BANK PERFORMANCE AND INSURANCE UPTAKE NEXUS: An Empirical Analysis of Kenya

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DECLARATION

This research paper is my original work and has not been presented for a degree award in any other university or any institution of higher learning.

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Declaration by Supervisor:

This research paper has been presented for examination with my approval as university supervisor.

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Date 3/11/2021

DR. B. ONKOBA ONGERI

DEDICATION

I dedicate this work to my dear husband Samuel and my beloved son Fidel for their invaluable support in my studies. I thank them for giving me the courage and determination to wither the storms of the course. God bless you.

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LIST OF ABBREVIATIONS

ADF Test-Augmented Dickey Fuller Test

AKI-Association of Kenyan Insurers

CBK-Central Bank of Kenya

DFTest-Dickey Fuller Test

ECM-Error correction model

IRA-Insurance Regulatory Authority

KBA-Kenya Bankers Association

KDIC-Kenya Deposit Insurance Corporation

KNBS-Kenya National Bureau of Statistics

ROA-Return on assets

ROE-Return on equity

VAR-Vector Autoregressive

VECM-Vector error correction model

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ABSTRACT

Banks and insurance companies are part of a country's financial system; they both provide intermediation services by converting savings into investment funds. By this, they are expected to be linked. However, few papers have ventured into this especially in the continent. This study therefore, sought to fill this by investigating causal relationship between bank performance and insurance uptake using quantitative approach without pre-determined causal direction. This was separated into the relationship between banks' activities and life insurance uptake as well as that between banks and nonlife insurance uptake. Consequently, life insurance density and nonlife insurance density were the two measures of insurance uptake while; banks performance was gauged through ROA, ROE and private credit density. Analyses relied on time series data obtained mainly from the annual statistical abstracts for the period 1974-2019. These were done under VAR model and VECM. Granger causality tests were used to determine the causal direction. Insurance uptake was found largely to have no causal relationship with bank performance in the long run. This was however not the case in the short run, where bank performance was found to granger cause insurance uptake in most of its variables. With this in mind, both insurers and the banking sector stand to benefit from measures to strengthen the banking sector, such should therefore be encouraged.

Key Words: Bank performance, Bancassurance, Credit risk and Financial intermediation.

CHAPTER ONE

INTRODUCTION

1.0. Background

The importance of banks to a modern economy cannot be over-emphasized. These financial intermediaries play a key role in connecting lenders and borrowers channelling funds to various economic activities which leads to growth (Azman-saini & Smith, 2010). In addition to their intermediation roles, banks also stimulate growth by providing safe payment systems and means for governments to control money supply through monetary policies. Banks are even more important in developing countries where other financial institutions are less developed and inaccessible to most borrowers (Greuning & Bratanovic, 2003). In such countries, their health directly determines that of the entire financial sector such that their mass failure is likely to lead to economic downturn. Studies have already linked mass bank failures to economic crisis (Bernanke, 1983).

Though slow to develop compared to the banking subsector, insurance industry is as important in a country's financial sector. A well-developed insurance subsector is as critical to a country's economic growth as other financial institutions (Levine, 2000; Cristea, Marcu & Cârstina, 2014; Lester, 2014; Weistbart, 2018), more so for developing countries like Kenya (Han et al. 2010). According to Ćurak, Lončar and Poposki (2009), insurance contribution to growth happens through the following channel. First as financial intermediaries, insurance companies (especially life insurance companies) are able to mobilise funds from many small savers and use the money to either directly fund big development projects or avail the funds to other big investors through their actions in the capital markets. Second, insurance companies offer risk transfer mechanisms which promote entrepreneurship, encourage risk taking, and ensures business continuation and speedy recovery in cases of losses from insured events. Transfer of risk also encourages innovation in risky, less desirable but economically beneficial enterprise ventures (Haiss & Sumegi, 2008; Webb, Grace & Skipper, 2002). Finally, insurance enhances the development of other institutions by offering them protection from credit risks allowing them to expand credit to productive activities. Similar arguments to the above are found in Skipper (1997).

By virtue of being in the same industry, banks and insurance companies are expected to be connected through their performance. They offer products which (in a way) compete as well as complement each other (Azman-Saini & Smith, 2011). From the insurance side, a life insurance policy act as a substitute which competes with other saving services offered by banks (Chen, Lee & Lee, 2012). On the other hand, a property insurance policy strengthens the use of the property as collateral for a loan thus complementing the loan (Azman-Saini & Smoth, 2011; Webb, Grace, Skipper, 2002). Banks loans complement insurance as well and are the main justification for credit linked insurance common in agriculture insurance. Sarris (2014) found insurance to be less desirable if not linked with credit or any investment mechanism.

Consequently, the relationship between banks and insurance companies in a country will depend on the products offered in the two subsectors and whether they compete or complement. A financial sector dominated by competition between the products of the two subsectors will exhibit a negative relationship between banks performance and insurance uptake while, an industry where products complement each other will exhibit a positive relationship. No relationship is expected if the two subsector's products are not related. Besides product relatedness, banks relation with insurers have also been argued to depend on other factors. Webb, Grace, and Skipper (2002) associated this to a country's levels of income and its citizens' risk appetite. They noted high substitutability between banks' saving accounts and life insurance in low income high risk tolerant population thus an expected negative relationship between banks and insurance companies in low income countries.

In addition to the above highlighted substitutability and complementarity between the two, recent development in financial sector has made such relationship more explicit. Bank nowadays are allowed in most countries to directly collaborate and compete with insurers in a move to offer value to their clients and improve their performance (Gonulal, Goulder & Lester, 2012). Collaboration mostly happens where one sells the other's product for commission. One case with increasing popularity is 'bancassurance' where banks sell insurance products for commission (Artikis, Mutenga & Staikouras, 2008; Gonulal, Goulder & Lester, 2012). There are also cases where insurance companies promote and facilitate processing of loans from certain banks through an insurance financing deal and earn commission in return. Besides collaborating, the two institution now compete directly in certain markets. In such markets, banks have expanded into insurance by operating insurance subsidiaries, generating and marketing their own insurance products or engaging in both. Insurance companies have as well ventured into banks' traditional market by for instant, marketing their own loan products directly or through their subsidiaries (Kist, 2001; Yuan, 2017). The US is a good case where bank face stiff competition from other financial institution which now also provide traditional commercial banking services (Markham & Broome, 2000; Yuan, 2017).

It is evident from the above that banks are expected to have a connection with insurance companies. This relationship remains intuitively and theoretically ambiguous hence its solution can only be found empirically. However, research in this area remains largely underdeveloped. It is only recently that researchers started showing interest with few papers coming in various part of the world (Sawadogo, 2020). First contributors in the area are found in the expansive finance-growth literature which generally aim to establish a link between a country's financial sector and economic growth. Their contribution (though incidental) are a consequence of their separation of financial sector into its components (i.e. banking, insurance subsectors, stock market, etc). Such studies include Adams et al. (2009); Pradhan, Bahmani and Kiran (2014); Kaushal and Ghosh (2017); Pradhan et al. (2017) and Pradhan et al. (2020).

Working with data from Sweden, Adams et al. (2009) found insurance activity to have a positive impact on the country's economic growth and banking sector. The same results were found by Kaushal and Ghosh (2017) in India. They found insurance development to positively affect long term development in the country's banking sector. However, no relationship was found between banks and insurance companies in the short run. Contradictory results are found in Pradhan, Bahmani and Kiran (2014); Pradhan et al. (2017) and Pradhan et al. (2020). Their evidence was more in favour of banks being beneficial to insurance companies. Pradhan et al. (2014) was for a panel of 17 G-20 members where a long run positive effect was found from banking to the insurance industry, with short run effects moving in both directions. Both Pradhan et al. (2017) and Pradhan et al. (2020) found no long run effects for a panel of 19 G-20 countries and 32 European countries respectively. In addition, both found a positive relationship to run largely from banking subsector to insurance subsector in the short run.

Besides finance-growth literature, direct studies linking banks and insurers have also emerged. A part from focusing on different population and time studies, some of these have added other factors likely to facilitate or dampen the bank-insurance linkage such as: a country's financial structure (Liu & Lee, 2019), and the extent of the country's exposure to the global market (Sawadogo, 2020). The already mentioned study by Liu and Lee (2019) found both life and non-life insurance to positively affect bank credit to the private sector in a majority of 36 countries in their sample. Their division of the sample based on financial structure revealed varying results especially in the short run making them to conclude that links between banks and insurers is country specific hence the reason for contradicting results in past literatures. While focusing on long-run effects alone, Sawadogo (2020) found bank credit to have positive long run influence on life insurance and total insurance uptake while having no impact on non-life policies. This was a panel study of 20 Sub-Saharan African (SSA) countries including Kenya which makes it the closest to our proposed study in focus and population. We deviated from it by focusing solely on Kenya. It is already argued that the differing results (in past studies) may be because of countries' diverse financial structure, stage in economic development and income levels (Liu et al. 2014; Liu & Zang, 2016; Liu & Lee, 2019) which make such results country specific (Liu & Lee, 2019). It is for this that Sawadogo's (2020) results, while informative, may not fit the Kenyan situation. We also go beyond long run effects and look at short run possibilities as well. Furthermore, we challenge the suitability of banks' private credit as a measure of performance thus in addition, uses return on assets (ROA) and return on equity (ROE), which are well established performance indicator in the finance literature.

Other studies which aimed at establishing direct link between insurance companies and banks include: Lorent (2010) and Liu et al. (2014). The former found a positive effect of private credit on life insurance density while Liu et al. (2014) found feedback positive relationship in the long run and varied relationship in the short run. Lorent (2010) was on a cross-section of 90 countries while Liu et al. (2014) based their findings on G-7 member countries.

As seen above, most of the existing papers in this area, linking bank and insurers directly, are on countries outside of Africa not to mention Kenya. What exist in Kenya are mainly studies whose conclusions create an indirect linkage between the two industries through their collaboration under bancassurance model. This may have been guided by recent support of bancassurance model in Kenya and elsewhere coupled with strong theoretically support as the most viable way to incorporate insurance in banking institutions (Artikis, Mutenga & Staikouras, 2008; Nurullah & Staikouras, 2008). Unlike the above papers, they tend to arrive at similar conclusions. In that sense, those that looked at the effect of bancassurance on bank performance mostly found positive influence (Muunda, 2013; Waweru, 2013; Mwangi, 2014) while those that investigated bancassurance effect on insurance uptake also found a positive impact (Muhoro, 2011; Ombonya, 2013; Maina, 2016; Njeri, 2017; Orora, 2018). Their problem is that they are mostly qualitative based on weak statistical analysis (if any) and ignored possible concurrent effect between the two sectors in their investigations. Also, by focusing on bancassurance, they left out a significant portion of banks and insurance companies activities making their findings pointers (at best) for this study. Insurance markets, including that of Kenya, is still dominated by non-bank agents and brokers; while a good number of banks in operation have no insurance agencies (Financial Sector Regulators Forum, 2020)[1]. Cognisant of the foregoing, our research took a broader approach to accommodate connection both through distributional channels like bancassurance and through product relatedness.

Closer study, in terms of investigating financial sector linkages but not in form of performance, is that by Lidiema (2018). This looked generally at how shocks are transmitted within the Kenyan financial sector. Using monthly data from 2004 to 2016, it found shocks from insurance uptake to affect bank loans and stock market performance. At the same time, shocks from banks were found to affect the entire financial sector performance including insurance intake.

[1] Only 26 of the 42 operating banks in 2020 offers bancassurance services (Financial Sector Regulators Forum, 2020)

1.1. **Problem Statement**

Theoretically, there is an expected linkage between players in the financial sector (Webb, Grace & Skipper, 2002; Prikazyuk & Olynik, 2017). Further, the linkage is to be more pronounced between the biggest players, this is what is expected between banks and insurance companies given their dominance in most financial systems. Arguably, the two offer related products which either compete and/or complement each other (Haiss & Sumegi, 2008, Liu et al. 2014). Loans and saving products (banks traditional services) have already been shown to compete and complement those of insurance companies. With the introduction of bancassurance, the link supposedly gets stronger. Insurance companies stand to benefit from it through increased sales while banks get more income through earned commission (Krstić, Vojvodić-Miljković & Mandić, 2011). Should this be true, then bank performance is expected to move together with insurance uptake. As discussed above, the link is yet to be fully studied.

Existing empirical literature in Kenya have looked at effects of bancassurance on bank performance (Gitau, 2013; Mwangi, 2014; Nyakomitta, 2017) and, the effect bancassurance has on insurance uptake (Ombonya, 2013; Njeri, 2017; Orora, 2018) while ignoring how bank performance directly relate with insurance uptake. This study aimed at filling this gap. Banks are only interested in bancassurance if it boosts their income, while insurance companies only use it so long as it makes them write more policies; success is not always guaranteed (Gonulal, Goulder & Lester, 2012). A win-win case is where banc-assurance accomplishes both at the same time, such that bank performance move together with uptake of insurance. Information on such movement (or lack of) is critical given bancassurance is a symbiotic financial industry innovation capable of bettering both the banking and insurance sub-sectors. Therefore, by taking note of product relatedness between insurers and bankers and the possible impact of bancassurance on either, we studied the relationship between banks performance and insurance uptake in Kenya.

1.2. **Research Questions**

To understand the relationship between Kenyan bank performance and insurance uptake, this study attempts to answer these questions:

i. Is there causality between Kenyan banks' performance and life insurance uptake?
ii. Does banks' performance relate with uptake of nonlife insurance in Kenya?

1.3. **Research Objectives**

The general objective of the study was to investigate the causal relationship between banks performance and insurance intake in Kenya.

Specifically, it aimed at achieving the following:

i. To establish causal relationship between Kenyan banks performance and uptake of life insurance.
ii. To investigate the relationship between bank performance and non-life insurance uptake in the country.

1.4. Justification

It is expected that the study's result would contribute both to existing literature on bank-insurers nexus and to policy. There is currently less interest, especially in the country, with regard to how insurance companies directly relate with banks. By examining this, this research provides answers to a question less asked and hence motivates others to study the relationship further. This is partly the reason we intended to make recommendations for further studies.

In term of policy. The results may be useful in policies meant to simultaneously regulate the sector. There is already an intentional move to consolidate the regulation of Kenya's financial sector. All five regulators frequently hold joint forums and jointly publish the Financial Sector Stability Report annually. Further, the cabinet already approved the drafted Financial Services Bill 2016 in 2017 (President, 2017)[2]. The bill aims at creating a single financial sector regulator. Such joint regulation need information on how the sectors relate which is offered here.

1.5. Organisation of the Study

The paper is organised as follows; chapter one presents the research background, research questions, objectives, and justification. Chapter two follows with a review of both theoretical and empirical literature. Chapter three gives a description of the study's methodology. Chapter four presents the findings before finishing with research conclusions and recommendations in chapter five.

[2] There are reports that the plan was put on hold in 2018 (Anyanzwa, 2019)

CHAPTER TWO

LITERATURE REVIEW

2.0. Introduction

This chapter reviews existing literature connected with the relationship between bank performance and insurance uptake. It explores the relevant theories in section 2.2, empirical papers in section 2.3, concluding with a summary of literature in section 2.4.

2.1. Theoretical Literature

This section looks at the theories that can be used to link banks and insurance companies. It gives a summary of the production theory, intermediation within banks, and the theory of consumption.

2.1.1. Theory of Production

Theory of production concerns the decision made by a firm in its production process. It explains how a firm determines the level of output and the level of inputs to use. Among the strong assumption made are that: firms exist mainly to make profit and so are profit maximisers, they are constrained in resources with alternative uses, and that every input is productive. Every firm in production uses a combination of inputs in a format determined by its available technology (Pindyck & Rubinfeld, 1995). There are numerous ways of combining inputs to produce the same level of output leading to the question of which combination to pick. The firm makes this decision by picking the combination that gives the maximum output given input costs and its available resources.

Having determined the inputs to use, the next decision is how much output to produce? Firms are profit maximisers and so will select the level of output that gives the most profit. Profit is the difference between revenues collected from output sales and costs incurred in the production process. The firm will therefore produce at the point where marginal cost equals marginal revenue.

Banks and insurance companies are faced with these decisions as well. A bank must decide on what inputs to use and their respective levels, the technology to use and the level of output to apply. Under this theory, banks and insurance companies are analysed as normal firms in operation mainly to make profit (Andries, 2009). Banks attracts deposits they use as inputs to produce loans of various types sold at different interest rates (Andries, 2009). To diversify their portfolio, banks also provide banc-assurance services by engaging in the sale of insurance services. Banc-assurance uses insurance services (from insurance firms) as its key input. Viewed as other products, a bank's level of banc-assurance services will be at the level it begets its maximum profit. Similar logic follows for insurers using banking services as input to produce insurance products.

2.1.2. Theory of Financial Intermediation (Banks as Intermediaries)

Intermediation is the linking of two parties. In discussing banks as intermediaries, distinction is made in the services they offer. The two broad functions are: brokerage services, and transformation of asset quality (Bhattacharya & Thakor, 1992; Allen & Santomero, 2001). The latter relates with their role in offering loans. In this regard, banks transform short term liabilities, in form of deposits, to long term assets in form of loans and other credit facilities (Bhattacharya & Thakor, 1992). This is what is always implied most of the time when discussing the role of banks; how such create liquidity within an economy without compromising long term investments. Through this, bank loans fund business activities including purchase of insurance products.

Turning to brokerage function. A broker is an intermediary whose role is to bring two parties with complementary needs. Theories of financial intermediation see brokers and other financial intermediaries to be results of market imperfection (Andries, 2009; Scholten & Wensveen, 2003) characterised by information asymmetry, high transactional cost, and market regulations. Information asymmetry is the most important imperfection. Banks come in to fill this information gap since their operation and experience makes them better informed than either of the parties (Scholten & Wensveen, 2003). The banks are allowed to intermediate since they are able to screen and interpret market signals better and are better at reusing information they have acquired over time from similar transactions (Andries, 2009). For this, the banks are paid commission.

The relationship between a bank and an insurance company through banc-assurance is an explicit example of financial intermediation through brokerage services. Common banc-assurance agreements usually have three parties: a buyer in need of insurance services, an insurer with the service and, a bank which merely connects the two parties. Even though in most cases it is the bank which the buyer knows, the bank is never a party to such insurance agreements (Fiordelisi & Ricci, 2011: Gonulal & Krishnamurthy, 2012). Insurance companies are theorised to prefer banks to other channels because of the following (Lester, 2014). Banks are able to use client relationships and information built from previous interactions to market insurance products better than other intermediaries. Second, such relationships help banks provide better product matches to clients' needs. Thirdly, banks have wide and better distributional channels used for their traditional products which they can use to market insurance services better. Lastly, they can leverage on their traditional products by selling such products with insurance services as a package (Lester, 2014).

2.13 Theory of Consumption

The main concern in theory of production is how individuals make their consumption choices which include the goods to consume and levels to consume. The following are assumed: rationality, that a person derives utility from every good or service consumed; existence of list of preference; and that every consumer is constrained by his level of resources. He chooses the amount of goods or services that maximises his utility given his resource endowment and the goods' prices. Subsequently, demand for a good or service depends on their prices and those of related products, available resources, consumer tastes and preferences.

Insurance is a service which gives a level of satisfaction to buyers. Buying insurance is made together with other purchasing decisions forming part of a consumer's list of preference. A person chooses to buy that level of insurance that maximises their level of satisfaction given its price, price of other products, and his resource endowment. Insurance demand therefore depends on: insurance premium, consumer income, consumers taste and preference, cultural and religious belief regarding insurance, credit availability and related products among others. Notably, anything that causes any of the above to change is expected to ultimately change insurance uptake. Banks actions can hence be modelled to affect insurance uptake through their role in consumer resource endowment and provision of related products. Banks affects consumers' resources endowment first through credit used for purchases including for insurance policies and second, by facilitating consumers' wealth creation through savings. Banks services at times compete and complement insurance services.

2.2 Empirical Literature

Empirical studies directly linking insurance uptake and the banking sector can be grouped into two groups. The first group is made of studies that were intended primarily to investigate growth-finance nexus. The second group are those that intentionally focused on the interlinkages among financial sector players.

2.2.1. Economic Growth-Finance Nexus Studies

Relevant contribution from this group emanates from studies that included banks and insurance companies as separate entities within the financial sector and, went ahead to inspect the relationship between the two subsectors. Such contributions are seen from Adams et al. (2009); Kaushal and Ghosh (2017); Pradhan, Bahmani and Kiran (2014); Pradhan et al. (2017); and Pradhan et al. (2020).

Set in Sweden, Adams et al. (2009) sought to investigate the relationship between insurance, commercial bank lending and economic growth for the period 1890-1998. They used time series data, modelled their relationship under VAR and performed Granger causality as proposed by Toda and Yamamoto (1995). They found insurance to positively influence bank lending and economic growth. Their respective variables for insurance and banking subsectors were: insurance density (measured as the real annual value of collected premium per capita) and bank lending (taken as total loans to non-bank public per capita). Similar results were found by Kaushal and Ghosh (2017) in India who sought to investigate the relationship between the country's economic growth and developments both in the banking and insurance sectors. They used monthly data from July 2004 to June 2013 which they analysed using VECM. Banking development was measured by private credit, insurance development by total monthly collected premium while economic growth was measured by the country's industry production index. Development in the insurance sector was found to positively affect bank development.

Pradhan, Bahmani and Kiran (2014) used data from 1980 to 2012 for 17 G-20 countries which they analysed individually for each country as well as for the panel. The objective was to find out how banks' activities relate with those of insurance and how this affects economic growth. Six measures of insurance sector activity were used i.e. life insurance density, non-life insurance density, total insurance density, life insurance penetration, non-life insurance penetration, and total insurance penetration. For banks activity, they used broad money supply as a percentage of gross domestic product. VECM was used to model the relationship and estimated both by fully modified OLS (FMOLS) and dynamic OLS (DOLS). Causality was reported to run in either direction for all measures of insurance sector except total insurance penetration in the short run. In the long run, banks had influence but only on life insurance development. All measures of non-life and total insurance were found insignificant, a pointer to the difference between life and non-life insurance. We to followed this by analysing life separate from non-life insurance. We however, left out total insurance given its likely correlation with both life and non-life insurance measures especially the dominant policy.

In what looked like an improvement of the above, Pradhan et al. (2017) studied the relationship between activities in the insurance sector, banking industry and economic growth in all 19 G-20 countries for 1980-2014 period. Here, four measures of insurance activities were used: life insurance density (both life and non-life), and insurance penetration (both life and non-life). For banking activities, they were measured by: credit to the private sector, banks' total domestic credit, and total domestic credit provided by the financial sector. Both VECM and panel VECM were used for country and panel analysis respectively and estimation done through FMOLS and DOLS estimators. Long run results were not significant for the panel and most of the countries except China and Saudi Arabia, where banks had positive influence on insurance uptake. In the short run, unidirectional causality was found from banking activities to insurance sector for both developed and developing country panel as well as in 11 countries. Unidirectional causality from insurance sector to banks was found in 5 countries and bidirectional causality in 3.

Prathan et al. (2020) added stock market in their investigation of causal relationship between economic growth and financial markets reform in 32 European countries. This was for the period 1996 to 2016 and was analysed by VAR. Unlike their previous work, they used competition between banks to measure development in the banking industry as opposed to banks credit used previously. These included: Lerner index, Boone indicator, five-firm concentration ratio, three-firm concentration ratio, and foreign ownership. Life insurance penetration, non-life insurance penetration, and total life penetration were used to measure development in the insurance sector. No relationship was found between bank competition and insurance development in the long run. In the short run, competition in the banking industry was found to largely improve development in the insurance sector. All the three measures of insurance penetration had statistically significant unidirectional effect from at least one measure of banking competition. In addition, bidirectional relationship was found between nonlife insurance and three of the five bank competition measures as well as between total insurance penetration and one bank competition measure. The only unidirectional effect from insurance sector to the banking industry was shown by total insurance penetration, total insurance penetration had unidirectional effect on two measures of banking competition.

2.2.2. Studies on Interlinkages between Players in the Financial Sector

Unlike contribution from growth literature which primarily targeted the financial sector as whole, this group primarily targeted the individual players within the sector. This is the direction we take hence consider them more relevant to our objective. Some of the studies in this group are: Lorent (2010); Liu and others (2014); Liu and Lee (2019); Sawadogo (2020), and Lidiemo (2018).

Lorent (2010) sought to study the additional determinants of life insurance a cross-section for 90 countries (developed and developing) in 2005. Its main focus and thus contribution was the addition of four measures for banking sector. These included private credit (as a measure of financial development), banking sector efficiency, bank concentration, and banks' regulation. Bank efficiency was measured by: net risk margin, bank income cost ratio and overhead cost, return on assets (ROA), return on equity (ROE) and bank-z-score. Bank concentration measured by dividing the assets of the three largest banks by their industry's total assets. Bank regulation was measured by: a bancassurance dummy, ease of entry index, and supervisory regulation index. Demand for life insurance was measured by life insurance density. They estimated a log-log demand function.

Their results showed strong positive effect of bank development on demand for life insurance, this was even stronger for developed countries as compared to developing one. Most of the banks efficiency measures were not significant except banks z-score which was found negative for the whole group, negative for developed countries subsample but, positive for the sample of developing countries. Finally, allowing bancassurance within banks was found to significantly increase demand for life insurance, for the group and both developed and developing countries.

Liu et al. (2014) investigated the relationship between bank credit and insurance activity in G-7 countries using annual data from 1980-2007. Their variables include real insurance density separated into life and non-life and real banking credit density. To perform their analysis, they used a rolling window boostrapped VAR/VECM mainly to due to their short period of analysis.

Granger causality done as proposed by Toda and Yamamoto (1995). In the long run, they reported a bidirectional causal relationship between bank credit and insurance density. This was for both life and non-life insurance separately. In addition, banks effect was found stronger on life insurance than on non-life while non-life insurance effect on bank credit was stronger than the effect life insurance had on bank credit. In the short run, no relationship of any kind was found in the UK, the US and Canada. For France and Japan, causality ran from insurance activities (life and non-life) to the banks while it ran from banks to life insurers in Italy, and moved in both ways for nonlife insurers and banks in Germany. This led the authors to conclude that such causality is country specific, a conclusion we support hence our focus on Kenya.

Besides investigating the link between insurance activities and banking credit, Liu and Lee (2019) went ahead and examined how financial structure affected such linkages. This was for a panel of 36 countries for 1980-2015 period. To capture the structure, they separated their sample into bank-based and market based financial systems; and further into developed financial and undeveloped financial systems. Consequently, they ended up with four subsamples; market-based developed systems, bank-based developed systems, market-based undeveloped systems, and bank-based undeveloped financial systems. Real insurance premiums per capita, (insurance density) and real banking credit per capita (banking credit density) were the respective measures of insurance activities and banking credit. Analysis performed under VAR and dynamic OLS (DOLS) estimators.

In the long run, a majority of the countries had insurance activities positively affecting bank credit (20 out of 36 countries for life insurance and 21 in case of nonlife insurance). Life insurance had a negative effect on banks credit in 8 countries while nonlife insurance negatively affected banks in 6 countries. With regard to structure, long run effect on bank credit is more pronounced in developed market-based systems compared to developed bank-based system, and undeveloped bank-based system than in undeveloped market-based systems. For non-life insurance, the positive effect is more on bank-based systems than in market-based system. Short run had differing results for each of the four group (in relation to the two insurance measures) leading to the general conclusion that financial structure and development affects the relationship between banks and insurance companies. This is supports our choice to study Kenya individually. Nonetheless, effects were more pronounced in market-based financial systems and developed financial systems.

Closer home, Sawadogo (2020) used data from a panel of 20 Sub-Saharan African countries (including Kenya) covering 1990 to 2017. The intention was to establish a relationship between private credit and insurance activities. In addition, the study examined how the relationship was affected by country's level of globalisation. Insurance activity was measured as annual premium per capita (life, nonlife and total) while banking credit density was used for banks. Results were found by estimating an insurance demand function modelled as an autoregressive distributed lag (ARDL) series with the factors being bank credit plus others as control. Banks credit was found to have long run positive and significant effect on total insurance activity. At the same time, this effect was found to increase with the level of a country's openness to the global market. Only long run results were reported.

While Sawadogo (2020) paper included Kenya in its sample, we feel that its results may not transfer directly to Kenya. As already discussed, relationship between banks and insurers tend to be country specific (Liu et al. 2014) given the varying structure of financial systems within differing economies (Liu & Lee, 2019).

In Kenya, Lidiema (2018) examined the intra-market linkages within the country's financial sector. Besides banks and insurance (which are our focus), he also included the stock and forex market. He mainly looked at how shocks are transmitted within the sector and how shocks from each player affects the rest individually. In that respect, he constructed impulse response functions based on the Bayesian VAR (BVAR) model. This was from monthly data from January 2004 to December 2016. The relevant variables included banks' lending (total loans) for banks and net insurance premium for the insurance subsector. Shocks originating from insurance premium uptake were found to affect credit uptake. At the same time, shocks emanating from loan uptake were found to affect insurance uptake. Interest rates shocks got transmitted to all the four subsectors. While the direction in which shocks transmit between two sectors is a likely indication of a relationship, such relationships do not amount to causality. We did more than establish shock transmission, we established a causal relationship between banks and insurance companies.

2.2.3 Overview of Literature

The connection between insurance companies and banks can be explained under three theories: theory of financial intermediation, theory of production and consumption theory. Under theory of financial intermediation, both banks and insurers funds projects by competing for public savings which make them rivals. At the same time, the theory postulates a complementary relationship when both or either act as an agent of the other. With respect to the theory of production, a bank and an insurance company are hypothesised as consumers of the other's products in their production process hence a complementary relationship between them. Lastly, under consumption theory, banks' activity enters into a consumer' insurance demand function by relaxing his budget constraint. Therefore, insurance uptake increases with banks performance. Given these, the relationship between insurance companies and banks is theoretically ambiguous.

Empirically, the relationship between insurers and the banking sector remain unsettled. Results vary depending on population. Country specific factors as: income levels (Webb, Grace &

Skipper, 2003), structure of their financial system and their financial systems' level of development (Liu et al., 2014) have been shown to affect such relationships. Thus, studies in other locations cannot directly be applied in Kenya. Past studies in this area are largely from other locations. The closest Kenyan study (to our objective) that we found, investigated shocks transmission within the country's financial sector which cannot make one to conclude causal relationship. We therefore investigated the causal relationship between performance in Kenyan banks and insurance uptake (both life and nonlife policies).

The common variables in previous research were insurance density, and insurance penetration for the insurance sector. The former was more common than insurance penetration. Further, most studies separated each of the two insurance variables into life and nonlife, some separated each of them into three (life, nonlife, and total), while others used total measures of both or either. We use the commonest variable, insurance density and separates it into life and nonlife insurance density. Bank credit density was the commonest bank activity measure. We therefore use bank credit density together with ROA and ROE. The last two were also used by Lorent (2010).

Finally, most studies model the relationship under VAR/VECM framework. ARDL and log-linear were also common. We chose VAR/VECM cause of its popularity and belief to better model the relationship.

CHAPTER THREE

METHODOLOGY

3.0. Introduction

This chapter discusses the models to be adapted for data analysis. It is sub-divided into three main sections. The first section is a brief discussion of the theoretical model which is then followed by the model to be estimated and finally, a description of the data and study population.

3.1. Theoretical Model

Given that this study's unit of analysis are firms (banks and insurance companies), the model is based on theory of production. The intention is to link bank performance with uptake of insurance under the theory. Even though the discussion can be shown from either banking or insurance sector, the discussion is approached from the banking side. In this sense, a model profit oriented bank is assumed. In its operations, the bank has to decide on the level of inputs to employ to maximise profit given a targeted output level. Ultimately, it is shown how banks performance relate with insurance services through a model bank's factor demand function. An exposition of this follows, this borrows from Varian (2005) in logic.

The following assumptions are made: the bank produces one output represented by B (e.g loans) sold at price P. In doing this, it uses two inputs: insurance services represented by S and others represented by X. Input prices are W_1 and W_2 for insurance and others respectively. Further, the bank's is assumed to have a Cobb-Douglas production function of the form below.

$$B = S^a X^b \ldots\ldots\ldots\ldots\ldots\ldots.(1)$$

Equation 1 also represents the banks targeted output levels. Production is at the point where the bank maximises it profit. Its maximisation problem is:

$$Max\ PB - SW_1 - XW_2 \dots\dots\dots\dots\dots\dots (2)$$

Replacing for B in equation 2 by equation 1 gives:

$$Max\ P.S^a X^b - SW_1 - XW_2 \dots\dots\dots\dots\dots\dots (3)$$

Solving (3) produces the following first order conditions:

$$PaS^{a-1}X^b - W_1 = 0 \dots\dots\dots\dots\dots. (4a)$$

$$PbS^a X^{b-1} - W_2 = 0 \dots\dots\dots\dots\dots. (4b)$$

Multiplying 4a by S and 4b by X and replacing for $S^a X^b$ by B, equation 4a and 4b is rewritten as 5a and 5b respectively

$$PaB = SW_1 \dots\dots\dots\dots\dots.. (5a)$$

$$PbB = XW_2 \dots\dots\dots\dots\dots.. (5b)$$

From 5a and 5b arises the factor demand functions for insurance (S*) and others (X*) respectively in 6a and 6b.

$$S^* = \frac{PaB}{W_1} \dots\dots\dots\dots\dots\dots. (6a)$$

$$X^* = \frac{PbB}{W_2} \dots\dots\dots\dots\dots\dots. (6b)$$

As seen in 6, the optimal level of each input demanded by the bank directly depends on the price of bank's output (P) and its level of output (B) and, indirectly on the respective factor prices (W_1 and W_2). Assuming further that all banks in Kenya behave the same as the representative bank model above, equation 6a becomes the banking industry demand function for insurance services showing the industry's consumed insurances to depend on its level of output. Assuming bank output price (P) and the price of insurance services (W_1) as given, equation 6a can be transformed to equation 7. This is the banking industry demand function for insurance services.

$$S^* = \mu B \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(7)$$

Notably, banking activities could be shown as a function of insurance services following the above argument for a representative insurance firm. Thus insurance depend on banks while at the same time banks output depend on insurance services.

3.2. Model Specification

By expanding equation 7, the relationship between banks performance and insurance uptake can be presented in a simple empirical model in equation 8, taking into consideration that past values are often better explanatory variables than current values (Granger, 1969).

$$s_t = \beta_0 + \sum_{p=1}^{p} \emptyset s_{t-p} + \sum_{p=1}^{p} \beta_p b_{t-p} + \epsilon_t \ldots\ldots\ldots..8$$

Where S_t is a measure of insurance uptake, b_{t-p} is the lags of bank performance (our sole explanatory variable to insurance uptake)[3], $\emptyset\ and\ \beta_p$ representing parameters to be estimated,

[3] Current studies under VAR tend to include only the variables of concern. Omitted variable problem is rarely a concern since the primary intention of VAR as argued by Sims (1980) is to investigate alternative models not premised on full

ϵ_t representing the error term and the subscript t being time series denotation. A similar equation can be written for bank performance (S_t) given that bank performance can also be affected by insurance uptake making our model a system of two equations. Therefore, equation 8 is transformed under a model which allows such investigation concurrently. VAR is such a model. VAR model assumes no directional relationship by treating all variables as endogenous (Verbeek, 2004), endogeneity is thus not a problem in VAR models. Further, unlike structural equations, VAR are always identified (Verbeek, 2004). VAR model sets every variable as a function of its own lagged values, lagged values of the other variables and, an error term. It has as many equations as the number of variables being investigated. Equation 9 gives a general presentation of a VAR model.

$$y_t = A_0 + \sum_{p=1}^{p} A_1 y_{t-p} + e_t \ldots\ldots\ldots..9$$

Where y_t represent a vector of endogenous variables (in our case, s_t and b_t), A_p a matrix of estimated parameters, and a vector of an error terms e_t . To estimate VAR, the variables have to be stationary otherwise the results are meaningless (Binh, 2013). But since most economic time series and non-stationary, VAR is rarely used with observed time series values. One solution is to eliminate non-stationarity by getting first differences of the variables before running VAR. Differencing is only appropriate when the variables are not cointegrated, for cointegrated variables, one must introduce an error correction component into the VAR (Verbeek, 2004). In that case, equations 9 is modified to 10 by introducing an error correction component. Equation 10 is a general presentation of an error correction model (ECM).

information (Christiano, 2012). Secondly, better forecasting is possible with few parameters, and thirdly, bias from such variable truncation has been shown to be of negligible concern (Christiano, 2012).

$$\Delta y_t = C_0 + \sum_{p=1}^{p} C_1 \Delta y_{t-1} + \lambda EC + v_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..10$$

Where: Δy_t is a vector of differenced endogenous variables; C_0 and C_1 are estimated parameter; EC a vector of error correction components; λ is error correction parameter (also in vector); and v_t the vector of error terms. The error correction parameter measures adjustment to deviations from long run relationship. Estimation of the unrestricted VAR (equations 9) or ECM (equation 10) depended on the results of statistical tests discussed in the next section. Both VAR and VECM were used.

3.3. Tests and Estimations

To make sure one works with the right models and not spurious regression models among other problems of non-stationary data, one need to begin the analysis by testing for non-stationarity. If the data is stationary then, proceed and estimate basic unrestricted VAR model as presented in equations 9 otherwise conduct co-integration tests. If not co-integrated then, difference the variables to make them stationary and use differenced values on the VAR model. Vector error correction model should be estimated if the variables are co-integrated. Estimating VAR and VECM require specifying the number of lags to use. We relied mostly on the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) to determine the number of lags while presenting other section criteria as well.

3.3.1. Stationarity Test

Stationarity test are basically test for a unit root. This is so since most economic data are integrated of order 1 [I(1)]. Both augmented Dickey-Fuller (ADF) test and KPSS Test

(Lagrange multiplier test) we employed. ADF test selected because of its simplicity and popularity while KPSS tested for comparison given it was developed to correct ADF weakness.

Augmented Dickey-Fuller Test (ADF Test)

ADF Tests are simply Dickey-Fuller Test (DF Test) modified to correct for autocorrelation by creating additional lags in DF Test equations. DF Tests are t-tests on the coefficients of lagged dependent variables in an autoregressive scheme. However, the t-ratio under this do not have the standard distribution hence they cannot be used, instead it uses special DF t-statistic (Verbeek, 2004). DF Test tests under the null hypothesis of a unit root against an alternative hypothesis of stationarity. One rejects the null if the absolute t statistics is larger than the critical t. The following are the three ADF equations applicable under the test depending on whether one includes a constant (eq. 12), includes a trend (eq. 13) or leaves both out (eq. 11).

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta\, y_{t-i} + u_t \ldots..11$$

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta\, y_{t-i} + u_t \ldots\ldots 12$$

$$\Delta y_t = \alpha + \gamma T + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta\, y_{t-i} + u_t \ldots\ldots..13$$

The coefficient on y_{t-1} is the basis for the test under null of $\delta = 0$, the respective t-ratio is calculated by ${}^{\hat{\delta}}\!/_{se(\hat{\delta})}$ with the denominator being the standard error.

KPSS Test (Langrage Multiplier Test)

KPSS Test was developed by Kwiatkowski, Phillips, Schmidt and Shin (1992) as a solution to the weak power of AD Test. AD Test is based on a null of unit root. Failure to reject this means failure to reject the presence of a unit root which does not necessarily mean presence of a unit root and might simply mean lack of sufficient data to reject the null (Verbeek, 2004). It is generally understood among statisticians that failure to reject a null hypothesis does not mean accepting the null (Verbeek, 2004). KPSS Test corrects this by testing under the null of stationarity and alternative of unit root. It is performed by first running an auxiliary regression of Y_t upon an intercept and a time trend t, saving the OLS residuals e_t and, using these to compute the partial sums $S_t = \sum_{s-1}^{t} e_s$ for all t. The test's test statistic is calculated as:

$$KPSS = \sum_{t=1}^{T} {S_t^2}/{\hat{\sigma}^2} \dots\dots\dots\dots\dots.14$$

$\hat{\sigma}^2$ is estimated variance. H_0 is rejected if calculated KPSS is larger than the critical value.

3.3.2. Test for Co-integration

The main problem of dealing with non-stationary series is spurious regression, where two variables not related appear to be so due to a trend. One way of solving this is by differencing the series to remove unit root before regression. The problem is that this also differences the error terms and might eliminate any unique long term relationship present among the concerned variables (Binh, 2013). Co-integration concept offers the solution. Two I(1) series are said to be co-integrated if they are combined by a stationary process. The importance of co-integration is its use in investigating long run relationships between variables; all variables with long run relationship are co-integrated (Asteriou & Hall, 2007). Hence it is prudent to test for co-integrating relationship before investigating the connection between non-stationary variables.

Engle-Granger Test for Co-integration

Co-integration will be tested using the Engle-Granger test for co-integration based on the works of Granger (1981) and, Engle and Granger (1987). It is simply done by either performing DF or ADF unit root tests on the residuals of the co-integrating relationship (Binh, 2013). AD and ADF tests have already been discussed above. Engle-Granger test follows a two-step procedure proposed in Engle and Granger (1987). First step involve checking whether the variables are I(1) by performing a unit root test and concluding no co-integration if both are I(0). Proceeding to step two is conditioned on both variables being I(1). Step two involves estimating a long run relationship, getting the residuals, and performing a unit root test on the residuals. Co-integration is confirmed if the residuals are I(0). It tests under the null of no co-integration.

Engle-Granger is chosen because of its simplicity and suitability in two variables analysis (Binh, 2013) as in our case. As already alluded above, the results from this determine the final regression model used. Unrestricted VAR on differenced values of bank performance and insurance uptake were used where there was no co-integration despite non-stationary while, vector error correction model was employed is cases of co-integrating variables.

3.3.3. Granger Causality Estimation

Causality is always defined in the sense of Granger (1969), where a variable X is said to Granger cause another Y if its past values accurately explain the changes in Y. In performing the test, four possibilities apply: X causing Y without a feedback, Y causing X without a feedback, X and Y having feedback causality, and no relationship between the variables. The most important assumption under this is that future cannot cause the past (Verbeek, 2004). The test is done under the null of X causing Y against alternative of X not causing Y. We will perfume Granger causality test finally to unveil the direction of the relationship between the variables.

How this is done will depend on our final model i.e. whether level VAR, differenced VAR or VECM. Basically for stationary series, the test is simply a test on the coefficient on the lagged explanatory variables. This becomes complicated when the series are both non stationary in which case three alternatives exist (Adams et al., 2009). First and where co-integration is absent, VAR is run on the differenced series and causality test performed on the variable changes. Second test apply under co-integration on the error correction model. The third alternative is on level VAR but with the modification of the model selection procedure, this is the Toda-Yamamoto test formalised in Toda & Yamamoto (1995).

3.4. Variables to Use

This study is concerned with the relationship between two variables; bank performance and insurance uptake. It used three measures of bank performance against two for insurance uptake. Bank performance was measured by return on assets (ROA), return on equity (ROE), and private credit density. ROA and ROE are the most common in existing papers and capture how a bank uses its existing assets and shareholders' equity respectively to generate income (Waweru, 2013). For insurance uptake, we used life insurance density and nonlife insurance density. This is summarised on table 1.

Table 1: Measurement of variables

Variable	How operationalised	How measured
Bank performance (B_t)	ROA	Net income/total assets
	ROE	Net income/equity
	Private credit density	Credit to private sector per capita
Insurance uptake (S_t)	Life insurance density	Life insurance premium per capita
	Nonlife insurance density	Nonlife insurance premium per capita

Source: Author (2021)

3.5. Data

3.5.1. Type and Sources

The study used secondary time series data. Data on bank performance were calculated from figures collected from annual Statistical Abstracts published by Kenya National Bureau of Statistics (KNBS) and accessed from their website. Figures from Bank Supervision Annual Reports published by the Central Bank of Kenya (CBK) on their website were used to complement calculations from the abstracts. Data on insurance uptake were solely collected from the Statistical Abstract. These data are aggregates for the entire banking and insurance industry and so our population covers the entirety of all firms that have made such classification from the year 1974 to 2019.

3.5.2. Data Analysis

Before estimating the model as described above, the collected data were processed, cleaned and preliminary analysis done. Preliminary analysis involved the computation of descriptive statistics like the mean, standard deviation among others. All these were prepared under Stata statistical software.

CHAPTER FOUR

RESULTS AND FINDINGS

4.0. Introduction

This chapter presents the results. It begins with the preliminary analysis of the data and procedures perfumed, follows with pre-analysis test results, finalising with the results from the models which is reported together with the post analysis results.

4.1. Pre-analysis Procedures and Test

This research paper relied on time series data. The final data relied on figures reported in the annual statistical abstract published by Kenya National Bureau of Statistics and available from their website. None of the variables existed in abstracts as was used, they had to be calculated and estimated from the abstracts' figures. For instance, to calculate the respective densities, we needed annual population data which we estimated from the population survey figures done every decade. This required assuming constant population growth rate within each decade. The data ranged from the year 1974 to 2019 making 46 years/data points. Table 2 gives a summary of the variables.

Table 2: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
ROA	46	17.13%	0.58%	0.49%	2.69%
ROE	46	17.43%	8.00%	1.41%	34.92%
Life insurance density (Ksh.)	46	344.68	496.45	11.91	1,889.36
Nonlife insurance density (Ksh.)	46	557.99	700.60	19.96	2,368.26
Credit density (Ksh.)	46	13,615.86	18,397.99	298.84	60,944.79

Source: Author (2021)

It can be seen that nonlife insurance uptake is higher than life. A situation attributed partly to legally mandatory covers like motor insurance and their importance in protecting business property. Life insurance is mostly taken on personal basis. Credit uptake is much higher than total uptake of insurance policies in the country a pointer to the development of Banks in relation to other players in the country. With respect to business volume, the banking sector in the country is more developed than insurance sector.

4.1.1. Unit Root Tests

Selecting an appropriate model needed testing for nonstationarity, this is normally the first step in an attempt to avoid spurious regression common when dealing with nonstationary time series. As expounded in chapter three, Augmented Dickey Fuller (ADF) and KPSS test were used. Table 3 and table 4 gives the respective result from the two procedures.

Table 3: Augmented Dickey Fuller Unit Root Test

Variable (in logs)	Test Statistic	P-value (Mackinnon approx.)
ROA*	-2.259	0.1855
ROE	-3.155	0.0228
Private Credit Density*	-0.553	0.8812
Life Insurance Density*	-0.542	0.8836
Nonlife Insurance Density*	-0.657	0.8577
Diff. ROA	-7.577	0.0000
Diff. ROE	-8.613	0.0000
Diff. Private Credit Density	-6.058	0.0000
Diff. Life Insurance Density	-9.028	0.0000
Diff. Nonlife Insurance Density	-7.370	0.0000
**Nonstationary series. Test done without specifying lags since result seemed not differ under various lags.*		

Source: Author (2021)

Table 4: KPSS Unit Root Test

Variable (in logs)	Statistics' Critical Values (5%)	Test Statistics			
	Lag order	0	1	2	3
ROA*	0.463	1.900 (0.0452)	1.06 (0.0532)	0.765 (0.0568)	0.617 (0.0633)
ROE	0.463	0.389 (0.0499)	0.237 (0.0689)	0.180 (0.0741)	0.153 (0.068)
Credit Density*	0.463	4.570 (0.0704)	2.360 (0.0661)	1.610 (0.0563)	1.240 (0.0547)
Life Insurance Density*	0.463	4.440 (0.0194)	2.330 (0.0286)	1.610 (0.0452)	1.240 (0.0732)
Nonlife Insurance Density*	0.463	4.520 (0.0285)	2.340 (0.0328)	1.610 (0.0484)	1.240 (0.0585)
**Nonstationary in at least one lag order. The bracket values are the statistics for the respective differenced variables, all are stationary*					

Source: Author (2021)

To be noted is that ADF test under the null of a unit root hence, rejecting the null implies stationarity. On the other side, KPSS test under the null of stationarity so it confirms presence of a unit root by rejecting the null. It can be seen that both tests concur in all their results. Non-stationarity is confirmed in all the variables except ROE which is stationary. Also, all their respective differenced values are stationary which mean they are I(1) except ROE which is I(0).

4.1.2. Test for Co-integration

Next, co-integration tests were performed to investigate long run relationship between banks and insurance companies. Each bank performance variable was tested singly with every insurance uptake variable under Engle-Granger framework as discussed in chapter three. ROE was excluded from the test since it was found stationary as already reported. Cointegration as is formally defined, is conditioned on a variable being nonstationarity. A total of four test were done and results were as in table 5.

Table 5: Co-integration Test Results

Tested Variables		Critical Values		
	Test Statistics	1%	5%	10%
ROA-Life insurance	-2.994	-4.151	-3.475	-3.140
ROA-Nonlife insurance	-3.039	-4.151	-3.475	-3.140
Credit-Life insurance**	-4.143	-4.151	-3.475	-3.140
Credit-Nonlife insurance***	-5.308	-4.151	-3.475	-3.140
****Co-integrated-1% significance level; ** Co-integrated-5% significance level*				

Source: Author (2021)

Cointegration was found between credit density and life insurance density and also between credit density and nonlife insurance. Confirmation check under Johansen cointegration test (not reported) confirmed the pick as the only co-integrating variables. Following this, and as explained in chapter three, we proceeded by estimating VAR models with differenced values for ROA and life insurance; ROA and nonlife insurance; ROE and life insurance; and ROE and nonlife insurance. For credit density, it relationships with life and nonlife insurance density were investigated under VEC as it was found to be co-integrated with each.

4.2. Model Estimation Results

As there were three bank performance variables and two insurance uptake variables, a total of six models were estimated each capturing one bank variable with one insurance variable. Of the six, four exhibited no long rung relationship as reported above hence were estimated under VAR on differenced series. We begin by presenting the VAR results first followed by those from VEC. Each begins with a presentation of lag selection criteria, followed by the estimated results before reporting the respective granger causality results. Emphasis was placed on AIC and SBIC lag selection criteria as mentioned in chapter three.

4.2.1. ROA and Life Insurance Density

Table 6 reports the selected lags for the relationship between ROA and life insurance density.

Table 6: Lag Selection Criteria for ROA and Life Insurance VAR

Lag	*LL*	*LR*	*df*	*P*	*FPE*	*AIC*	*HQIC*	*SBIC*
0	-18.98700				0.009543	1.023760	1.054200	1.10735
1	-11.16390	15.6460	4	0.004	0.007923*	0.837262*	0.928577*	1.08803*
2	-8.53695	5.2538	4	0.262	0.008488	0.904241	1.056430	1.32219
3	-3.75601	9.5619*	4	0.048	0.008206	0.866147	1.079220	1.45127
4	-2.62097	2.2701	4	0.686	0.009511	1.005900	1.279850	1.75820
**Shows the selected lag number*								

Source: Author (2021)

Both AIC and SBIC selected 1 lag in addition to FPE and HQIC criteria. Table 7 are the results from the VAR model with 1 lag.

Table 7: ROA-Life Insurance VAR Results

Dependent Variable	Explanatory variable	Coefficient	Std. Error	z	P>|z|
ROA	ROA				
	L1.	-0.1565017	0.1458896	-1.07	0.283
	Life Insurance				
	L1.	-0.1487767	0.1187623	-1.25	0.210
	Constant				
		0.0181938	0.0457616	0.40	0.691
Life Insurance	ROA				
	L1.	0.3483918	0.1675048	2.08	0.038
	Life Insurance				
	L1.	-0.3112944	0.1363583	-2.28	0.022
	Constant				
		0.1461738	0.0525416	2.78	0.005
F-test on ROA equation (p=0.2671), F-test on life insurance density equation (p=0.0073)					

Source: Author (2021)

First to note, was that the model passed stability test and suffered no autocorrelation with the selected lags (see appendices for results). Second, insurance equation was the only significant equation as per its reported F-test (p-value of 0.0073). Moreover, all variables on it were significant. Thirdly, ROA entered the equation with a positive sign while life insurance had a negative sign. Consequently, ROA positively affects life insurance by a lag of 1 year while life insurance's past figures reduces those of its subsequent one year. This however does not amount to overall causality of ROA on life insurance. Granger causality was therefore done to gauge the direction and results are on table 8.

Table 8: Granger Causality Wald Test (ROA and Life Insurance)

Equation	Excluded	Ch^2	df	$P>Ch^2$
ROA	Life Insurance Density	1.5693	1	0.210
ROA	All	1.5693	1	0.210
Life Insurance Density	ROA	4.3259	1	0.038
Life Insurance Density	All	4.3259	1	0.038
H0: No causal effect from exclude variable				

Source: Author (2021)

The null hypothesis of no causality is rejected for ROA in life insurance equation. Therefore, there is a unidirectional causal relationship running from ROA to life insurance density in the short-run. Given that the parameter on ROA in table 7 was positive and significant, it means that ROA positively affects life insurance density in the short run.

4.2.2. ROA and Nonlife Insurance Density

After life insurance, we now report results on the relationship ROA has with nonlife insurance. Table 9 shows how the optimal lags were selected.

Table 9: Lag Selection for ROA and Nonlife Insurance VAR

Lag	*LL*	*LR*	*Df*	*P*	*FPE*	*AIC*	*HQIC*	*SBIC*
0	11.9549				0.002109*	-0.485603*	-0.455164*	-0.402014*
1	12.9663	2.0229	4	0.732	0.002442	-0.339819	-0.248503	-0.089052
2	19.2912	12.650*	4	0.013	0.002184	-0.453228	-0.301035	-0.035283
3	20.0569	1.5315	4	0.821	0.002568	-0.295459	-0.08239	0.289663
4	20.7666	1.4195	4	0.841	0.003039	-0.134958	0.138988	0.617342

Source: Author (2021)

AIC and SBIC selected use of zero lag in addition to FPE and SBIC criteria, pointing at possible lack of any causal relationship between the ROA and nonlife insurance density. However, we proceeded with the model using 2 lags as selected by LR criterion.

Table 10: ROA-Nonlife Insurance VAR Results

Dependent Variable	Explanatory variable	Coefficient	Std. Error	z	P>|z|
ROA	ROA				
	L1.	-0.1651281	0.1577205	-1.05	0.295
	L2.	-0.0774951	0.1591766	-0.49	0.626
	Nonlife Insurance				
	L1.	-0.0399326	0.2518742	-0.16	0.874
	L2.	-0.2621414	0.2496735	-1.05	0.294
	Constant				
		0.0351813	0.0606820	0.58	0.562
Nonlife Insurance	ROA				
	L1.	0.1011599	0.0925331	1.09	0.274
	L2.	0.0074044	0.0933874	0.08	0.937
	Nonlife Insurance				
	L1.	-0.1383454	0.1477722	-0.94	0.349
	L2.	-0.3813608	0.1464811	-2.60	0.009
	Constant				
		0.1603495	0.0356016	4.50	0.000
F-test on ROA equation (p=0.7042), F-test on Nonlife insurance density equation (p=0.0441)					

Source: Author (2021)

Model was found stable and, with no autocorrelation problem for the selected lags (see appendices for tests results). Also, nonlife insurance density equation was found to be the only equation which fits the relationship between ROA and nonlife insurance density. ROA equation failed the test hence statistically unlikely to represent the relationship. Further, only the second lag of nonlife insurance and the constant were found statistically significant on the nonlife insurance equation. The lag of nonlife was negative on its own function meaning that premium collected each year has a downward effect on what is collected on the second following year. Turning to causality, granger type test was done and results presented in table 11.

Table 11: Granger Causality Wald Test (ROA and Nonlife Insurance)

Equation	Excluded	Ch^2	df	$P>Ch^2$
ROA	Nonlife Insurance Density	1.1060	1	0.575
ROA	All	1.1060	1	0.575
Nonlife Insurance Density	ROA	1.1966	1	0.550
Nonlife Insurance Density	All	1.1966	1	0.550

Source: Author (2021)

No causal relationship was found between ROA and nonlife insurance density of any direction in the short-run.

4.2.3. ROE and Life Insurance Density

As was reported from the stationarity test results, ROE was found stationary while life insurance density had a unit root. Working with their level values present a problem. As a result, both were differenced like in the above two estimations already discussed even though ROE needed no differencing to be used under VAR. It was differenced to levels it value with that of life insurance density.

Table 12: Lag Selection ROE and Life Insurance VAR

Lag	*LL*	*LR*	*Df*	*P*	*FPE*	*AIC*	*HQIC*	*SBIC*
0	-45.6725				0.035076	2.32549	2.35593	2.40908*
1	-39.4972	12.3500	4	0.015	0.031560	2.21938	2.31069	2.47014
2	-33.8087	11.3770	4	0.023	0.029121	2.13701	2.28920	2.55495
3	-26.9754	13.667*	4	0.008	0.025471	1.99880	2.21187*	2.58392
4	-22.4390	9.0727	4	0.059	0.025007*	1.97264*	2.24658	2.72494

Source: Author (2021)

AIC and SBIC gave different lag selections with the latter suggesting no lag which translate to bad fit under VAR. SBIC was thus ignored and four lags as, chosen by AIC, used to estimate the VAR model. The results are presented on table 13.

Table 13: ROE-Life Insurance VAR Results

Dependent Variable	Explanatory Variable	Coefficient	Std. Error	z	P>|z|
ROE	ROE				
	L1.	-0.3037398	0.1556709	-1.95	0.051
	L2.	-0.0092690	0.1593730	-0.06	0.954
	L3.	0.1129066	0.1417688	0.80	0.426
	L4.	-0.2762592	0.1392776	-1.98	0.047
	Life Insurance				
	L1.	0.1797436	0.2290700	0.78	0.433
	L2.	0.2763331	0.2460717	1.12	0.261
	L3.	0.1685654	0.2475204	0.68	0.496
	L4.	0.0895534	0.2284681	0.39	0.695
	Constant				
		-0.0769637	0.1101293	-0.70	0.485
Life Insurance	ROE				
	L1.	0.3323052	0.1030583	3.22	0.001
	L2.	0.0411258	0.1055092	0.39	0.697
	L3.	-0.0063939	0.0938547	-0.07	0.946
	L4.	-0.1672475	0.0922055	-1.81	0.070
	Life Insurance				
	L1.	-0.7354177	0.1516505	-4.85	0.000
	L2.	-0.7525399	0.1629061	-4.62	0.000
	L3.	-0.6217887	0.1638652	-3.79	0.000
	L4.	-0.2624424	0.1512520	-1.74	0.083
	Constant				
		0.3824826	0.0729085	5.25	0.000
ROE equation was weakly significantly fitted (p=0.0575), life insurance density equation fit was strongly significant (p=0.000)					

Source: Author (2021)

The model was found stable with no serial correlation problem (see appendices). All the equations were well fitted at least at 10% significance level even though life insurance density showed a better fit at 1% significance level. Two parameters were found significant on ROE equation i.e. first lag of ROE and its 4th lag all with negative signs. With regard to life insurance equation, all its lagged values plus the constant were statistically significant at least at 10% significance level. First ROE lag (at 1% sig level) and its 4th lag (at 10% sig level) were also significant on the life insurance equation. Further, all the life insurance lagged values had negative signs similar to the ROA-life insurance case reported earlier. Nonlife insurance lag was also negative on its own equation when modelled with ROA. Table 14 are the causality results.

Table 14: Granger Causality Wald Test (ROE and Life Insurance)

Equation	Excluded	Ch^2	df	$P>Ch^2$
ROE	Life Insurance Density	1.4002	1	0.844
ROE	All	1.4002	1	0.844
Life Insurance Density	ROE	13.237	1	0.010
Life Insurance Density	All	13.237	1	0.010

Source: Author (2021)

Table 14 presents evidence of a strong unidirectional causal relationship moving from ROE to life insurance density (at 1% significance level). This means more life insurance services are bought as bank investors earn more from their investment in banks.

4.2.4. ROE and Nonlife Insurance Density

Table 15: ROE and Nonlife Insurance VAR Lag Selection

Lag	LL	LR	df	P	FPE	AIC	HQIC	SBIC
0	-17.136700				0.008719	0.933497	0.963935	1.01709*
1	-12.228200	9.817	4	0.044	0.008345	0.889180	0.980496	1.13995
2	-6.413100	11.63	4	0.020	0.007653*	0.800639*	0.952831*	1.21858
3	-4.177070	4.4721	4	0.346	0.008377	0.886686	1.099760	1.47181
4	0.690724	9.7356*	4	0.045	0.008092	0.844355	1.118300	1.59665

Source: Author (2021)

Two lags were selected based on AIC in addition to FPE and HQIC criteria. VAR results on table 16.

Table 16: ROE-Nonlife Insurance VAR Results

Dependent Variable	Explanatory Variable	Coefficient	Std. Error	Z	P>|z|
ROE	ROE				
	*L1.	-0.2622255	0.1533220	-1.71	0.087
	L2.	-0.0637910	0.1637526	-0.39	0.697
	Nonlife Insurance				
	L1.	0.2950702	0.4093901	0.72	0.471
	L2.	-0.1029187	0.3857756	-0.27	0.790
	Constant				
		-0.0489658	0.0954424	-0.51	0.608
Nonlife Insurance	ROE				
	***L1.	0.1765210	0.0507789	3.48	0.001
	L2.	0.0413269	0.0542335	0.76	0.446
	Nonlife Insurance				
	L1.	-0.1339265	0.1355865	-0.99	0.323
	***L2.	-0.4251340	0.1277656	-3.33	0.001
	***Constant				
		0.1694097	0.0316097	5.36	0.000
*F-test on ROE equation (p=0.3766), F-test on Nonlife insurance density equation (p=0.0001);*10% sig at 10%; **Sig at 5%; ***1%*					

Source: Author (2021)

As in the case of ROA, nonlife insurance equation is the only significant one. Three parameters were significant at 1% significance level: first lag of ROE on nonlife insurance equation with a positive sign, second lag of nonlife insurance on its on equation with a negative sign, and a positive constant. ROE entered its own equation negatively at 10 significant level. Causality was established under granger as reported on table 17.

Table 17: Granger Causality Wald Test (ROE and Nonlife Insurance)

Equation	Excluded	Ch^2	df	$P>Ch^2$
ROE	Nonlife Insurance Density	.61025	4	0.737
ROE	All	.61025	4	0.737
Nonlife Insurance Density	ROE	12.093	4	0.002
Nonlife Insurance Density	All	12.093	4	0.002

Source: Author (2021)

ROE was found to granger cause nonlife insurance uptake in the short run. The positive sign on the short-run parameter, implies this to be a positive causal relationship. No causality moved from Nonlife insurance to ROE same as lack of evidence on concurrent causality between the variables.

4.2.5. Credit Density and Life Insurance Density

In analysing the relationship between credit density and life insurance, we used VECM. The variables were found to have a long run relationship as reported under co-integration results, making VECM the appropriate model to establish their relationship. Unlike in the previous sections, we do not report results from the formal lag selection criteria; we ignored their selection for failing to result in better models. Instead, our selection was based on trial and testing. Both AIC and BIC settled on 1 lag the use of which was found to suffer from autocorrelation. Based on Gonzalo's (1994) recommendation of adding the number of lags when faced with auto-correlated VEC model, we experimented with additional lags up to 4 lags. Use of lags beyond 4 risked reducing our sample size, which at 45 (for differenced values) was already small. Experimenting with 3 and 4 lags not only produced skewed residuals but also gave insignificant adjustment parameters making us to settle on 2 lags. Table 18 give the VECM results.

Table 18: VECM Results-Credit Density and Life Insurance Density

		Coefficient	Std. Error	Z	p>|z|
Credit density equation	Adjustment Parameter				
		-0.1423328	0.0634044	-2.24	0.025
	Diff. Credit Density				
	L1	0.1178046	0.1496440	0.79	0.431
	L2	0.3929969	0.1514487	2.59	0.009
	Diff. Life Insurance Density				
	L1	-0.1824289	0.0634523	-2.88	0.004
	L2	-0.1357217	0.0554868	-2.45	0.014
	Constant				
		0.1428236	0.0361064	3.96	0.000
Life insurance density equation	Adjustment Parameter				
		0.4921620	0.1871490	2.63	0.009
	Diff. Credit Density				
	L1	-0.1588867	0.4417003	-0.36	0.719
	L2	-0.3820820	0.4470270	-0.85	0.393
	Diff. Life Insurance Density				
	L1	-0.1134725	0.1872906	-0.61	0.545
	L2	-0.1433066	0.1637790	-0.88	0.382
	Constant				
		0.0413045	0.1065742	0.39	0.698
Johansen Normalization Restriction Imposed					
Co-integrating relationship	Credit density	1	.	.	.
	Life insurance density	-1.0708130	0.0507456	-21.10	0.000
	Constant	-2.9497130	.	.	.
All the 3 equations were significantly well fitted: credit density equation (p value=0.0004) life insurance density (p-value=0.0000) and the cointegrated equation (p-value=0.000). Reported p-values are at 5% significance level. Diff=differenced					

Source: Author (2021)

With 2 lags, the model passed both stability test besides having no autocorrelation problem for the included number of lags (see appendices for test results). Also, all the long run adjustment parameters were significant and of the expected signs given the sign of life insurance parameter on the co-integrated relationship. In this sense, the two variables were found to adjust each other towards their respective equilibrium level in the long run. In other words, there is a bidirectional positive causal relationship between life insurance uptake and private credit.

In the short run, the following parameters were found significant: the second lag of credit density on its own equation (positive sign); all the two lags of insurance density on bank credit density equation (negative sign) and the constant on the credit function. Granger causality test was performed to establish if these amounted to causal relationship. The process involved joint F-test on the coefficient of the lagged explanatory variable' differences. Results are in table 19.

Table 19: Granger Causality Test-Credit and Life Insurance

Test	Chi^2	$p>\|Ch^2\|$
H0: Coeff on lagged life insurance density in credit density equation=0	9.53	0.0085
H0: Coeff on lagged credit density in life insurance density equation=0	0.86	0.6509
**Performs F-test for joint significance on coefficient on the lagged explanatory variables*		

Source: Author (2021)

A unidirectional causality was found from life insurance to credit expansion at 1% significance level. This effect is negative as evidenced by the negative sign on life insurance coefficient in the bank credit equation. In other words, bank credit tends to reduce as more people take life insurance services.

4.2.6. Credit Density and Nonlife Insurance Density

Formal lag selection criteria were also ignored here too for giving insignificant adjustment parameters. Similar results were found with four lags while three lags had serially correlated errors in at least 1 lag. Modelling with two lags was not only stable but, also had uncorrelated error terms and produced significant adjustment parameters in both equations. Its results are given in table 20.

Table 20: VECM Results-Credit Density and Nonlife Insurance Density

		Coefficient	Std. Error	z	p>|z|
Credit density equation	Adjustment Parameter				
		-0.3150921	0.1480663	-2.13	0.033
	Diff. Credit Density				
	L1	0.2045641	0.1728576	1.18	0.237
	L2	0.3379870	0.1593865	2.12	0.034
	Diff. Nonlife Ins Density				
	L1	-0.1164433	0.1375498	-0.85	0.397
	L2	-0.0448229	0.1171782	-0.38	0.702
	Constant				
		0.0825171	0.0327201	2.52	0.012
Nonlife insurance density equation	Adjustment Parameter				
		0.4674590	0.2105853	2.22	0.026
	Diff. Credit Density				
	L1	0.1170435	0.2458444	0.48	0.634
	L2	0.2753800	0.2266853	1.21	0.224
	Diff. Nonlife Ins Density				
	L1	0.0728335	0.1956284	0.37	0.710
	L2	-0.2169478	0.1666552	-1.30	0.193
	Constant				
		0.0556209	0.0465358	1.20	0.232
Johansen normalization restriction imposed					
Co-integrating relationship	Credit Density	1	.	.	.
	Nonlife Insurance density	-1.135295	0.0252828	-44.90	0.000
	Constant	-2.204434	.	.	.
All the 3 equations were significantly well fitted: credit density equation (p value=0.0000), nonlife insurance density equation (p-value=0.0000) and the cointegrated equation (p-value=0.0000). Reported p-values are at 5% significance level. Diff=differenced					

Source: Author (2021)

All the adjustment parameters have the expected signs besides being statistically significant. Therefore, nonlife insurance density and credit density corrects each other's values in the long run therefore, a bidirectional causality between them. In the short run, no parameter was found significant on the nonlife insurance equation while both the second lag of credit density (with a positive sign) and the constant term were significant on the credit density equation. Nonetheless, we proceeded with short term granger causality test presented in table 21.

Table 21: Granger Causality Test-Credit and Nonlife Insurance

Test	Chi^2	$p>\|Ch^2\|$
H0: Coefficient on lagged nonlife insurance in credit equation=0	0.72	0.6972
H0: Coefficient on lagged credit density in nonlife insurance equation=0	1.58	0.4547
**Performs F-test for joint significance on coefficient on the lagged explanatory variables*		

Source: Author (2021)

Lagged coefficients of respective explanatory variables were found were not significant in both equations. Consequently, there was no short-run causality between credit density and nonlife insurance density.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0. Introduction

This paper outlines the conclusion of the study. It begins by giving the summary of the findings followed by making conclusions and lastly giving recommendations.

5.1 Summaries and Conclusions

This research began with one main objective; to investigate the causal relationship between Kenyan banks performance and insurance uptake. This was separated into two specific objectives: establishing relationship between Kenyan banks performance and life insurance uptake and, that between bank performance and nonlife insurance uptake. Theory of production was used to link the two subsectors and estimations done under VAR/VECM framework. Data was in time series aggregations from all commercial banks and insurance companies that operated in the year 1974 through to 2019. Raw data used were mostly from the annual statistical abstracts published by the Kenyan National Statistical Bureau (KNBS). Figures in the annual bank supervision reports were used to compare and validate banking figures calculated from the abstracts. Data was converted to normal logs and analysed using Stata software. These were the results.

No long-run causal relationship was found between ROA and life insurance density same to that between ROA and nonlife insurance density. At the same time, no causal tie was found between ROE and life insurance or between ROE and nonlife insurance. The only long-run effects were found between credit density and life insurance density and; between credit and nonlife insurance density. In a short, of the three bank performance measures, only one was found to have causal linkage with the insurance uptake measures. Consequently, little evidence exists in support of a long run causal link between bank performance and uptake of both life and nonlife insurance services in the country. This contradicts both complementarity and substitutability hypotheses which see the actions of either a bank or insurer to enhance or diminish performance of the other.

This conclusion is largely not in contradiction with past studies on the topic as it seems. It is only that it included two variables (ROA and ROE) largely left out in economic literature, though dominant in bank performance related finance literature. Confining our conclusions to the most commonly used banking performance variable (credit density) make the results in agreement with a number of past studies. For instance; Liu et al. (2014), Liu and Lee (2019) and Sawadogo (2020) that measured bank performance as bank credit. Since Pradhan et al. (2020) found no relationship between banking competition and insurance uptake, insurance uptake may be seen to affect bank credit in the long run without affecting the bank's overall performance. Still, Pradhan et al. (2019) failed to find any long run relationship in 17 out of 19 G-20 countries while using bank credit density.

Turning to short run results (with respect to Granger causality), nonlife insurance showed no statistically significant causal relationship with both bank credit and ROA. It was however found to be affected positively and unilaterally by ROE. Since nonlife insurance had no causal relationship with two of three selected banks variables, we answer our second research question by concluding lack of a causal relationship between bank performance and nonlife insurance in the short run. With regard to the first objective, life insurance was found to be influenced positively both by ROA and ROE while on its part positively affecting short term bank credit. In this case, causality chiefly moved from bank performance to life insurance hence the conclusion of a short run positive effect of bank performance on Kenyan life insurance uptake.

Generalising the above to achieve the study's main objective, bank performance was found to granger cause short term insurance uptake in three instances (from ROA to life, ROE to life and ROE to nonlife insurance uptake); there was one instance of insurance uptake influencing banks (from life to bank credit) and; two instance of non-causality between the two sectors (between credit and nonlife and, ROA and nonlife). Therefore, banks' performance has an overall positive impact on the country's short run insurance demand. Such may be attributed to the large size of the banking sector with respect to that of the insurance industry. Alternatively, the effect may be because more banks have ventured into in insurance business compared to insurers engaging in banking services.

5.2. Recommendations

5.2.1. Policy Recommendations

Results presented here show that Kenyan banks and insurance companies are largely independent when viewed in a longer time perspective. This is despite bank credit being connected with the level of insurance uptake in the long run. Insurers however, seem to depend on the banking sector in the short run without themselves having any influence on banks. Therefore, it is critical that when formulating policies aimed at promoting insurance uptake, then the country's bank performance should be considered. Nonetheless, such should have a short term outlook as the effect is likely to fade in the long run except for bank credit. Long term insurance outlook should only consider private bank credit.

Policy makers for the country's banking sector should on their part never lose sight of the country's long term insurance uptake particularly those aimed at improving credit access in the long term. Effects of insurance uptake should be considered when formulating such policies.

5.2.2. Further Studies

This study attempted to bring the banking sector and insurance sector in a holistic view. It faulted studies on effect of banc-assurance on either insurance uptake or bank performance for leaving out interlinkages between the sector through other channels. Nonetheless, it might have camouflaged the effect bancassurance has on the links since bancassurance has existed for a much lesser period compared with the 46 years studied here. Future studies can pick this and segregate the data into pre and post bancassurance errors. Others might look at the overall linkages in the financial sector by adding stock market variables among others while, some might look at any of the sectors studied here with other financial market players e.g. stock market and banks.

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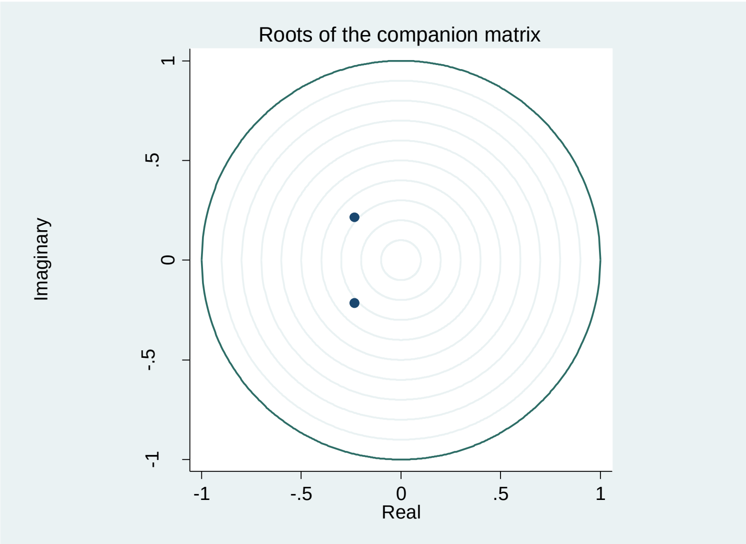
APPENDICES

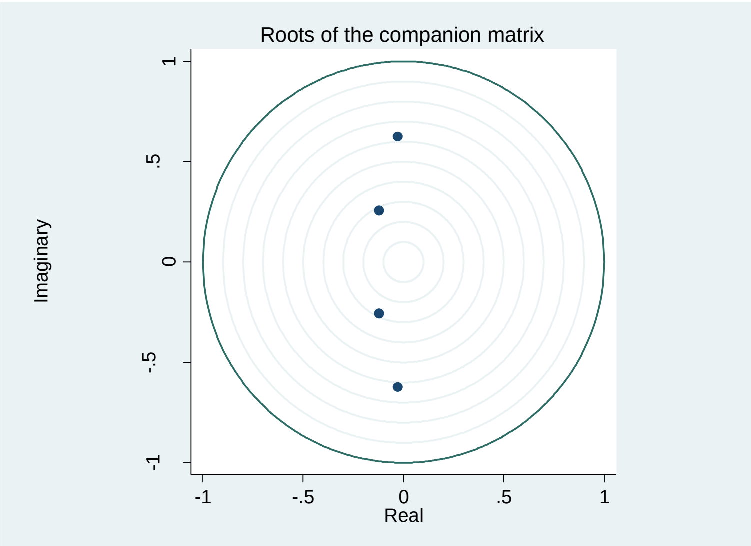
Appendix 1: Model Stability Test Results

Performed by calculating Eigen values real and imaginary. Stability is confirmed there is value outside of the unit circle. All models used satisfied this as presented on a) through f).

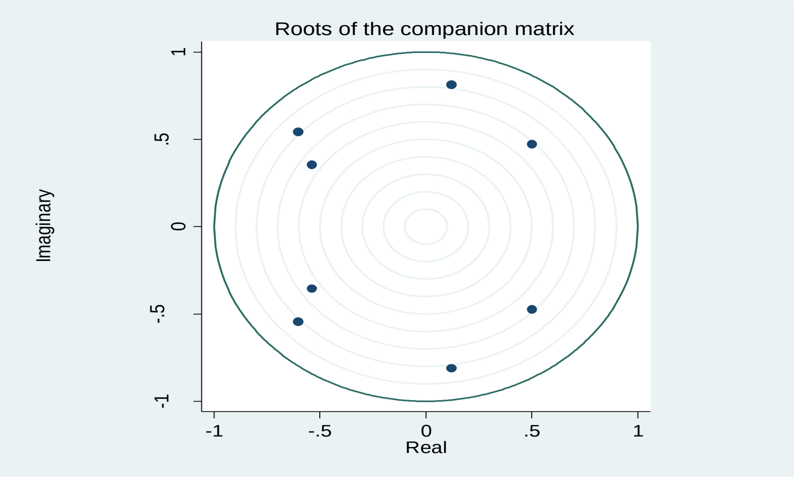
a). ROA-life insurance density VAR stability test



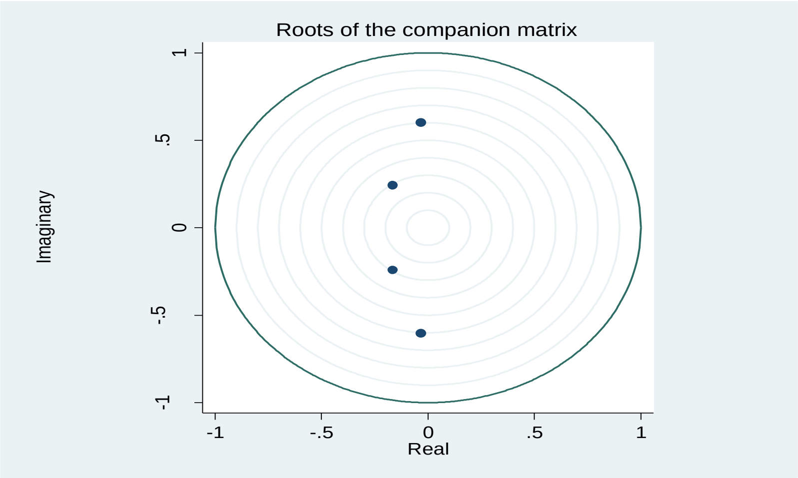
b). ROA-nonlife insurance density VAR stability test



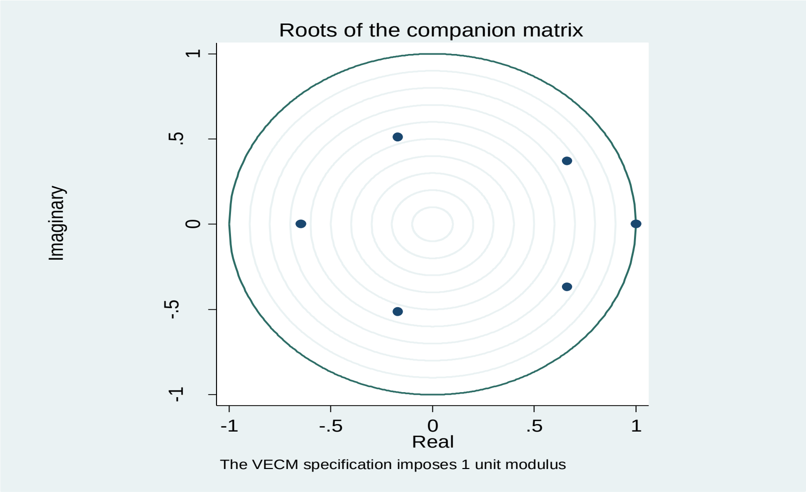
c). ROE-life insurance density VAR stability test



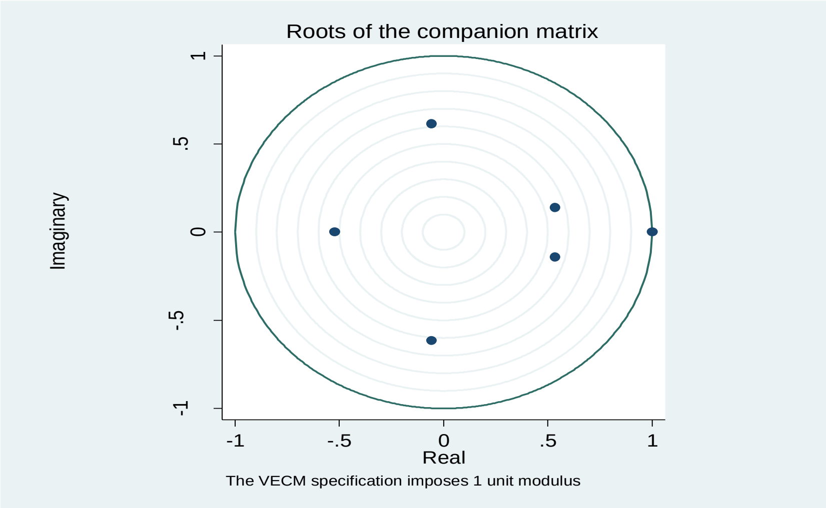
d). ROE-nonlife insurance density VAR stability test



e). Credit density-life insurance density VECM stability test



f). Credit density-nonlife insurance density VECM stability test



Appendix 2: Test for Autocorrelation in the Lagged Values in Models

a). ROA-life insurance density VAR autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	4.3314	4	0.36301
2	9.2973	4	0.05408
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			

b). ROA-nonlife insurance density VAR autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	2.9490	4	0.56639
2	2.4099	4	0.66084
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			

c). ROE-life insurance density VAR autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	2.9149	4	0.57217
2	2.7758	4	0.59601
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			

d). ROE-nonlife insurance density VAR autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	2.7193	4	0.60584
2	2.9986	4	0.55806
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			

e). Credit density-life insurance density VECM autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	3.7632	4	0.43900
2	6.7722	4	0.14842
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			

f). Credit density-nonlife insurance density VECM autocorrelation Test

Lags	Chi^2	df	$P>Ch^2$
1	2.4880	4	0.64678
2	4.2883	4	0.36839
**This is a Langrage Multiplier test. Tests presence of serial correlation on the used lagged values. Test H_0: No autocorrelation at lag order*			