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The Moderating Effect of Automation on Firm Specific Factors and Performance of Initial Public Offering Stocks at The Nairobi Securities Exchange In Kenya

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Abstract

Performance of IPO stocks depicts two anomalies: initial underpricing and long run underperformance. A plethora of studies have established the causes of these IPO puzzle to include information asymmetry, institutional ownership, IPO size, market volatility, the intrinsic value of the IPO and issue characteristics among others. None of these studies on IPO performance as far as research has shown considered moderating effect of automation of securities market on firm specific factors. Kenya's equity market capitalization has been on a downward trend being surpassed by fixed income securities. IPO stocks performance offer long-term as well as short-term capital to companies. This study attempts to establish whether there is a nexus between NSE automation and firm specific factors regarding performance of IPO stocks at NSE. Longitudinal and descriptive study designs were used on the secondary panel data. Multiple linear regression was used to analyze the data with Stata statistical software. The Hausman test was used to determine between fixed and random effect model. The results showed that automation had negative correlation with firm age and positive correlation with firm size. The study will assist the Kenyan government in developing financial stability measures and investors in making informed decisions.

Keywords: Automation, Firm specific factors, Initial Public Offerings, Nairobi Securities Exchange.

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1. Introduction

In Kenya, dealing in shares and stocks started in the 1920s, when the country was still a British colony. There was neither formal market, nor rules to govern the stock broking activities (Kemboi and Tarus, 2012). Trading took place based on gentlemen's agreements, in which commissions were charged, with clients being obligated to honor their contractual commitments of making good delivery and settling any costs (Nyasha and Odhiambo, 2014). Francis Drummond established the first professional brokerage firm in 1951 and together with the then Finance Minister approached London Stock Exchange in 1953 with the idea of establishing a Stock Exchange in East Africa. A constitution of a voluntary association of stockbrokers was formed and registered under the Societies Act in 1954. This was the birth of the Nairobi Securities Exchange.

The automation of depository and settlement operations in 2004, the implementation of the Automated Trading System in 2006 and Wide Area Network in 2007, installation of a Broker Back Office in 2011 and the launch of automated market surveillance system called Capizar in 2012 transformed Kenyan securities market to globally accepted standards and competitively positioned it as a preferred investment destination. Operationalization of an electronic trading platform should allow the market Regulator, Exchange and securities investors to reap the benefits of technology (Onyuma, 2020). Technological changes revolutionized the way financial securities are traded. Every step of the trading process, from order entry to trading venue to back office, is now automated, thereby reducing the costs incurred by market intermediaries. By reducing the frictions and costs of trading, technology has the potential to enable more efficient risk sharing, facilitate hedging, improve liquidity, and make prices more efficient; ultimately reduce firms' cost of capital. The Nairobi Securities Exchange was fully automated in 2006.

Automation entails the implementation of a computerized and electronic system for trading and settlement purposes. Automated trading is thus a subsection of microelectronic trading that focus on computer algorithms for policymaking and implementation of order submission (Attafuah, 2020). It has been observed that electronic trading enhances efficient settlement and reduces transaction processing costs, any opportunity costs and associated risks (Simiyu, et al. 2014). Technological breakthrough does not only benefit Capital markets automation as one of the players of the financial trading game, but also all the players in the sector (Omuchesi, et al. 2014). Security exchange automation started in the 1970s and the transaction of securities became electronically traded through the support of information and communication technology (Jain, 2005). Introduction of fully automated electronic trading systems, is one of the of six capital market specific and related reforms. Others are stock market liberalization, enforcement of insider trading laws, privatization programs, structural pension reform, and institutional reform (De la Torre, et al. 2006). According to Mwangi (2015), after automation, the stock volumes increased in the Finance and Investment, Industrial and allied and alternative investment market segments.

An initial public offering is a security sold to the general public for the first time with the expectation that a liquid market will develop (Ritter, 1998). Due to its importance, IPOs have been a subject of much academic interest, resulting in numerous research papers related to various elements in the process of going public (Rudsengen, 2021). The market of stock is one of the most significant aspects of the economy as it offers long-term as well as short-term capital to companies and investment opportunities to both primary and secondary investors. Trading in the stock market is well organized and regulated by the Stock Exchange Authorities. The returns from equity investments vary to the movement of share prices (Nyanaro and Elly, 2017).

The financial reform process emphasizes the development of the securities market as an alternative source of long-term capital in emerging market which is crucial for economic development given the positive relationship between long-term capital and economic growth (Obura and Anyango, 2016). As a priority therefore, Development Plan (1997) of the Government of the Republic of Kenya noted the need to shift from the expensive short-term finance in favor of cheaper long-term finance for sustainable industrialization to be achieved.

IPO stocks performance depict a number of anomalies in the behavior of their prices in long-term performance. The impact of these anomalies is mainly related to the firm' characteristics, like the size of the firm, the age, the offer size, and the sector. Some of researchers found that the shares return of small companies is higher than the shares return of large ones (Fawaz and Osama, 2015). Previous studies provided mixed findings and were mostly carried out between six and ten year longitudinal study periods. For instance: Hanbing, et al. (2019) used Cumulative Abnormal Returns (CAR) and Buy and Hold Abnormal Returns (BHAR) as bases of measuring IPO stock performance in China from 2002 to 2007 and the results were different under each of the methods. Alshiab, (2018) examined 162 Middle East and North Africa (MENA) Initial Public Offerings for the period 2001-2015. The results were mixed: over-performance of the benchmark portfolio over the short-run, but underperformed over the long-run, underperformance of the benchmark portfolio over the following 60 months post-listing date and cyclical performance: changes from over-performance to under- performance and vice versa. In Kenya, Wamari (2014) established growth in BHAR in some firms and decline in others between 2000 and 2006, while Mwendwa, (2014) using CAR between 2006 and 2011found no or insignificant change in returns.

The importance of this study is hinged on the fact that IPO stocks provide a life line to long term funds to firms. For instance, in 2010 the Global IPO volume was US$ 280 billion (Philippe, 2012). The first half of 2021 saw 1,070 IPOs with total proceeds of US$222 billion (Ernest & Young Global IPO trends, 2021). In Kenya between 2006 and 2021 an amount of Kshs 13 billion was raised from IPO stocks (CMA, Kenya 2021). Despite this, United States of America experienced a decline in IPO firms from an average of 310 annually between 1980 and 2000 to 99 from 2000 Gao, et al. (2013). The Central Bank of Kenya (2020) posits that Kenya's equity market capitalization declined by 17.2% in June 2020 compared to 20.8%

increase in the year to December 2019. These trends are not in tandem with the initial purpose for which firms floated IPOs and hence require to be addressed.

A number of gaps were observed in the previous studies: first, the period of study (Marc, et al. 2007) while studying United Kingdom firm size and performance of IPO stocks used only three years. The same is applicable to Kinyanjui, (2015) on IPO stock performance at NSE in Kenya using 6 years. Secondly, fewer numbers of firms were studied. For instance (Mburugu, et. al. 2018) used 6 firms when they analyzed the long run performance IPOs and effects in the Kenyan stock market. Thirdly, most studies did not use superior data analytical tools for example Gatumo, (2017) used causal design by regressing the raw total return against the determinants of short run IPO performance at NSE while Amoll, (2015) used SPSS.

Globally, performance of IPO stocks depicts two anomalies: initial underpricing and long run underperformance. The positive initial return ranged from 3.30% in Russia to 270.10% in United Arab Emirates during the period 1959 to 2019 (Loughran, et el. 2020). Mumtaz and Ahmed, (2016) globally analyzed 20 studies on long run IPO performance in over 10 countries during the period of 1994 to 2008 and established average underperformance of - 22.3 % within an average trading period of 42 months. In Kenya, Mburugu (2021) established that during the five year period from 2007 to 2014, the mean long run IPO price CAR at NSE was -0.49%. According to (CBK, 2020) Kenya's equity market capitalization declined by 17.2% in June 2020 compared to 20.8% increase in 2019.

The IPO stocks performance play a crucial role in an economy by offering long-term as well as short-term capital to companies and enables them to gain greater liquidity and better access to capital. Globally, in the second Quarter of 2021 IPO deal numbers and proceeds were 597 raising US$111.6 billion (Ernest & Young IPO trends 2021). In Africa, there were 9 IPOs raising US$ 1.2 billion in 2019 (Africa Capital Markets Watch, 2019 p.2). Between 2006 and 2021, 10 firms issued their IPOs at the NSE raising Kshs 13 billion (CMA, Kenya 2021).

The stability of IPO stocks performance is important to investors whose returns to their investment in form of dividends and capital gain will grow and to the government through increased withholding tax collection from dividend payments and increase in Gross Domestic Product (GDP) arising from re-investment of IPO stock returns by both investors and firms. The multiplier effect is country's economic growth. The capital flight by foreign investors being experienced at the NSE whereby during the second quarter of 2021 hit Kshs 2 billion (African-markets, 2022) will reduce.

Previous studies established mixed and inconclusive findings on IPO stock performance. Few studies have used moderating variables which play a crucial role in determining the direction of the effects of predictor against response variables as discussed by Namazi and Namazi, (2016). This is the gap this study intends to fill and might lift the veil on IPO puzzle.

2. Literature review

This paper was hinged on two theoretical streams: Dow Theory on market prices reflecting every significant factor that affects supply and demand and Winner's curse theory on underpricing of IPOs as a competitive outcome of informed and uninformed investors. Empirical studies carried out in relation to IPO stock performance, firm specific factors and automation of NSE are presented in this section.

2.1 Empirical review

Empirical evidence, in terms of long-run IPO performance seems to be less concrete when compared against studies of shorter-term abnormal performance due to: first long-term pricing behavior causes researchers to have reservations about aftermarket efficiency; to exploit the underpricing and performance, investors would have to rely on actively trading strategies; and there is a substantial variations in the results of the underpricing if researchers use different methodologies to detect abnormal performance (Mumtaz and Ahmed, 2016)Assaf (2015) employed GARCH *(p, q)* and *GARCH (p, q)-M* models to find out the impact of electronic trading on both volatility and risk-return relationship before and after automation in the Toronto Stock Exchange. Prior research had shown that there had been significant changes in the structure of volatility and the risk-return relationship. This was consistent with the interpretation that there had been an increased flow of the information in to the market during post automation period supporting the view that automation provides more cost efficient method of acquiring market exposure. The risk-return parameter was found to be positive and statistically significant. The findings showed a considerable upward shift in the parameter occurring during the post-automation period of TSE 300 and TSE 35 returns, but a downturn shift of TSE 100 and TSE 200 returns.

Attafuah (2020) researched on the impact of automation on Ghana stock market performance and established a positive relationship between automation and market efficiency, exchange rate and interest rate on the volume of stock traded. It was found out that macroeconomic policies of Ghana were characterized by volatile and generally high inflation, high interest rates and large exchange rate swings.

Omuchesi, et al. (2014) established that the introduction of the Automatic Trading System did not have statistically significant effect on market efficiency. Therefore, automation didn't provide the expected benefits of improving efficiency of the Nairobi Securities Exchange. They used monthly market returns from NSE 20-Share index and monthly closing equity price list from 2002 to 2012. The pre-automation period was from January 2002 to June 2006 while post-automation was from July 2008 to December 2012. A longitudinal research design was applied to the secondary data.

Simiyu, at al. (2014), examined the effect of automation on trading volume of companies listed on the Nairobi Securities Exchange. The target population was 61 listed companies under the Main Investment Market Segment and the Alternative

Investment Market Segment. The study took 3 years behind and 3 years ahead in order to eliminate any season-ability effects. The results showed that automation increased volume of companies 'equities traded during these periods.

2.2 Hypotheses development

The hypotheses development of this study was guided by:

Firm specific factors which are specific characteristics that are unique to a given firm as disclosed in the IPO prospectus (Loughran and Ritter 2002). These characteristics are unique to specific companies and raise a perception in the mind of the users of that information regarding the performance and future of the company (M'muriungi, et al. 2019). Sholichah (2018) used firm size, age of company, offering size, reputation of underwriter and profitability.

Initial Public Offerings which is a security sold to the general public for the first time with the expectation that a liquid market will develop (Ritter, 1998). The company IPO's success and failure is highly associated with the IPO's after market price performance (Farooq, et al. 2018).

2.2.1 Moderating effect of automation on the relationship between firm size and performance of IPO stocks listed at the NSE

Nairobi Securities Exchange in Kenya was automated in 2006. Automation involves the implementation of a computerized and electronic system for trading and settlement purposes. Automated trading is a subsection of microelectronic trading that focus on computer algorithms for policymaking and implementation of order submission (Attafuah, 2020). This study used Case 2 as outlined by Baron and Kenny (1986) since automation is dichotomous given the fact that the periods of study are divided into two – post and pre-automation whereby automation happened in 2006. Similar basis of measurement was applied by (Omuchesi, et al. 2014) except that the study did not consider implementation period of 54 months in their sample of post automation periods. The study tested the following null hypothesis:

Firm Size is market capitalization of firms at the end of the first day of the IPO (Switzer and Zhai, 2019). The same basis of measurement of firm size was used by Fawaz and Osama (2015). Market capitalization is measured using market movements by measuring the total value of stock in a particular stock market and aggregating the market value of the quoted stocks (Asewe, et. al 2013). The study tested the following null hypothesis.

H_{01}: Automation has no significant moderating effect on the relationship between firm size and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya.

$$\text{Firm size (SIZE)} = \ln(\text{market capitalization})$$

2.2.2 Moderating effect of automation on the relationship between firm age and performance of IPO stocks listed at the NSE

Firm age is the difference between the year of IPO and year of incorporation of the firm (Mutai, 2018). It represents the number of years from firm incorporation to IPO listing. It can also be measured by: the day and date of going public (Fawaz & Osama, 2015). The study tested the following null hypothesis.

H_{02} : Automation has no significant moderating effect on the relationship between firm age and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya.

Firm Age (AGE) = Number of years from incorporation to IPO

2.2.3 Comparison of performance of IPO stocks at NSE and NSE 20 share index as a benchmark

IPO Stock performance relates to the returns that an IPO fetches in the market. Stock returns are calculated by comparing the closing price on the trading day for each observation period with the IPO price (Angga, et al. 2020). The study tested the following null hypothesis.

H_{03}: Performance of IPO stocks at NSE is not significantly different from NSE share index as a benchmark.

Performance of IPO stocks = Actual stock share price at closing of the month using both BHAR (Buy and Hold Abnormal Returns and CAR (Cumulative Abnormal Returns)

2.2.4 Comparison of performance of IPO stocks at NSE and CAPM as a benchmark

The Capital Asset Pricing Model is used to describe the relationship between the expected return of risk asset and the risk in investment market to obtain the equilibrium price of risky assets (Banz, 1981). This model was first proposed by the American Economist Sharpe (1964). It is found by:

$$E(R_{it}) = R_f + \beta_t (R_f - R_m) \quad (1)$$

Where:

$E(R_{it})$ is the expected return of firm *i* stock in month *t.*

R_f is the risk free rate represented by interest rate on CBK treasury bills.

β_t is the beta coefficient which is a correlation coefficient and calculated as follows:

R_m is the beta coefficient which is a correlation coefficient and calculated as follows:

$$\beta = n[\Sigma xy] - [\Sigma x \Sigma y] \div n[\Sigma x^2] - [\Sigma x]^2 \quad (2)$$

Where "x" is the NSE 20 share index return, "y" is the actual firm return and "n" is the number of months.

R_m is the market return measured by NSE 20 share index return. The study tested the following null hypothesis.

H_{04}: Performance of IPO stocks at NSE is not significantly different from CAPM as a benchmark.

3. Methodology

Newing (2011) defines research methodology as a process concerned with what the researcher will actually do in order to address the specific objectives and research questions developed during a study. It is a way to systematically solve the research problem and may be understood as a science of studying how research is done scientifically. It entails various steps that are generally adopted by a researcher in studying the research problem along with the logic behind them (Kothari, 2004).

3.1 Research design

This study used descriptive and longitudinal study designs. Descriptive design is simple and allows the researcher to study and describe the distribution of one or more variables, without regard to any causal or other hypotheses (Aggarwal and Ranganathan 2019). Longitudinal studies employ continuous or repeated measures to follow particular individuals over prolonged periods of time-often years or decades. They are generally observational in nature, with quantitative and/or qualitative data being collected on any combination of exposures and outcomes, without any external influence being applied (Caruana, et al. 2015).

This research design was used by various studies: Esumanba, et al. (2015), Korir and Cheruiyot (2014), Sarra, et al. (2011), Kaya (2012), Wetukha (2013), Amoll (2015), Bohdanowicz (2015), Mokaya and Jagongo (2015), Fawaz and Osama (2015), Simiyu, et al. (2016), Chibeka (2014) and Fauzi and Wahyudi (2016), Zandi, et al. (2020).

In an event study, we need to determine the event, the event date, the event window, the estimation window & the estimation model (Pandey and Kumari, 2021). The automation of NSE took place in 2006.The performance of IPO stocks before and after this event was studied and analyzed. These strategies were used by Omuchesi et al., (2014), Kaya (2012), Odipo, et al. (2020).

3.2 Target population, sampling frame and sampling technique

The target population of this study was all 64 companies listed on the NSE. This was split between firms that undertook IPOs from 1994 to 2005 for pre automation and from 2006 to 2019 for post automation. This comprised of 6 and 9 firms respectively. The reason why listed companies were chosen was due to the

availability and the reliability of the financial statements since their annual financial reports can easily be found from CMA and are subject to the mandatory audit by the Office of the Auditor General as per the Public Finance Management Act 2012. The sampling frame of the study was the 15 firms which went public between 1994 and 2019. These comprise of both pre automation IPOs (1994 to 2005) and post automation IPOs (2006 to 2019). Total monthly observations were 1,242. However, firms that were delisted by NSE (Access Kenya and African Lakes) were excluded. Similar sampling frame was used by Omuchesi and Bosire (2014), Simiyu, et al. (2014) and Mwangi (2015).

Since the population was small, census method was applied. This means the sample size was all the 15 firms. This was in line with the objectives of the study and the research design. The study adopted non probability purposive sampling technique. This technique was used because it proposes that the focus is only on the specific target group of the population which was the 15 firms that issued IPOs during the period 1994-2019. Sampling from a population is often more practical and allows data to be collected faster and at lower cost (Turner, 2020).

3.3 Sources of data and data collection instruments

The source of data was secondary data which was collected using secondary data collection sheet and document analysis method. The data was extracted from annual reports of listed firms and various websites namely Capital Markets Authority, African financials and Omniscience.

3.4 Data analysis

STATA statistical software was used to analyze data. The data comprised of the monthly Buy and Hold Abnormal Returns (BHARs) and Cumulative Abnormal Returns (CARs) for 96 months (8years) before automation and 156 months (13 years) after automation. Multiple linear regression models were applied. The study was not able to obtain data from January 1994 to April 1997.

3.5 Performance measurement of IPO stocks

Two methods were applied to measure the performance of IPO stocks. These were the Cumulative Abnormal Returns and Buy and Hold Abnormal Returns. These are explained as follows:

3.5.1 Abnormal Returns (ARs) and Cumulative Abnormal Returns (CARs)

Abnormal Returns are the difference between the firm actual return represented by share price index and the expected return calculated using CAPM as proposed independently by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966).

$AR_{it} = R_{it} - E(R_{it})$ (3)

Where:

AR_{it} is the abnormal return of firm *i* stock in month *t*.

R_{it} is the actual return of firm *i* stock in month *t.*

$E(R_{it})$ is the expected return of firm *i* stock in month *t.*

$E(R_{it})$ was calculated using the CAPM as follows:

$E(R_{it}) = R_f + \beta_t (R_f - R_m)$ (4)

Where:

$E(R_{it})$ is the expected return of firm *i* stock in month *t.*

R_f is the risk free rate represented by interest rate on CBK treasury bills.

β_t is the beta coefficient which is a correlation coefficient and calculated as follows:

$$\beta = n[\Sigma xy] - [\Sigma x \Sigma y] \div n[\Sigma x^2] - [\Sigma x]^2$$

Where "x" is the NSE 20 share index return, "y" is the actual firm return and "n" is the number of months.

R_m is the market return measured by NSE 20 share index return

Cumulative abnormal returns (CARs) will be calculated as follows:

$$CAR_{it} = \sum_{t=1}^{T} AR_{it} \quad (5)$$

This formula was used by Barber, B., & Lyon, J. (1997) in their study of "Detecting long run abnormal returns: the empirical power and specification of the test statistics".

3.5.2 Buy and Hold Abnormal Returns (BHARs)

Poulsen and Nielsen (2017) defines Buy and Hold Abnormal Returns as the difference between the return of buying and holding an IPO for three years or earlier of firm's delisting and the buy and hold return of the applied benchmark for the same period. The argument in favor of using BHAR to CAR is that no monthly rebalancing is assumed. It is used to measure the relative holding period of a company stock. Gatumo (2017) states that BHAR = ∏(1+ raw total return)- ∏(1+ return of market). It is a strategy where a stock is purchased at the first closing market price after going public and held until its "*T"* anniversary. This study used the following formula that compares market and normal buy and hold return:

$$BHAR_{iT} = \left[\prod_{t=1}^{T} (1+r_{it})-1\right]-\left[\prod_{t=1}^{T} (1+r_{it})-1\right] \quad (6)$$

Where:
T: is the total time period of 252 months with 96 months and 156 months for pre and post automation respectively.
t: is the actual time period
r_{it}: Normal/Actual return during period t
r_{mt}: Market return during period t (NSE 20 share index)

Where BHAR= [((1+ return of month 1) * (1+ return of month 2)*….*(1+return of month 12)) - 1] - [((1+ Market return of month 1) * (1+ Market return of month 2)*….*(1+Market return of month 12) - 1].
Barber, B., & Lyon, J. (1997) in their study of "Detecting long run abnormal returns: the empirical power and specification of the test statistics" used annual BHAR as the holding period interval.

3.6 Model specification

The model developed in this study was designed to test the hypotheses. Previous studies that used this model are: Ritter (1991) applied CARs with monthly portfolio rebalancing, Fawaz and Osama (2015) used similar benchmarks on analysis of Jordanian IPOs, Osei, et al. (2012) used the CARs on IPO underpricing in Ghana and Nigeria and Mokaya and Jagongo (2015) in Kenya. Abnormal Returns will be the difference between the firm actual return represented by share price index and the expected return calculated using CAPM as proposed independently by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). BHAR are the difference between the return of purchasing and holding the IPO. The argument in favour of using BHAR measures relatively to CAR is that no monthly rebalancing is assumed.

$$CAR = f[(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + e_1) + \beta_{0\ldots2}] \quad (7)$$

$$CAR = f[\beta_0 + z(\beta_1 x_1 + \beta_2 x_2 + e_1) + \beta_{0\ldots2}] \quad (8)$$

$$BHAR = f[(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + e_2) + \beta_{0\ldots2}] \quad (9)$$

$$BHAR = f[\beta_0 + z(\beta_1 x_1 + \beta_2 x_2 + e_2) + \beta_{0\ldots2}] \quad (10)$$

Where $z =$ event period of automation

The model was applicable for before and after automation for each measure of IPO performance.

And where:

x_1: The firm size measured by market capitalization of the firm.

x_2: The age of the firm is measured by the date of incorporation and date of going public.

$\beta_{0\ldots.2}$: The coefficients representing benchmarks (Nairobi 20 Share Index and CAPM)

$e_{1\ldots.2}$: Error terms which are assumed to be normally distributed with mean zero and constant variance.

4. Results and Discussions

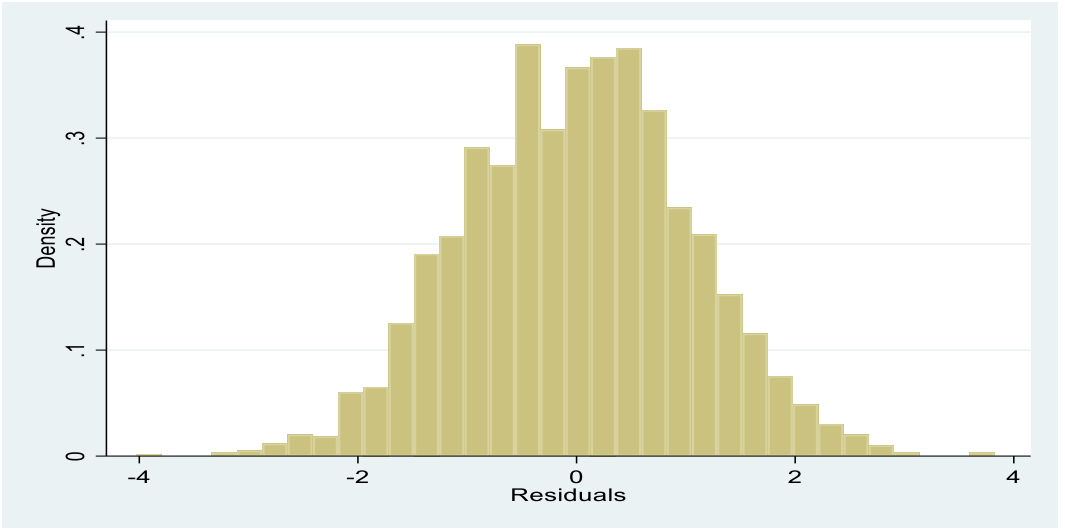
This section provides the results and discussions of the study findings which are presented as per the study objectives and hypotheses. Descriptive statistics, inferential statistics and the discussions of the results are also presented.

4.1 Descriptive statistics

Table 1 provides descriptive statistics for the variables used in the analysis. A total of 15 firms were studied from May 1997 to December 2019 with 2,586 monthly observations based on when the firms floated their shares on NSE. The average firm size is approximately Ksh 45.152 billion equivalent to ln24.533 in terms of market capitalization, whereby the largest had a value of Kshs 1.262 trillion equivalent to ln27.864. All the firms considered in the analysis averaged 25 years as from the date they were incorporated up to the time they were listed at the NSE. The average actual return was 6.7%.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnsize	2586	24.533	1.912	17.91	27.864
age	2586	25.226	10.177	4	44
CAPM	2586	0.087	0.043	-0.255	0.279
NSE	2586	-0.001	0.054	-0.226	0.174
Actual Returns	2586	0.067	0.26	-0.623	1.663
AR	2586	-0.02	0.265	-0.705	1.589
CAR	2586	-4.421	17.434	-27.166	114.424
BHAR	2586	357.941	2945.444	-1.119	37813.95



Graph 1: Normality test under CAR and BHAR

4.2 Fixed and random effects regression

The test as shown in table 2 indicates that there is no sufficient evidence to show that the fixed effect regression model is significantly different to the random effect regression (p=0.253). This shows that the random effect model is better than the fixed effect regression model.

Table 2: Comparison between Fixed and Random Effect Regression – Hausman (1978) specification test

	Coef.
Chi-square test value	4.08
P-value	.253

4.3 Inferential statistics

Inferential statistics are a broad category of techniques that go beyond describing a data set. They can help researchers draw conclusions from a sample to a population and be used to examine differences among groups and the relationships among variables. The t test is used to compare two group means by determining whether group differences are likely to have occurred randomly by chance or systematically indicating a real difference (Guetterman, 2019).

4.3.1 Performance of IPOs issued compared to two benchmarks

The study compared the performance of the portfolio to that of the bench marked stocks in the market. The study compared the average return of the portfolio to that of NSE and the CAPM based on the independent sample t-test. The results of the test were as illustrated in table below:

Table 3: Independent t test: NSE and CAPM

	obs	Mean1	Mean2	dif	St Err	t value	p value
NSE - Actual	2586	-.001	0.067	-.067	.005	-13.55	0
CAPM - Actual	2586	.087	0.067	.02	.005	3.9	0

The results in the table shows that the portfolio average return was significantly higher than that of NSE on average t (5170) = -13.55, p<0.001. This shows that the portfolio performance in the market is better than that of NSE. Comparing the average stock return to that of CAPM, the study showed that the average return for CAPM was significantly higher than that of the portfolio t (5170) = 3.9, p<0.001. This shows that the portfolio performance is below the expected level in the market and therefore this can be improved on. These findings are closer to the ones found by Kinyanjui (2015) when he established that Kenya's IPOs stock performance ranged closely to the benchmark. However, they contradict those established by Odipo, Olweny and Oluoch (2020) whereby NSE and Matching firms performed better than firms that issued equity and firms that issued equity performed better than CAPM as benchmark.

4.3.2 Regression model

Table 4 represents the model summary for the panel regression model used in the analysis. R-squared value was 0.152 implying that 15.2% of the total variation in abnormal return was explained by the changes in the independent variables used in the model. For example, 15.2% of the variation in AR was as a result in changes in age of firms and firm size while 39% of variation in AR was caused by other factors not considered in the study.

Table 4: Model summary

Model summary	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.390[a]	.152	.151	16.072
a. Predictors: (Constant), ln(Firm Size) and Age				

4.3.3 Panel regression output

The panel regression output is presented in table 5. The panel regression result showed that both firm age and size were statistically significant at 5% level of significance. All other factors held constant, the firms realized negative performance both under CAR and BHAR with (cons=-65.763) and (cons=-7,438.198) respectively. Hence the exogenous factors have the same effect of firm performance under CAR and BHAR with higher magnitude when BHAR is used.
Firm sizes, as in bivariate panel regression, positively influence AR of the firms

under CAR and BHAR performance measurement bases (ln=3.142) and (ln=385.879) respectively. As with the other factors, the magnitude of the effect was higher under BHAR. An increase in firm size by 10% would lead to an improvement in firm's performance by 31.42% and 3858.79 % under CAR and BHAR measurements respectively.

Firm age has a negative effect of firm performance when CAR and BHAR measurements of performance were used with -0.215 and -26.476 respectively albeit more for BHAR. An increase in the age of the firm by one year is associated with a decline in firm's performance by Kshs 0.21 and Kshs 26.5 when CAR and BHAR are used respectively.

Table 5: Panel regression output

Dependent variables	Independent variables	Co-ef	Std. Error	T	P-value	95.0% Conf. Interval	
Firm performance (CAR)	(Constant)	-65.763	4.256	-15.452	0	-74.108	-57.417
	ln(Firm Size)	3.142	0.173	18.161	0	2.803	3.481
	Age	-0.215	0.034	-6.394	0	-0.28	-0.149
Firm performance (BHAR)	(Constant)	-7438.198	746.564	-9.963	0	-8902.123	-5974.273
	ln(Firm Size)	385.879	30.348	12.715	0	326.371	445.388
	Age	-26.476	5.886	-4.498	0	-38.017	-14.935

4.3.4 Analysis of Variance

Analysis of variance result is presented in Table 6. The F-statistic indicates that the model was stable and appropriate since significance level was below 0.05.

Table 6: Analysis of Variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	119930.559	4	29982.64	116.079	.000[b]
	Residual	666660.162	2581	258.295		
	Total	786590.721	2585			
a. Dependent Variable: CAR						
b. Predictors: (Constant),), ln(Firm_Size), Age						

4.3.5 Moderating effect of automation on the relationship between firm specific factors and performance of IPO stocks

The null hypothesis that automation has no significant moderating effect on the relationship between firm size and age on performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya is rejected and alternative hypothesis is accepted instead. For example, automation has a positive and statistically significant

effect on the relationship between firm size on IPO performance and negative one between firm age and IPO performance. The findings are similar to Simiyu, Osero and Odoyo (2014) who established that automation increased volume of companies equities traded at NSE; Asewe *et al*., (2013) concluded in their study that there was a statistical significant difference between manual and automation in the stock market performance during the year of transition, 2005 to 2006 at the NSE; Attafuah (2020) found a positive relationship between automation and market efficiency in Ghana stock market and lastly Onyuma (2020) established that at NSE the market returns in the post-automation period were higher and more volatile than those in the pre-automation period.

Table 7: Moderating effect of automation

Variable	Cof.	Std. Error	t	P-value
Age moderated	-0.1403	0.6053	-5.7833	0.0000
Firm size moderated	0.2530	0.0370	6.7550	0.0000

4.3.6 Summary of decisions on tested hypotheses

This is presented in table 8 below:

Table 8: Summary of decisions on tested hypotheses

Hypothesis Number	Null hypothesis	P-Value	Result
$\mathbf{H_{01}}$	Automation has no significant moderating effect on the relationship between firm size and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya.	0.000	Reject
$\mathbf{H_{02}}$	Automation has no significant moderating effect on the relationship between firm age and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya.	0.000	Reject
$\mathbf{H_{03}}$	Performance of IPO stocks at NSE is not significantly different from NSE share index as a benchmark	0.000	Reject
$\mathbf{H_{04}}$	Performance of IPO stocks at NSE is not significantly different from CAPM as a benchmark.	0.000	Reject

5. Summary, Conclusions and Recommendations

5.1 Summary and conclusions of findings

The summary and conclusions of findings has been presented below as per the study objectives. These findings are supported by secondary data collected regarding firm specific factors, moderating effect of NSE automation and actual IPO stocks performance against the benchmarks. The results of analysis of these variables using parametric (t-tests, chi-square), non- parametric (Pearson correlation coefficient), multiple regressions and the analysis of variances have been presented in the preceding sub-sections.

5.1.1 Moderating effect of automation on firm size and performance of IPO stocks at NSE

The first objective of the study was to determine the moderating effect of automation on firm size and performance of IPO stocks at NSE. Descriptive statistics together with multiple regression analysis and analysis of variance were used to arrive at the study findings. The findings were that automation had a positive and statistically significant effect on the relationship between firm size and IPO stocks performance. This implies that larger firms would need to automate their processes due to high number of transactions. They hence benefit from automation which can increase their performance.

Arising from this finding it is concluded that the null hypothesis $\mathbf{H_{01}}$ which stated that automation has no significant moderating effect on the relationship between firm size and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya where automation was measured by pre and post automation periods of NSE is rejected since automation has a statistically significant effect on IPO stocks performance at NSE in Kenya.

5.1.2 Moderating effect of automation on firm age and performance of IPO stocks at NSE

The second objective of the study was to find out the moderating effect of automation on firm age and performance of IPO stocks at the NSE. Descriptive statistics, regression analysis and analysis of variance were carried out. The findings were that automation had a negative and statistically significant effect on the relationship between, firm age and IPO stocks performance at NSE. Younger firms can easily embrace technological changes and therefore improve on their performance

In conclusion therefore, the second hypothesis: $\mathbf{H_{02}}$ which stated that automation has no significant moderating effect on the relationship between firm age and performance of IPO stocks listed at the Nairobi Securities Exchange in Kenya is rejected since automation was found to have a significant negative statistical effect on IPO stocks performance at NSE in Kenya.

5.1.3 Performance of IPO stocks and NSE share index

The third hypothesis: $\mathbf{H_{03}}$ was that performance of IPO stocks is not significantly different from NSE share index as a benchmark. When this hypothesis was tested the results showed that performance of IPO stocks were higher than NSE share index. This shows that NSE share index as a benchmark has a statistically significant effect on performance of IPO stocks.

5.1.4 Performance of IPO stocks and CAPM as benchmark

The fourth hypothesis:
$\mathbf{H_{04}}$ was that performance of IPO stocks is not significantly different from CAPM as a benchmark. When this hypothesis was tested the results showed that the average return for CAPM was significantly higher than that of the portfolio. This implies that the portfolio performance is below the expected level in the market and therefore this can be improved on. Therefore CAPM benchmark has a statistically significant effect on performance of IPO stocks.

5.2 Recommendations

Automation of NSE has a statistically significant effect on firm specific factors of age and size. This implies that automation of NSE has amplified or increased the effect of firm size and reduced the effect of firm age on IPO stock performance. Given the importance of firm size and movement towards firm mergers being experienced in the Kenya's corporate world, continual improvement of technological advancement at NSE cannot be overemphasized. Since firm age is discrete in the sense that it cannot change, emphasize is now to be placed on firm size. Therefore this study recommends that NSE should continue to invest in improving technology since this act as a catalyst to firm performance. Thus with increased technology trading at NSE is simplified and can take place simultaneously.

5.3 Areas for further research

The recent trends at the NSE point toward preference of debt market to equity market and hence investors are starting to have appetite for bond market more that IPO market. This is driven by certain and fixed returns on bonds. Research needs to be undertaken to establish to what extent these returns can be affected by both micro and macro firm factors.

Secondly, this study looked at only financial performance which was measured by shares returns. Further study should be on non-financial performance which is gaining a lot of interest by investors. These include customer satisfaction, employee retention, integrated reporting, GRI (Global Reporting Initiative) whereby Global Standards for Sustainable reporting have now been developed, environmental social governance, technological advancement, company/brand reputation, product development among other measures.

References

[1] Africa Capital Markets Watch (2020). www.pwc.co.za/capitalmarketswatch

[2] African financial markets (2022). https://www.african-markets.com/en/

[3] Aggarwal, R., & Ranganathan, P. (2019). Study designs: Part 2 – Descriptive studies. Perspect Clin Res. 10(1): 34–36. Doi: 10.4103/picr.PICR_154_18

[4] AlShiab, M. (2018). Initial Public Offerings Short and Long Term Performance of MENA Countries. European Scientific Journal Vol.14, No.10 ISSN: 1857 – 7881. Pp. 234-251

[5] Amoll, O. (2015). Effects of board of director's composition on financial performance of companies listed at NSE. Un published MBA project, University of Nairobi.

[6] Angga, P., Adler H., and Jenry, C., (2020). Long-Run IPO Performance in Indonesia Stock Exchange: Period 2008 – 2018. International Journal of Advanced Science and Technology, 29(06), 4633 – 4651

[7] Asewe, S., Mule, R., Ndichu, P., Aila, F., Okungu, A., Michoki, M., Onchonga, D., & Momanyi, G. (2013). Determining automation effect on market efficiency. European scientific journal edition vol.9 number 31.

[8] Assaf, A. (2015). Automation stock market volatility and risk return relationship: Evidence from CATs. Journal of Investment management and financial innovations

[9] Attafuah, E. (2020). Impact of automation on stock market performance: Evidence from the stock market performance. Finance and Management Engineering journal of Africa Vol.2. Issue 5. Dama Academic Scholarly & Scientific Research society.

[10] Banz, R.W. (1981). The relationship between return and market value of common atocks. Journal of financial economics,9,3-18.

[11] Baron, R., & Kenny, D. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. Journal of Personality and Social Psychology, Vol. 51, No. 6, 1173-1182.

[12] Bohdanowicz (2015). The impact of ownership structure on supervisory board size and diversity. Evidence from Polish two – tier board model. Procedia economics and finance 23 1420-1425.

[13] Capital Markets Authority (2021). Capital Markets Authority, Kenya. Quarterly bulletin.

[14] Caruana, E., Roman, M., Hernandez-Sanchez, J., & Sollis, Piergiorgio (2015). Longitudinal studies. Journal of thoracic disease 7(11): E537–E540, Doi: 10.3978/j.issn.2072-1439.2015.10.63

[15] Central Bank of Kenya (2020). The Kenya Financial Stability Report, October 2020. Issue No. 11. https: www. Centralbank,go,ke

[16] Chibeka, D. (2014). Effect of Initial Public Offering pricing on long run stock returns of companies listed at NSE. Un published Master of Science Thesis. University of Nairobi.

[17] De la Torre, A., & Schmukler, S. (2006). Emerging capital markets and globalization: The Latin American experience. Stanford University Press, Palo Alto and the World Bank, Washington DC.
[18] Ernest and Young Global IPO trends 2021 quarter two.
[19] Esumanba, S., Kpanie, A., & Bawuah, B. (2015). Firm specific determinants of underpricing on the Ghana stock market. International review of management and business research vol. 4(1) pp. 336-342
[20] Farooq, M., Akbar, S., Alim, K., & Sourath (2018). Impact of firm characteristics on IPOs short run performance: Evidence from Pakistan. Journal of Business and Tourism volume 4 number 2
[21] Fauzi, R & Wahyudi, I. (2016). The effect of firm and stock characteristics on stock returns: stock market crash analysis. The journal of finance and data sciences2. 112-124. http://www.keaipublishing.com/en/journals/jfds/
[22] Fawaz, A. S., & Osama, A.T. (2015). Firm characteristics and long run abnormal returns after IPOs: A Jordanian financial market experience. International journal of Economics and Finance;Vol. 7, no.3 pp. 109-122. https://doi.org/10.5539/ijef.v7n3p109
[23] Gao, X., Ritter, J., & Zhu, Z. (2013). Where have all the IPOs gone? The Journal of Financial and Quantitative Analysis Vol. 48, pp. 1663-1692. Cambridge University Press
[24] Gatumo, F. (2017). What influences short run performance of Initial Public Offerings in Kenya. Journal of Business and Management Volume 19, Issue 5. https://doi.org/10.9790/487X-1905062931
[25] Guetterman, T. (2019). Basics of statistics for primary care research. Fam Med Com Health Doi: 10.1136/ fmch-2018-000067
[26] Hanbing, Z., Jarrett, J. E., & Pan, X. (2019). The Post-IPO Performance in the PRC. International Journal of Business and Management, 14(11), 109-138. doi: 10.5539/ijbm.v14n11p109
[27] Jain, P.K. (2005). Financial market design and the equity premium: Electronic vs. floor trading, Journal of Finance, 60, 6, 2955-2985
[28] Kaya, T. (2012). The short term performance of initial public offerings in Istanbul stock exchange: 2010-2011 application, Journal of Business, Economics and Finance, 1 (1), pp. 64-76
[29] Kemboi, J.K., & Tarus, D.K. (2012). Macroeconomic determinants of stock market development in emerging markets: Evidence from Kenya. Research Journal of Finance and Accounting, 3(5), 57-68.
[30] Kinyanjui, R. (2015). Long-term performance of initial public offerings at Nairobi Securities Exchange market, Kenya. Unpublished MSC project in Commerce KCA University, Kenya.
[31] Korir, A., & Cheruiyot, T. (2014). Board demographics and financial performance of firms listed in NSE, Kenya. International journal of humanities and Social Science. Vol. 4. No. 11(1).
[32] Kothari, C. (2004). Research Methodology: Methods & Techniques, 2nd ed. New Delhi, India: New age International Publishers.

[33] Lintner, J (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets . The Review of Economics and Statistics. Vol. 47, No. 1 pp. 13-37.https://doi.org/10.2307/1924119

[34] Loughran, T., & Jay R. Ritter (2002). Why don't issuers get upset about leaving money on the table in IPOs? Review of Financial Studies 15, 413-444. https://doi.org/10.1093/rfs/15.2.413

[35] Loughran, T., Ritter, J., & Rydqvist (2020). Initial Public Offerings – International Insights. Pacific-Basin Finance Journal. Vol.2.

[36] Marc Goergen, Khurshed, A., & Mudambi, R. (2007). The strategy of going public: How UK companies choose their listing contracts. Journal of Business Finance and Accounting, 33, 306-328

[37] Mburugu, S. (2021). Analysis of the long run performance of initial public offers and effects in the Kenyan stock market. International Letters of Social and Humanistic Sciences 90:11-25. DOI: 10.18052/www.scipress.com/ILSHS.90.11

[38] Mburugu, S., Nyamute, D. W., Iraya, D. C., & Mwangi, D. M. (2018). An Analysis of the Long-Run Performance IPOs and Effects in the Kenyan Stock Market. Journal of Finance and Accounting, 1(2), 28 - 42. Retrieved from https://stratfordjournals.org/journals/index.php/journal-of-accounting/article/view/118

[39] M'muriungi, C., Muturi, W., & Oluoch, O. (2019). Effect of firm characteristics on stock returns of non-financial listed companies in Kenya. International Journal of Business Management and Economic Research (IJBMER), Vol 10(2), 1561-1573

[40] Mokaya, M. A., & Jagongo, A. (2015). The Effect of Ownership Structure on The Financial Performance of Firms Listed at the Nairobi Securities Exchange. International Journal of Finance and Accounting 4 (11), 1-17.

[41] Mossin, J. (1966) Equilibrium in a Capital Asset Market. Econometrica, 34, 768-783.http://dx.doi.org/10.2307/1910098

[42] Mumtaz, M., & Ahmed, A. (2016). Long run pricing performance of Initial Public Offerings (IPOS) in Pakistan. Sh working paper series Number 4. National University of Sciences and Technology.

[43] Mutai, J. (2018). Effects of firm characteristics on the post-IPO performance by listed companies on the Nairobi Securities Exchange (NSE), Kenya. African Journal of Education, Science and Technology, Vol 4, No. 4

[44] Mwangi (2015). The effect of automation on stock market trade volume at NSE. Un published Master of Science Thesis, University of Nairobi, Kenya.

[45] Mwendwa, M. (2014). Effects of IPO on long run stock price performance of companies listed at the NSE. Un published project. University of Nairobi, Kenya

[46] Namazi, M., & Namazi, N. (2016). Conceptual Analysis of Moderator and Mediator Variables in Business Research. Journal of Procedia Economics and Finance pp. 540 – 554

[47] Newing, H. (2011). Conducting Research in Conservation: Social Science Methods and Practice. New York: Routledge

[48] Nyanaro, E., & Elly, D (2017). The Relationship between Stock Market Performance and Economic Growth in the East African Community. African development finance journal. 110-132 ISSN 2522-3186. http://journals.uonbi.ac.ke/index.php/adfj

[49] Nyasha, S., & Odhiambo, N. (2014). The dynamics of stock market development in Kenya. Journal of applied business research. Vol 30.

[50] Obura, J., & Anyango, C. (2016). Moderating effect of interest rates on relationship between foreign exchange rate fluctuation and market performance of NSE. Universal Journal of Accounting and Finance 4, 27-34. https://doi.org/10.13189/ujaf.2016.040201

[51] Odipo, M., Olweny,T., & Oluoch, O. (2020). Microeconomic Firm Characteristics and Long Run Returns: The Case of Firms That Issued Equity at Nairobi Securities Exchange. Journal of Advances in Economics and Finance. Volume 5. 53-65.

[52] Omuchesi, J., Bosire, M., & Muiru, M (2014). The effect of automation on stock market efficiency: A case of Nairobi Securities Exchange. A research journal of Finance and Accounting. Vol 5. 71-79. https://doi.org/10.9790/5933-0537179

[53] Onyuma, S. (2020). Exchange Automation and Adaptive Efficiency at the Kenyan Securities Market. European Journal of Business and Management. ISSN 2222-2839 (Online) Vol.12, No.15. 43-64

[54] Osei K.A., Adjasi C.K., & Fiawoyife E.U. (2012). Underpricing of Initial Public Offerings on Africa stock markets: Ghana and Nigeria. The Africa Economic Research Consortium, Nairobi.

[55] Pandey, D., & Kumari,V.(2021). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. International Review of Economics & Finance. 467–483. Doi: 10.1016/j.iref.2020.09.014

[56] Philippe, E. (2012). IPO: A global guide, expanded second edition. Hong Kong University Press.

[57] Ritter J. (1998). Initial public offerings. Warren Gorham and Lamont handbook of modern finance volume 2. No.1, 5-30

[58] Ritter, J. (1991). The long run performance of initial public offerings. Journal of finance Vol.1

[59] Rudsengen, O. (2021). The Board of Directors and Underpricing in the Nordic Countries. The Relationship between Board Characteristics and Short-term Underpricing of IPOs. Un published Master thesis, Economics and Business Administration .Norwegian School of Economics

[60] Sarra, B.S., Abdelkader, B., & Neila, B.T. (2011). Determinants of IPO underpricing: evidence from Tunisia. The International Journal of Business and Finance Research: 5, 13-32.

[61] Sharpe,W (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. The Journal of Finance, Vol. 19, No. 3 (Sep., 1964), pp. 425-442. http://www.jstor.org/stable/2977928

[62] Sholichah, M. (2018). The company characteristics initial return and long term performance stock initial public offerings listing in Indonesia Stock Exchange. International journal of advanced research 6(3) 988-997.

[63] Simiyu, F., Mutunga, T., Barasa, F., & Matete, S. (2016). Effects of initial public offerings on long run performance of stocks listed on NSE market. Quest Journals of research in business and management volume 4, Issue 5 pp.43-50.

[64] Simiyu, R., Osero, S., & Odoyo, F. (2014). The effect of automation on trading volumes of listed companies at NSE, Kenya. A research journal of Finance and Accounting. Vol 5. Number 10.

[65] Switzer, L., & Zhai, X. (2019). IPO performance and the size effect: evidence for the United States and Canada. Un published thesis, John Molson School of Business, Concordia University, Montreal Canada.

[66] Treynor, J (1961). Market Vale, Time and Risk. https://ssrn.com/abstract=2600356 or http://dx.doi.org/10.2139/ssrn.2600356

[67] Turner, D. (2020). Sampling Methods in Research Design. American Headache Society. Wiley Periodicals, Inc. Doi: 10.1111/head.13707

[68] Wamari, E. (2014). The effect of Initial Public Offers on Long run stock performance. Evidence from the Nairobi Securities Exchange. International journal of Science and Research publications. Vol. 4 Issue 10: 1-9

[69] Wetukha (2013). The relationship between board composition and financial performance of listed firms at the NSE. Un published MBA thesis. University of Nairobi.

[70] Zandi, G.,Singh, J.,Mohamad, S., & Ehsanullah, S. (2020). Ownership Structure and Firm Performance. International Journal of Financial Research Vol. 11, No. 2; 293-300. https://doi.org/10.5430/ijfr.v11n2p293