RELATIONSHIP BETWEEN FINANCIAL RISK AND FINANCIAL PERFORMANCE OF LISTED FIRMS IN THE MANUFACTURING AND ALLIED SECTOR OF THE NAIROBI SECURITIES EXCHANGE

BY

NORMAN KANGETHE MWANGI

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DECLARATION

This research project is my original work and has not been submitted for the award of a degree at the University of Nairobi or any other university.

Signature ..... Date .....

NORMAN KANGETHE MWANGI

D61/85724/2016

This research project has been submitted for examination with my approval as the candidate's supervisor.

Signature ..... Date .....

MS. HELLEN KINYUA

Lecturer, Department of Finance and Accounting,

School of Business, University of Nairobi.

This research project has been submitted for examination with my approval as the candidate's supervisor.

Signature ..... Date .....

DR. KENNEDY OKIRO

Lecturer, Department of Finance and Accounting,

School of Business, University of Nairobi.

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DEDICATION

This research project is dedicated to my friends and family whose support and encouragement has propelled me this far.

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LIST OF ABBREVIATIONS

CAPM	–	Capital Asset Pricing Model
CBK	–	Central Bank of Kenya
CFO	–	Chief Financial Officer
CMA	–	Capital Markets Authority
CMR	–	Capital Management Risk
FP	–	Financial Performance
GDP	–	Gross Domestic Product
GLS	–	Generalised Least Squares
GMM	–	Generalised Method of Moments
IR	–	Interest Rate Risk
KAM	–	Kenya Association of Manufacturers
KNBS	–	Kenya National Bureau of Statistics
LM	–	Lagrange Multiplier
LR	–	Liquidity Risk
MAPI	–	Manufacturers Alliance for Productivity and Innovation
MM	–	Modigliani & Miller
NSE	–	Nairobi Securities Exchange
OLS	–	Ordinary Least Squares
ROA	–	Return on Assets
ROE	–	Return on Equity
SR	–	Solvency Risk
TOL	–	Tolerance (Inverse of VIF)
USD	–	United States Dollar
VIF	–	Variance Inflating Factor
WACC	–	Weighted Average Cost of Capital
XR	–	Exchange Rate Risk

ABSTRACT

The study's main objective of was to determine the relationship between financial risk and financial performance (FP) of manufacturing firms listed on the Nairobi Securities Exchange. The study's specific objectives were to determine the relationships between solvency risk and FP, liquidity risk and FP, interest rate risk and FP and exchange rate risk and FP. Theories relied upon by the study include the financial distress theory, Modigliani and Miller capital structure theories, modern portfolio theory by Markowitz and the capital asset pricing model. The study's research design was descriptive, and it used secondary data sourced from the audited accounts of the firms and from the Central Bank of Kenya's official website. Data was analysed using panel data methods. The Breusch-Pagan LM test was used to compare the pooled OLS model and the random effects model, and upon detection of significant individual effects, the random effects model was selected. The Hausman test was then used to compare the random effects model and the fixed effects model, and the random effects model was selected as the true model for the data. The final model results showed that solvency risk (SR) had a negative effect that was significant on FP with a coefficient of -0.5529, liquidity risk (LR) had an insignificant positive effect on FP with a coefficient of 0.0022, interest rate risk (IR) had an insignificant negative effect on FP with a coefficient of -0.0372, and exchange rate risk (XR) had an insignificant positive effect on FP with a coefficient of 0.0085. The model's y intercept of 0.3289 was also significant. Size of the firm had a significant positive effect on FP with a coefficient of 0.2217. The model's chi square statistic of 258.391 on 5 degrees of freedom was also significant. The model had an adjusted R squared of 0.7860, meaning that 78.6% of the variation in FP could be explained by financial risk and size, the control variable, with 21.4% of the variation being explained by factors not included in the regression model. The researcher recommends that companies optimise their capital structures so as to avoid the negative effect that solvency risk has on their FP. Companies are also advised to take advantage of the positive effect that firm size has on performance by investing in assets and considering strategic mergers.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Financial risk is a major concern for companies in all industries because of the effect that it poses to a company's bottom line and financial position (Myint & Famery, 2012). Financial risk comes from various sources among them interest rate fluctuations, exchange rate fluctuations and the actions of parties to a business transaction (Myint & Famery, 2012). These sources are the basis for classification of financial risks. Interest in financial risk has been increasing in recent years, an increase attributed to the effects of the financial crisis of 2008 and the increased complexity of financial products available in stock markets world over (Miller, 2014). The effect that financial risk has on the bottom line of companies is what has led researchers to explore the relationship between financial risk and financial performance (FP). According to Selvam, Gayathri, Vasanth, Lingaraja and Marxiaoli (2016) FP itself is multidimensional and it covers profitability, growth and market value. Studies exploring this relationship have noted a mixed relationship, with results indicating a positive, negative or no relationship.

The theoretical basis of the relationship between financial risk and FP is anchored on four theories namely financial distress theory, Modigliani and Miller's capital structure theorems, Markowitz's portfolio selection theory and the capital asset pricing model. The financial distress theory, first proposed by Gordon (1971), explains how a company's debt obligations can affect its FP and increase the risk of bankruptcy. Capital structure theories by Modigliani and Miller explain how the capital structure of a company can affect its

value. The modern portfolio theory (Markowitz, 1952) explains how risk, represented by standard deviation of returns, can be used in creating optimum portfolios. The capital asset pricing model explains the effect that financial risk has on marketable securities prices.

The manufacturing industry has unique supply chain structures, which are usually more complex than those of other industries. These unique structures expose manufacturing companies to many risks from within and outside their value chains (Deloitte & MAPI, 2015). Some of these risks among them exchange rate, interest rate, solvency and liquidity risks are of a financial nature. Exchange rate fluctuations increase both foreign currency liabilities and the cost of imported inputs. Interest rate fluctuations cause an increase in borrowing cost. Low liquidity and inadequate solvency could result in a company defaulting on its obligations, therefore incurring other costs such as penalties and interest. It could also result in a company having low working capital, which reduces money available for inputs, thereby reducing profitability (Myint & Famery, 2012).

1.1.1 Financial Risk

Financial risk is the likelihood of financial loss resulting from an entity's exposure to undesirable events (Myint & Famery, 2012). There are various ways of classifying financial risks. Myint and Famery (2012) identify five key financial risks namely interest rate, currency, inflation, credit and commodity risks. Fang (2016) identifies four financial risks namely investment risk, financing risk, income distribution risk and capital recovery risk (Fang, 2016). Tafri, Hamid, Meera and Omar (2009) identify credit, liquidity and interest rate risks. Haque and Wani (2015) identify the above three, plus capital risk, and solvency risk. There is no consensus in classifying financial risk.

Financial risk literature shows that most indicators of financial risk rely on financial ratios. These can be split into liquidity, coverage, operating, leverage and investment ratios. Liquidity ratios measure the ability to cover current obligations using liquid assets (Lucic, 2014). They include the current ratio, whose ideal levels are between 1.5 and 2, and the quick ratio, whose ideal value is 1 (Błach, 2010). Coverage ratios measure the ability to service debt. Operating ratios measure management performance (Lucic, 2014). Financial leverage measures how sensitive net income is to variations in operating results (Solomon & Muntean, 2012) and to capital structure risk (Błach, 2010). Investment risks are measured using efficiency ratios (Li & Si, 2013).

1.1.2 Financial Performance

Financial performance is an indicator of a firm's ability to apply its assets to its main business in order to earn revenue (Mauwa, 2016). A review of literature indicates that researchers use different metrics, with studies revealing that there are as many as 56 different performance indicators used by researchers (Selvam et al, 2016). Accounting measures of profitability, however, make up the bulk of the indicators, with 52% of the studies relying on them (Selvam et al, 2016).

However, Selvam et al (2016) note that despite profitability being the most common metric, FP is actually multidimensional, and it can be split into three aspects namely profitability, market value and growth performance. Profitability measures how an entity is able to generate profits, and it is based on the firm's historical earnings. Market value performance is measured using market capitalisation. Growth measures the company's historical ability to increase in size. Growth from a financial perspective can be measured by the increase in

assets, revenue or income. Other growth indicators include market share and number of employees (Selvam et al, 2016). FP is measured using either return on assets (ROA) (Oyedokun, Olatuji, & Sanyaolu, 2018; Haque & Wani, 2015), return on equity (ROE), or both (Amin, Sanusi, Kusairi, & Abdallah, 2014; Ismail, Samad, & Romaiha, 2018).

1.1.3 Financial Risk and Financial Performance

Research on financial risk's relationship to FP indicates three types of relationships as identified by researchers; positive, negative (inverse) and mixed. Yegon, Sang, & Cheruiyot (2014) noted that financial leverage and FP had a significant positive relationship. Audax (2018) found that financial leverage, liquidity and FP had a significant positive relationship (Audax, 2018). Amin et al (2014), however, noted that financial risk and FP had a significant inverse relationship. Mixed results have been noted by Ismail, Samad, & Romaiha (2018) who found that operational risk, capital risk, and performance had significant relationships but liquidity risk and credit risk did not have a relationship with performance. Haque & Wani (2015) found that liquidity risk, interest risk and FP had an insignificant positive relationship, capital risk, solvency risk and FP had a significant positive relationship and credit risk and FP had an insignificant negative relationship. Kubai (2016) found that total debt had a negative relationship with FP but liquidity had a positive relationship with FP. Njenga (2014) noted that the ratio between debt and equity and ROA and ROE had no significant relationships.

The theoretically expected relationship between financial risk and FP is also mixed. Financial distress theory predicts a negative relationship between financial risk ratios, particularly those incorporating debt, and FP. This is due to increased borrowing costs. The

capital structure irrelevance theorem explains that a firm's capital structure has no effect on its value. Capital structure risk ratios would therefore not affect performance. The capital structure relevance theorem recognises a tax shield benefit, so capital structure ratios would have a positive relationship with performance. The modern portfolio theory and the capital asset pricing model both track volatility of stock returns, which is affected by FP. Investors are risk averse, so if borrowing costs increased and negatively affected profitability, investors would sell the stock and this reduces the ability of the company to raise funds. It is therefore expected that financial risk would negatively affect FP.

1.1.4 Manufacturing and Allied Firms Listed at the NSE

The Nairobi Securities Exchange (NSE), founded in 1954, Kenya's only securities exchange. The exchange was demutualised six decades later in 2014, and is now a self-listed exchange (NSE, 2019a). It offers both equity and debt securities. The NSE is a vital player in the Kenyan economy. It encourages saving and investing in the country and it helps companies access capital through issuing of equity and debt as securities. The Capital Markets Authority (CMA) regulates the NSE (NSE, 2019a).

The NSE has 65 listed firms which are grouped into 13 sectors (NSE, 2019b). One of those sectors is the Manufacturing and Allied Sector, which is currently made up of 9 companies as shown on Appendix I. The low number of listed manufacturing firms is due to the prevalence of family-owned businesses and the presence of a large informal sector in manufacturing (Were, 2016). Firms under the manufacturing and allied sector are involved in the manufacture of various products among them industrial gases, tobacco, industrial chemicals, liquor, household items, foodstuff and plastic products.

Despite the manufacturing sector being a key contributor to the country's GDP, its percentage contribution has been consistently declining, standing at 10.7, 10.0, 9.4, 9.1 and 8.4 in 2013, 2014, 2015, 2016 and 2017 respectively (KNBS, 2018). The steady decline has been attributed to a lower growth rate than other sectors of the economy (Were, 2016), stagnation in value addition for the past 10 years (Parliamentary Budget Office, 2018) and closure of major manufacturing entities (Wafula, 2016). However, as research shows, financial reasons such as high finance costs, insufficient finances and financial risks also greatly affect the FP of manufacturing entities (Ruirie, 2012; Wanyama, 2016; Were, 2016). The sector's shyness from other sources of financing apart from debt is also a source of limitation on its growth (Were, 2016).

1.2 Research Problem

The manufacturing sector in Kenya has been facing financial difficulties resulting in the closure of major companies like Nestle, Colgate Palmolive and Kenya Fluorspar (Wafula, 2016). The achievements of the targets set by the country's Vision 2030 and the government's Big 4 Agenda, however, depends on the sustainable growth of the manufacturing sector. The steady decline of the sector's contribution over the years is, however, not promising, and it warrants a review of the problems afflicting the industry. Review of literature shows that financial risks are among the factors affecting the FP of entities in this sector. The review, however, shows that the relationship between financial risk and FP is not conclusive. Lack of conclusive results impedes decision making as pertains to the management approaches to be applied in order to reduce the impact of financial risks. The existence of key conceptual and contextual research gaps also makes it difficult to determine which results can be generalised to the manufacturing sector.

Four key research gaps have been identified from an analysis of literature. Two of them are contextual, namely limited amount of research in non-financial industries and a predominance of research on financial risk practices as compared to research on effects of financial risk in Kenya. The other two are conceptual, namely the failure to incorporate interest rate and exchange rate risk as variables in the regression model and the preference for ordinary least squares (OLS) regression which ignores firm-specific effects in the data.

An analysis of research done on the relationship between the two variables indicates that researchers have focused on the financial services industry, particularly the banking and insurance industries (Myint & Famery, 2012; Abubakar, 2015). This is also the case with local research on the two variables (Korir, 2010; Njeri, 2014; Lelgo & Obwogi, 2018).

An analysis of research on the manufacturing sector also indicates a focus on qualitative studies which aim at identifying the responses being taken by the management of manufacturing entities in mitigating financial risk exposure such as having a financial risk policy and use of derivatives in hedging against financial risks. International studies that review how financial risk management practices affect FP have been carried out (Islam & Tedford, 2012; Nwite, 2014). Locally, the same focus on financial management practices is seen (Wanyama, 2016; Mugenda, Momanyi, & Naibei, 2012; Mwelu, Rulangaranga, Watundu, Kaberuka, & Tindiwensi, 2014; Njeri, 2014; Mburu, 2015). This research approach is qualitative. However, as noted by the researcher, there are fewer quantitative studies exploring the effect of the actual risk level of the firm on its performance, as compared to qualitative studies.

Studies exploring the relationship between financial risk and FP in manufacturing also focus on the capital structure aspects of risk (Kubai, 2016; Audax, 2018; Njenga, 2014)

while ignoring other financial risks that have been studied in other industries including increasing interest rates and fluctuations in exchange rates (Obudho, 2014). This is also the case with international studies covering the manufacturing sector (Ajibola, Okere, & Oyedeji, 2018; Abubakar, 2015). These studies, therefore, do not paint a complete picture of financial risk in the manufacturing industry.

Many studies exploring the relationship between the variables have also pooled the data and carried out ordinary least squares (OLS) regression without comparing the consistency of the model to other models that factor in firm-specific effects. This has been done despite the researchers having access to rich datasets. This approach has been observed for both international studies (Haque & Wani, 2015) and for all the local studies seen by the researcher that cover the manufacturing sector (Kubai, 2016; Audax, 2018; Njenga, 2014). Firm-specific effects are best exposed by models that analyse panel data. The two main models in analysing panels are the fixed effects model and the random effects model.

This research therefore aimed at closing the research gaps identified above by focusing on a wider range of quantitative aspects of financial risk with the aim of determining their effect on FP of firms in the manufacturing industry in Kenya, while assessing firm-specific effects in the regression model. The researcher aimed at answering this research question: How do the various financial risks relate to the financial performance of listed manufacturing companies at the NSE?

1.3 Objective of the Study

The study's research objective was to determine the relationship between financial risk and the financial performance for companies listed under the manufacturing and allied sector of the Nairobi Securities Exchange.

1.4 Value of the Study

This study aimed at closing the key research gaps identified namely the focus on financial services industry, few quantitative studies, few financial risk variables and methodological gaps, therefore contributing to the academic knowledge in this area. The study offers a broader quantitative approach to the analysis of financial risk in the manufacturing industry, which has been lacking. The study also proposed an analytical approach that made use of a rich longitudinal dataset and panel data methods in order to select the best analytical model for inference.

The study results will assist policy makers in government, particularly the State Department for Investment and Industry. By determining the significance of different aspects of financial risk, the study will assist policy makers in determining how to prioritise policies so as to ensure that the risks with the largest impact on performance of manufacturing entities are addressed before those with a lesser impact.

Finally, the results of the study will offer risk management practitioners and Chief Finance Officers (CFOs) of manufacturing entities a view of how each financial risk metric relates to the performance of manufacturing entities, with the view of informing appropriate strategic action on the companies' part. This study also aims at influencing best practices in risk management in the manufacturing industry.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter covers research exploring the relationship between the study variables. The first part covers the theoretical framework of the concept of financial risk. The second part covers determinants of financial performance. The third part covers global and local empirical studies. The fourth part covers the conceptual framework for the study. The fifth and last part summarises the reviewed literature.

2.2 Theoretical Framework

This part covers the theories upon which the study is anchored. Each theory is explained, linked to the variables and critiqued.

2.2.1 Financial Distress Theory

A theory of financial distress was first proposed by Gordon (1971) who defined financial distress as a reduction in a firm's earning power that then increases the chances of the firm defaulting on its debt obligations (Gordon, 1971). This increase in probability of default can be viewed as financial risk. A more specific definition was given by Whitaker (1999) who defined the early stage of financial distress for a firm to be the first year when the firm's cash inflows fall below the maturities of its long-term debt (Whitaker, 1999). The most famous empirical work on financial distress is by Altman (1968) who presented a multiple discriminant model that made use of financial ratios to predict bankruptcy of listed firms in manufacturing sector in the United States. The model has also been adapted for

non-listed firms and for firms in emerging markets (Altman, 2000). The theory, together with the various bankruptcy prediction models, indicates that financial statement information can be used to predict a firm's financial health.

Criticisms of the theory of financial distress have focused more on the specific distress prediction models such as the Z-Score, which has been criticised for not being a good long run predictor of bankruptcy, with univariate ratio analysis being seen to be better at predicting bankruptcy in the long run (Maricica & Georgeta, 2012). The theory informs the study by explaining how the risk of a company defaulting on its obligations can be detected using financial statement information. The theory also explains why some researchers note that financial risk, as measured by various financial ratios which incorporate long term or short term debt, is significantly inversely related to FP. Increasing debt levels raise financial distress due to the increasing fixed interest costs, therefore resulting into a negative impact on profitability (Shen, Chen, Kao, & Yeh, 2009).

2.2.2 Capital Structure Theorems by Modigliani and Miller

Modigliani and Miller (1958) explained how the financial structure of an entity impacts its market valuation. Market value represents the investors' risk-adjusted expected returns. Since investors can take on debt privately to finance the purchase of un-leveraged stocks or sell off highly leveraged stock, to the investor the capital structure of the firm is not relevant (Modigliani & Miller, 1958). The theory's basic assumptions include efficient and frictionless markets with free flow of information, no taxes, corporation costs or bankruptcy costs. This is the capital structure irrelevance theorem (Ahmeti & Prenaj, 2015). Modigliani and Miller later published a paper modifying some earlier assumptions,

indicating that there is a tax benefit for issuing bonds, which increases the company's value in proportion to its debt (Miller & Modigliani, 1961). However, upon factoring in riskiness of debt, which increases in proportion to its weight, WACC remains the same regardless of capital structure because higher debt raises the required rate of return, therefore netting off the debt benefit (Ahmeti & Prenaj, 2015).

Criticisms of MM theorems are based largely on the absence of a real-world market with the assumptions of efficiency and the absence of market frictions such as taxes, different borrowing rates between individuals and corporations and the presence of bankruptcy costs. However, the theorems continue to attract interest because they state that a firm's capital structure would not have a role in its value if it was not for the natural imperfections in the markets (Ahmeti & Prenaj, 2015). The capital structure theorems inform this study through their explanation of the effect that debt and equity components, on which most financial risk ratios are based, have on a firm's value. The capital structure irrelevance theorem explains why some researchers found no relationship between financial risk and FP. The capital structure relevance theorem, on the other hand, explains why some researchers noted that financial risk had a significant positive relationship with FP, attributed to the tax shield effect (Solomon & Muntean, 2012).

2.2.3 Modern Portfolio Theory by Markowitz

Markowitz (1952) was the first to come up with a statistical way of optimally allocating assets in a portfolio based on their risk-return profile. His theory established the approach of selecting a portfolio that has the best risk-return characteristics as opposed to selecting individual assets with individually-optimal risk-return relationships. This was meant to

take advantage of the internal negative correlation between the portfolio assets for diversification (Markowitz, 1952). His propositions, combined with Tobin's risk aversion interpretation of liquidity preference (Tobin, 1958) and contributions from Merton who described how the efficient frontier could be derived analytically (Merton, 1972), enabled the creation of the graphical method of determining the minimum-variance portfolio (Lelgo & Obwogi, 2018; Corelli, 2016). This theory plus subsequent contributions have since then served as the foundation of knowledge in selecting portfolios of risky assets.

The theory serves to explain the risk-return relationship for market-traded securities, and is considered to be the theoretical foundation of methods of market-based financial risk measurement such as value at risk (Lelgo & Obwogi, 2018). The Modern Portfolio Theory is the foundation of the Capital Asset Pricing model, which is a single-security derivation of the theory (Bodie, Kane, & Marcus, 2014).

Financial performance is multifaceted and market performance is one of its aspects. Portfolio Selection theory can be used in explaining why some researchers have noted that financial risk and stock returns have an inverse relationship (Mwaurah, Muturi, & Waititu, 2017). An increase in debt causes an increase in interest costs and reduces financial returns, which lowers expected returns, causing investors to sell the stock. This creates a cycle of reduced stock demand and lower stock return.

The Modern Portfolio Theory informs the conceptual framework by explaining how actions of investors are affected by liquidity risk and solvency risk. Firms depend on investors for raising capital for their operations. High borrowing costs negatively impact on FP. Investors then divest the firm's stock from their portfolios, which creates a cycle where stock returns are low. This keeps demand for the stock low. This in turn makes it

difficult for the company to raise capital for future projects, therefore missing out on profitable investments and negatively affecting future FP.

2.2.4 Capital Asset Pricing Model

This model was developed by Sharpe (1964), Lintner (1965). It is a method of pricing marketable assets that uses the risk premium approach to calculate the return investors expect from an asset. Assets prices are determined by adding the product of the asset beta and the premium of the market to the risk-free return rate. Beta is the fraction of the asset's covariance with the market over the variance of the market (Bodie, Kane, & Marcus, 2014). CAPM is considered simple and intuitive, hence its ubiquity despite other more complex models such as the Arbitrage Pricing Model by Ross (1976) and the Fama-French models (Fama & French, 1996; Fama & French, 2015).

CAPM, like the Modern Portfolio Theory, can explain why some researchers note that financial risk and stock returns have an inverse relationship. Increased financial risk, caused by increase in debt levels, causes an increase in interest costs and therefore lower financial returns. This results in low demand for the stock which increases volatility of market returns, therefore increasing beta and increasing the level of returns expected, and if the stock price is lower than expected return, investors sell the stock and set in place a cycle of low returns. CAPM informs the conceptual framework by linking investor actions to the availability of capital for future projects and its effect on future profits. High financing costs results in low profits and therefore low demand for stock, and lower capacity to raise capital for future projects, therefore lower financial returns in the future.

2.3 Determinants of Financial Performance

The CAMELS rating system can be used in analysing determinants of FP. CAMELS stands for adequacy of capital, quality of assets, management practices, level of earnings, the firm's liquidity level and how sensitive a firm is to risks in its external environment (Stackhouse, 2018). These can be broken down into internal determinants and external determinants, where the first five are internal and the sixth is external. Internal determinants, also called micro factors, are those that are in direct contact with the entity and affect the performance of the entity directly, whereas external factors, also called macro-factors, are factors in the external environment such as the economy (Mauwa, 2016). Each determinant is explored in detail below.

2.3.1 Capital Adequacy

Capital adequacy plays a part in FP where companies facing funding shortages are seen to experience slow growth (Ruirie, 2012). This shortage of funding has been attributed to lack of adequate collateral for loans (Ruirie, 2012) and the failure by manufacturing entities to seek other sources of capital other than debt (Were, 2016). Capital adequacy, as represented by the ratio between working capital and assets, is a key component of the Z-Score discriminant model (Altman, 2000).

2.3.2 Assets

The assets of a company are employed in the generation of revenue. It is therefore expected that assets, and asset quality, would affect the FP of a company. This has been observed by Audax (2018) who noted that size of the firm had a positive linear relationship with FP. This relationship is attributed to economies of scale (Audax, 2018). Research in the

banking industry has also shown asset quality to be a key determinant of FP for commercial banks, with the ratio having a significant negative correlation with FP (Muriithi, 2016).

2.3.3 Management

Management has been noted by researchers such as Mulu (2013) as a key determinant in FP. Mulu (2013) found that operational risks resulting from governance issues, policies, organisational strategy and structure impact on an entity's performance (Mulu, 2013). Mutuku & Muturi (2016) noted that constraints in innovation and management significantly affected performance of SME firms (Mutuku & Muturi, 2016). Rurie (2012) also noted a significant influence of business skills on the growth of manufacturing SMEs in the Industrial Area of Nairobi.

2.3.4 Earnings

Earnings were identified as a determinant of FP by Matar and Eneizan (2018) where profitability was seen to be positively related to ROA (Matar & Eneizan, 2018). Selvam et al (2016) also identified profitability as not only a dimension but also a determinant of FP. Profitability also correlates with market value because it is a historical indicator of a company's performance (Selvam et al, 2016).

2.3.5 Liquidity

Matar and Eneizan (2018) also identified liquidity as a determinant of FP where it was seen to be positively related to ROA. Liquidity allows a company to pay its obligations while staying prepared for eventualities that may require cash outflows. Maintaining an adequate liquidity level is therefore a financial risk management technique (Matar & Eneizan, 2018).

2.3.6 External Risks

Selvam et al (2016), in their multi-dimensional performance model, noted that the level of satisfaction of the company's customers and employees, the company's performance in its environmental audit and social responsibility affect performance (Selvam et al., 2016). Political instability, which is common in Kenya during general elections, has also been seen to affect FP (Ruirie, 2012).

2.4 Empirical Studies

This section explores in detail both international and local studies that analyse financial risk's relationship with financial performance.

2.4.1 International Studies

Shen, Chen, Kao and Yeh (2009) analysed the effect that liquidity has on bank performance in 12 developed economies in North America, Europe and Asia. These were split into market-based economies, which rely more heavily on equity financing, and bank-based economies which rely more on debt. An unbalance panel dataset was used, covering the periods 1994 to 2006. Analysis was done using a two-stage least squares instrumental variable regression. The results indicated that liquidity and performance were negatively related in market-based economies due to higher cost of funds, but were not related in bank-based economies. The study recognises the heterogeneity problem and addresses it through use of panel data methods. This study reveals that for market-based economies, investors pay attention to risk and are likely to divest from high-risk companies, therefore effecting the companies' ability to raise capital, which affects long term performance. Study results

for bank-based economies are in line with the capital structure irrelevance theorem (Modigliani & Miller, 1963), where increase in leverage does not affect a company's value.

A study in Malaysia by Tafri et al (2009) explored the effect that financial risk had on the FP of banks. The sample was split into sub-samples of conventional and Islamic banks. The study collected data for 10 years between 1996 and 2005. ROA and ROE were the metrics used in representing FP. The metrics selected to represent financial risk were liquidity, interest rate fluctuation and credit risk. The study applied a panel data approach. The results indicated that liquidity risk did not affect profitability whereas credit risk had an inverse relationship with both measures of profitability. Interest rate risk (only for conventional banks) was inversely related to ROE but positively related to ROA. The researchers recommended that similar studies be extended to other areas other than banking (Tafri, Hamid, Meera, & Omar, 2009). This study addresses the heterogeneity problem through panel data methods. These results are also in line with the capital structure relevance theorem (Modigliani & Miller, 1958) where higher borrowing results in a tax shield effect that improves firm performance and firm value. The study also shows that the two FP metrics, ROE and ROA, have different relationships with financial risk metrics. However, no explanation is given for this mixed relationship.

A similar study by Haque and Wani (2015) conducted in India investigated how financial risk affects bank FP. The study sampled 10 banks, half of them privately owned and the other half government owned. The study gathered data 5 years of data from financial reports from 2009 to 2013. ROA was used to represent FP whereas financial risk had 5 proxy ratios. The study applied multiple regression. Results showed that FP was inversely related to credit risk, positively related to capital risk and had no relationship with interest

rate, liquidity and solvency risks. The study uses various ratios to represent financial risks. However, exchange rate risk is not analysed. The data used for study is a short panel, with more individual entities studied than the number of years studied (Gujarati & Porter, 2009). A heterogeneity problem is therefore expected. The researchers, however, did not address this problem since they applied a multiple regression approach, ignoring firm-specific effects in the model.

Studies reviewed by the researcher covering firms in the manufacturing industry use capital structure ratios as proxies for financial risk. Matar & Eneizan (2018) investigated the various variables that have an effect on FP of entities involved in manufacturing in Jordan. They analysed financial statements of 23 companies. ROA represented performance, whereas variables for risk were leverage, firm size, liquidity, revenue and profitability. They then performed a multiple regression analysis, from which they found out that liquidity, profitability and revenue were positively related to ROA, whereas leverage and firm size were negatively related to ROA (Matar & Eneizan, 2018). The study uses various ratios for financial risks and therefore captures a more complete view of financial risk. This study uses a short panel, and heterogeneity between variables of different firms is expected. However, this has not been addressed in the study.

Ajibola, Okere & Oyedeji (2018) analysed companies involved in manufacturing in Nigeria with the focus being on capital structure's effect on performance. 10 companies were sampled. Data for the 10-year period from 2005-2014 was collected. ROA and ROE represented performance. Capital structure components that represent financial risk were 3 different debt to assets ratios. Panel data multiple regression was conducted. Study results showed that ROE had a significant positive relationship with total debt and long-term debt

but ROA had an insignificant negative relationship with all risk ratios (Ajibola, Okere, & Oyedeji, 2018). This study addresses the heterogeneity problem by using panel data methods. The study results also show different relationships between each of the two FP proxies and financial risk, but offers no explanation for the mixed relationship. The proxies for financial risk are also only based on capital structure, and other risks such as risks posed by exchange rate and interest rate fluctuations have not been analysed. The analytical model, therefore, does not show a complete picture of financial risk.

In the region, Amin et al (2014) investigated how financial risk impacts on FP of Tanzanian banks. 21 banks in Tanzania were sampled. Financial statement information for 10 years from 2003 to 2012 was gathered and analysed. ROA and ROE represented performance. Financial risk was represented by metrics for liquidity, credit and interest rate risks. The fixed effects model was estimated through instrumental variables. Study results indicated that financial risk affected ROA in a significantly positive way. ROE was, however, affected in a significantly negative way by financial risk. The reverse effect was also tested, where ROA and ROE were seen to have an inverse effect on financial risk. This study uses a short panel and it addresses the heterogeneity problem by using panel data models. The study shows a mixed relationship between financial risk and FP. However, no explanation is given for this mixed relationship.

2.4.2 Local Studies

A study by Muriithi (2016) explored how financial risk impacts on the FP of the banking industry. The study covered 10 years from 2005 to 2014 and collected financial statement data from all 43 Kenyan banks. ROE was used as the metric for performance. Metrics for

financial risk were several risk ratios. Unbalanced panel data analysis and ratio analysis were conducted. The study revealed that liquidity, market, credit and operational risks had a significant negative influence on performance. The cost to income ratio was the financial risk ratio with the highest level of significance (Muriithi, 2016). The study is a short panel and it addresses the heterogeneity problem by using panel data methods. The researcher uses ROE as the metric for performance and justifies this by stating that it is a better gauge for profitability since it compares earnings to capital, therefore giving a view of profitability from the shareholder's perspective (Muriithi, 2016). ROE, however, does not indicate how well a company is able to generate profits from its assets.

Obudho (2014) analysed companies in the Kenyan insurance industry in order to determine the impact that financial risk had on their performance. The study was a census of the 49 companies in the industry and utilised financial statement information for 5 years from 2009 to 2013. ROA represented FP whereas several risk ratios for solvency, liquidity and interest rate fluctuation represented financial risk. The study applied multiple regression. Results showed a significant negative effect for year on year change in interest rate, equity to assets and the current ratio on FP (Obudho, 2014). The study made use of a short panel but did not address the issue of heterogeneity between firms. The study, however, used a broader set of financial ratios, therefore giving a more complete picture of financial risk.

Local researchers studying manufacturing entities, similar to international researchers, use capital structure components as proxies for financial risk. Kubai (2016) assessed the effect that financial risk has on FP of manufacturing companies. The researcher collected financial information covering 2009 to 2015 for 10 listed firms. The proxy for performance was ROE whereas the capital structure ratios associated with financial risk were total debt

to equity and current ratios. The study made use of multiple regression. Study results showed total debt and FP to have an inverse relationship whereas liquidity and performance had a positive relationship (Kubai, 2016). The study relied on capital structure ratios and therefore does not give a complete picture of financial risk. The study also did not test for heterogeneity despite using a short panel.

Njenga (2014) also studied the manufacturing industry using financial information for 5 Kenyan listed manufacturing firms covering seven years between 2006 and 2012. The proxy for capital structure, which is also a risk metric, was debt to equity ratio. FP was represented by two metrics, namely ROA and ROE. Univariate regression analysis was used. Study results showed no relationship between debt to equity and either ROA or ROE (Njenga, 2014). This study's methodology does not model the complete picture of the relationship between the variables since regression was done separately for each financial risk metric against the two FP proxies.

A study by Audax (2018) explored the impact that financial leverage and liquidity had on the FP of Kenyan listed manufacturing firms. Financial statement information for all 10 firms in the sector was analysed for six years from 2011 to 2016. ROA and ROE were the representative ratios for FP. Leverage and liquidity were the representative metrics for financial risk. Multiple regression analysis was conducted. Results indicated a significant positive effect for both liquidity and leverage on performance (Audax, 2018). The results are in line with the capital structure relevance theorem. However existence of heterogeneity between firms was not tested. The study also relies on capital structure risk ratios which do not show a complete picture of financial risk.

2.5 Conceptual Framework

A conceptual framework refers to a description of aspects selected for testing that form the basis of the enquiry (Kumar, 2011). The diagram below shows specific aspects of financial risk and those of FP selected for this study. Firm size, which has been shown in literature to influence FP (Audax, 2018; Obudho, 2014), has been selected as the control variable.

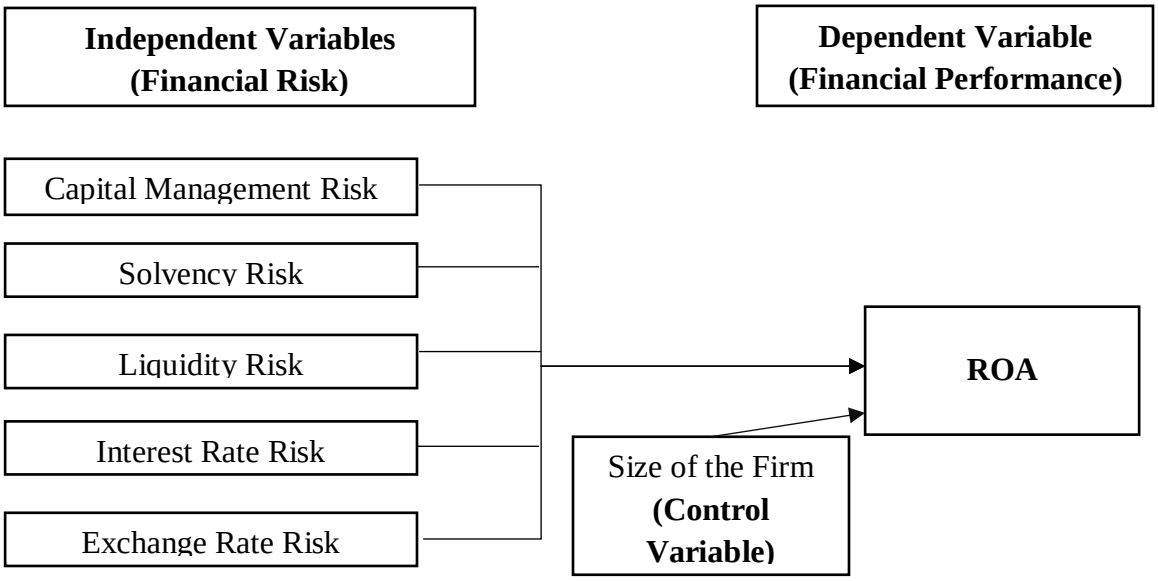

Figure 2.1: Conceptual Framework (by Researcher)

2.6 Summary of Literature Review

Results indicate that financial risk has mixed relationships with FP. Audax (2018) noted that the relationship was positive. Muriithi (2016) and Obudho (2014) found a negative relationship whereas Tafri et al (2009), Shen et al (2009), Haque and Wani (2015), Matar and Eneizan (2018) and Kubai (2016) noted positive relationships for some financial risk proxies and negative relationships for others. Researchers who used ROA and ROE in their analysis as dependent variables noted mixed relationships, with Ajibola, Okere, & Oyedeji (2018) noting that financial risk proxies and ROE had a positive relationship, yet the same risk metrics had a negative relationship with ROA. Amin et al (2014) noted that financial

risk proxies and ROA had a positive relationship but the same risk measures had a negative relationship with ROE. Njenga (2014) found no relationship.

Contextual gaps in the study of the two variables are based on the sectors studied and predominance of research on financial risk management locally. The researcher noted that few researchers have explored financial risk versus FP for firms in the manufacturing industry. Most studies exploring this relationship are in the banking and insurance industries, with a few in microfinance. Research reviewed also tends to focus on financial risk management practices and not financial risk itself.

Conceptual gaps in the study of the two variables are based on a focus on capital structure risks and ignoring individual effects in the analytical model. Most of the research seen by the researcher focuses on financial risks related to capital structure, therefore ignoring external risks such as exchange rate fluctuations and changes in interest rates. Both of these risks have been incorporated in the analytical model discussed in the subsequent chapter. Researchers, particularly in Kenya, have also used either univariate or multivariate regression analysis, despite their data being both cross-sectional and longitudinal. These research results may therefore suffer from a heterogeneity problem due to ignoring of firm-specific effects in the analytical model, which leads to inconsistent regression models. This study aimed at solving this problem by adopting panel data models.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The methodology utilised in the study is discussed in this chapter. Issues discussed include research design, population, collection of data and the analysis approach.

3.2 Research Design

A research design is the strategy formulated with the objective of answering the research questions posed (Kumar, 2011). The study made use of the descriptive research design since it intended on describing the way in which the independent and dependent variables relate (Cooper & Schindler, 2014).

Research design can also be classified based on the number of contacts with the population (Kumar, 2011). In this regard, the study was longitudinal because the financial information gathered for each firm was for the 10-year period from 2009 to 2018. This gave the researcher a rich dataset that was used to analyse firm-specific effects in the regression. The proxy for FP was the dependent variable whereas the proxies for financial risk were the independent variables. Both dependent and independent variables were extracted from the firms' financial statements, except for interest rate and exchange rate fluctuations which were sourced from the CBK's official website.

3.3 Population

A study population is made up of the people, occurrences or records that contain the information required for the study (Cooper & Schindler, 2014). The NSE currently lists 9 manufacturing companies as outlined in Appendix I. These companies constituted the study's target population. Due to the small number of firms, all 9 firms were considered for inclusion in the study, making this study a census.

3.4 Data Collection

Data collection is the technique applied in gathering information from the sample (Sreejesh, Mohapatra, & Anusree, 2014). The study made use of secondary financial data. For the dependent variable (ROA), 3 of the 5 independent variables i.e. capital management risk (CMR), solvency risk (SR) and liquidity risk (LR) and the control variable of size of the firm (SIZE), data was gathered from the listed firms' audited accounts. These accounts were downloaded from the official website of the NSE and from the corporate websites of the firms. Data for two independent variables namely interest rate risk (IR) and exchange rate risk (XR) was sourced from the official website of the Central Bank of Kenya. The ratios calculated after data collection have been outlined on Appendix II.

3.5 Data Analysis

Data analysis involves reducing data for ease of handling, summarisation, identification of patterns in the data and statistical analysis (Cooper & Schindler, 2014). Once the data was collected, it was tabulated in Microsoft Excel and all relevant ratios calculated for each year for each firm. Data was then arranged as a panel, with a column coded to represent

the firms as per Appendix I, and another column coded from 2009 to 2018 to represent the years.

The complete dataset was expected to constitute 90 observations. This dataset was then converted to 'csv' format and read into the R Studio environment, which uses R statistical programming language version for analysis. The statistical method applied was panel regression, and the statistical package used was the 'PLM' package, which stands for Panel Linear Models (Croissant & Millo, 2008).

The study used ROA as the proxy for FP in order to represent the firms' ability to generate returns from their assets (Muriithi, 2016). The analytical model used in the study was adapted from Obudho (2014) and slightly modified to include the KES-USD rate as a proxy for exchange rate risk as specified by Maniagi (2018). The rate is a good proxy because the USD has been noted by researchers to be the largest source of exchange rate risk both for firms and for economic sectors (Maniagi, 2018). The model is specified as follows:

$$ROA_{i,t} = \beta_0 + \beta_1 CMR_{i,t} + \beta_2 SR_{i,t} + \beta_3 LR_{i,t} + \beta_4 IR_{i,t} + \beta_5 XR_{i,t} + \beta_6 SIZE_{i,t} + \varepsilon_{i,t}$$

Where;

- **ROA*i,t*** = Return on Assets of each firm for each year –> i.e. Net Income/Total Assets
- **CMR*i,t*** = Capital Management Risk of each firm for each year –> i.e. (Capital + Reserves)/Total Assets
- **SR*i,t*** = Solvency Risk of each firm for each year –> i.e. Total Debt/Total Assets
- **LR*i,t*** = Liquidity Risk of each firm for each year –> i.e. Current Assets/Current Liabilities

- **IR*i,t*** = Interest Rate Risk of each firm for each year –> i.e. variation in interest rate for the year as compared to the previous year
- **XR*i,t*** = Exchange Rate Risk of each firm for each year –> i.e. the standard deviation of the mean USD to KES exchange for the year
- **SIZE*i,t*** = Size of each firm for each year –> i.e. the logarithm of total assets
- **β_0, β_1, β_2, β_3, β_4, β_5, β_6** = Slope coefficients for the model and the independent variables
- **$\varepsilon_{i,t}$** = The model's error term

After diagnostic tests, the regression model selected was the random effects model represented by the equation below:

$$Y_{i,t} = \beta_0 + \beta_j X'_{i,t} + (\alpha_i + \varepsilon_{i,t})$$

Where:

- "$Y_{i,t}$" is the dependent variable as observed for each firm in each year
- "β_0" represents the model's y intercept
- "β_j" represents the various independent variable coefficients
- "$X'_{i,t}$" represents all the independent variables for each firm in each year
- "$\alpha_i + \varepsilon_{i,t}$" is the composite error term containing both the individual random effects represented by "α_i" and the idiosyncratic error term represented by "$\varepsilon_{i,t}$"

3.5.1 Operationalisation of Variables

Operationalisation of variables refers to the consideration of how the variables will be measured (Kumar, 2011). The table below indicates how each independent and dependent variable was operationalised:

Variable	Type of Variable	Measurement
ROA	Dependent	Net Income/Total Assets
CMR	Independent	(Capital + Reserves)/Total Assets
SR	Independent	Total Debt/Total Assets
LR	Independent	Current Assets/Current Liabilities
IR	Independent	$\frac{\text{Interest Rate Year}_1 - \text{Interest Rate Year}_0}{\text{Interest Rate Year}_0}$
XR	Independent	Standard Deviation (Mean KES-USD Rate)
SIZE	Control Variable	Ln(Total Assets)

Table 3.1: Operationalisation of Variables (by Researcher)

3.6 Diagnostic Tests

Diagnostic tests are checks applied to data in order to allow the researcher to determine the best analytical technique (Cooper & Schindler, 2014). A multicollinearity test was applied in order to determine whether each variable had unique contribution to the regression analysis. A panel unit root test was also conducted with the aim of determining the whether the data was stationarity. The Breusch-Pagan LM test was carried out as a decision criterion for selecting the consistent model between the pooled OLS model and the random effects model. A Hausman test was then carried out to determine the better model between the random effects model and the fixed effects model. Diagnostic tests were also performed on the residuals so as to test the model's conformity to the assumptions of the regression

model. These tests were the Pesaran cross-sectional dependence test, the Breusch-Godfrey serial correlation test and the Shapiro-Wilk normality test.

3.7 Tests of Significance

A test of significance is one designed to ascertain whether the sample information is sufficient to justify a hypothesis being rejected or not (Cooper & Schindler, 2014). The p-value was used as the main determinant of the significance of the model and the variable coefficients. For this study, this had been pegged at an alpha of 0.05, where the model and variable coefficients with a p-value below this were considered statistically significant. The final model selected was the random effects model, therefore the chi-square deviance was computed and the chi-square statistic was used in determining the significance of the final model. The adjusted R-squared was the metric for the accuracy of the mode.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the research findings including the response rate, results of the exploratory analysis, initial diagnostic tests, regression models, model selection and final model diagnostic tests.

4.2 Response Rate

The study was a census of the 9 companies classified under the manufacturing and allied sector of the Nairobi Securities Exchange, with data collected for 10 years from 2009 to 2018. The complete dataset was expected to constitute 90 observations. However, two companies were dropped from the study for having sizeable operations outside the country, which exposes them to economic risks not being experienced by other Kenyan companies, which may skew the results of the analysis.

Flame Tree Group is an investments holding company with subsidiaries across Africa and the United Arab Emirates, and its books of accounts consolidate all operations without any indication on what proportions relate to the Kenyan subsidiaries. Due to this reason, the company was dropped from the analysis. The other company, Eveready East Africa PLC, shut down its Nakuru factory in 2014 and now manufactures its batteries in Egypt (Wafula, 2016). With this move, the company is expected to have divested from its manufacturing assets, which would make ratios that rely on assets such as ROA and log of total assets to be outliers. The company was therefore dropped from the study.

The data analysed therefore covers 7 companies, with data collected over a 10 year period, which constitutes 70 observations. This gives a response rate of 77.78%. The dataset is a balanced panel because it contains an equal number of time periods for each firm.

4.3 Descriptive Statistics

Below is a summary of the variables' descriptive statistics.

	ROA	CMR	SR	LR	IR	XR	SIZE
Minimum	-0.9622	-0.9142	0.0218	0.0290	-0.2022	0.3477	-0.4259
1st Quartile	0.0418	0.2845	0.2609	1.1760	-0.0590	1.1260	-0.0286
Median	0.0832	0.5251	0.4727	1.8060	-0.0284	1.3223	0.0490
Mean	0.0942	0.4923	0.5058	4.1880	0.0040	2.2739	0.0742
3rd Quartile	0.2145	0.7391	0.7155	2.3240	0.0542	3.6052	0.1250
Maximum	0.4972	0.9782	1.9142	44.9180	0.3358	6.1642	0.8020
St. Deviation	0.2026	0.3478	0.3482	7.9360	0.1251	1.7984	0.1890

Table 4.1: Descriptive Statistics (by Researcher)

A review of the standard deviations indicates that the variables vary significantly from the mean, with is caused by the data being collected from various companies with different capital structures. This points to the existence of individual effects in the data. The highest standard deviation is that of liquidity risk, which means that working capital management techniques vary greatly between the companies analysed.

A review of the maximum and minimum values also indicates the existence of very high and very low values. These values are not outliers, rather they are observations from companies with very different capital structures and working capital management approaches. For example the maximum value of 44.9180 for liquidity risk is observed from Carbacid Investments Plc, whose 10 liquidity ratios constitute the top 10 liquidity ratios

for the entire dataset. This points to a very different business model on the company's part, another pointer to individual effects in the data.

FP ranges from very low ROA ratios of -0.96, attributed to Mumias Sugar Company Limited resulting from the financial problems the company has been facing in recent years, to 0.49 attributed to Carbacid Investments Plc, which is the same company with the highest liquidity ratios in the dataset. FP therefore varies widely between companies.

For the ratios extracted from the CBK's, exchange rate risk has the highest standard deviation. This is expected, given the fluctuations in the KES-USD rate over the years. Interest rate risk, however, has a low standard deviation, caused by the regulation of interest rates by CBK and the more recent capping of interest rates from September 2016.

4.4 Correlation Analysis

Correlation analysis is important in showing how strong the linear relationships between the study variables are. It is particularly important in detecting multicollinearity between independent variables. The table below shows the results of the Pearson product moment correlation analysis:

		ROA	CMR	SR	LR	IR	XR	SIZE
ROA	Correlation	1.0000	0.6798	-0.6831	0.4028	0.1317	0.1973	0.4941
	P Value		<0.0000	<0.0000	0.0005	0.2772	0.1015	<0.0000
CMR	Correlation	0.6798	1.0000	-0.9981	0.5000	0.0733	0.1183	0.2680
	P Value	<0.0000		<0.0000	<0.0000	0.5464	0.3293	0.0249
SR	Correlation	-0.6831	-0.9981	1.0000	-0.4976	-0.0908	-0.1158	-0.2656
	P Value	<0.0000	<0.0000		<0.0000	0.4548	0.3397	0.0263
LR	Correlation	0.4028	0.5000	-0.4976	1.0000	0.0026	0.0327	0.1287
	P Value	0.0005	<0.0000	<0.0000		0.9832	0.7879	0.2883
IR	Correlation	0.1317	0.0733	-0.0908	0.0026	1.0000	0.4281	0.2076
	P Value	0.2772	0.5464	0.4548	0.9832		0.0002	0.0846
XR	Correlation	0.1973	0.1183	-0.1158	0.0327	0.4281	1.0000	0.2409
	P Value	0.1015	0.3293	0.3397	0.7879	0.0002		0.0446
SIZE	Correlation	0.4941	0.2680	-0.2656	0.1287	0.2076	0.2409	1.0000
	P Value	0.0000	0.0249	0.0263	0.2883	0.0846	0.0446	

Table 4.2: Results of First Correlation Analysis (by Researcher)

The analysis indicates the presence of a very high negative correlation, which is statistically significant, between capital management risk (CMR) and solvency risk (SR). This points to multicollinearity between the two variables. This must, however, be verified through formal multicollinearity tests.

4.5 Multicollinearity Tests

Multicollinearity means the presence a linear relationship of an exact nature between two variables (Gujarati & Porter, 2009). The existence of exact linear relationships between two variables means that the two variables are actually one variable from the perspective of the model. The table below shows results for three multicollinearity tests:

	VIF	TOL	Klein
CMR	304.4588	0.0033	1
SR	303.2815	0.0033	1
LR	1.3363	0.7483	0
IR	1.4070	0.7108	0
XR	1.3048	0.7664	0
SIZE	1.1526	0.8676	0

Table 4.3: Results of First Multicollinearity Test (by Researcher)

The Variance Inflating Factor (VIF) levels for CMR and SR are higher than the cut-off value of 10, which indicates a high multicollinearity between the two variables. The tolerance (TOL), which is the inverse of VIF (Gujarati & Porter, 2009), is also close to zero, indicating high multicollinearity. Klein's test for multicollinearity also indicates a value of 1, which means that multicollinearity between the two variables has been detected.

These results confirm the results of the correlation analysis. Such high multicollinearity means that both variables do not contribute unique explanatory value to the regression model and use of both could affect the results. As such, one of the variables should be dropped. The researcher opted to drop CMR so as to retain SR, which is used more often in literature and therefore helps with comparability of the study to other studies.

A second multicollinearity test was carried out after CMR was dropped as an independent variable. The table below shows results for the three multicollinearity tests:

	VIF	TOL	Klein
SR	1.4134	0.7075	0
LR	1.3324	0.7505	0
IR	1.2445	0.8036	0
XR	1.2642	0.7910	0
SIZE	1.1445	0.8737	0

Table 4.4: Results of Second Multicollinearity Test (by Researcher)

The results indicate that the VIF is below 10, the TOL is high, and Klein's test value is 0, meaning that multicollinearity is not detected for any of the remaining variables. The variables can therefore be used in regression without affecting the results.

4.6 Panel Unit Root Test

A unit root refers to a situation where the root of the algebraic equation of a process evaluates to one. If a series has a unit root, this causes the series to be non-stationary, which violates the stationarity assumption for time series estimation (Gujarati & Porter, 2009). Several unit root tests have been proposed for panel data, among them the Levin-Lin-Chu test, which was used in this study. The test's null hypothesis is the data has a unit root and is therefore not stationary (Gujarati & Porter, 2009). Below is a table showing test results.

Levin-Lin-Chu Unit-Root Test	
Data	cbind(ROA, SR, LR, IR, XR, SIZE)
test statistic	z = -4.0808, p-value = 2.244e-05
alternative hypothesis	Stationarity

Table 4.5: Results of the Levin-Lin-Chu Panel Unit Root Test (by Researcher)

The test's p-value is lower than 0.05, which means that the test statistic is statistically significant. This means that the data is stationary and can be used in regression.

4.7 Regression Results

The study conducted a multiple regression of the 5 explanatory variables retained after multicollinearity tests on the dependent variable represented by ROA. Since the dataset is a panel, estimates for three models namely the pooled OLS, random effects and fixed effects models were done and diagnostic tests used in choosing the best model.

4.7.1 Pooled OLS Regression

The pooled OLS regression model ignores the panel nature of data and pools all observations into one long series of observations. The model is appropriate when there are no significant individual effects in the data. The table below outlines the results of the Pooled OLS Regression.

Pooled OLS Model					
Balanced Panel: n = 7, T = 10, N = 70					
	Coefficient	**Std. Error**	**t-statistic**	**p-value**	**Significance**
(Intercept)	0.2058	0.0460	4.4698	3.27E-05	***
SR	-0.3189	0.0560	-5.6895	3.42E-07	***
LR	0.0022	0.0024	0.9244	0.3588	
IR	-0.0167	0.1464	-0.1140	0.9096	
XR	0.0064	0.0103	0.6254	0.5339	
SIZE	0.3494	0.0929	3.7599	0.0004	***
Other Model Information					
Significance Codes:		‘***’ 0.001	‘**’ 0.01	‘*’ 0.05	‘.’ 0.1
Total Sum of Squares:		2.8331			
Residual Sum of Squares:		1.1898			
R-Squared:		0.5800			
Adj. R-Squared:		0.5472			
F-statistic:		17.6776 on 5 and 64 DF, p-value: 5.7771e-11			

Table 4.6: Results of the Pooled OLS Regression Model (by Researcher)

The results above indicate that solvency risk has a significant negative effect on FP. Size of the firm has a significant positive effect on FP. The other financial risk proxies have no significant effect on FP, with liquidity risk and exchange rate risk having an insignificant positive effect and interest rate risk having an insignificant negative effect on FP. The model's adjusted R squared is 0.5472, which means that the model can predict 54.72% of the variation in ROA. The model's ANOVA results in an F–statistic of 17.6776, which is significant, with a p-value of 5.7771e-11, which is below 0.05 and close to zero. This model is, however, only the true model if there are no significant individual effects in the data, which are checked using the Breusch-Pagan Lagrange Multiplier test.

4.7.2 Breusch-Pagan Lagrange Multiplier Test

The Breusch-Pagan Lagrange Multiplier test is a test for significance of the individual effects in the data. The test checks whether the variance of the model's errors depends on the model's independent variables, that is whether the correlation between the model's errors and its independent variables is statistically significant (Katchova, 2015). If the correlation is significant, the Pooled OLS model will be inconsistent, so one should opt for the random effects model. The test's null hypothesis is that the linear relationship between the model's errors and its independent variables is not significant and so no presence of individual effects. Below are the results of the Breusch-Pagan LM test.

Lagrange Multiplier Test (Honda) for balanced panels	
Data	ROA ~ SR + LR + IR + XR + SIZE
test statistic	normal = 10.365, p-value < 2.2e-16
alternative hypothesis	significant effects

Table 4.7: Results of the Breusch-Pagan LM Test (by Researcher)

The test has a p-value that is below 0.05, indicating that the test statistic is significant. This shows that there are significant individual effects in the data. The random effects model should therefore be estimated.

4.7.3 Random Effects Model

The random effects model is a transformed model that assumes that the data contains individual effects that vary randomly over time, and therefore these are included as part of the error term. The error term is, therefore, a composite error term made up of the random individual effects and the idiosyncratic error (Katchova, 2015). The transformation used in this study is the Swamy-Arora transformation (Croissant & Millo, 2008). This transformation uses the Generalised Least Squares (GLS) approach which takes into account the complex error term correlation structure (Gujarati & Porter, 2009). The table below outlines the results of the random effects model.

One Way (Individual) Random Effects Model (Swamy-Arora Transformation)					
Balanced Panel: n = 7, T = 10, N = 70					
	Coefficient	**Std. Error**	**z-statistic**	**p-value**	**Significance**
(Intercept)	0.3289	0.0533	6.1673	6.94E-10	***
SR	-0.5529	0.0438	-12.6347	< 2.2e-16	***
LR	0.0022	0.0019	1.1795	0.2382	
IR	-0.0372	0.0756	-0.4921	0.6226	
XR	0.0085	0.0053	1.6013	0.1093	
SIZE	0.2217	0.0495	4.4764	7.59E-06	***
Other Model Information					
Significance Codes:	'***' 0.001	'**' 0.01	'*' 0.05	'.' 0.1	
Total Sum of Squares:	1.5934				
Residual Sum of Squares:	0.3163				
R-Squared:	0.8015				
Adj. R-Squared:	0.7860				
Chi Square:	258.391 on 5 Degrees of Freedom, p-value: < 2.22e-16				
Effects		**var**	**std.dev**	**share**	
Idiosyncratic		0.0046	0.0678	0.267	
Individual		0.0126	0.1123	0.733	
theta/lambda: **0.8124**					

Table 4.8: Results of the Random Effects Regression Model (by Researcher)

Similar to the Pooled OLS model, the random effects model indicates that solvency risk has a significant negative effect on FP, while size of the firm has a significant positive effect. Liquidity risk and exchange rate risk have an insignificant positive effect and interest rate risk has an insignificant negative effect. The model's adjusted R squared is, however, much higher than that of the Pooled OLS, standing at 0.7860, which means that the model can predict 78.6% of the variation in ROA. The model, being a GLS estimation, uses chi-square deviance to test for model significance. The chi-square statistic is 258.391 on 5 degrees of freedom, which is significant, with a p-value of < 2.22e-16, which is below

0.05 and close to zero. The random effects model also supplies information on the extent to which individual effects account for variation in the data. This is represented by theta, also known as lambda (Katchova, 2015), which for this model is 0.8124, meaning that 81.24% of the variation is accounted for by individual effects.

The model, however, can only be confirmed as the true model after the Hausman test which compares the results of the random effects and those of the fixed effects model. One must, therefore, estimate the fixed effects model before carrying out the Hausman test.

4.7.4 Fixed Effects Model

The fixed effects model assumes that the data contains individual effects that are fixed for each individual over time. The estimator performs a time-demeaning for all variables, then performs an OLS estimation. Each individual has its own intercept, so the final model does not have a y intercept. The table below shows the results of the fixed effects model:

One Way (Individual) Fixed Effects Model (Within Estimator)					
Balanced Panel: n = 7, T = 10, N = 70					
	Coefficient	**Std. Error**	**t-statistic**	**p-value**	**Significance**
SR	-0.5781	0.0435	-13.2818	< 2.2e-16	***
LR	0.0026	0.0019	1.3966	0.1679	
IR	-0.0402	0.0730	-0.5508	0.5839	
XR	0.0085	0.0051	1.6622	0.1019	
SIZE	0.2138	0.0479	4.4657	3.74E-05	***
Other Model Information					
Significance:	'***' 0.001	'**' 0.01	'*' 0.05	'.' 0.1	
Total Sum of Squares:	1.5482				
Residual Sum of Squares:	0.2669				
R-Squared:	0.8276				
Adj. R-Squared:	0.7949				
F-statistic:	55.6948 on 5 and 58 DF, p-value: < 2.22e-16				

Table 4.9: Results of the Fixed Effects Regression Model (by Researcher)

Similar to the results of the Pooled OLS model and the random effects model, the fixed effects model indicates that solvency risk has a significant negative effect on FP, while size of the firm has a significant positive effect. Liquidity risk and exchange rate risk also have an insignificant positive effect and interest rate risk has an insignificant negative effect. The model's adjusted R squared is, higher than both Pooled OLS and the random effects model, standing at 0.7949, which means that the model can predict 79.49% of the variation in ROA. The model's ANOVA has an F-statistic of 55.6948, which is significant, with a p-value of < 2.22e-16, which is below 0.05 and close to zero.

In order to decide on the better model between the fixed effects and random effects model, one must carry out a Hausman test.

4.7.5 Hausman Test

The Hausman test evaluates the correlation between the individual effects and the independent variables. If the correlation is significant, then one of the models between the fixed effects model and the random effects model will be inconsistent, in which case one should opt for the fixed effects model since it is always consistent. If not, then both models are consistent, in which case one should opt for the random effects model which is fully efficient when it is also consistent (Katchova, 2015). Below are the results of the test.

Hausman Test	
Data	ROA ~ SR + LR + IR + XR + SIZE
test statistic	chisq = 9.3523, df = 5, p-value = 0.09581
alternative hypothesis	one model is inconsistent

Table 4.10: Results of the Hausman Test (by Researcher)

The test's p-value is higher than 0.05, so the test statistic is statistically insignificant, so both models are consistent. This means that we should opt for the random effects model.

4.8 Diagnostic Tests on the Residuals

Residuals are the differences between the actual values and estimated values of the predicted variable (Gujarati & Porter, 2009). These can provide an indication on the accuracy of the model. A cross-sectional dependence test, serial correlation test and normality test were conducted on the residuals of the random effects model with the aim of testing for the accuracy of the final model and the accuracy of the tests used in arriving at the final model.

4.8.1 Cross-Sectional Dependence Test

Cross-sectional dependence is a situation where error term values from one individual depend on error term values of another individual (Basak & Das, 2018). Cross-sectional dependence of the error term has been noted to cause inflation of model significance tests and instability of the Hausman test (Basak & Das, 2018). As such, the Pesaran cross-sectional dependence (CD) test was done. The test has a null hypothesis of no cross-sectional dependence. The table below shows the test results.

Pesaran Cross-Sectional Dependence Test	
Data	ROA ~ SR + LR + IR + XR + SIZE
test statistic	z = -1.2462, p-value = 0.2127
alternative hypothesis	cross-sectional dependence

Table 4.11: Results of the Pesaran Cross-Sectional Dependence Test (by Researcher)

The test's p-value is above 0.05, which means that the test statistic is not significant, indicating that there is no cross-sectional dependence. The model's chi-square statistic and the Hausman test can therefore be relied upon.

4.8.2 Serial Correlation Test

Serial correlation is the existence of lag correlations of a series with itself. Absence of serial correlation in the residuals is a key assumptions of linear models (Gujarati & Porter, 2009). Serial correlation in a model's residuals indicates that the model has not attained minimum variance, and is therefore not optimal (Gujarati & Porter, 2009). Serial correlation can be tested using the Breusch-Godfrey panel data test for serial correlation, whose null hypothesis is that there is no serial correlation. The table below shows the test results.

Breusch-Godfrey Serial Correlation Test	
Data	ROA ~ SR + LR + IR + XR + SIZE
test statistic	chisq = 9.2649, df = 10, p-value = 0.5072
alternative hypothesis	serial correlation in idiosyncratic errors

Table 4.12: Results of the Breusch-Godfrey Serial Correlation Test (by Researcher)

The test's p-value is above 0.05, which means that the test statistic is insignificant, indicating that there is no serial correlation in the residuals. The model has therefore attained minimum variance and is optimal.

4.8.3 Normality Test

Normality of the residuals refers to the distribution of the residuals conforming to the bell shape curve of the normal distribution. Non-normally distributed errors would indicate that

the model's true variance has been underestimated (Gujarati & Porter, 2009). The plot below can be used to visualise the distribution of the residuals.

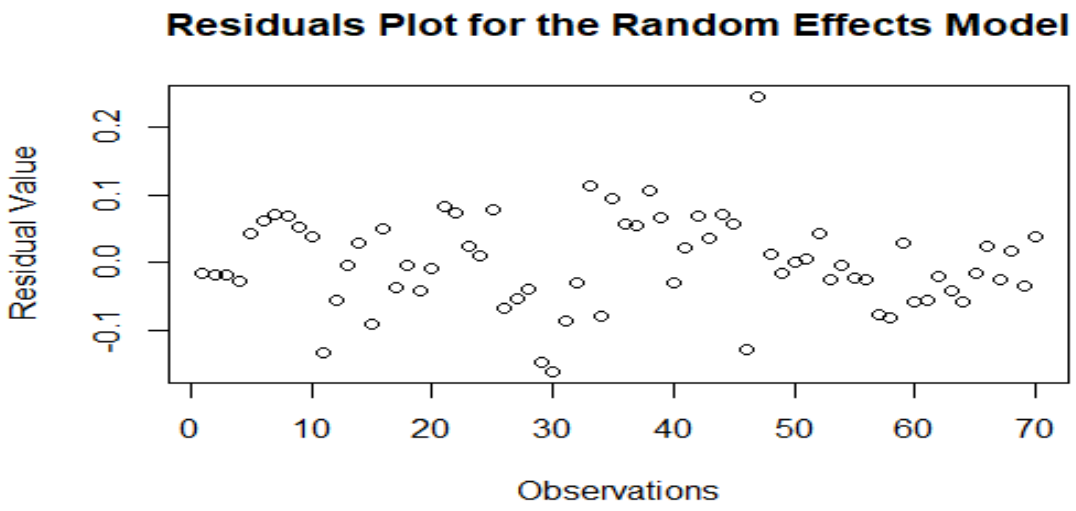

Figure 4.1: Plot of the Residuals of the Random Effects Model (by Researcher)

The plot shows that the residual values are randomly scattered around zero. However, a formal test must be carried out in order to confirm normality. The Shapiro-Wilk test can be used to test for normality. The test's null hypothesis is that the data is normally distributed. The table below shows the test results.

Shapiro-Wilk Normality Test on Residuals	
Data	summary(random)$residuals
test statistic	W = 0.97189, p-value = 0.1165
alternative hypothesis	residuals not normally distributed

Table 4.13: Results of the Shapiro-Wilk Normality Test (by Researcher)

The test's p-value is above 0.05, which means that the test statistic is insignificant, indicating that the residuals are normally distributed. The model's variance has therefore been correctly estimated.

4.9 Interpretation of the Findings

Correlation analysis for the variables uncovered the presence of very high correlation between capital management risk (CMR) and solvency risk (SR). There was also moderately high correlation between the other independent variables. Tests detected multicollinearity between that the two variables. As such, CMR was dropped from the analysis. A second multicollinearity test conducted after CMR was dropped did not detect any multicollinearity between the remaining variables, despite the existence of moderately high correlation between them. The variables therefore contributed unique explanatory value to the model. Below is a table of the correlation analysis for the remaining variables.

		ROA	SR	LR	IR	XR	SIZE
ROA	Correlation	1.0000	-0.6831	0.4028	0.1317	0.1973	0.4941
	P Value		<0.0000	0.0005	0.2772	0.1015	<0.0000
SR	Correlation	-0.6831	1.0000	-0.4976	-0.0908	-0.1158	-0.2656
	P Value	<0.0000		<0.0000	0.4548	0.3397	0.0263
LR	Correlation	0.4028	-0.4976	1.0000	0.0026	0.0327	0.1287
	P Value	0.0005	<0.0000		0.9832	0.7879	0.2883
IR	Correlation	0.1317	-0.0908	0.0026	1.0000	0.4281	0.2076
	P Value	0.2772	0.4548	0.9832		0.0002	0.0846
XR	Correlation	0.1973	-0.1158	0.0327	0.4281	1.0000	0.2409
	P Value	0.1015	0.3397	0.7879	0.0002		0.0446
SIZE	Correlation	0.4941	-0.2656	0.1287	0.2076	0.2409	1.0000
	P Value	0.0000	0.0263	0.2883	0.0846	0.0446	

Table 4.14: Results of Second Correlation Analysis (by Researcher)

Regression analysis was conducted using three models namely the pooled OLS, random effects and fixed effects models. All three models were significant. However, both the random effects and fixed effects models had a much higher adjusted R squared of 0.7860 and 0.7949 respectively as compared to that of the pooled OLS of 0.5472. This is a pointer to individual effects in the data. This was confirmed by the Breusch-Pagan LM test which

was significant, indicating existence of significant individual effects. The Hausman test was, however, insignificant, which indicated that both models were consistent. The random effects model was therefore selected as the final model since it is the most efficient model as long as it is also consistent. The final regression model is shown below:

ROA = 0.3289 – 0.5529SR + 0.0022LR – 0.0372IR + 0.0085XR + 0.2217SIZE.

This was a regression model arrived at using generalised least squares (GLS) estimation. The model's chi-square statistic was 258.391 on 5 degrees of freedom, and the p-value was < 2.22e-16, which is highly significant. The adjusted R squared was 0.7860, indicating that the model is able to account for 78.6% of the variation in the dependent variable.

The regression model indicates that financial risk has a significantly negative effect on FP in the manufacturing sector. Solvency risk (SR) has the highest effect, and as per the model results, every unit increase in SR causes a 55.29% proportional decrease in FP. These results agree with the results of Kubai (2016) who also noted a significant negative relationship between the variables.

The other three proxies of financial risk namely liquidity risk (LR), interest rate risk (IR) and exchange rate risk (XR) have insignificant effects on FP, causing a 0.22%, -3.72% and 0.85% proportional change respectively. For liquidity, the results are in line with findings by Njenga (2014) who also found no significant relationship, but contradict results by Muriithi (2016) who noted a significant negative relationship and both Kubai (2016) and Audax (2018) who noted a significant positive relationship.

Insignificance of interest rate risk may stem from the fact that manufacturing companies have major investments in assets that can be used as collateral, therefore allowing them to

borrow long-term, thereby avoiding the negative effect of short term fluctuations in interest rates. The other reason could be that interest rates are regulated by the central bank and do not vary too much, plus the recent capping of interest rates that has stabilised them and prevented fluctuations. Exchange rate risk's insignificant effect on performance could be a result of use of hedging strategies such as forwards, which some researchers noted a majority of companies in the manufacturing sector to be using (Wanyama, 2016).

The final model also indicates that size has a significant positive effect on FP. Every increase in size by one unit causes a proportional 22.17% increase in ROA. This is in line with findings by Audax (2018) and Muriithi (2016), and is attributed to the positive influence of economies of scale.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter outlines the study's summary, the conclusions of the study arrived at after analysis, policy recommendations based on study findings, the study's limitations and recommendations to researchers for areas of further study.

5.2 Summary

This study set out to determine the relationship between financial risk and FP of firms in the manufacturing and allied sector of the NSE. Literature on the topic was reviewed and four key gaps identified namely limited research in non-financial industries, few studies on financial risk in manufacturing, use of few financial risk proxies and ignoring of individual effects in the regression models. The study collected and analysed financial data for 10 years from 2009 to 2018 from annual financial statements of 7 firms in the manufacturing and allied sector of the NSE and from the CBK's website.

Three regression models namely the Pooled OLS, the fixed effects model and the random effects model were estimated, after which the Breusch-Pagan LM test and the Hausman test justified the selection of the random effects model as the true model for the study. Results from the selected model, random effects model, indicate that solvency risk has a significant negative relationship with FP, while size of the firm has a significant positive relationship with FP. Liquidity risk, interest rate risk and exchange rate risk had insignificant relationships with financial risk.

The model's chi-square deviance test resulted in a chi-square statistic of 258.391 with a p-value of < 2.22e-16, which is an indication that the model is significant. The final regression equation established after analysis is ROA = 0.3289 – 0.5529SR + 0.0022LR – 0.0372IR + 0.0085XR + 0.2217SIZE. The model coefficients shows that solvency risk and firm size have the largest effect on FP levels, a fact that is confirmed by the high significance level of these two variables.

5.3 Conclusion

From the final regression model, the study concludes that financial risk has a negative effect on FP. Solvency risk, represented by the total debt to total assets ratio, was the significant risk metric. This means that increase in debt levels has a negatively affects FP of manufacturing entities on the NSE. This effect can be attributed to high borrowing costs. Liquidity risk, interest rate risk and exchange rate risk have no significant effect on the FP. However, size of the firm, counteracts the negative effect of financial risk by having a positive effect on FP, an effect which is attributed to economies of scale.

5.4 Policy Recommendations

The researcher recommends that manufacturing entities should consider having optimal borrowing levels that do not negatively affect FP. This can be arrived at by considering increased use of equity as a source of funding, either through rights issues to existing members or clawing back a larger portion of profits made.

The researcher also recommends that manufacturing entities should consider expansion, where feasible, as not only a strategy to increase market share but also a profit maximisation strategy. This is because the study has noted that firm size positively affects

FP. Other strategies proposed include vertical and horizontal mergers in order to benefit from this positive effect.

Finally, the researcher recommends that government should encourage growth of manufacturing entities through targeted policies such as tax incentives on investments in assets and lower taxes on reinvested profits. This will create a multiplier effect where companies take advantage of tax incentives to reinvest profits for purchase of assets, thereby increasing profitability and setting in place a virtuous cycle.

5.5 Limitations of the Study

The accuracy of study results is limited to the accuracy of reported financial statement information of the firms studied and also the accuracy of interest rate and exchange rate information extracted from the CBK's website.

The study period, despite being 10 years, is also not long enough to establish a long-term relationship between the variables. This is because companies and the economies in which they operate change over time, and ten years of data may exclude effects that persist over a much longer term.

The study also focused only on the listed manufacturing firms, which are usually more profitable, a key criterion for listing, and are usually larger in terms of total assets. The results of the study may, therefore, not be applicable to non-listed firms, especially Small and Medium Enterprises (SMEs), which have a very different capital structure.

5.6 Areas of Further Research

The study established that solvency risk significantly affects FP, with other risk proxies having an insignificant effect. This analysis, however, has not explored interaction effects between financial risk proxies and firm size, so as to determine whether firm size has a moderating effect on financial risk levels of entities in the manufacturing sector. This would be an interesting area for researchers studying financial risk.

The model specified in the study also focuses on the long-run relationship between the variables. An interesting analysis would be one where the researcher estimates a dynamic model using the Generalised Method of Moments where dependent variable lags are used as independent variables. This would help establish the short-run effect of financial risk on FP, with prior year results used as a control variable.

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APPENDICES

Appendix I: List of Companies studied

No.	Name	Code	Included in the Study / Dropped from the Study
1	British American Tobacco Kenya PLC	BATK	Included
2	BOC Kenya PLC	BOCK	Included
3	Carbacid Investments PLC	CARB	Included
4	East African Breweries Limited	EABL	Included
5	Eveready	EVER	Dropped*
6	Flame Tree Group	FTGL	Dropped*
7	Kenya Orchards Limited	KOCL	Included
8	Mumias Sugar Company Limited	MSCL	Included
9	Unga Group PLC	UNGL	Included

Key

** See Section 4.2 for details*

Appendix II: Summary of Data Collected

CO. INFO		RATIOS CALCULATED					
Company	**Year**	**ROA**	**SR**	**LR**	**IR**	**XR**	**SIZE**
BATK	2018	0.2303	0.4745	1.6657	-0.0443	0.8228	0.0041
BATK	2017	0.1889	0.5578	1.3239	-0.1754	0.3477	-0.0367
BATK	2016	0.2311	0.5198	1.4246	0.0259	0.4444	0.0181
BATK	2015	0.2766	0.5079	1.5043	-0.0217	4.8474	0.0001
BATK	2014	0.2366	0.5482	1.2580	-0.0459	1.3822	0.0928
BATK	2013	0.2271	0.5382	1.2809	-0.1191	1.2124	0.1113
BATK	2012	0.2230	0.3784	1.1913	0.3056	1.1718	0.0821
BATK	2011	0.2293	0.5255	1.3217	0.0481	6.1642	0.1980
BATK	2010	0.1594	0.5387	1.1704	-0.0301	1.9837	0.0651
BATK	2009	0.1423	0.5502	0.9123	0.0562	1.9001	0.0239
BOCK	2018	0.0521	0.2634	1.9799	-0.0443	0.8228	-0.0324
BOCK	2017	0.0302	0.2598	2.0060	-0.1754	0.3477	-0.0041
BOCK	2016	0.0664	0.2341	2.2753	0.0259	0.4444	-0.0407
BOCK	2015	0.0729	0.2600	2.0238	-0.0217	4.8474	0.0238
BOCK	2014	0.1069	0.2353	2.0204	-0.0459	1.3822	-0.1494
BOCK	2013	0.0830	0.2030	2.1301	-0.1191	1.2124	0.2971
BOCK	2012	0.1066	0.2710	1.9453	0.3056	1.1718	0.1014
BOCK	2011	0.0681	0.2703	1.7595	0.0481	6.1642	-0.1531
BOCK	2010	0.0339	0.2478	2.4294	-0.0301	1.9837	0.0088
BOCK	2009	0.0690	0.2321	2.5542	0.0562	1.9001	0.4938
CARB	2018	0.1492	0.0218	25.7074	-0.0370	1.2441	0.0487
CARB	2017	0.1522	0.0339	26.6873	-0.2022	0.9935	0.0025
CARB	2016	0.1405	0.1139	6.0214	0.1124	1.2290	-0.0816
CARB	2015	0.2262	0.2243	2.9900	-0.0645	4.6160	0.5077
CARB	2014	0.2417	0.0240	25.1732	-0.0698	0.8166	0.0719
CARB	2013	0.4374	0.0278	24.6392	-0.0267	1.1585	0.3052
CARB	2012	0.3402	0.0294	19.6441	0.3358	6.0469	0.1007
CARB	2011	0.3390	0.0320	15.5878	-0.0500	3.3260	0.1178
CARB	2010	0.3547	0.0470	9.9147	0.0113	2.1572	0.1131
CARB	2009	0.4972	0.0266	44.9177	0.0672	3.6983	0.2675
EABL	2018	0.0308	0.7565	0.3427	-0.0580	1.2490	0.0982
EABL	2017	0.1653	0.6678	0.6681	-0.1721	0.9839	0.0423
EABL	2016	0.1744	0.7239	0.4638	0.0933	1.2624	0.0704
EABL	2015	0.1470	0.7084	0.8077	-0.0593	3.9429	0.0181
EABL	2014	0.1322	0.7710	0.9042	-0.0825	0.7684	0.2128
EABL	2013	0.1050	0.7792	0.8304	0.0145	1.1260	-0.0601

EABL	2012	0.1650	0.7569	0.9618	0.2988	5.9337	0.8020
EABL	2011	0.3056	0.4910	1.0278	-0.0518	2.6466	-0.0313
EABL	2010	0.2685	0.4753	1.0887	0.0194	1.6915	0.4612
EABL	2009	0.2981	0.1108	2.7837	0.0657	4.7479	-0.1876
KOCL	2018	0.0776	0.7884	2.1138	-0.0443	0.8228	0.0564
KOCL	2017	0.0530	0.8577	1.7132	-0.1754	0.3477	0.1934
KOCL	2016	0.0422	0.8909	2.0214	0.0259	0.4444	0.1253
KOCL	2015	0.3673	0.9235	2.0757	-0.0217	4.8474	0.4500
KOCL	2014	-0.5032	1.4549	1.7738	-0.0459	1.3822	-0.3409
KOCL	2013	0.0342	0.9649	1.9261	-0.1191	1.2124	0.0238
KOCL	2012	0.0036	0.9982	1.7286	0.3056	1.1718	-0.0206
KOCL	2011	0.0101	1.0010	1.5433	0.0481	6.1642	-0.0569
KOCL	2010	0.0075	1.0097	1.2914	-0.0301	1.9837	-0.0550
KOCL	2009	-0.0365	1.0157	1.1480	0.0562	1.9001	-0.0036
MSCL	2018	-0.9622	1.9142	0.0290	-0.0580	1.2490	-0.4259
MSCL	2017	-0.2812	0.9686	0.1093	-0.1721	0.9839	-0.1066
MSCL	2016	-0.1775	0.7179	0.1807	0.0933	1.2624	0.2645
MSCL	2015	-0.2258	0.7049	0.1879	-0.0593	3.9429	-0.1357
MSCL	2014	-0.1149	0.5484	0.4093	-0.0825	0.7684	-0.1416
MSCL	2013	-0.0615	0.5105	0.8396	0.0145	1.1260	-0.0092
MSCL	2012	0.0735	0.4261	1.2643	0.2988	5.9337	0.1674
MSCL	2011	0.0834	0.3754	2.1986	-0.0518	2.6466	0.2344
MSCL	2010	0.0858	0.4000	2.0021	0.0194	1.6915	0.0480
MSCL	2009	0.0921	0.4255	1.3594	0.0657	4.7479	0.2109
UNGL	2018	0.0789	0.4353	2.1418	-0.0580	1.2490	0.0493
UNGL	2017	-0.0007	0.4807	1.6579	-0.1721	0.9839	0.1241
UNGL	2016	0.0609	0.3890	2.2986	0.0933	1.2624	-0.0334
UNGL	2015	0.0720	0.3841	2.3685	-0.0593	3.9429	0.0731
UNGL	2014	0.0591	0.4160	2.3322	-0.0825	0.7684	-0.0101
UNGL	2013	0.0417	0.4708	1.8427	0.0145	1.1260	0.2366
UNGL	2012	0.0544	0.3800	2.3495	0.2988	5.9337	0.1142
UNGL	2011	0.0773	0.3440	2.5245	-0.0518	2.6466	0.1198
UNGL	2010	0.0466	0.3356	2.5438	0.0194	1.6915	-0.0944
UNGL	2009	0.0333	0.4347	1.8383	0.0657	4.7479	0.1560