current performance, compared to older companies with a longer operating history. In addition, he points out that senior executives, who are constantly mindful of the link between their own reputation, the risk of losing their job and the share price, tend to focus on short term measures like EPS. Further he comments that when companies, under severe pressure to meet market expectations, underperform EPS estimates by only a few cents, experience "double digit nosedives" in share prices.

Sharma (2011), indicated that share prices and EPS move in the same direction. The correlations obtained were positive, indicating that variables moved in the same direction and are therefore strongly correlated. Moreover, Sharma also found significant correlations between EPS and share prices, as well as dividends per share and share prices. Such findings are not unexpected, because dividends depend upon earnings. Menaje (2012), demonstrated that EPS impacts share prices significantly, which is in line with the findings of this, as well as other studies by Almumani (2014) and Iqbal et al. (2015).

2.2 Panel Data

Panel studies according to Andreß (2017), are a type of research approach that analyses data collected on individuals and families, as well as firms, governments, and other entities, across time. Surveys, official statistics, and other sources, such as process-produced data, can all be used to generate the data.In the 1940s, F. Lazarsfeld employed panel data for the first time in an analysis of public opinion based on market research gathered over time. The Erie County Research, the first typical panel survey, was undertaken by Columbia University's Bureau of Applied Social Research during the 1940 presidential campaign (Andreß, 2017). Panel studies are currently commonly used in social science research because they offer more dependable results than other research methods. The complexities of panel research design, on the other hand, present both challenges and opportunities. Particularly at the individual level, the most important reason to collect panel data is to investigate the process of change through time. (Mo Wang et., 2017).

According to Fredriksson and Oliveira (2019), scholars disagree on the extent to which panel data should be employed in research . Some feel that panel data, like cross-sectional data analysis, can be used to investigate levels and trends across time; however, cross-sectional data analysis does not provide information about individual change. Others say that panel data should only be used to analyse change since "panel attrition," or persons falling out of the observation/survey while long-term patterns are being researched, is possible.Broadly, the academic community believes that focusing simply on change would be a waste of money, because while panel data can provide a plethora of information on levels and trends, cross-sectional surveys sometimes ignore key features. Although it is possible to combine several cross-sections over time to perform the same analysis, such a "pooled cross-sectional design" would only provide "synthetic cohorts" because individuals observed in each period may vary over periods, whereas the panel design provides "true cohorts," or the same entities who have been monitored repetitively over time (Fredriksson and Oliveira, 2019).

Zhao et al. (2018), defines panel data to be often known as longitudinal data and as a type of data that contains a large number of people's time-series observations.. Wang et al. (2020), describe panel data as a collection of quantities gathered from several persons and organised chronologically over even time intervals. Panel data has a cross section dimension that relates to the cross section units themselves, as well as a time dimension that refers to the time periods that the cross section units are detected.Panel data refers to groups with the subscript i denoting individuals and subscript t for time to denote observations of time. Hence, double subscripts are entailed in a panel regression e.g. y_{it} denotes the value of a variable y pertaining to cross section unit i observed in time t . Likewise, x_{it} denotes the value of another variable x pertaining to cross section unit i observed in time t .At least three elements drive the geometric expansion of panel data studies: the demanding approach, improved ability to model the complex nature of human nature, and the availability of data.

Panel data differs from cross-sectional analysis. Panel data enables a researcher to analyse cross section effects which are the variation across companies, and time series effects which are the changes across time.In the use of panel data two conditions are of importance: one is that data should be from multiple entities collected over time. However, there may be constraints imposed by the amount of observations and the connection between the two. The recommendation is that a high number of entities and a short period of time be used in order to avoid over identification and to have appropriate degrees of freedom. Cross-section units are represented by n while the time period units are represented by t in panel regression. A standard panel data set model stacks the $y_i^{'}s$ and $x_i^{'}s$ as

$y = X\beta + c + \varepsilon$
X is a $\sum_i T_i xk$ matrix
β is a k×1 matrix
c is a $\sum_i T_i x1$ matrix, associated with unobservable varibales
y and ε are a k×1 matrices

Masila (2016) used a panel regression model to investigate how financial leverage influences the growth of listed agricultural enterprises in Kenya from 2010 to 2017. The study's goal was to contribute to the debate about the impact of financial leverage on the growth of publicly traded agricultural enterprises. The paper analysed annual secondary data accessible for all NSE-listed agricultural enterprises, specifically their audited financial statements and reports, as well as the NSE handbook. Panel data was chosen for the study because it included both cross-sectional and time series characteristics that could vary across time. This assisted in reducing biases by controlling variable omission. A fixed effect model was employed to accommodate for differences in each firm's intercepts while keeping consistent slopes. The study tested for heteroscedasticity using the Breusch-Pagan and Eicker-Huber tests.A Hausman test for fixed and random effects was also done to select the best model for the study Growth was assessed in terms of asset growth, which combined annual assets purchased and determined percentage variations in order to evaluate the firm's growth.The study discovered that leverage and profitability positively impacted a firm's growth whereas age was negatively connected with firm growth.

Ayako et al. (2015) used panel data to examine the determinants influencing the performance of 41 non-financial companies listed on the Nairobi Securities Exchange (NSE) from 2003 to 2013. The findings of a Hausman test indicated using a random effects model for ROA and a fixed effects model for ROE. The empirical results of both ROA and ROE estimation demonstrate that corporate governance was statistically important in affecting business performance. Firm size and liquidity, on the other hand, were found to be statistically unimportant in determining these firms' success. The study indicated, in line with earlier research, that board size, board independence, and liquidity are important drivers of a firm's financial performance. As a result, the study recommended that a company maintain optimal board size and board independence. The report suggested doing comparative studies on the factors impacting the financial performance of financial and non-financial enterprises listed on the Nairobi securities exchange, as well as those that are not. Furthermore, it suggests that additional research be conducted to examine the determinants influencing company success at a cross-country level, such as within the East African Community.

Mabeya and Kariuki (2019) conducted a study to determine the effects of financial structure on firm value of non-financial enterprises listed on the Nairobi Securities Exchange. Long-term debt, current liabilities, share capital, and retained earnings were studied as independent factors, with firm value as the dependent variable. Tobin's Q was utilised to determine company value, while Pearson correlation and regression analysis were employed to evaluate panel data obtained from 36 firms selected from among Kenya's 50 listed non-financial firms. Secondary panel data was gathered from audited and publicised financial reports from 2012 to 2016. To assess the nature of the panel data and the optimal model for analysis, a panel data diagnostic test was performed. According to the findings, current liabilities and retained earnings have a considerable positive effect on business value, whereas long-term debt and share capital have insignificant positive and negative effects on firm value, respectively. This study accomplished its goals and objectives. The study did, however, recommend topics for additional research. To begin, future research should investigate the impact of financial structure on enterprise value for both financial and non-financial firms. Second, the study gathered information from 2012 to 2016. The study also suggested that future studies focus on a longer time period, such as 10 years, to better understand the phenomenon. (Mabeya and Kariuki, 2019).

Jirata (2014) noted various benefits associated with the usage of panel data. Panel data has several advantages over cross-sectional or time-series data because it combines inter-individual differences with intra-individual dynamics. Panel data can also be used to estimate model parameters more precisely. Panel data have more degrees of freedom and sample variability than cross-sectional data, which may be viewed as a panel with $T = 1$, or time-series data, which can be viewed as a panel with $N = 1$, allowing for more efficient econometric estimations. Panel data can also capture the complexities of human behaviour better than single cross-section or time-series data. Developing and testing more sophisticated behavioural hypotheses is one of them. Managing the impact of factors that have been left out. It is sometimes asserted that the real reason why certain effects are discovered or not discovered is that some variables in one's model specification that are connected with the included explanatory variables are overlooked Jirata (2014),. Panel data can be utilised to mitigate the effects of missing or unobserved variables because they provide information on both intertemporal dynamics and entity uniqueness.

Further,according to Jirata (2014), dynamic relationships are also uncovered using Panel Analysis. Because economic behaviour is fundamentally dynamic, the bulk of econometrically significant interactions, whether explicitly or implicitly, are dynamic. Instead of predicting individual outcomes using data on the individual in question, more accurate predictions for individual outcomes can be achieved by pooling data. If individual acts are comparable conditional on specified criteria, panel data can be used to understand a person's behaviour by observing the behaviour of others. Thus, by integrating observations of the individual in question with data about other individuals, a more precise picture of their behaviour can be generated. Panel data also serve as micro-foundations for the investigation of aggregate data.In aggregate data analysis, the "representative agent" assumption is commonly utilised. The "homogeneity" vs. "heterogeneity" dispute can be examined using panel data containing time-series observations for a large number of people.

Other advantages include making statistical inferences and calculation easier. Two major advantages of panel data are the two dimensions: a cross-sectional dimension and a time series dimension.Panel data can also minimize estimation biases that may arise from aggregating groups into a single time series. However, if panel data are available and cross-sectional unit observations are independent, the central limit theorem across cross-sectional units can be used to prove that many estimators' limiting distributions remain asymptotically normal.Also in Errors in measurement and Dynamic Tobit models. For instance in large sample approximation of the distributions of the least-squares or maximum likelihood estimators are no longer normally distributed when time series data are not stationary.

2.3 Characterization of Panel Data

2.3.1 Wide and Long Panel Datasets

Chaturvedi (2016), discusses the different ways that panel datasets can be coded including Wide and Long panel datasets. According to Chaturvedi, long format datasets include all of the observations of each variable from all groups and time periods into a single column. Each individual will have many records in the lengthy format. Some variables that do not change over time are the same in each record, whereas others change with time. A "time" variable that marks the time in each record, as well as an "id" variable that organizes entries from the same person, are also required in the long format. Each individual will have one record in a wide dataset. Different columns are used to code observations made at different times. Every time-varying measure has its own set of columns in the wide format. When panel data is stored in a wide data format, the observations for a single variable from different groups are stored in separate columns. The repeated responses of a subject will be in a single row in the wide format, with each response in its own column. Each row in the lengthy format represents one time point per subject. As a result, each subject will have many rows of data. Any variables that remain constant over time will have the same value across all rows (Chaturvedi, 2016).

According to Allaire et.al. (2022), applied researchers frequently acquire, store, and evaluate data in a variety of formats. For repeated measures, traditional ANOVA and MANOVA approaches, as well as structural equation models for longitudinal data, assume a wide format. Multilevel approaches and statistical graphs, on the other hand, only work with the long format. Both formats however have their advantages. The wide format has no redundancy or repetition if the data is collected at the same time points. In this format, basic statistical procedures such as computing means, change scores, age-to-age correlations between time points, and the t-test are simple. The long format is ideal for dealing with intermittent or missing units. In addition, the long format includes an explicit time variable that can be used in analysis. The long format makes graphs and statistical analyses easier (Allaire et.al. 2022).

2.3.2 Balanced Panel Data versus Unbalanced Panel Data

Kerstens and Van de Woestyne (2014) considered unbalanced panel data and balanced panel data as panel data characterizations. According to them, balanced panel datasets have the same amount of observations for all groups, whereas unbalanced panel datasets have missing values for some of the groups at times. The number of time periods T in a balanced panel is the same for all participants I. Otherwise, the panel is imbalanced. Certain panel data methods are only applicable to well-balanced datasets. If the panel datasets are unbalanced, they may need to be shortened to contain only the consecutive periods for which all people in the cross section have observations. In a balanced panel, all panel members have measurements in all periods in the form of cross-sectional data, or each panel member is monitored every year. If a balanced panel has n panel members and t periods, the number of observations (N) in the dataset must be $N = nt$. An unbalanced panel has a varied amount of observations for each panel member in a data collection, or at least one panel member is not observed every time. If an unbalanced panel has n panel members and t times, then the stringent inequality for the number of observations (N) in the dataset is as follows: $n \times T$.

2.3.3 Panel data with short time dimensions vs long time dimensions

According to Kerstens and Van de Woestyne (2014), a short panel is one that observes a large cross section of individuals for a few time periods rather than a long panel that observes a small cross section of countries for many time periods. The enhanced precision in estimation is a significant benefit of panel data.For a panel dataset with a short time dimension $N > T$. For this panel dataset, which is commonly referred to as a micro panel, the shortness of the time dimension is potentially beneficial in that we do not have to worry about issues surrounding panel unit roots and panel co-integration. For a long time dimension panel dataset $N < T$. For this panel dataset, which is commonly referred to as a macro panel, the long length of the time dimension is potentially problematic in that we must worry about issues surrounding panel unit roots and panel co-integration. Micro panels are more common than macro panels

3 PANEL DATA MODELS

3.1 Methodology

3.1.1 Research design

This study adopted an explanatory non-experimental research design to investigate the factors influencing the financial performance of non-financial listed at the Nairobi Securities Exchange, Kenya. Explanatory research seeks to establish causal relationship between variables (Saunders et al., 2009 ; Robson 2002). According to Kerlinger and Lee (2000) an explanatory non-experimental research design is appropriate where the researcher is attempting to explain how the phenomenon operates by identifying the underlying factors that produce change in it, in which case there is no manipulation of the independent variable.

The study employed exploratory data analysis (EDA) to summarise the major aspects of the data using statistical graphics and other data visualisation tools. This technique allows us to visualise data trends in relation to our study interests. As a result, exploratory data analysis can unearth as much information about the raw data as possible by charting various curves to see if the data meets the underlying assumption before any formal model fitting is performed.

3.1.2 Data source and its description

Secondary data that was used in the study was obtained from annual financial statements, annual financial and cash flow reports for all non-financial firms listed and trading with NSE for the period between 2008-2017. The data was then consolidated and based on the model variables. The conditions for the Firms in the final sample was;they must have traded consistently at the NSE for the period 2008-2017, and must have all financial and annual reports necessary for this study.

3.1.3 Study variables

The dependent variable for the study was earning per share (EPS) which was obtained by dividing profit after interest, tax and preferred dividend with number of ordinary shares. The independent variables were short term debt, long term debts, retained earnings and share capital.

3.2 Types of models

Individual behaviour is described by panel data models both over time and across individuals. Models are classified into three types: the fixed effects models, pooling models, and the random effects models. Panel data have both temporal and spatial aspects. The spatial dimension is the observation unit, such as entities while the temporal is the time interval between measurements that are repeated such as year.

The general linear regression model is written as:

$$y_{it} = \beta_0 + \beta_1 X_{it,1} + \beta_2 X_{it,2} + ... + \beta_k X_{it,k} + v_{it} \qquad i = 1,..N; t = 1,...T, k = 1,...,K \qquad \textbf{3.1}$$

Where:
-i denotes the observation unit.
-t denotes the time period
-k denotes the kth explanatory variable
-β_0 denotes the intercept
-β_k denotes the explanatory variable coefficient
-v_{it} denotes the error term.*

v_{it} in Equation 2.1 can further be broken down into two components:

- A cross-sectional unit-specific error a_i

- An idiosyncratic error υ_{it}.

$$v_{it} = a_i + \upsilon_{it} \qquad \textbf{3.2}$$

Splitting error terms benefit us in that if we can eliminate some of them, we will be better off in terms of lowering worries about omitted variable bias produced by unmeasured unit-specific factors.The cross-sectional unit-specific error, a_i, remains constant across time, but the idiosyncratic error, υ_{it}, changes across cross-sectional units and time (Baltagi, 2001; Greene, 2003; Griffiths et al., 1993;Gujarati, 2003; Maddala, 2001; Wooldridge, 2006).

By incorporating Equation 3.2 into Equation 3.1, we can get the following equation:

$$y_{it} = \beta_0 + \beta_1 X_{it,1} + \beta_2 X_{it,2} + \ldots + \beta_k X_{it,k} + a_i + \upsilon_{it} \quad \textbf{3.3}$$

An error component model is defined as Equation 3.3. Unobserved factors are the time-constant and unit-specific error, a_i. The estimating methods of error component models are categorised based on how the error term, a_i, is treated.The random effects model considers the error to be random.The fixed effects model considers it to be estimated coefficients whereas the pooled OLS model does not distinguish it from other error types. (Baltagi, 2001; Greene, 2003; Maddala, 2001; Wooldridge, 2006).

The generalized statistical model for panel data with unobserved effects on the response variable is given by

$$Y_{i,t} = \alpha + \beta X_{i,t} + \varepsilon_{i,t} \quad \textbf{(3.4)}$$

where

$Y_{i,t}$ denotes the response variable at time (t)
β denotes the Vertical vector (k×1) of the independent estimated parameters for each independent variable.
$X_{i,t}$ denotes the matrix (T_n× k) of the independent variables that affect the response variable of firm i at time t.
$\varepsilon_{i,t}$ denotes the vertical vector ($T_n \times 1$) of the random error of firm i at time t.

In our study,the model will be defined as:

$$EPS_{i,t} = \beta_0 + \beta_1 SD_{i,t} + \beta_2 LL_{i,t} + \beta_3 RE_{i,t} + \beta_4 SC_{i,t} + \varepsilon_{i,t} \quad \textbf{(3.5)}$$

3.2.1 The fixed effects model

In many applications including econometrics and biostatistics, a fixed effects model refers to a regression model in which the group means are fixed, that is they are non-random as opposed to a random effects model in which the group means are a random sample from a population (Gomes,2022). In a fixed effects model, each group means is a group-specific fixed quantity. Data can be grouped according to several observed factors. The group means could be modeled as fixed or random effects for each grouping (Gomes, 2022). Fixed effects represent the subject-specific means in panel data where longitudinal observations exist for the same subject. According to Greene (2011), due to the heterogeneity that is unobserved when this heterogeneity is constant across time fixed effects aid in adjusting for omitted bias in variables .

Differencing can eliminate such heterogeneity from the data. This is done by calculating a first difference, which eliminates any time-invariant components of the model. Heterogeneity elimination can also be done by subtracting the group-level average across the period. The fixed effect model assumes that Individual-specific effects are associated with the independent variables while the random effects assume that individual-specific effects are uncorrelated with the independent variables. If the random effects assumption is correct, the random effects estimator outperforms the fixed effects estimator. If this assumption is not met, the random effects estimator is inconsistent.

Individual-specific effects α_i can be associated with the regressors x in the fixed effects model. As intercepts, we include α_i. Each individual has a unique intercept term and slope parameters.

$$y_{it} = \alpha_i + x_{it}^{'}\beta + u_{it} \quad (3.6)$$

Consider the following linear unobserved effects model for observations and time periods:

$$y_{it} = X_{it}\beta + \alpha_i + u_{it} \ For \ t = 1, ..., T \ and \ i = 1, ..., N \quad (3.7)$$

where
y_{it} denotes the dependent variable for entity i at time t.
X_{it} denotes the time-variant 1×k
β denotes the k×1 matrix of parameters
α_i denotes the unobserved time-invariant individual effect
u_{it} denotes the error term

The FE model permits α_i to be associated with X_{it} the regressor matrix. The RE model, assumes that the α_i which is unobserved is independent of X_{it} for all $t = 1, ...T$. Strict exogeneity is still necessary for the idiosyncratic error term υ_{it}. But unlike X_{it}, α_i cannot be detected directly.

3.2.2 The Random effects model

Also known as a variance components model, a random effects model is a type of mixed model. A RE model is defined by Gomes (2022) as a statistical model in which the model parameters are random variables. RE model allows for individual effects models since no fixed effects are assumed when employed in panel analysis (Gomes,2022). RE models can help adjust when the heterogeneity is consistent across time and not connected with independent factors. This can be done by differencing because the first difference removes any time-invariant components of the model. The random-effects model is based on the assumption that explanatory factors have stable associations with the response variable across all observations, but that these fixed effects can vary from one observation to the next. (Wooldridge, 2010).

The RE Model is founded on the assumption that the individual-specific effects α_i are distributed independently of the regressor. Each individual has the same slope parameters and a composite error term $\varepsilon_{it} = \alpha_i + e_{it}$. We include α_i in the error term.

$$y_{it} = X_{it}^{'}\beta + (\alpha_i + e_{it}). \tag{3.8}$$

Here $var(\varepsilon_{it}) = \sigma_\alpha^2 + \sigma_e^2$ and $cov\ (\varepsilon_{it}, \varepsilon_{is}) = \sigma_\alpha^2$
So $\rho_\varepsilon = cor(\varepsilon_{it}, \varepsilon_{is}) = \sigma_\alpha^2 / (\sigma_\alpha^2 + \sigma_e^2)$

(ρ) is the error's interclass correlation. ρ is the proportion of the variance in error caused by individual differences. If the individual effects outweigh the idiosyncratic error, it approaches 1.

Assume m major elementary schools are chosen at random among a huge population in a country. Also a ssume that n students of the same age are drawn at random from each school. Their performance on a conventional aptitude test is determined. Assuming Y_{ij} is the jth student's score at the ith school. A straightforward technique to model this variable is

$$Y_{ij} = \mu + U_i + W_{ij}, \tag{3.9}$$

where U_i denotes the school-specific random effect.It measures the difference between the average score at school i and the average score in the entire country. .μ denotes the entire population average test score. The term W_{ij} is the individual-specific random effect. It measures the deviation of the j-th pupil's score from the average for the i -th school
For a basic model such as

$$y_{it} = x_{it}^{'}\beta + z_i^{'}y + \varepsilon_{it} \tag{3.10}$$

With E (ε_i / X)= 0 and Rank (X)= full rank. We introduce heterogeneity through β_i. But, this may introduce additional N parameters. A solution is to model β_i.

3.2.3 Pooled OLS model

The panel structure of the data is ignored by the pooled model. The pooled model is estimated using OLS. $z_i^{'}y$ is a fixed value. $z_i = \alpha$ and is unrelated to x_{it}. Dependence on y_{it} may enter via the variance. Observations on individual i are thus linearly independent.

In this instance,

$$y_{it} = x_{it}^{'}\beta + \alpha + \varepsilon_{it} \tag{3.11}$$

We estimate k+1 parameters here. OLS reliably calculates α and β.

3.2.4 Dynamic Panel Models

By using lagged endogenous terms to avoid the association problems between different factors,The inclusion of the dependent variable as a regressor is performed in accordance with the work reported by classical authors such as Arellano and Bond (1991); Arellano and Bover (1995); and Blundell and Bond (1998), defining$(Y) : Y_{it-n}$.Through instrumental variables, dynamic panels enable the incorporation of a structure that is endogenous into the model.
The regressor is included as the lag of Y_{it} due to the causality that is time related. The second term corresponds to the lag of the independent variables (X_{it}) and the dependent variable ($Y_{(it-n)}$).

$$Y_{it} = \alpha Y_{it-n} + \beta_i X_{it} + \omega_{it} \tag{3.12}$$

Where:
Y_{it}: denotes the dependent variable of individuals i in time t
Y_{it-n}: denotes the lag of dependent variable. Individuals i, time $t-1$
α:denotes the constant/intercept
β_i: denotes the variable coefficient i
X_{it}: denotes the Independent variable i in time t
$\omega_{it} : \varepsilon_i + \mu_{it}$

Furthermore, not only lagged variables can be employed as instruments of endogenous variables, but also other independent variables not correlated to the model's error term can be employed. The Generalized Method of Moments (GMM) and the Instrumental variables (IV) are effective estimate strategies for dynamic models. Dynamic models seek to capture the existence of the persistence of habit and contracts. Due to bias issues, OLS cannot be applied to dynamic models also the dependent variables in dynamic panel models are lagging.

3.2.5 Pseudo Panel (or Quasi Panel)

A pseudo panel dataset resembles a conventional panel dataset but lacks all of the elements of a full-fledged panel dataset.. Pseudo panels are also used to evaluate the impact of a specific policy for example a subsidy program on some outcome variable example family incomes. For this purpose, a technique called difference-in-difference (DID) estimation is used. The label DID arises because the policy impact is calculated as the impact on the outcome variable after the policy intervention minus what the value of the outcome variable would have been in the absence of a policy intervention .The label pseudo panel arises in DID estimation because we observe the treatment groups those that are exposed to the policy change and control groups, those not exposed to the policy change before and after the policy change. As one would expect, for DID estimation results to be meaningful the treatment and control group members must be carefully selected so that they are similar before the policy change. This is the only way to ensure that the differences in the outcome variables after the policy change are due to the policy intervention.

3.3 Panel data estimators

The panel data models can be estimated with several estimators. The estimators differ based on whether they consider the between or within variation in the data. Their properties (consistency) differ based on which model is appropriate. Estimators that are consistent and efficient are preferred. Consistency is checked for first and then efficiency.

Consistency
The distribution of $\hat{\beta}_n$ collapses on β as n becomes large:
$\rho lim \hat{\beta}_n = \beta$
Consistency is established based on the law of large numbers. If an estimator is consistent, more observations will tend to provide more precise and accurate estimates.

Efficiency
The efficiency which is the minimum variance is usually established relative to specific classes of estimators. For example, if OLS is efficient it has a minimum variance among the class of linear, unbiased estimator (Gauss-Markov Theorem).The maximum likelihood given the correct distributional assumptions is asymptotically efficient among consistent estimators.

3.3.1 Fixed effects estimator

Since α_i is not observable, it cannot be directly controlled for. The FE model eliminates α_i by demeaning the variables using the *within* transformation.

$$y_{it} - \bar{y}_i = (X_{it} - \bar{X}_i)\beta + (\alpha_i - \bar{\alpha}_i) + (u_{it} - \bar{u}_i) \Rightarrow \ddot{y}_{it} = \ddot{X}_{it}\beta + \ddot{u}_{it}. \tag{3.13}$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ and $\bar{u}_i = \frac{1}{T}\sum_{t=1}^{T} u_{it}$

Since α_i is constant ,$\bar{\alpha}_i = \alpha_i$ and hence the effect is eliminated. The FE estimator $\hat{\beta}_{FE}$ is then obtained by an OLS regression of $\ddot{y}$ on $\ddot{X}$.

This model is numerically but not computationally equivalent to the fixed effect model. The inside transformation has at least three variants. One method would be to exclude the first individual owing to multi-collinearity and include a dummy variable for each individual $i > 1$,. This only works if the total number of series and global parameters is fewer than the total number of observations. It is not always recommended because the dummy variable technique is particularly demanding in terms of computer memory utilization.

The second strategy is to use repeated reiterations to estimate local and global values. This method is significantly more computationally efficient than the dummy variable method. The third technique nested estimation incorporates local estimates for specific series into the model formulation. It necessitates advanced programming skills and access to the model programming code but is the most computationally and memory-efficient way.

3.3.2 Pooled OLS estimator

To estimate the parameters, the pooled OLS estimator employs both between and within variance. The pooled OLS estimator is constructed by combining the data over i and t into a single long regression with NT observations and estimating it using OLS:

$$y_{it} = \alpha + x_{it}^{'}\beta + (\alpha_i - \alpha + e_{it}) \tag{3.14}$$

The pooled OLS regressor is consistent if the correct model is the pooled model and the regressors are uncorrelated with the error terms. The pooled OLS regressor is inconsistent if the true model has fixed effects. We require panel-corrected standard errors.

3.3.3 Between estimator

Only the between variation is used by the between estimator - across individuals. All variables' time averages are used. The average experience of a person with job experience of 9, 10, and 11 years measured across three periods is 10. For each individual, this is an OLS estimation of the time-averaged dependent variable based on the time-averaged regressors.

$$\bar{y}_i = \alpha + \bar{x}_i^{'}\beta + (\alpha_i - \alpha + \bar{e}_i) \tag{3.15}$$

N is the number of observations. The time variation is ignored, and the data is compacted with one observation per individual; also, this estimator is rarely employed since the RE estimators and the pooled estimators are much more efficient.

3.3.4 Within estimator or fixed effects estimator

The within estimator takes into account the inside variance across time. It employs time-demeaned variables, which are individual-specific deviations from time-averaged values. The average experience of a person with job experience of 9, 10, and 11 years measured across three periods is 10. As a result, the time-demeaned values are -1, 0 and 1. This is an OLS estimation of the time-disparate dependent variable on the time-disparate regressors.

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)^{'}\beta + (e_{it} - \bar{e}_i) \tag{3.16}$$

Some software package estimate:

$$y_{it} - \bar{y}_i + \bar{y} = \alpha + (x_{it} - \bar{x}_i + \bar{x})^{'}\beta + (e_{it} - \bar{e}_i + \bar{e}) \tag{3.17}$$

The number of observations is NT.

Individual effects α_i cancel each other out. In this case, α represents the average of the individual effects. The inside estimator has the drawback of dropping time-invariant variables from the model and not identifying their coefficients. A female/male will have a female dummy variable with a value of 1/0, thus the values minus the mean values derived over time for each individual will be zero. If we want to investigate the effects of time-invariant variables, we must examine other models, OLS, or estimators.

3.3.5 First-differences estimator

The one-period changes for each individual are used by the first-difference estimator. It employs first-differenced variables, which are individual-specific one-period changes. If a person has 9 years, 10 years, and 11 years of work experience assessed over three periods, the first difference experiences are lacking (.), 1, and 1.
This is an OLS estimation of the dependent variable's one-period changes based on the regressors' one-period changes..

$$y_{it} - y_{i,t-1} = (x_{it} - x_{i,t-1})' \beta + (e_{it} - e_{i,t-1}) \quad (3.18)$$

N (T-1) is the number of observations .Because of differencing, we lose the first observation for each individual. Individual effects α_i cancel each other out. The first-differences model has the drawback that time-invariant variables are deleted from the model and the coefficients are not determined.

3.3.6 Random effects estimator

This is an OLS estimation of the transformed model.

$$y_{it} - \hat{\lambda}\bar{y}_i = (1-\hat{\lambda})\mu + (x_{it} - \hat{\lambda}\bar{x}_i)' \beta + \nu_{it} \quad (3.19)$$

$$\nu_{it} = (1-\bar{\lambda})\alpha_i + (e_{it} - \hat{\lambda}\bar{e}_i) \quad (3.20)$$

The number of observations is NT. The individual-specific effects α_i are in the error term.$\bar{\lambda} = 0$ corresponds to pooled OLS and $\bar{\lambda} \ = 1$ corresponds to the within (fixed effects) estimator. The estimates for random effects are a weighted average of the estimates for between and within. Under the random effects model, the random effects estimator is completely efficient.

3.4 Model and Estimators

Table 1. Model and their estimators

Estimator/True model	Pooled model	Random effects model	Fixed effects model
Pooled OLS estimator	Consistent	Consistent	Inconsistent
Between estimator	Consistent	Consistent	Inconsistent
Within or fixed effects estimator	Consistent	Consistent	Consistent
First differences estimator	Consistent	Consistent	Consistent
Random effects estimator	Consistent	Consistent	Inconsistent

Although the fixed effects estimator always provides consistent estimates, it may not be the most efficient. If the relevant model is the fixed effects model, the random effects estimator is inconsistent. If the relevant model is a random effects model, the random effects estimator is consistent and most efficient.

3.4.1 Choosing between fixed and random effects

Breusch-Pagan Lagrange Multiplier test

This is an OLS residual-based test for RE model. It determines whether σ_u^2 or equivalently $cor(u_{it}, u_{is})$ is significantly different from zero. If the LM test is significant, the RE model is used rather than the OLS model.However, we still need to differentiate between fixed and random impacts.

Hausman test

Because the random effects estimator is more efficient, we should employ it if the Hausman test allows it. Use the fixed effects model if it does not support it. The Hausman test determines whether or not there is a statistically significant difference between the RE and FE estimators. The Hausman test statistic can only be computed for time-varying regressors. The Hausman test statistics is as follows:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})' V(\hat{\beta}_{RE} - (V(\hat{\beta}_{RE}))(\hat{\beta}_{RE} - \hat{\beta}_{FE}) \quad \textbf{(3.21)}$$

It is chi-square distributed with degrees of freedom equal to the number of parameters for the time-varying regressors. If the Hausman test is insignificant we use the random effects. If the Hausman test is significant we use the fixed effects.

4 PANEL UNIT ROOT TESTS

4.1 Introduction

There have been several approaches to testing a unit root in panel data. Quah (1992, 1994) initiated research in this area and proposed asymptotically normal tests for a unit root. Thereafter, Levin and Lin (1992; LL) devised an adjusted t-test for a unit root for various panel data models. As with the Levin and Lin unit root test, it is uncommon for the time series analysis unlike with panel data analysis to assume that all groups, that is, individuals, firms, or countries have the same AR (autoregressive) coefficient under both the null and alternative hypotheses. Im et al. (1995; IPS hereafter) considered using averages of the likelihood ratio and augmented Dickey-Fuller tests. These tests are built on more general assumptions than LL's test and seem to outperform LL's test in finite samples according to the simulation results in IPS.

Before fitting the model in equation (3.5) above, the properties of the time series for each variable over the study period need to be examined and the order of integration determined by employing a two-panel data unit roots test which includes Levin, Lin, and Chu (2002) test (LLC test) and lm at el(2003) test or (IPS test).

4.2 A Comparison of the IPS and LLC

4.2.1 The Levin, Lin, and Chu (2002)

The test assumes that every unit in the panel has the same AR(1) coefficient, but it also allows for individual effects, temporal effects, and perhaps a time trend. To allow for serial correlation in the mistakes, lags in the dependent variable may be included. When lags are added, the test can be seen as a pooled Dickey-Fuller test or an Augmented Dickey-Fuller (ADF) test, with the null hypothesis being non-stationary . Under the null hypothesis of non-stationarity, the t-star statistic is distributed standard normal after transformation.

This test incorporates three models for assessing the presence of a unit root: the very first assumes that the model lacks both the intercept and the time trend, the second has the intercept but no time trend, and the third has both the time trend and the intercept.

(Jaroslava, 2005).

$$4y_{i,t} = \beta y_{ti-1} + \mu_{i,t} \ldots\ldots\ldots\ldots (\text{model } 1) \quad (4.1)$$

$$4y_{i,t} = \alpha_0 + \beta y_{ti-1} + \mu_{i,t} \ldots\ldots\ldots\ldots (\text{model } 2) \quad (4.2)$$

$$4y_{i,t} = \alpha_0 + y_{i,t} + \beta y_{ti-1} + \mu_{i,t} \ldots\ldots\ldots (\text{model } 3) \quad (4.3)$$

While testing the following hypotheses, the three models assume the independence of the error term.

$H_0 : \beta = 0$ vs $H_1 : \beta < 0$ (model 1)
$H_0 : \beta = 0, \quad \alpha_i = 0$ $H_1 : \beta < 0, \quad \alpha_i \in$ R (model 2)
$H_0 : \beta = 0, \quad y_i = 0$ $H_1 : \beta < 0, \quad y_i \in$ R (model 3)
for i = 1,2,3,...,N

Series Assumption

1. Constant (Intercept)
2. Constant and Trend
3. None

LLC Test For Earnings Per Share

Table 2. LLC Test for EPS

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic	p-value
Unadjusted t -22.2139	
Adjusted t* -5.7714	0.0000

Table 3. LLC Test for EPS

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -36.9604	
Adjusted t* -25.9244	0.0000

Table 4. LLC Test for EPS

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Not Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -15.6183	
Adjusted t* -15.0316	0.0000

The Levin–Lin–Chu bias-adjusted t statistic with the intercept only is -5.7714 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Similarly, The Levin–Lin–Chu bias-adjusted t statistic with both the intercept and time trend is -25.9244 with a p-value of 0.0000, and the Levin–Lin–Chu bias-adjusted t statistic without the constant and the time trend is -15.0316 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Therefore, panels of the series of EPS are stationary.

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LLC Test For Short Term Debt

Table 5. LLC Test for STD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -19.2199	
Adjusted t* -11.8423	0.0000

Table 6. LLC Test for STD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -21.7076	
Adjusted t* -13.2279	0.0000

Table 7. LLC Test for STD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Not included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -4.5829	
Adjusted t* -4.4023	0.0000

H0: Panels contain unit roots
Ha: Panels are stationary

The null hypothesis is that the series contains a unit root, and the alternative is that the series is stationary. As the output indicates, the Levin–Lin–Chu test assumes a common autoregressive parameter for all panels, so this test does not allow for the possibility that some firms' short-term debt contains unit roots while others do not. The Levin–Lin–Chu test with panel-specific means but no time trend requires that the number of time periods grows more quickly than the number of panels, so the ratio of panels to time periods tends to zero. The test involves fitting an augmented Dickey-Fuller regression for each panel. To estimate the long-run variance of the series, xtunitroot by default uses the Bartlett kernel using 6 lags as selected by the method proposed by Levin, Lin, and Chu.

The Levin–Lin–Chu bias-adjusted t statistic without the time trend is -11.843, with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Similarly, The Levin–Lin–Chu bias-adjusted t statistic with the time trend is -13.2239 with a p-value of 0.0000, and the Levin–Lin–Chu bias-adjusted t statistic without the constant and the time trend is -4.4023 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are still stationary. Therefore, we reject the null hypothesis and conclude that the series of short-term debt is stationary.

LLC Test For Long Term Debt

Table 8. LLC Test for LTD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -20.2541	
Adjusted t* -14.4239	0.0000

Table 9. LLC Test for LTD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -35.2186	
Adjusted t* -28.4161	0.0000

Table 10. LLC Test for LTD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Not included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -6.5018	
Adjusted t* -6.2289	0.0000

The Levin–Lin–Chu bias-adjusted t statistic with the intercept only is -14.4239 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Similarly, The Levin–Lin–Chu bias-adjusted t statistic with both the intercept and time trend is -28.4161 with a p-value of 0.0000, and the Levin–Lin–Chu bias-adjusted t statistic without the constant and the time trend is -6.2289 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Therefore, panels of the series of long-term debt are stationary.

LLC Test For Retained Earnings

Table 11. LLC Test for RE

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -18.1666	
Adjusted t* -10.5619	0.0000

Table 12. LLC Test for RE

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -25.5244	
Adjusted t* -15.4477	0.0000

Table 13. LLC Test for RE

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Not included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -10.6097	
Adjusted t* -10.1639	0.0000

The Levin–Lin–Chu bias-adjusted t statistic with the intercept only is -10.5619 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Similarly, The Levin–Lin–Chu bias-adjusted t statistic with both the intercept and time trend is -15.4477 with a p-value of 0.0000, and the Levin–Lin–Chu bias-adjusted t statistic without the constant and the time trend is -10.1639 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Therefore, panels of the series of retained earnings are stationary.

LLC Test For Share Capital

Table 14. LLC Test for SC

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -16.9992	
Adjusted t* -9.5587	0.0000

Table 15. LLC Test for SC

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Included	
Time trend: Included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -20.9617	
Adjusted t* -10.4696	0.0000

Table 16. LLC Test for SC

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Common	Asymptotics: $N/T->0$
Panel means: Not included	
Time trend: Not included	
LR variance: Bartlett kernel, 6.00 lags average (chosen by LLC)	
Statistic p-value	
Unadjusted t -8.0963	
Adjusted t* -7.7520	0.0000

The Levin–Lin–Chu bias-adjusted t statistic with the intercept only is -9.5587 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Similarly, The Levin–Lin–Chu bias-adjusted t statistic with both the intercept and time trend is -10.4696 with a p-value of 0.0000, and the Levin–Lin–Chu bias-adjusted t statistic without the constant and the time trend is -7.7520 with a p-value of 0.0000. At the 5 % level, we reject the Null Hypothesis and conclude that the panels are stationary. Therefore, panels of the series of share capital are stationary.

LLC Test Comparison

The panel unit root test, as the most preferred approach with the highest validity in the literature, is used for testing stationarity in the study. The results of Levin, Lin, and Chu (2002) (LLC) and Im, Pesaran and Shin (2003) (IPS) unit root tests for all variables are shown in Table 17 below.

Table 17. LLC Test Comparison

Variables		LLC		
		Intercept	Trend and Intercept	None
EPS	Adjusted t	-5.7714	-25.9244	-15.0316
	p-value	0.0000	0.0000	0.0000
Short Term Debt	Adjusted t	-11.8423	-13.2279	-4.4023
	p-value	0.0000	0.0000	0.0000
Long Term Debt	Adjusted t	-14.4239	-28.4161	-6.2289
	p-value	0.0000	0.0000	0.0000
Retained Earnings	Adjusted t	-10.5619	-15.4477	-10.1639
	p-value	0.0000	0.0000	0.0000
Share Capital	Adjusted t	-9.5587	-10.4696	-7.7520
	p-value	0.0000	0.0000	0.0000

4.2.2 Im-Pesaran-Shin Unit-Root Test

Im, Pesaran, and Shin developed IPS to estimate the t-test for unit roots in heterogeneous panels (IPS, 2003). Individual effects, time trends, and common time effects are all supported. The IPS test posits that all series are non-stationary under the null hypothesis based on the mean of the individual Dickey-Fuller t-statistics of each unit in the panel. To allow for serial correlation in the mistakes, lags in the dependent variable may be included. In IPS, the specific critical values of the t-bar statistic are given. IPS are consistent under the alternative that only a fraction of the series are stationary, as opposed to the Levin and Lin (1993) test, which assumes that all series are stationary. Despite the fact that the IPS test is characterised as a generalisation of the LL tests, the IPS test is a method of combining evidence on the unit root hypothesis from the N unit root tests done on the N cross-section units. For individual series of serial correlation, IPS recommends using the ADF t-test. The IPS test examines the significance of the findings of N-independent hypothesis testing.

This test employs a likelihood framework and proposes a much more versatile and straightforward computation procedure for the panel unit root test using T-bar statistics. As a result, it can be used on both stationary and non-stationary series. Furthermore, the IPS test allows for serial residual correlation and dynamic heterogeneity, as well as incorrect cross-group variances (Im et al, 2003).

The IPS test is based on the model

$$\triangle y_{i,t} = \alpha_0 + \beta_i y_{ti-1} + \varepsilon_{i,t} \qquad i = 1,2,3,... \tag{4.4}$$

Therefore IPS test presents the individual effects model with no time trend and the following hypothesis is tested.

$H_0 : \beta_i = 0$ vs $H_1 : \beta_i < 0$
for i=1,2,3,...N

IPS Test for EPS

Table 18. Im-Pesaran-Shin Unit-Root Test for EPS

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T, N \to \infty$
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-6.8359 0.0000

Table 19. IPS Test for EPS

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \to \infty$
Panel means: Included	sequentially
Time trend: Included	

ADF regressions: 1 lag

	Statistic p-value
W-t-bar	-7.6417 0.0000

H_0: **All Panels contain unit roots**
H_1: **Some Panels are stationary**

The IPS unit-root test, as illustrated in tables 18 and 19, asserts that the null hypothesis is that all panels have unit roots, but the alternative is that certain panels are stationary. Unlike the LLC test, this test takes into account the potential that certain firms' EPS has unit roots while others do not. In IPS, the specific critical values of the t-bar statistic are given. The IPS W-t statistic with the panel means without the time trend is -6.8359, with a p-value of 0.0000. At the 5 percent level, we reject the Null Hypothesis and conclude that some panels are stationary. Similarly, the IPS W-t statistic with a time trend is -7.6417 with a p-value of 0.0000. At the 5 percent level, we reject the Null Hypothesis and conclude that some panels are stationary. Therefore, we reject the null hypothesis and conclude that the series of EPS has some panels as stationary.

IPS for STD

Table 20. IPS Unit-Root Test for STD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T, N \rightarrow \infty$
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-5.9173 0.0000

Table 21. IPS Unit Root Test for STD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T, N \rightarrow \infty$
Panel means: Included	sequentially
Time trend: Included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-3.7894 0.0001

The IPS W-t statistic with the panel means without the time trend in table 10 is -5.9173, with a p-value of 0.0000. We reject the Null Hypothesis at the 5% level and infer that some panels are stationary. Table 21 shows that the IPS W-t statistic with a temporal trend is -3.7894 with a p-value of 0.0000. We reject the Null Hypothesis at the 5% level and infer that some panels are stationary. As a result, we reject the null hypothesis and conclude that some panels in the series of variable STD are stationary.

IPS Unit-Root Test for LTD

Table 22. IPS Unit-Root Test for LTD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \to \infty$
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-7.1294 0.0000

Table 23. IPS Unit-Root Test for LTD

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \to \infty$
Panel means: Included	sequentially
Time trend: Included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-6.5420 0.0001

We reject the Null Hypothesis at the 5% level and infer that some panels are stationary. This is because, as shown in table 22, the IPS W-t statistic with the panel means and without the temporal trend is -7.1294, with a p-value of 0.0000. We reject the null hypothesis since our p-value is less than 0.05 and infer that some panels are stationary. Similarly, the IPS W-t statistic with a temporal trend is -6.5420 with a p-value of 0.0000 in table 23. At 5%, we reject the Null Hypothesis and get the same conclusion that certain panels are stationary. As a result, at the 5% level, we conclude that the series of variable LTD has some panels that are stationary.

IPS for RE

Table 24. IPS for RE

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \to \infty$
Panel means: Included	sequentially
Time trend: Not included	

ADF regressions: 1 lag

	Statistic p-value
W-t-bar	-5.4916 0.0000

Table 25. IPS for RE

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \to \infty$
Panel means: Included	sequentially
Time trend: Included	

ADF regressions: 1 lag

	Statistic p-value
W-t-bar	-3.7391 0.0001

At the 5% level, we reject the null hypothesis and conclude that the panels are stationary. This is owing to the IPS W-t statistic having a p-value of 0.0000 when panel means and temporal trend are omitted, as seen in table 24. Because our p-value is less than 0.05, we reject the null hypothesis and conclude that some panels are stationary. According to table 25, the IPS W-t statistic with a temporal trend is also identical, with a p-value of 0.0000 and a value of -3.7391. We reject the null hypothesis and reach the same conclusion that some panels are stationary at 5%.

IPS Unit-Root Test for Share Capital

Table 26. IPS Unit-Root Test for SC

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \rightarrow \infty$
Panel means: Included	sequentially
Time trend: Not included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-5.0946 0.0000

Table 27. Im-Pesaran-Shin Unit-Root Test for SC

H_0: All panels contain unit roots	Number of panels=36
H_1: Some panels are stationary	Number of periods=10
AR parameter: Panel-specific	Asymptotics: $T,N \rightarrow \infty$
Panel means: Included	sequentially
Time trend: Included	
ADF regressions: 1 lag	
	Statistic p-value
W-t-bar	-2.3893 0.0084

The p-value for the W-t statistic without the time trend is 0.0000 and the value is -5.0946 as in Table 26. Because the p-value is less than 0.05, we reject the null hypothesis at the 5% level and infer that some panels are stationary. The p-value for the IPS W-t statistic with the temporal trend is also 0.0000 and equals -2.3893, as shown in table 27. At the 5% level, we reject the null hypothesis and conclude that some panels are stationary. As a result, we conclude that some panels in the variable share capital series are stationary.

5 RESEARCH FINDINGS AND DISCUSSIONS

5.1 Introduction

This chapter covers the pattern of the results and their analysis in connection to the study's aims and hypotheses. The chapter includes descriptive statistical analysis, trend analysis, and the outcomes of the modelling methodologies utilised to meet the research aim and objectives.

5.2 Descriptive Statistics

5.2.1 Variable Description

Table 28. Variables description

	panel variable:	F ID (strongly balanced)
	time variable:	Year, 2008 to 2017
	delta:	1 unit
I Contains data		
obs:	360	
vars:	8	
size	28080	

Table 28 shows that the panel variable company Id is well balanced during a ten-year period. A balanced panel necessitates the presence of all entities at all times. Balanced data reduces noise generated by unit heterogeneity. by allowing for the observation of the same unit over many time periods making it more preferable.

Table 29. Variables description

Variable		Mean	Std. Dev.	Min	Max	Observations
EPS	overall	-74.04385	1634.399	-27576.92	4995.941	N= 360
	between		496.7661	-2619.576	525.2196	n= 36
	within		1559.061	-25031.39	4396.678	T= 10
STD	overall	-9089.848	9017.073	-27414	3696.017	N= 360
	between		3008.315	-15096.7	-1789.669	n= 36
	within		8513.785	-29137.65	6179.852	T= 10
LTD	overall	4.224943	551.4469	-10411.02	112	N=360
	between		174.4505	-1011.902	55.6	n=36
	within		523.8546	-9394.893	1123.127	T=10
RE	overall	-25.62288	215.1303	-912	3696.017	N=360
	between		63.28186	-117.8	313.0017	n=36
	within		205.8564	-819.8229	3357.392	T=10
SC	overall	-8514.596	9090.679	-27326	3696.017	N=360
	between		3309.035	-14937.9	-855.8	n=36
	within		8483.233	-29480.5	6532.304	T=10

Because there are 36 entities and 10 time periods, the total number of observations in table 29 is 360. The Within statistics are calculated using summary statistics from time periods of 10 years irrespective of firm.Overall statistics are regular statistics based on 360 observations. The Between statistics are obtained using summary statistics from the 36 entities irrespective of the time period.

Table 30. Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max	CV
Earnings Per Share	360	6.468265	15.03232	-46.744	100.0483	2.324011
Short Term Debt	360	0.29146	0.255896	0.007901	2.535623	0.87798
Long Term Debt	360	0.200195	0.186595	0.000000	1.126967	0.932066
Retained Earnings	360	0.276984	0.327572	-1.60575	1.05154	1.182639
Share Capital	360	0.100219	0.156585	0.001601	1.139994	1.562428

Table 30 summarises the descriptive statistics for earnings per share change, short-term debt, long-term debt, retained earnings, and share capital. Earnings per share had a mean value of 6.468265, with a low of -46.744, a high of 100.0483, and a standard deviation of 15.03232, according to the descriptive findings. Positive earnings per share show that the company profited, while negative earnings per share indicate that the company lost money. The mean value of short-term debt was 0.29146, with a low of 0.007901 and a high of 2.535623. The variation in standard deviation was 0.255896. This means that short-term debt financing fulfilled 29.146 percent of total non-financial funding demands.

Similarly, long-term debt had a mean of 0.200195, a low of 0.000000, a high of 1.126967, and a standard deviation of 0.186595. Retained Earnings averaged 0.276984, ranging from -1.60575 to 1.05154. The standard deviation of retained earnings was 0.327572. This means that on average, 27.6984 percent of NSE-listed non-financial enterprises' retained earnings were utilised to fund their operations. The average share capital was 0.100219, ranging from 0.001601 to 1.139994 with a standard deviation of 0.156585. According to the statistics, the sale of shares fulfilled 10.0219 percent of the aggregate funding needs of non-financial enterprises listed on the NSE.

5.3 Trend Analysis

This section presents results of the variables.It includes the descriptive analysis,the different trends of the variables. The panel data models and the selection of the panel data model most appropriate for this study..

5.3.1 Earning Per Share Trend Line

Financial growth of the listed firms was measured using growth in earning per share .The trend line in figure 1 shows financial growth of the listed non-financial firms at the NSE measured using earning per share.

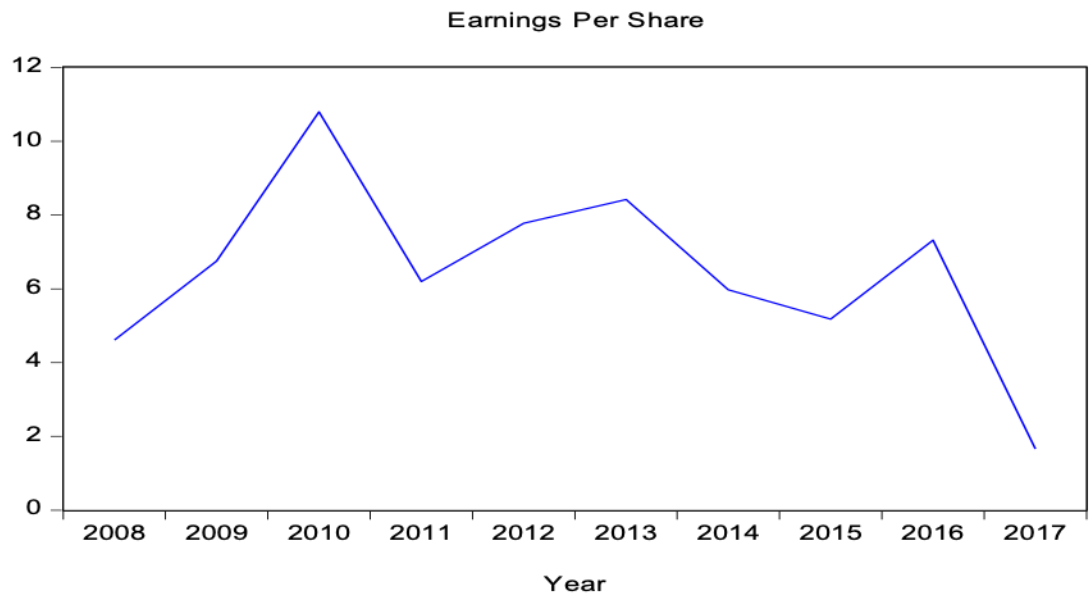

Figure 1. Growth in Earnings Per Share

Earnings per share is a key accounting indication of risk, entity performance, and corporate success. Because changes in EPS are frequently reflected in share price behaviour, it is used to estimate possible increase in future share prices. As demonstrated above, the EPS trend line grew steadily from 2008 to its peak in 2010. It fell precipitously in 2011 before rebounding in 2012 and 2013. Earnings per share began to erode steadily until the year 2016, when it plunged rapidly to its lowest level in 2017. According to Robbetze, de Villiers, and Harmse (2017), EPS is the best predictor of share price volatility. Smart and Graham (2012) agree, arguing that an entity's growth rate is determined by performance indicators such as earnings per share (EPS), which are disclosed in financial statements of firms in accordance with the specifications of the specific accounting standards used in the respective country. Furthermore, experts contend that EPS has evolved into a valuable investment choice tool for investors because it predicts future prospects and growth (Mlonzi, Kruger & Ntoesane, 2011).

5.3.2 Short Term Debt Trend Line

Figure 2 depicts the trend of short-term debt of Nairobi Securities Exchange-listed non-financial firms..

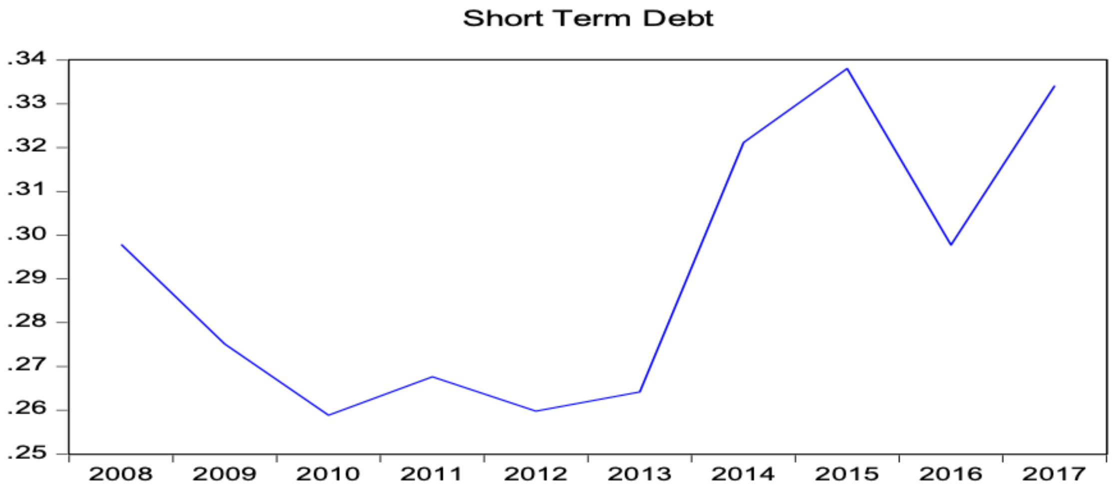

Figure 2. Short Term Debt Trend Line

The value of short-term debt is critical in establishing a company's financial performance.A shown above,short-term debt was at its lowest in 2010, before climbing to its highest level in 2015. This could signal that short-term debt funding was more readily available than long-term debt, which is typically connected with high-value collateral and, at times, stringent covenants, making it unappealing. The large proportion of asset financing via short-term debt could signal that short-term debt financing was less expensive and hence more accessible than long-term debt, which is typically coupled with high-value collateral and, at times, onerous covenants, making it unappealing.Mohammadzadeh (2013) discovered in a study on how capital structure influences the profitability of pharmaceutical enterprises in Iran that both short-term and long-term debt had significant negative effects on pharmaceutical firm profitability. These findings, however, contradict Mwangi, Muathe, and Kosimbei (2014), who determined that the majority of NSE enterprises employ long-term loans to fund their assets.

5.3.3 Long Term Debt Trend Line

Figure 3 shows the trend of long-term debt of the listed non-financial firms at the Nairobi securities Exchange.

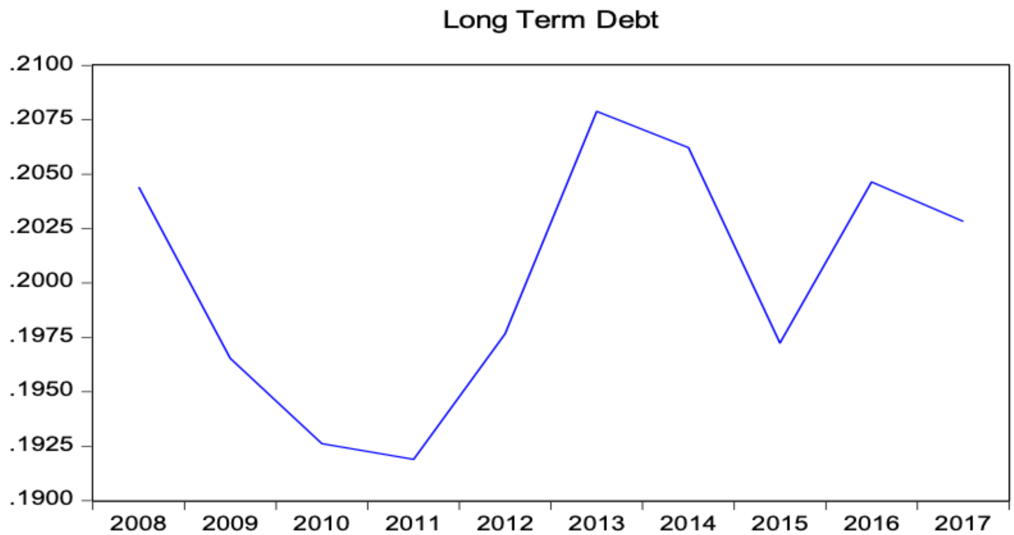

Figure 3. Long Term Debt Trend Line

Long-term loan financing fell from 2008 to its lowest level in 2010. However, it drastically increased again from 2011 to its peak in 2013. Long-term debt is money owed to lenders for longer than a year from the date of the current balance sheet. According to Ebaid (2009)'s research, there is no substantial association between long-term debt and return on assets. Long-term debts are the most preferred source of debt financing among well-established corporate entities, owing to their asset base, and collateral is required by many deposit-taking banking institutions. One of the major hurdles to larger investment and financial expansion of the organisation is a lack of long-term finance. Salawu and Agboola (2008) found that profitability, tangibility, and business size are positively connected to total debt and long-term debt, while growth opportunities are negatively related to total debt, using a panel of thirty-three big firms. Also according to Githire and Muturi (2015), long-term debt has a favourable and significant impact on the firm's financial success.

5.3.4 Share Capital Trend Line

Figure 4 shows the trend of share capital of the listed non-financial firms at the Nairobi securities Exchange

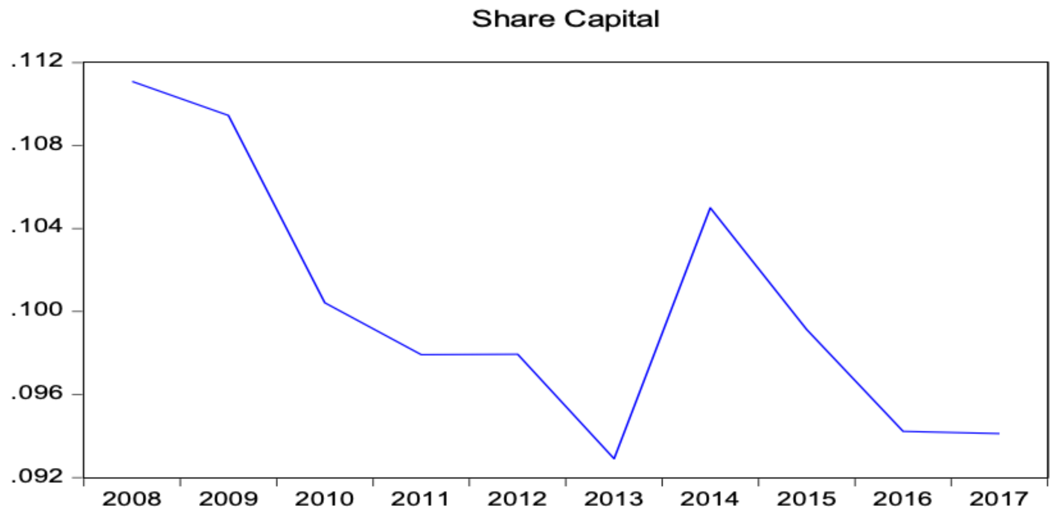

Figure 4. Share Capital Trend Line

Share capital is a company's total capital divided into shares.As shown above,share capital peaked in 2008 and gradually decreased to its lowest level in 2013. In 2014, share capital increased progressively before changing in later years. A joint stock corporation must have capital to finance its operations. Shares are issued in exchange for cash or other considerations to raise funds. Younus et al., (2014) discovered a weak positive association between share capital firm performances in a study on the impact of capital structure and financial performance of Sugar firms registered on the Karachi Stock Exchange Pakistan. However according to Oma and Memba (2018). share capital has a negative but negligible effect on business profitability.

5.3.5 Retained Earnings Trend Line

Figure 5 shows the trend of retained earnings of the listed non-financial firms at the Nairobi securities Exchange

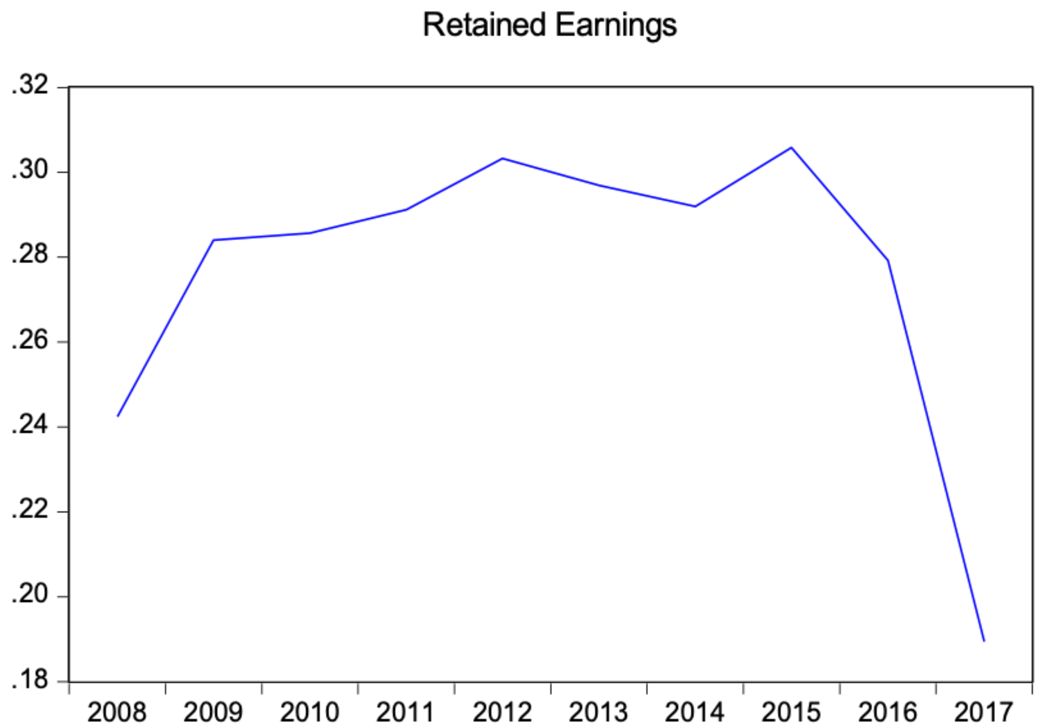

Figure 5. Retained Earnings Trend Line

Retained earnings refer to the percentage of a company's income that is maintained for reinvestment or debt repayment rather than being given out as dividends to shareholders.Retained profits were at their lowest in 2017 and their highest in 2015.Notably, retained earnings are a cost borne by stock investors. They are internal sources of capital available to the firm, according to Orwel (2010), and have numerous advantages. Retained earnings are a readily available internal source. Furthermore, retentions are less expensive than external equity, do not result in ownership dilution, and have a positive connotation because stakeholders believe the firm has potential investment prospects (Dinayak, 2014).

5.4 Panel Data Modelling

Unlike traditional regression, panel data regression requires a precise estimation modelling phase. In general, parameter estimation in regression analysis with cross-section data is performed using the Ordinary Least Squares (OLS). The regression Method Data Panel will provide an estimation result that is the Best Linear Unbiased Estimation (BLUE). These approaches, among others, can be used to estimate the regression model using panel data.

5.4.1 Pooled Least Square (PLS) / The Ordinary Least Square (OLS) approach

The pooled OLS is a pooled linear regression that does not include fixed or random factors. To estimate the panel data model, this approach use the Ordinary Least Squares (OLS) methodology . It is assumed that the intercept and slope are constant regardless of unit or time span. Because this model does not address time or individual dimensions, it is believed that the behaviour of the organizations' data is consistent across time.
The form of the panel data regression equation is,

$$\gamma_{it} = \alpha + \beta' X_{it} + \varepsilon_{it}, \quad i = 1,2...N, t = 1,2...T \tag{5.1}$$

where N = the Number of individuals or cross section and T is the number of time periods.

This model can be used to construct the equation NxT, which is equivalent to the T equation of cross and as many N equations of coherent time or time series.

OLS: β_0+β_1 short-term debt+β_2 long-term debt+β_3 retained earnings+β_4 share capital+ε_i

where β_0 is the constant or intercept, β_1 is the coefficient of the slope of short-term debt, β_2 is the slope of long-term debt, β_3 is the slope of retained earnings, β_4 is the slope of share capital and ε_i is the error term.

Table 31. regression EPS STD LTD RE SC

Source	SS	df	MS	Number of obs=360
Model	154986558	4	38746639.4	F(4,355)=17.11
				Prob>F=0.0000
Residual	803996111	355	2264777.78	R-squared=0.1616
Total	958982669	359	2671260.92	Adj R-squared=0.1522
				Root MSE=1504.9

EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
STD	.240946	.0097138	2.48	0.014	.0049908	.0431985
LTD	.8640876	.1483795	5.82	0.000	.5722743	1.155901
RE	.9517492	3899394	2.44	0.015	.1848674	1.718631
SC	.0070163	.0095978	0.73	0.465	-.0118594	.025892
cons	225.4497	123.3595	1.83	0.068	-17.15757	468.057

Based on the output in table 20, the summary of regression result panel data common effects model is:

1. Periods :The number of time periods or series included in the analysis. The time period used in this panel data regression is 2008 to 2017. As a result, the number of years used in the analysis is ten.
2. Column Variable: a list of variables that are being investigated. In this panel data regression, the response variable is EPS change, while the predictor variables are share capital, short-term debt, retained earnings,and long-term debt.
3. Balanced Total Panel observations: The term balanced refers to a state of equilibrium in which the amount of time spent on each firm is constant. Total number of observations in the analysis is 36 x 10 = 360.
4. Cross section: The number of cross sections included in the analysis. The panel is made up of as many as 36 firms.

R^2 is 0.1616 .This indicates that the model accounts for 16 percent of the total variance in the change in EPS.
The regression equation is,

EPS =225.4497 +0.0241 short-term debt + 0.8641 long-term debt + 0.9517 retained earnings+ 0.0070 share capital

Hypothesis Regression Panel Data Model Common Effects

1. Prob (F-Statistics): The p-value of the F test, determine how significant the simultaneous influence of the predictor variable on the response variable is. If the p-value is less than the threshold limit, say 0.05, then accepting H_1 indicates that the simultaneous influence of the predictor variable on the responder variable was statistically significant. The inverse is true: if the p-value is greater than the critical limit, accept H_0, indicating that the simultaneous influence of predictor factors on the response variable is not statistically relevant.We conclude that the estimates of the model's coefficient are jointly significant with p-value of 0.0000 which is $p < 0.05$.
2. R Squared: is the extent of the influence of the predictor variables to explain the dependent variables concurrently. If the score is greater than 0.5, the predictor variable's

capacity to explain the response variable is strong. The inverse is true: if the value is less than 0.5, the predictor variable's capacity to explain the response variable is weak. The R Squared score in this panel data regression is 0.1616, indicating that the predictor variable is not particularly effective at explaining the response variable.

3. Adjusted R Squared: the intensity of predictor variables' influence to simultaneously explain the response variable by observing the standard error. The adjusted R-squared, which quantifies the fraction of total EPS variation accounted by X after accounting for degrees of freedom lost due to the inclusion of regression variables, is 0.1522 percent. This suggests that the predictor variable does not explain the response variable very well.

A positive regression coefficient implies that as the value of the independent independent variable increases, so does the mean of the dependent variable.On the other hand, a negative coefficient shows that as the independent variable decreases, so does the mean of the predictor variable. The ability to analyse the influence of each variable in isolation from the others is critical because it allows you to examine the effect of each variable in isolation from the others.The coefficient value also indicates how much the mean of the dependent variable changes when the independent variable is changed by one unit while the other variables in the model remain constant. . The coefficient of short-term debt is 0.240946 and the p-value is 0.014 meaning that for every 1 unit change in short-term debt, EPS is estimated to increase by 0.240946 holding other factors constant, and is statistically significant at the 5 percent level. Similarly, the coefficient of long-term debt is 0.8640876 and the p-value is 0.000. The panel's long-term debt is statistically significant since the p-value is less than 0.05 and EPS is estimated to increase by 0.8641 following a unit change in long-term debt while holding all other variables constant.

The regression coefficient for Retained Earnings is 0.9517492 meaning one unit increase in retained earnings leads to a 0.9517492 positive change in EPS holding other variables constant and is statistically significant since the p-value 0.015 is less than 0.05. Also, the regression coefficient of share capital is 0.0070163 meaning that EPS changes by 0.0070163 for every unit increase in share capital but unlike other variables, the p-value for share capital is 0.465 which is more than 0.05. This means that at the 5 percent level, share capital is not statistically significant when other factors are held constant. Although this model seems to fit the data, there could be a possibility that each firm or year has different initial earnings per share. That is, each firm may have its own initial earnings per share. It is the Y-intercept that is significantly different from those of other non-financial firms and the error terms may also vary across firms and/or years. The former question suspects fixed effects, whereas the latter asks if there is any random effect. Thus we proceed to the fixed effects and random effects models. A pooled regression of y on z and x ignores the individual effect μ, and therefore isn't appropriate. The μ_i can be captured using dummy variables in the least squares dummy variables method.

5.4.2 Fixed Effects Model

The fixed effects model statistically reflects observable quantities in terms of explanatory factors where the quantities are viewed as non-random. It fluctuates in a non-stochastic manner over i and t.This approach believes that individual differences can be addressed by using a different intercept. Different intercepts can occur due to changes in labour, managerial, and incentive cultures when attempting to estimate fixed effects model panel data using a dummy variable approach to account the differences between intercept businesses. Regardless, the intercept is the same across firms. When we assume fixed effects, we impose time-independent effects on each entity that may be associated with regressors (Gujarati 2006, Gujarati 1996). (Gujarati and Porter 2009).This estimate model is also known as the Least Squares Dummy Variable technique (LSDV). The LSDV is a derivation method that employs explicit dummy variables. The fixed effects model differs from the common effects model, but it still employs the least squares concept. Because the modelling assumption of producing a consistent intercept for each cross-section and time is deemed less plausible, more models are required to describe the difference. Fixed effects assume that individual differences may be addressed by a different intercept.

The phrase fixed effects estimator, also known as the inside estimator in panel data analysis, refers to an estimator for the coefficients in the regression model. Fixed effects models have been used to address social and economic issues (Ahmed and Sobhi 2009), Baltagi (2008), Treisman (2000), and others (Hsiao and Kamil 1997). Because the fixed-effects model accounts for all time-invariant variations between people, the estimated coefficients of the fixed-effects models cannot be skewed by omitted time-invariant factors such as gender or religion.However, Fixed-effects models have the disadvantage of not being able to study time-invariant sources of dependent variables.
For the study,we use the LSDV approach to estimate for the fixed effects.

The Least-squares Dummy Variable (LSDV)

The "standard" panel data model is:

$$y_{it} = z_i\alpha + x_{it} + \mu_i + \varepsilon_{it}, \quad t = 1\ldots T_i, i = 1...n \tag{5.2}$$

We construct a set of n dummy variables $D1_{it}, \ldots, Dn_{it}$ where $Dr_{it} = 1$ if $i = r$ and 0 otherwise, for $r = 1...n$.
Thus Dr_{it} tells us whether observation it relates to person r.

The model is now:

$$y_{it} = z_i\alpha + x_{it}\beta + \mu_i D1_{it} + +nDn_{it} + \varepsilon_{it} \tag{5.3}$$

Thus $\mu_i ... \mu_n$ are now seen as the coefficients of a set of n dummy variables.
The Frisch-Waugh theorem on partitioned regression tells us that a multiple regression of y on (z,x) and $(D1...Dn)$ can be done in two stages:

Stage 1: regress y on $(D1...Dn)$ and each of the variables in (z,x) on $(D1...Dn)$; replace y and (z,x) by their residuals from these regressions $\implies$ $y*$ and $(z*,x*)$.
Stage 2: regress $y*$ on $(z*,x*)$.
It can be shown that, in our case, the residuals $y*$ and $(z*,x*)$ are:

$$\begin{aligned} y*_{it} &= y_{it} - \bar{y}_i \\ x_{it} &= x_{it} - \bar{x}_i \\ z_i &= z_i - \bar{z}_i = 0 \end{aligned}$$

Thus, least-squares dummy variables (LSDV) is equivalent to a regression of $y_{it} - \bar{y}_i$ on $x_{it} - \bar{x}_i$, with z eliminated from the model (since z is collinear with $D1...Dn$).

Where: ω_i is unobserved heterogeneity (firm dependent error term). ω_i is fixed over time but varies cross-sectionally.

Our fixed effects model is

$$Y_{it} = \beta_{0i} + \beta_1 X_{(1,it)} + \beta_2 X_{(2,it)} + \beta_3 X_{(3,it)} + \beta_4 X_{(4,it)} + \varepsilon_{it} \tag{5.4}$$

Fixed-effects models explicitly account for the effect of firm heterogeneity.

$$Y_{it} = \beta_0 + \beta_1 X_{(1,it)} + \beta_2 X_{(2,it)} + \beta_3 X_{(3,it)} + \beta_4 X_{(4,it)} + \varepsilon_{it} \tag{5.5}$$

$$Y_{it} = \beta_0 + \beta_1 X_{(1,it)} + \beta_2 X_{(2,it)} + \beta_3 X_{(3,it)} + \beta_4 X_{(4,it)} + FirmFixedEffects + v_{it} \tag{5.6}$$

$$Y_{it} = \beta_0 + \beta_1 X_{(1,it)} + \beta_2 X_{(2,it)} + \beta_3 X_{(3,it)} + \beta_4 X_{(4,it)} + \omega_i + v_{it} \tag{5.7}$$

The LSDV model takes heterogeneity into account by allowing for several intercepts, one for each firm in the pooled data. It accomplishes this through the usage of dummy variables. The within estimator and the LSDV estimator both produce the same coefficients for the equation, according to the Frisch-Waugh-Lovell theorem.

Consider a basic linear unobserved effect panel data model, for example:

$$Y_{it} = \beta x'_{it} + c_i + \lambda t + \mu_{it}, \quad t = 1, ..., T \tag{5.8}$$

where the vector x'_{it} contains the independent variables and μ_{it} is an error term. The number of individuals is N. Assume that the unobserved individual effect may be correlated with x'_{it} (fixed effects assumption).

A one-way model does not include time effects, for example;

$$Y_{it} = \beta x'_{it} + c_i + \mu_{it}, \quad t = 1..., T \tag{5.9}$$

but a two-way model additionally does include time effects:

$$Y_{it} = \beta x'_{it} + c_i + \lambda t + \mu_{it}, \quad t = 1, ..., T \tag{5.10}$$

The demeaning approach is equivalent to the LSDV. It has the advantage of being more intuitively evident and not requiring any changes to the standard errors. It has the disadvantage of needing the addition of new dummy variables, one for each unit, which makes the model complex, especially when the number of units is considerable. This model was built by inserting dummy variables for the units. There are two options: (1) include one dummy variable for each unit but leave out the intercept, or (2) include one variable for all but one variable and include an intercept. A dummy variable is a binary variable that is coded to either 1 or 0, and it is often used in regression analysis to analyse group and time effects. The LSDV is a method of accounting for the sector's uniqueness (Okoroafor ,2012). This is accomplished by allowing the intercept to vary for each sector while assuming that the slope coefficients remain constant across sectors or time periods (Hsiao 2003). The least square dummy variable regression model was used to investigate changes in profits per share when all of the coefficients differed among enterprises The dummy variable is set to 1 for firm 1 and 0 for all other non-financial enterprises, and so on.

Consider $Y_{it} = \alpha_1 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \alpha_4 D_{4i} + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X3_{it} + \beta_4 X4_{it} + \varepsilon_{it}$

where $D2 = 1$ if the observation belongs to long-term debt and 0 otherwise; $D3 = 1$ if the observation belongs to retained earnings and 0 otherwise; $D4 = 1$ if the observation belongs to share capital and 0 otherwise. $\alpha 1$ represents the intercept of short-term debt while $\alpha 2$, $\alpha 3$, and $\alpha 4$ are the differential intercept coefficients, telling us how much the intercepts of long-term debt, retained earnings, and share capital differs from the intercept of short-term debt which is our comparison sector. The LSDV model can be extended when the intercepts and slope coefficients are assumed to be different for all the sectors. The output of the fixed effect is as follows:

LSDV 1

Under this model, intercepts vary only across firms to account for heterogeneity but not across time as shown in table 21.

Table 32. regress EPS STD LTD RE SC F ID

Source	SS	df	MS	Number of obs=360		
Model	223580715	39	5732838.85	F(39,320)=2.49		
				Prob>F=0.0000		
Residual	735401954	320	2298131.1	R-squared=0.2331		
Total	958982669	359	2671260.92	Adj R-squared=0.1397		
				Root MSE=1516		
STD	.0228838	.0104828	2.18	0.030	.0022598	.0435078
LTD	.8682769	.1575131	5.51	0.000	.5583848	1.178169
RE	.9851706	.4095328	2.41	0.017	.1794536	1.790888
SC	.00394	.0104308	0.38	0.706	-.0165816	.0244616
IF ID 2	506.0852	692.2664	0.73	0.465	-855.8832	1868.054
IF ID 3	-30.6829	694.5458	-0.04	0.965	-1397.136	1335.77
IF ID 4	-128.6838	691.33	-0.19	0.852	-1488.81	1231.442
IF ID 5	526.5005	693.6158	0.76	0.448	-838.1227	1891.124
IF ID 6	-70.70365	693.2463	-0.10	0.919	-1434.6	1293.193
IF ID 7	210.4606	692.5468	0.30	0.761	-1152.059	1572.981
IF ID 8	73.4629	692.5596	0.11	0.916	-1289.082	1436.008
IF ID 9	367.0028	692.6235	0.53	0.597	-995.6682	1729.674
IF ID 10	-2442.274	694.6326	-3.52	0.001	-3808.897	-1075.65
IF ID 11	16.04524	700.6601	0.02	0.982	-1362.437	1394.527
IF ID 12	96.68784	694.7626	0.14	0.889	-1270.192	1463.567
IF ID 13	82.95204	697.2482	0.12	0.905	-1288.817	1454.722
IF ID 14	69.39526	694.6246	0.10	0.920	-1297.213	1436.003

Table 33. regress EPS STD LTD RE SC F ID (continuation)

IF ID 15	-6.522336	691.0545	-0.01	0.992	-1366.106	1353.062
IF ID 16	243.0656	694.6399	0.35	0.727	-1123.572	1609.704
IF ID 17	72.54979	691.997	0.10	0.917	-1288.889	1433.988
IF ID 18	59.09995	692.0128	0.09	0.932	-1302.37	1420.569
IF ID 19	2.101949	693.2957	0.00	0.998	-1361.892	1366.095
IF ID 20	54.5553	693.3521	0.08	0.937	-1309.549	1418.66
IF ID 21	-28.40281	698.1449	-0.04	0.968	-1401.937	1345.131
IF ID 22	-8.335338	694.3254	-0.01	0.990	-1374.355	1357.684
IF ID 23	19.88474	692.066	0.03	0.977	-1341.689	1381.459
IF ID 24	48.45554	696.9025	0.07	0.945	-1322.634	1419.545
IF ID 25	22.42688	689.9243	0.03	0.974	-1334.934	1379.787
IF ID 26	62.69717	690.0358	0.09	0.928	-1294.883	1420.277
IF ID 27	80.40475	691.1382	0.12	0.907	-1279.344	1440.154
IF ID 28	157.4668	693.9041	0.23	0.821	-1207.724	1522.657
IF ID 29	75.95189	693.7431	0.11	0.913	-1288.922	1440.826
IF ID 30	59.50534	695.2105	0.09	0.932	-1308.255	1427.266
IF ID 31	123.5898	694.6591	0.18	0.859	-1243.086	1490.266
IF ID 32	80.20666	696.2473	0.12	0.908	-1289.594	1450.007
IF ID 33	28.18757	710.9928	0.04	0.968	-1370.623	1426.998
IF ID 34	-85.07627	692.5545	-0.12	0.902	-1447.611	1277.459
IF ID 35	-14.00992	690.7393	-0.02	0.984	-1372.974	1344.954
IF ID 36	-151.4444	695.4046	-0.22	0.828	-1519.587	1216.698
cons	184.2938	506.4229	0.36	0.716	-812.0451	1180.633

R-square represents the amount of Y variance explained by X. Our R squared is 0.2331, as illustrated above. This means that the independent variables in the model accounted for 23.31 percent of the total variation, while white noise accounted for the remaining 76.69 percent. The t-values examine if each coefficient differs from zero. To reject this, the t-value must be more than 1.96 with a 95 percent confidence level.The higher the t-value the higher the relevance of the variable. According to the results above, the t-values for the short-term debt, long-term debt, retained earnings, and share capital is 2.18, 5.51, 2.41, and 0.38 respectively. Since the t-values of all the independent variables are higher than 1.96 apart from that of share capital, we conclude that the variables have a significant influence on the EPS apart from the share capital. The Coefficients of the regressors indicate how much Y changes when X increases by one unit. The slope coefficient of short-term debt is 0.0228838, long-term debt is 0.8682769, retained earnings is 0.9851706, and share capital is 0.00394. This means that for every unit increase of short-term debt, long-term debt retained earnings, and share capital, EPS increases by 0.0228838, 0.8682769, 0.9851706, and 0.00394 respectively.

The two-tail p-values examine if each coefficient differs from zero. To reject this, the p-value must be less than 0.05 (95%); if so, we infer that the variable has a substantial influence on the dependent variable earnings per share. The p-value for the variable short-term debt is 0.030, as shown above, and because it is less than 0.05, we conclude that the variable has a substantial influence on EPS. Similarly, we infer that long-term debt has a significant impact on EPS because its p-value is less than 0.05.The p-value for retained earnings is 0.017, which is less than 0.05, indicating that it is statistically significant in determining EPS fluctuations. However, because it has a p-value greater than 0.05, share capital has no meaningful influence on EPS variations.

LSDV 3

Under this model, intercepts are time-varying and also vary across firms as can be seen in table 23.

Table 34. regress EPS STD LTD RE SC Year F ID

Source	SS	df	MS	Number of obs=360	
Model	242261344	48	5047111.33	F(48,311)=2.19	
				Prob>F=0.0000	
Residual	716721325	311	2304570.18	R-squared=0.2526	
Total	958982669	359	2671260.92	Adj R-squared=0.1373	
				Root MSE=1518.1	

EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
STD	.0173253	.011238	1.54	0.124	-.0047867	.0394374
LTD	.8846539	.1593907	5.55	0.000	.5710333	1.198274
RE	1.00861	.4172041	2.42	0.016	.1877099	1.829509
SC	.0064097	.0107313	0.60	0.551	-.0147055	.0275248
Year 2009	-219.7739	368.0733	-0.60	0.551	-944.0027	504.4549
Year 2010	-209.542	370.5726	-0.57	0.572	-938.6885	519.6045
Year 2011	-207.3067	367.2285	-0.56	0.573	-929.8733	515.2599
Year 2012	-133.8731	375.2237	-0.36	0.721	-872.1712	604.425
Year 2013	-143.2646	372.3496	-0.38	0.701	-875.9076	589.3784
Year 2014	-888.3357	376.3724	-2.36	0.019	-1628.894	-147.7775
Year 2015	-217.5719	369.663	-0.59	0.557	-944.9286	509.7847
Year 2016	-65.61342	367.2623	-0.18	0.858	-788.2465	657.0197
Year 2017	-150.0251	374.9218	-0.40	0.689	-887.7292	587.6791
F ID 2	527.3669	694.0281	0.76	0.448	-838.2175	1892.951
F ID 3	-18.01047	696.287	-0.03	0.979	-1388.04	1352.019
F ID 4	-126.1498	692.8125	-0.18	0.856	-1489.342	1237.043
F ID 5	539.2156	695.4137	0.78	0.439	-829.095	1907.526
F ID 6	-67.64517	694.8572	-0.10	0.923	-1434.861	1299.571
F ID 7	187.1834	693.933	0.27	0.788	-1178.214	1552.581
F ID 8	73.80056	694.0353	0.11	0.915	-1291.798	1439.399
F ID 9	395.4994	694.5698	0.57	0.569	-971.1508	1762.15

Table 35. regress EPS STD LTD RE SC Year F ID (continuation)

F ID 10	-2440.619	696.3459	-3.50	0.001	-3810.764	-1070.474
F ID 11	60.68483	703.5098	0.09	0.931	-1323.556	1444.926
F ID 12	110.0201	696.5449	0.16	0.875	-1260.516	1480.557
F ID 13	94.06922	699.1289	0.13	0.893	-1281.552	1469.69
F ID 14	66.30147	696.0999	0.10	0.924	-1303.359	1435.962
F ID 15	4.228666	692.5876	0.01	0.995	-1358.521	1366.979
F ID 16	212.8816	696.1391	0.31	0.760	-1156.856	1582.62
F ID 17	67.78746	693.3915	0.10	0.922	-1296.544	1432.119
F ID 18	67.99173	693.5095	0.10	0.922	-1296.572	1432.556
F ID 19	21.96875	695.0167	0.03	0.975	-1345.561	1389.498
F ID 20	69.05534	695.0308	0.10	0.921	-1298.502	1436.613
F ID 21	-30.87433	699.9849	-0.04	0.965	-1408.179	1346.431
F ID 22	35.48497	696.7132	0.05	0.959	-1335.383	1406.353
F ID 23	23.83441	693.5245	0.03	0.973	-1340.759	1388.428
F ID 24	75.52638	699.0413	0.11	0.914	-1299.922	1450.975
F ID 25	22.55841	691.3272	0.03	0.974	-1337.712	1382.828
F ID 26	64.65728	691.3766	0.09	0.926	-1295.71	1425.024
F ID 27	80.70658	692.5566	0.12	0.907	-1281.983	1443.396
F ID 28	154.9403	695.5062	0.22	0.824	-1213.552	1523.433
F ID 29	99.03691	695.6407	0.14	0.887	-1269.72	1467.794
F ID 30	69.33947	696.8358	0.10	0.921	-1301.769	1440.448
F ID 31	97.84744	696.063	0.14	0.888	-1271.741	1467.436
F ID 32	98.97704	698.1804	0.14	0.887	-1274.777	1472.732
F ID 33	64.30674	713.6458	0.09	0.928	-1339.878	1468.491
F ID 34	-95.34682	693.8082	-0.14	0.891	-1460.499	1269.805
F ID 35	-1.120082	692.243	-0.00	0.999	-1363.192	1360.952
F ID 36	-119.1825	697.3775	-0.17	0.864	-1491.357	1252.992
cons	370.1439	554.5454	0.67	0.505	-720.9914	1461.279

Our R squared is 0.2526, as seen in table 23. This means that the independent variables in the model accounted for 25.26 percent of the overall variation, while white noise accounted for the remaining unexplained variation. The F -test for the overall model demonstrates that all of the coefficients in the model are not zero because it is less than 0.005. The t-values for the short-term debt, long-term debt, retained earnings, and share capital is 1.54, 5.55, 2.42, and 0.60 respectively. Since the t-values of the long-term debt and retained earnings are higher than the t-table value which is 1.96, we conclude that the variables have a significant influence on the EPS but short-term debt and share capital do not have a high influence on the changes in EPS at 5 percent significant level. The Regression coefficient of short-term debt is 0.173253 which means that a unit increase in the short-term debt leads to a 0.173253 increase in EPS. The Regression coefficient of long-term debt is 0.8846539 which means that a unit increase in the long-term debt leads to a 0.8846539 increase in EPS.

Similarly, since the regression coefficient for retained earnings is 1.00861, a unit change in retained earnings leads to a 1.00861 increase in EPS, and since the share capital is 0.0064097, a unit change in share capital leads to a 0.0064097 change in EPS. As seen in table 23, the p-value for the variable short-term debt is 0.0124 since it is below 0.05 we conclude that the variable has a significant influence on EPS. The p-value for the long-term debt also has a significant influence on EPS since its p-value is 0.000 and is below 0.05. The p-value for retained earnings is 0.016 which is also below 0.05 so we also conclude that it is statistically significant in influencing the changes in EPS. But since the p-value for share capital is 0.60 which is higher than 0.05, we conclude that share capital has no significant influence on the changes in EPS.

Comparing LSDV 1 and LSDV 3

Table 36. Comparing LSDV 1 and LSDV 3

(1)	-IYear 2009=0
(2)	-IYear 2010=0
(3)	-IYear 2011=0
(4)	-IYear 2012=0
(5)	-IYear 2013=0
(6)	-IYear 2014=0
(7)	-IYear 2015=0
(8)	-IYear 2016=0
(9)	-IYear 2017=0

$F(9, 311) = 0.90$

$Prob > F = 0.5249$

H_0: LSDV 3 is a better model
H_1:LSDV 1 is a better model

Using the testparm command to choose between the two LSDV models, shows that we reject the null hypothesis that LSDV 3 is better than LSDV 1. Therefore, we consider the results of LSDV 1 which is also similar to running the fixed effects model as follows:

Table 37. Comparing LSDV 1 and LSDV 3

Fixed-effects (within) regression	Number of obs=360
Group variable: F ID	Number of groups =36
R-sq:	Obs per group:
within=0.1572	min=10
between=0.2048	avg=10.0
overall=0.1612	max=10
	F(4,320)=14.93
corr(μ_i, Xb)=0.0196	Prob>F=0.000

Table 38. Comparing LSDV 1 and LSDV 3

EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval
STD	.228838	.104828	2.18	0.030	.0022598	.0435078
LTD	.8682769	.1575131	5.51	0.000	.5583848	1.178169
RE	.9851706	.4095328	2.41	0.017	.1794536	1.790888
SC	.00394	.0104308	0.38	0.706	-.0165816	.0244616
cons	189.0884	128.5703	1.47	0.142	-63.86141	442.0383
sigma μ	443.93492					
sigma e	1515.9588					
rho	.07898264					
	F test that all $\mu_i = 0$:	F(35, 320)= 0.85		Prob>F=0.7089		

Table 27 shows that using the F test, all of the independent variables are jointly significant prob>F =0.0000. Short-term debt is statistically significant on its own, with a p-value of

0.030, which is less than 0.05. Long-term debt is also statistically significant on its own, with a p-value of 0.000, which is less than 0.05. With a p-value of 0.017, retained earnings are likewise significant, but share capital is not significant with a p-value of 0.706, which is greater than 0.05.

The state dummies are equal to zero, according to the testing hypothesis. The F-test is an example of this. The table's final line is a F test to ensure that all μ_i are equal to zero: F(35, 320) = 0.85 Prob > F = 0.7089 . With a p-value of.0000, we can accept the null that the dummies are all equal to zero. As a result, we find that the pooling model is superior—firm fixed effects are insignificant.

5.4.3 Random Effects Model (RE)

This model will estimate panel data where interference variables may be linked across time and across people. The discrepancy between intercepts is accommodated by the error terms of each company in the random effects model. The random effects model has the advantage of eliminating heteroscedasticity. The Error Component Concept (ECM) or Generalized Least Squares (GLS) approach is another name for this model. In essence, the random effects model differs from the common effects and fixed effects models, particularly since it employs the maximum likelihood or generic least squares principle rather than the principle of ordinary least squares. In the random effects model, residuals can be linked across time as well as between individuals or cross sections. As a result, this model makes the assumption that the intercept differs for each individual and that the intercept is a random variable. So there are two residual components in the random effects model. The first is the residual as a whole, which is a cross-section and time series combination. The second residual is an individual residue that is a random character of the $i-th$ unit observation and is constant.
The regression equation of panel data of the random effects model is as follows:

$$_{it} = \alpha_i + \beta' X_{it} + \mu_i + \varepsilon_{it}, \quad i = 1,2,....,N, t = 1,2,....,T \tag{5.12}$$

Where:
N = number of individuals or cross-section
T = the number of time periods.
ε_{it} = is the residual as a whole where the residual is a combination of cross-section and time series.
μ_i = is the individual residual which is the random characteristic of unit observation the i-th and remains at all times.

If some explanatory factors remain consistent over time, the RE estimator would be useful. It is assumed that group effects are uncorrelated with regressors, hence this assumption must be tested. The FE estimator calculates the link using time variation within a cross-sectional unit. The BE estimator measures the relationship using cross-sectional RE estimator.

Table 39. Random effects model

Random-effects GLS regression	Number of obs =360
Group variable: F ID	Number of groups=36
R-sq:	Obs per group:
within=0.1569	min=10
between=0.2136	avg=10.0
overall=0.1616	max=10
	Wald $\chi^2(4)$= 68.43
corr(μ_i, X) =0 (assumed)	$Prob > \chi^2$=0.000

Table 40. Random effects model

EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval
STD	.0240946	.0097138	2.48	0.013	.0050559	.0431334
LTD	.8640876	.1483795	5.82	0.000	.5732692	1.154906
RE	.9517492	.3899394	2.44	0.015	.1874819	1.716016
SC	.0070163	.0095978	0.73	0.465	-.011795	.0258277
cons	225.4497	123.3595	1.83	0.068	-16.33046	467.2299
σ_μ	0					
σ_e	1515.9588					
ρ	0					

For numerous reasons, this differs from the fixed effects estimates. We begin by estimating the time-invariant variables. Second, these results take into account both variation between firms and variation within firms over time, though the impact on both the magnitude of the coefficients and their standard errors is minimal..

5.4.4 Model Comparison

Table 41. Model Comparison

Estimates	Pooled OLS		Fixed effects		Random effects	
	β	Se	β	Se	β	Se
β_0	225.4497	123.3595	189.0884	128.5703	225.4497	123.3595
β_{1-STD}	0.0240946	0.0097138	0.0228838	0.0104828	0.0240946	0.0097138
β_{2-LTD}	0.8640876	0.1483795	0.8682769	0.1575131	0.8640876	0.1483795
β_{3-RE}	0.9517492	0.3899394	0.9851706	0.4095328	0.9517492	0.3899394
β_{4-SC}	0.0070163	0.0095978	0.00394	0.0104308	0.0070163	0.0095978
R-squared						
overall	0.1616		0.1612		0.1616	
Within			0.1572		0.1569	
between			0.2048		0.2136	

Table 41 displays the regression coefficients as well as the standard error of estimate of β and adjusted R squared. The results of the pooled OLS model are almost identical to those of the random effects model, as shown in the table. However, because the pooled OLS disregards unmeasured heterogeneity, intrinsic issues occur. Because zero conditional mean error fails for the combined error, the pooled OLS is frequently biased and inconsistent. As a result, the random effects model is recommended for this research.The total R-squared for the pooled OLS and the random effects models is 0.1616, whereas the fixed effects model is 0.1612. This means that in the fixed model, the variables explain 16.12% of the variation in profits per share, whereas in the random effects and pooled OLS models, the variables explain 16.16% of the variation in earnings per share. The results of the pooled OLS model and the Random effects model explain 0.04 percent more variation than the fixed effects model.

A statistic's standard error specified as an estimate of a parameter, is the standard deviation of its sampling distribution or an estimate of that standard deviation. If the statistic is the sample mean, the phrase standard error of the mean is used. The standard error reveals how near any given sample from that population's mean is to the genuine population mean. When the standard error increases, meaning that the means become more distributed, the likelihood that any given mean is an erroneous depiction of the genuine population mean increases.

The standard error of the regression, as opposed to R-squared, can be used to gauge the precision of the predictions. Approximately 95% of the observations should lie within plus/minus 2*standard error of the regression from the regression line, corresponding to a 95% prediction interval. Calculating the regression standard error may be more significant than calculating R-squared if you want to utilise a regression model to generate predictions. The standard error for short-term debt in the fixed effects model is 0.0104828, which is more than the standard error in the random effects model, which is 0.0097138. We choose the random effects model since it has a lesser error because the larger the standard error, the less accurate the statistic. .For long-term debt, the standard error for the fixed effects model is larger at 0.1575131 while the random effects model is 0.1483795.

Here we also prefer the random effects model to the fixed since the standard error is smaller. Similarly for retained earnings, we prefer the random effects model over the fixed effects model since 0.3899394 is less than 0.4095328. We still choose the random effects model for the variable share capital since 0.0095978 is less than 0.0104308. Following the observations above we conclude that the random effects model is better than the fixed effects model for this data set since a smaller standard error indicates that the means are closer together, and thus it is more likely that the sample mean is an accurate representation of the true population mean. Furthermore, random effects models have at least two key advantages to fixed effect models: the ability to account for unequal school effectiveness using random coefficients models, and the ability to estimate shrunken residuals. Furthermore, a fixed-effects model can predict only the levels/categories of characteristics that were used for training. A random-effects model, on the other hand, allows for predictions about the population from which the sample is drawn.

5.5 Panel Data Model Selection

To select the most appropriate model, there are several tests that can be done, such as:

5.5.1 Hausman Test

When analysing panel data, one must decide whether to use a random effects model or a fixed effects model (Baltagi, 2005).The Hausman test is a statistical test that determines if whether best fixed effects or random effects model is utilised. The requirement is to carry out procedures in a series, starting with a fixed effect and then moving on to a random effect. The study used Hausman's specification test to choose between fixed and random effects models.

The hypothesis to be tested is:
H_0: Random effect is appropriate
H_1: Fixed effect is appropriate

If the result is:
H_0: we select RE $(p > 0.05)$
H_1: we select FE $(p < 0.05)$

The results of the Hausman test are as seen in table 42.

Table 42. Hausman fixed and random test

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(Vb-VB)) S.E.
STD	.0228838	.0240946	-.0012109	.003941
LTD	.8682769	.8640876	.0041893	.0528574
RE	.9851706	.9517492	.0334214	.1251575
SC	.00394	.0070163	-.0030763	.0040846

b=consistent under H_0 and H_1

B= inconsistent under H_1, efficient under H_0.

Test: Difference in coefficient not systematic

$\chi^2(4)=(b-B)'[(Vb-VB)^(-1)](b-B)$

$\chi^2(4)=1.22$

$Prob > \chi^2=0.8741$

The null hypothesis of the Hausman test is that the random effects model is preferred to the fixed effects model. To predict the panel model using growth in the Earnings Per Share model, the Hausman test revealed a chi-square of 1.22 with a p-value of 0.8741.

We fail to reject the null hypothesis that the random effects model is the appropriate model in comparison to the fixed effects model because the p-value is greater than 0.05 at 0.8741. Thus through the Hausman test results, we conclude that the random effects model is the appropriate model when financial growth is measured using growth in earnings per share. We then proceed with the Lagrangian Multiplier test to determine whether we still choose the Random effect model or the Pooled Least Square model.

5.5.2 Test Lagrange Multiplier

The score test, also known as the Lagrange Multiplier (LM) test, is a hypothesis test used to determine whether certain parameter constraints have been violated. The Breusch-Pagan Lagrange Multiplier Test is used to test whether random effects in panel data models are meaningful. The Error Components Model or the two-error structure approach are other names for the Random Effects Model. The introduction of dummy variables in the Fixed Effects Model causes some obvious difficulties. As a result, the Random Effects Model offers a novel way for accounting for cross-sectional and time-specific effects in panel data. In place of dummy variables, like in fixed-effects models, cross-sectional and time-specific effects are added as error terms.

If result is:
H_0: $\sigma_\varepsilon^2 = 0$, that is, Random effects are insignificant $(p > 0.05)$.
H_1: $\sigma_\varepsilon^2 \neq 0$, that is, Random effects are significant -Select RE $(p < 0.05)$.

Table 43. Breusch and Pagan Lagrangian multiplier test for random effects

EPS(F ID,t)=Xb+μ(F ID)+e(F ID,t)

Estimated results:

	Var	sd=sqrt(Var)
EPS	2671261	1634.399
e	2298131	1515.959
μ	0	0

Test: Var(μ)=0

$\bar{\chi}^2(01) = 0.00$

Prob>$\bar{\chi}^2$=0.010

The results in table 43 indicate that we reject the null that $var(\mu_i) = 0$ with a high degree of confidence (p-value = 0.010). This implies that the random effects model is a more appropriate model than an OLS model.

5.6 Correlation Analysis

A pairwise correlation analysis was employed in this study to better understand the connection between the dependent and independent variables. The technique is intended to detect multicollinearity and is good for deleting highly associated variables.

Table 44. Correlation between Financial Structure and Growth in Earnings Per Share

	EPS	Short Term Debt	Long Term Debt	Retained Earnings	Share Capital
EPS	1.000				
Short Term Debt	0.2108	1.000			
	0.0001				
Long Term Debt	0.3399	0.1185	1.000		
	0.000	0.0245			
Retained Earnings	0.2288	0.2229 0.2259	1.000		
	0.000	0.000	0.000		
Share Capital	0.1495	0.3933	0.1104	0.2072	1.000
	0.0045	0.000	0.0362	0.0001	

The correlation studies revealed a significant positive and significant relationship between short-term debt and earnings per share. Long-term debt was also discovered to have a large and positive link with earnings per share. It was also revealed that share capital had a moderately strong positive relationship with earnings per share. Retained earnings also have a strong positive and significant relationship with EPS.

5.7 Normality Test

The study tested the null hypothesis that the data was normally distributed.
H_0: The data is normally distributed
H_1: The data is not normally distributed

Bera and Jarque (1981) tests of normality were performed. We reject the null hypothesis and conclude that the data does not come from a normally distributed population if the test p-value is less than the predetermined significance level of 0.05. If the p-value is greater than the preset significance level of 0.05, we do not reject the null hypothesis. If the data is not normally distributed, a non-parametric test will be most appropriate.The normality assumption $\mu t \sim N(0, \sigma^2)$ was required in order to conduct single or joint hypotheses tests about the model parameters (Brooks, 2008).

Table 45 shows the normality results for the non-financial firms.

Table 45. Normality Test

Variable	Observation	Skewness	Kurtosis	p-value
Earnings Per Share	360	1.0670	0.7324	.166
Short Term Debt	360	2.0211	0.6413	.825
Long Term Debt	360	4.8153	0.5104	.967
Retained Earnings	360	3.0634	0.5679	.084
Share Capital	360	1.2035	0.8241	.487

Table 45 illustrates the skewness and kurtosis tests findings for non-financial organisations. According to the results of the normalcy test utilising the skewness and kurtosis tests, the p-values for short-term debt, long-term debt, retained earnings, and share capital were 0.166,0.825,0.967,0.084, and 0.487, respectively. We cannot reject the null hypothesis that the data is normally distributed because the p-values are all bigger than the preset significance level of 0.05.

5.8 Multicollinearity Test

In this work, the variance inflation factors (VIF) were utilised to assess multicollinearity. VIF values more than 10 suggest the presence of Multicollinearity, according to Alin (2010). Table 46 revealed a VIF of 10 for all variables, showing that the variables were not statistically related and hence no Multicollinearity existed. This implies that the variables are appropriate for further modelling using panel regression analysis. Multicollinearity is defined by William (2013) as the presence of correlations between predictor variables. In severe cases of perfect correlations between predictor variables, multicollinearity can exist, meaning that a unique least squares solution to a regression analysis cannot be obtained. Because multicollinearity inflates standard errors and confidence intervals, and the predictor variable coefficient estimates become unstable (Daoud, 2017).

Because the VIF of all variables was less than 10, there was no statistical significance for multicollinearity, according to the results in table 46. When utilising profits per share as a financial growth measure, the VIF values for long-term debt, retained earnings, share capital, and short-term debt were all less than 10. As a result, the variables are not linearly related, and panel regression modelling might be used to evaluate the impact of long-term debt, retained earnings, share capital, and short-term debt on company growth in the study's listed non-financial firms.

Table 46. Multicollinearity Test

	Growth in Earnings	Per Share
Variable	1/VIF	VIF
d. Retained Earnings	1.16	0.865498
d. Long Term Debt	1.14	0.874819
Short Term Debt	1.03	0.967385
Share Capital	1.02	0.977179
Mean VIF	1.09	

5.9 Autocorrelation Test

The study tested the null hypothesis that residuals of this regression model did not have a serial correlation.

H_0: Residuals of this regression model do not have serial correlation
H_1: Residuals of this regression model have serial correlation

To examine if there was any association between error terms over time, a serial correlation test was run. In this study, the Wooldridge test for serial correlation was used to detect the presence of autocorrelation in the linear panel data. If the panel data has serial correlation, the Feasible Generalized Least Squares (FGLS) estimation is used. The null hypothesis for this test was that there was no first-order serial/autocorrelation in the data. As shown in table 47, when Serial Correlation was employed as a measure of financial growth with EPS growth, the test statistic produced an F-test of 0.419 and a p-value of 0.5215, both of which were greater than 0.05. As a result, we do not reject the null hypothesis that there is no first-order serial/auto correlation.

Table 47. Serial Correlation Tests

Growth in EPS
Wooldridge test for autocorrelation in panel data
H_0: no first-order autocorrelation
F (1, 35) =.419
Prob > F = 0.5215

5.10 Heteroscedasticity

The Breusch-Pagan test was used to assess heteroskedasticity. The null hypothesis states that the variance of error terms is constant and homoskedastic. Table 48 results reveal that the error terms are heteroscedastic, since the p-value of EPS is more than 0.05. As a result, the null hypothesis of constant variance was accepted, justifying the lack of heteroskedasticity in the data.

Table 48. Heteroskedasticity Test Results

Breusch-Pagan / Cook-Weisberg test for Heteroscedasticity
H_0: Constant variance
Variable: fitted values Growth in EPS
$\chi^2(1) = 0.7003$
Prob > χ^2 = 0.6429

5.11 Panel Regression

5.11.1 Effect of Short-Term Debt on Financial Growth

The RE model was employed to determine whether there was a significant relationship between STD and EPS. Table 49 depicts the panel regression model on STD with growth in EPSas a measure of financial growth.

Table 49. Effect of STD on EPS

Growth in EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
Short Term Debt	0.038201	0.009365	4.08	0.000	0.019847	0.056555
β_0	2.731963	1.198171	2.28	0.023	0.383591	5.080334
R-squared:	0.4599					
Wald $\chi^2(1)$	16.64					
Prob	0.0000					

The fitted model from the result is

Growth in EPS = 2.731963 + 0.038201STD
where:
EPS = Earnings Per Share
STD = Short Term Debt

Table 49 shows that the R-squared coefficient of determination is 0.4599. Short-term debt, according to the model, explains 45.99 percent of the volatility in earnings per share growth. This means that short-term debt controls 45.99 percent of the EPS growth range. Because the determined p-value of 0.000 is smaller than 0.05, the results, β =0.038201 and p value of 0.000, confirm that short-term debt has a significantly positive influence on profits per share growth. As a result, short-term debt has a statistically significant effect on profit per share growth. This implies that a unit increase in short-term debt results in a 0.038201-unit increase in earnings per share growth when other components remain unchanged.

5.11.2 Effect of Long-Term Debt on Financial Growth

A random model was developed to see whether there was a substantial relationship between long-term debt and volatility in profit per share growth. Table 50 depicts the panel regression model for LTD versus EPS.

Table 50. Effect of LTD on EPS

Growth in EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
Short Term Debt	0.500407	0.110795	4.52	0.000	0.283253	0.717561
β_0	-1.08621	0.9262236	-1.17	0.241	-2.9016	0.729182
R-squared:	0.216					
Wald $\chi^2(1)$	20.40					
Prob	0.0000					

The fitted model from the result is

Growth in EPS = -1.08621 - 0.500407LTD
where:
EPS = Earnings Per Share
LTD = Long Term Debt

Table 50 shows that the R-squared coefficient of determination is 0.216. Long-term debt, according to the model, explains 21.6 percent of the volatility in profits per share. This means that long-term debt accounts for 21.6 percent of the volatility in earnings per share. With β equal to 0.500407 and a p-value of 0.000, the data confirms that long-term debt has a positive influence on earnings per share growth. The effect of long-term debt on the change in earnings per share is statistically significant because the determined p-value of 0.0000 is less than 0.05. This means that when other conditions remain constant, a unit increase in long-term debt translates in a 0.500407 unit increase in earnings per share.

5.11.3 Effect of Retained Earnings on Financial Growth

A random effects model was developed to determine whether there was a significant relationship between RE and EPS. The panel regression model for retained earnings versus EPS is shown in Table 51.

Table 51. Effect of RE on EPS)

Growth in EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
Short Term Debt	1.421105	0.373815	3.8	0.000	0.688441	2.15377
β_0	-1.27142	0.925728	-1.37	0.17	-3.08582	0.542971
R-squared:	0.0237					
Wald $\chi^2(1)$	14.45					
Prob	0.0001					

The fitted model from the result is

Growth in EPS = -1.27142 + 1.421105RE
where:
EPS = Earnings Per Share
RE = Retained Earnings

The study discovered a positive and statistically significant relationship between RE and EPS. Table 51 shows that the coefficient of determination R-squared is 0.0237. The model claims that RE account for 2.37 percent of the fluctuation in EPS. This suggests that RE contribute for 2.37 percent of EPS variances. The regression coefficient was 1.421105. This indicates that a unit increase in RE results in a 1.421105 unit increase in EPS while all other parameters remain constant. Because the calculated p-value of 0.000 is less than 0.05, the effect of RE on EPS is statistically significant.

5.11.4 Effect of Share Capital on Financial Growth

A Random panel model was used to determine whether there was a significant relationship between share capital and EPS change. Table 52 depicts the panel regression model for share capital and EPS change.

Table 52. Effect of SC on EPS

Growth in EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
Short Term Debt	0.026871	0.009395	2.86	0.004	0.008456	0.045285
β_0	1.547499	1.169374	1.32	0.186	-0.74443	3.83943
R-squared:	0.3273					
Wald $\chi^2(1)$	8.18					
Prob	0.0042					

The fitted model from the result is

Growth in EPS = 1.547499 + 0.026871LTD
where:
EPS = Earnings Per Share
SC = Share Capital

Table 52 shows that the R-squared coefficient of determination is 0.3273. Share capital, according to the model, explains 32.73 percent of the variation in profits per share growth. This means that the fluctuation in earnings per share is influenced by share capital 32.73 percent of the time. With a positive regression coefficient of 0.026871 and a p-value of 0.004, share capital has a positive effect on earnings per share growth. We find that the effect of share capital on earnings per share is statistically significant because the p-value of 0.004 is less than 0.05. This means that while all other factors stay constant, a unit increase in share capital results in a 0.026871 unit increase in earnings per share growth.

5.11.5 Overall Panel Regression

An overall panel regression analysis was performed between the independent variables of short-term debt, long-term debt, retained earnings, and share capital and the dependent variable of financial performance as evaluated by earnings per share growth. The panel regression on earnings per share increase is shown in Table 53.

Table 53. Panel Regression of the Effect of Financial Structure on Growth in EPS

Growth in EPS	Coef.	Std. Err.	t	P>|t|	[95 Conf.	Interval]
Short Term Debt	0.0240946	0.009714	2.48	0.013	0.005056	0.043133
Long Term Debt	0.8640876	0.14838	5.82	0.000	0.573269	1.154906
Retained Earnings	0.9517492	0.389939	2.44	0.015	0.187482	1.716016
Share Capital	0.0070163	0.009598	0.73	0.465	-0.011795	0.025828
β_0	225.4497	123.3595	1.83	0.068	-16.33046	467.2299
R-squared:	=0.2136					
Wald $\chi^2(4)$	=68.43					
Prob > χ^2	=0.0000					

The panel regression model is;

Growth in EPS = 2.254497 + 0.024095STD1 + 0.864088LTD2 + 0.951749RE3 + 0.007016SC4
where:
EPS = Earnings Per Share
STD = Short Term Debt
LTD = Long Term Debt
RE = Retained Earnings
SC = Share Capital

The R-squared value was used to assess how well the model fit the data. An R-squared coefficient of determination of 0.2136 validated the investigation. This means that fluctuations in EPS are accounted for by 21.36 percent of STD,LTD,SC and RE . According to the research, STD has a favourable influence on EPS. The variable STD has a regression coefficient of 0.024095. The p-value was 0.013, less than 0.05. The t-statistic was 2.48, which was higher above the crucial value of 1.96. This suggests that there is a considerable positive association between STD and EPS.

Long-term debt had a strong beneficial effect on earnings per share variance. A p-value of 0.000, less than 0.05, and a calculated t-statistic of 5.82, greater than the essential t-statistic of 1.96 confirmed this. The LTD regression coefficient was 0.864088. This means that every unit rise in LTD translates in an increase in EPS of 0.864088 units. The results also demonstrated that RE had a considerable beneficial influence on EPS. The coefficient of regression for retained profits was 0.951749.

The share capital coefficient was 0.0070163. Because the p-value of 0.465 is greater than 0.05, this suggests that SC was insignificant. SC symbolises the value generated to a corporation in the past by its shareholders. A joint stock corporation must have money in order to operate. The computed t-statistic of 0.73 was likewise less than the crucial value of 1.96. SC symbolises the value generated to a corporation in the past by its shareholders. A joint stock corporation must have money in order to operate.

5.12 Summary of the Chapter

This chapter presented an analysis of the data gathered as well as a review of the findings. Descriptive statistics, correlation analysis and regression analysis were used in the study. Means, standard deviations, minimum and maximum values, and coefficients of variation were used in obtaining descriptive results for earnings per share, short-term debt, long-term debt, retained earnings and share capital. The best fit for the data was determined to be a random panel model, and panel regression analysis results revealed that short-term debt, long-term debt and retained earnings had a positive and statistically significant relationship with earnings per share, but share capital had no statistical significance. Even for the overall model, short term debt, long-term debt and retained earnings were all positively and significantly related to financial growth as measured by earnings per share growth in the overall panel model. The relationship between share capital and financial growth, as measured by earnings per share growth, was positive but insignificant.

6 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter summarizes the major findings of this study, draws relevant conclusions, and makes recommendations for practice and future research based on the study's findings. The purpose of the study was to determine the impact of short-term debt, long-term debt, retained earnings and share capital on the financial growth of non-financial firms listed on the Nairobi Securities Exchange.

6.2 Summary of Major Findings

This section contained a summary of the findings.

6.2.1 Effect of Short-Term Debt on Financial Growth

The first specific objective of the study was to assess the magnitude of short-term debt on the financial performance of nonfinancial firms listed on the Nairobi Securities Exchange. The findings revealed that short-term debt was positively and significantly correlated with financial growth as measured by earnings per share growth. Short-term debt was discovered to be adequate in explaining financial growth. Furthermore, the findings revealed that short-term debt is a good predictor of financial growth. Panel regression coefficient results revealed that short-term debt has a positive and significant impact on financial growth as measured by earnings per share growth.

6.2.2 Effect of Long-Term Debt on Financial Growth

The second specific objective of the study was to analyze the influence of long-term debt on the financial performance of non-financial companies listed on the Nairobi Securities Exchange. Results revealed that long-term debt was positively and significantly related to financial growth as measured by earnings per share. Long-term debt was found to be an adequate explanation for financial growth. Furthermore, the findings revealed that long-term debt is a good predictor of financial growth. According to the panel regression coefficient results, long-term debt has a positive and significant effect on financial growth. Long-term debt was also found to have a positive and significant effect on financial growth as measured by earnings per share.

6.2.3 Effect of Retained Earnings on Financial Growth

The third objective of the study was to determine the extent retained earnings affected the financial performance of non-financial firms listed on the Nairobi Securities Exchange. The findings revealed that retained earnings were positively and significantly related to financial growth as measured by earnings per share. Retained earnings were discovered to be satisfactory in explaining financial growth. Furthermore, the findings revealed that retained earnings are a good predictor of financial growth explaining 2.37 percent of the variation in earnings per share growth. The results of the panel regression coefficient revealed that retained earnings have a positive and significant effect on financial growth as measured by earnings per share. The findings also revealed that retained earnings have a positive and significant impact on financial growth.

6.2.4 Effect of Share Capital on Financial Growth

Panel regression of coefficient results showed that, share capital has a positive but insignificant effect on financial growth measured by growth in earning per share. The results showed that,there was no significant association between financial growth and share capital.This was because share capital had a p-value of 0.465 which was above the 0.05,thus we failed to reject the null hypothesis that there was no significant relationship between the two variables.Also a one unit change in share capital only led to a 0.0070163 change in the earnings per share.

6.3 Conclusion

Panel data has advantages over cross-sectional or time series data because it combines inter-individual differences and intra-individual dynamics. It has a greater capacity for capturing the complexities of human behavior, and panel data allows for more accurate inference of model parameters. The goal of this research was to find the best panel data model for regressing factors that affect the financial performance of non-financial firms.The assumptions underlying the fixed and random effect approaches are also explored, as well as their strengths, shortcomings, and complexities that arise while implementing estimation.

6.3.1 Short Term Debt

Short-term obligations should be used to fund short-term assets, whereas long-term liabilities should be used to fund long-term assets (Guin, 2011). The primary focus of short-term finance is the examination of actions influencing current assets and current liabilities.The findings show that short-term debt has a positive and significant link with financial growth as assessed by earnings per share growth. EPS is a critical accounting indication of risk, entity performance, and increased competitiveness. Because EPS changes are typically reflected in share price behaviour, it is used to estimate probable future share price increase. Earnings per share (EPS) is a useful investment choice tool for investors because it signals future prospects and growth.

6.3.2 Long Term Debt

Long-term debts are the most favoured source of debt financing among well-established corporate entities.This owes to the fact that many deposit-taking financial institutions require collateral.-term debt and also long-term debts have better asset base .Findings of long-term debt showed to have a positive and significant link with financial growth as assessed by earnings per share. A high degree of long-term debt is detrimental to the firm's ability to operate effectively since it increases the chance of bankruptcy. Long-term debt requires the firm and debt issuers to adhere to rigorous contractual covenants, which are often associated with substantial agency and financial distress costs.

6.3.3 Retained Earnings

Retained earnings are a readily available internal source. Furthermore, retentions are less expensive than external equity, do not result in ownership dilution, and have a positive connotation because stakeholders perceive the firm as having potential investment opportunities. Growing corporations pay lower dividends, reinvest more of their revenues, and deliver a greater proportion of their overall returns as capital gains.Retained earnings, according to the study, have a positive and significant link with financial growth as assessed by EPS. Retained earnings are the most important sources of a company's growth financing. The amount of internal funds conveys information about the firm's growth prospects.

6.3.4 Share Capital

According to the study, share capital has a positive but insignificant relationship with financial growth as measured by earnings per share growth. Share capital is a company's total capital divided into shares. A joint stock company must have the capital to finance its operations. Share capital represents the value contributed to a company by its shareholders at some point in the past.

6.4 Recommendations

There are several extensions that can be used to estimate the panel data model; Previous studies frequently assumed that data is distributed cross-sectional independently and identically. Our findings indicate that future research should concentrate on cross-sectional heterogeneity. A common method is to use either fixed or random effects models. However, there is disagreement in the applied literature about how to best choose between fixed and random effects. As a result, researchers and analysts should further demonstrate how to select random and fixed models in order to develop novel methods such as the likelihood ratio test, RMSE of estimates, and so on, and compare them to the Hausman test. A covariance structure approach can also be used to investigate various extensions to fixed and random-effects models. These extensions, while not demonstrated in this study, have theoretical implications. As a result, a much wider range of fascinating questions can be addressed.

Past studies have also proposed several instrumental variable estimators for an intermediate model between fixed effects and random effects, allowing for consistent estimation of both the coefficients on time-varying and time-invariant regressors. It would be interesting to investigate the asymptotic large N and large T properties of these instrumental variable estimators, as well as the model tests based on them. This study recommends that the panel data model be used to analyze any econometric problem involving both cross-sectional and time series data. As a result, modeling of joint dependence, simultaneous equations models, the random intercept model, varying parameter models (e.g., Hsiao 1992, 2003; Hsiao and Pesaran 2006), unbalanced panel, measurement errors (e.g., Griliches and Hausman 1986; Wanbeek and Koning 1989), nonparametric or semiparametric approach, bootstrap approach, repeated cross-section data un Finding estimators that are efficient or nearly so but have better finite sample properties than the best estimators is a critical area of study.

This research has contributed to our understanding of panel data modelling and financial performance, as well as the influence on non-financial enterprises listed on the Nairobi Securities Exchange. It is obvious that organisations' financial performance fluctuates greatly depending on their financial status. According to the report, academics and scholars should assess the best source of financing while also advising when and why one form of financing is favoured over another. According to the findings of this study, a firm's financial success varies greatly depending on the industry in which it works. The characteristics linked with the success of non-financial enterprises and financial firms may differ dramatically in terms of how organisations' operations are financed.The financing arrangements of manufacturing enterprises may differ dramatically from those of agricultural firms. A comparison research to establish the effect of other factors on the financial growth of non-financial enterprises versus financial firms listed on the Nairobi Securities Exchange is necessary due to sector-specific effects. Furthermore, more research is needed to determine which other factors influence the financial success of non-financial enterprises.

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Appendix A: List of Non-Financial Firms Listed at NSE

Commercial and Services

1. Atlas African Industries Limited
2. Deacons (East Africa) Plc
3. Express Kenya Limited
4. Kenya Airways Limited
5. Longhorn Publishers Limited
6. Nairobi Business Ventures Limited
7. Nation Media Group Limited
8. Standard Group Limited
9. TPS Eastern Africa Plc
10. Uchumi Supermarket Limited
11. WPP Scangroup Limited

Manufacturing Allied

12. B.O.C Kenya Limited
13. British American Tobacco Kenya Limited
14. Carbacid Investments Limited
15. East African Breweries Limited
16. Flame Tree Group Holdings Limited
17. Kenya Orchards Limited
18. Mumias Sugar Co. Limited
19. Unga Group Limited

Agricultural

20. Eaagads Limited
21. Kakuzi Limited
22. Kapchorua Tea Co. Limited
23. The Limuru Tea Co. Limited
24. Sasini Limited
25. Williamson Tea Kenya Limited
26. Rea Vipingo Plantations Limited

Investment

1. Centum Investment Co. Limited
2. Home Afrika Limited
3. Kurwitu Ventures Limited
4. Olympia Capital Holdings Limited
5. Trans-Century Limited

Construction Allied

6. ARM Cement Limited
7. Bamburi Cement Limited
8. Crown Paints Kenya Limited
9. E.A.Cables Limited
10. E.A.Portland Cement Co. Limited

Energy Petroleum

11. KenGen Co. Limited

12. KenolKobil Limited
13. Kenya Power Lighting Limited
14. Total Kenya Limited
15. Umeme Limited

Automobiles Accessories

1. Car General (K) Limited
2. Sameer Africa Limited

Real Estate Investment Trust

1. Stanlib Fahari I-Reit

Telecommunication Technology

1. Safaricom Limited

(Source: NSE, 2017)