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Carbon Footprint and Performance of Quoted Insurance Firms in Sub-Saharan African Countries

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A B S T R A C T

Purpose: This study examined the effect of the rate of carbon footprints in an economy on the financial performance of listed insurance companies in selected countries in the sub-Saharan African region. It is argued in the study that factors that are external to the insurance industry (carbon footprint) intensify risks faced by the insurance firms.

Methodology: The study employs secondary data from the sampled insurance firms' annual audited financial statements. Data was collected from forty-five (45) insurance firms in eight (8) selected sub-Saharan African countries from 2010 to 2019. A dynamic estimation procedure was adopted based on the system GMM estimation technique using dependent variables (ROA, ROE and Tobin's Q), explanatory variable CO_2 emission and moderating variables of firm's size, economic growth and inflation rate.

Results/Findings: The results from the study reveal that the pattern of effects of carbon footprints differ in terms of the measurement used for a performance indicator. In particular, the study found that the level of carbon footprint in the economy exerts significant negative effects on all the performance indicators of insurance firms. Optimal risk and sustainable insurance procedures are therefore recommended in the study.

A R T I C L E   I N F O

Keywords:
Climate Change, Carbon Dioxide Emissions, Ecological Footprint, Insurance Industry

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1.0 INTRODUCTION

The problem of environmental preservation is now being discussed in both the scientific community and in society at large. Emissions and global warming are signs of the state of our environment. For characterizing carbon dioxide (CO2) emissions, the idea of a carbon footprint is a beneficial technique (Jovic, Lakovic and Jovevskic, 2018). With a focus on carbon dioxide, the carbon footprint has developed into a powerful and well-liked instrument for calculating greenhouse gas emissions (GHG) brought on by human activity. It has also become crucial for increasing awareness and fostering ecologically beneficial behaviours. Additionally, it might be applied to planning initiatives for climate preservation and adaptation to its changes, as well as for creating and administering a low-carbon economy (Fantozzi & Bartocci, 2016; Wiśniewski & Kistowski, 2017).

One component of the ecological footprint is the carbon footprint. In other words, Wackernagel and Rees' ecological footprint, which they established, led to the development of the carbon footprint (1996). Since carbon footprints only track the atmospheric emissions of greenhouse gases that contribute to climate change, they are more narrowly focused than ecological footprints. The entire quantity of greenhouse gas emissions that anything - a person, organization, event, or product - has created is known as a carbon footprint. The gases that cause the "greenhouse effect" and contribute to global warming and climate change are known as greenhouse gases (Wackernagel, 2008).

Addressing climate change necessitates taking into account risk, unpredictability, and long-term goals, all of which are central to the insurance sector. Unsurprisingly, the insurance sector has long recognized the need to assess how the effects of climate change may affect their capacity to maintain high levels of insurance coverage and their ability to manage growing claim costs. Direct effects of climate change or global warming on the insurance business include rising premium costs, transferring more risk to policyholders through increased deductibles, and a lack of private sector insurance options for people residing in dangerous geographic areas (Ahmed, Siwar and Sarkar, 2013).

Investigation of the influence of carbon footprint on the performance of insurance firms has not received much attention from researchers. To the best of the authors' knowledge, this may be one of the few studies investigating the effects of the carbon footprint on the financial performance of listed insurance firms for selected Sub-Saharan African countries. Researchers such as Wagner (2007), Herweijer, Ranger and Ward (2009), Botzen, Van den Bergh and Bouwe (2010), Carroll, Evans, Patton and Zimolzak (2012), Ahmed, Siwar and Sarkar (2013), Porrini and Schwarze (2014) and Keskitalo, Vulturius and Scholten (2014), have all merely argued that carbon footprint exerts a significant and direct impact on insurance firms' financial performance without empirically validating or invalidating their argument. An attempt is made here to fill this gap by adding to the few existing cross-country-level studies using the dataset of listed insurance companies in selected sub-Saharan African countries. The insurance markets of Botswana, Kenya, Ghana, Mauritius, South Africa, Nigeria, Uganda, and Zimbabwe are included explicitly in our research.

The remainder of the paper is divided into the following sections: The literature review is covered in section two, and the study's methodology is covered in section three. Section four presents the outcomes of the data analysis and discusses the results, while section five covers the study's conclusions and recommendations.

2.0 LITERATURE REVIEW

2.1 Conceptual Clarification

2.1.1 Firm Performance

According to Brealey, Myers, and Marcus (2009), an organization's performance is a gauge of how efficiently it uses the resources from its core business processes to generate income over a specific time. However, the current body of research often distinguishes between two forms of company performance: inventive performance and financial or economic performance. For example, Hagedoorn and Cloodt (2003) claim that whereas innovative performance is typically expressed in terms of expenditures, patents, percentage of innovative sales, or self-reported innovations, financial or economic performance is frequently expressed in terms of growth of sales, turnover, employment, or stock prices. Although the two forms of performance are frequently connected (Damanpour & Evan, 1984), literature frequently treats the two as distinct notions or only emphasizes one of the two (Knoben & Oerlemans, 2006).

Performance is measured using a variety of factors, but the metrics most frequently employed in the literature at this time include returns on assets (ROA), returns on equity (ROE), returns on investments (ROI), and net interest margin (NIM). The aforementioned accounting measurements of performance are primarily used. Tobin Q, a market performance metric, is another firm performance indicator that has recently caught the attention of academics (Zeitun & Tian, 2007). It is calculated as the ratio of the book value of all assets to the sum of the market value of equity and the book value of liabilities. This analysis will use Tobin's Q, ROA, and ROE as performance substitutes.

2.1.2 Carbon Footprint

According to Wiedmann and Minx (2008), a product's carbon footprint is a measurement of the entire quantity of carbon dioxide emissions that are exclusively due to human activity (including that of individuals, populations, governments, businesses, organizations, processes, and industrial sectors) including goods and services. This term includes all internal and direct exterior emissions (off-site, external, embodied, upstream, downstream). According to Pandey, Agrawal, and Pandey (2011), a person, organization, process, product, or event's carbon footprint is the amount of greenhouse gases (GHGs) emitted into the atmosphere within a specific boundary represented as CO_2-equivalent. In most cases, the term "carbon footprint" is used as a general term to refer to emissions of carbon dioxide or greenhouse gases, expressed in CO_2 equivalent, produced to support human activities. These gases include methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFC), perfluorocarbons (PFCs), and sulphur hexafluoride (SF_6). The notion of a carbon footprint was developed in response to the requirement to consider the impact of all these gases on the environment (Jovic et al., 2018).

2.1.3 Method of Calculating Carbon Footprint

According to Matthews, Hendrickson, and Weber (2008), in order to use a technique to compute carbon footprints, the scope must be appropriately defined in order to determine what counts and how to prevent carbon footprints from being repeated in the aggregate. The three scopes Matthews, Hendrickson, and Weber (2008) propose are as follows:

Scope 1 relates to the accounting of direct GHG emissions from sources the firm owns or controls (e.g. the emissions from combustion in owned or controlled boilers, furnaces, and vehicles).

The accounting of indirect GHG emissions from the production of bought power consumed by the enterprise is covered under scope 2.

Scope 3 refers to indirect GHG emissions that result from the company's operations but come from sources it does not own or control (e.g. extraction and production of purchased materials, transportation of purchased fuels).

Calculating carbon footprints represented as CO_2 equivalents involves multiplying the different GHG emissions by their capacity to cause 100 years of global warming. The formula used to determine the carbon footprint of a particular activity has the following basic form: Carbon footprint of a given activity = Activity data (mass/volume/kWh/km) Emission factor (CO_2e per unit).

2.1.4 Climate-Related Risks Affecting the Financial Stability of the Insurance Sector

Over the past several years, carbon footprinting has gained popularity in the finance industry to calculate and disclose carbon emissions from internal operations and investment holdings. Physical and transition risks are two main categories of climate-related hazards that impact the insurance industry's financial stability.

Physical risks include those to the insurance and reinsurance industries from rising property and casualty claims and losses on investments in real estate or equity of businesses affected by climate-related events on the liability and asset sides (growing costs and frequency of natural catastrophes). These dangers are generally understood, but more quantification is required (United Nations Environmental Programme, 2016). Changes in physical risks should be accounted for in the insurance sector's risk modelling to reduce the impact on the sector's financial stability. For example, the business models for insurance might face significant problems due to increased physical dangers, which could change the ratio of premiums to claims and expose insurance firms to uninsured losses. In addition, the inability of policyholders to get private insurance coverage due to increased rates might make it more difficult for them to maintain financial stability, which could affect mortgage financing and property prices (Carney, 2015).

Risks linked with the transition to a low-carbon economy include interruptions and shifts that might impact a firm's asset value or operating expenses. Policy changes, market dynamics, technology advancements, or reputational considerations may all be driving forces behind transition risks. Stranded assets, or the possibility of financial losses from investments losing value (for instance, coal reserves) as a result of climate change mitigation, or a shift in consumer and investor preferences toward greener goods and technology, are examples of transition risks (United Nations Environmental Programme, 2014).

2.1.5 Effect of Carbon Footprint on the Insurance Industry

Extreme weather conditions pose a significant risk to health and life insurance companies and property insurers. For instance, a warmer planet has increased the incidence of natural disasters and the promises that go along with them in several product categories (Wagner, 2007). The insurance sector sets product prices based on historical loss data and probability. This historical pricing procedure becomes more complex and ambiguous due to climate change since previous events are no longer a good indicator of the future. With the changing global climate, insurers want greater rates (Ahmed et al., 2013). According to Webster and Clarke (2015), the insurance sector could cover all increased claims brought on by climate change by raising insurance premiums for energy producers. This would be a form of insurance-led levy that recognizes both the sector's current carbon emissions and its carbon inheritance. Similarly, Porrini and Schwarze (2014) assert that governments may gain a lot from deploying an insurance tool that could pay for harm and serve as a financial incentive for risk-reduction actions (Botzen et al., 2010; Keskitalo et al., 2014).

Carroll, Evans, Patton, and Zimolzak (2012) view the dangers of climate change in terms of liability for the insurance sector, but not the risks to society if the insurance industry is to address climate change. However, the effects of climate change on the commercial insurance sector's profitability are unlikely to be significant since insurers may transfer new risks to policyholders as long as they are adequately and immediately informed about the effects of climate change (Tol, 1998). Notably, if nations across the world uphold the Paris Agreement of 2015 to limit global warming to 1.5 or 2 degrees Celsius, a sizable number of assets in particular industries may become "stranded," meaning they will no longer have value or provide money. Insurance companies are thus reassessing their risk models, particularly their dependence on previous trends. For instance, a 2018 study in the journal Nature Climate Change anticipated that by the year 2030, between $1 trillion and $4 trillion in assets in the oil and gas sector would become stranded.

Such a setback may significantly impact the financial performance of insurance firms. For starters, it would result in decreased premiums for the insurance companies which had insured such assets. Additionally, if an insurer holds shares of businesses with stranded assets, those holdings may harm investment returns (Makower, 2019). According to Botzen et al. (2010), there is also the possibility that climate change could open up new economic opportunities for insurance providers, such as encouraging the creation of insurance policies and/or terms and conditions that reward risk mitigation (Herweijer et al., 2009). According to Botzen et al. (2010), insurance companies that create a comprehensive climate strategy and implement it into every aspect of their operations stand to gain the following advantages.

First, a solid climate strategy may support the underwriting company by encouraging the creation of new insurance products and expanding the target market. For example, a $23 trillion investment in renewable energy is expected to be made in emerging nations by 2030, according to a projection by the International Finance Corporation (IFC). As a result, the newly founded businesses and assets will provide insurers with a sizable and growing underwriting market.

Second, mounting research suggests that insurers considering environmental, social, and governance (ESG) issues, such as climate change, would likely achieve better investment outcomes (IFC, 2016). Third, insurers who lead on climate change and incorporate climate risk into their investing practises would be better positioned to compete for third-party investment mandates, especially from institutional investors like pension funds.

Fourth, insurance businesses with ambitious climate targets and transparent reporting will likely improve their reputations and strengthen their ability to attract and retain talent (IFC, 2016).

Researchers such as Wagner (2007); Herweijer et al. (2009); Botzen et al. (2010); Carroll et al. (2012); Porrini & Schwarze (2014); Keskitalo et al. (2014); Ahmed et al., (2013) among others have all argue that carbon footprint exerts a significant and direct impact on insurance firm financial performance. However, the authors could not find previous empirical studies on the link between carbon footprint and performance of insurance firms; hence we review only conceptual literature on carbon footprint and performance of insurance firms.

3.0 METHODOLOGY

In this study, the causal research design was utilized. The nature of the data is Longitudinal. The causal research design entails evaluating the cause/effect relationship between two dependent and independent variables to draw statistical inferences. The variables involved are ex-post in nature which the researchers do not have the power to influence because they have already occurred. Thus, the research structure combines cross-sectional data with time-series properties to form a panel data set.

The population of this study comprised all the insurance firms listed in the eight (8) selected sub-Saharan Africa Countries Stock Exchanges as of 31st December 2019. Fifty-three (53) insurance firms listed in the Stock Exchanges of the eight (8) selected sub-Saharan African countries comprise the population. Using a combination of purposive and stratified sampling techniques, 45 insurance firms were selected from the total of fifty-three (53) listed insurance firms in the Stock Exchanges of the eight countries based on the following stratification: Botswana, one (1), Ghana, two (2), Kenya, three (3), Mauritius, four (4), Nigeria, twenty-four (24), South-Africa, eight (8), Uganda, one (1), Zimbabwe, two (2). Based on the availability of annual reports from the insurance company's website for the research period (that is, 2010–2019), the sample filtering approach was also used to choose insurance businesses from each nation. In addition, the study used secondary data gathered from the selected insurance companies' audited annual financial reports for the reference period. The different firms' websites provided the audited annual reports. The fact that such data are simply and quickly accessible from the websites of the relevant insurance providers made the use of secondary data possible.

3.1 Theoretical Framework

The systems theory, which describes how the interplay of the external environment (carbon footprint) affects the company's performance, serves as the study's theoretical foundation. According to Laszlo and Krippner (1998), systems theory provides a robust conceptual framework for understanding how people interact with one another and the accompanying cognitive structures and processes unique to them in society and nature. It is focused on the comprehensive and integrated study of phenomena and occurrences. In order to identify a boundary-maintaining object or process, the word refers to a complex of interdependent components and the interactions between them. The general systems theory sees the entire universe as a composite of elements that coexist, interact, and relate to one another.

3.2 Specification of Model

This work developed a model that was supported by system theory. The study utilized three models because the study uses both accounting base performance and market-based performance indicators (ROA, ROE, and Tobin's q). Also, we employed the annual tons of CO_2 emission in a country per year as the proxy for carbon footprint. At the same time, the control variables were firm size, economic growth and inflation rate. The functional forms of the models are stated below;

$$ROA_{it} = f\ (CFP, FSIZE, GDPPC, INFL) \qquad (3.1)$$

$$ROE_{it} = f\ (CFP, FSIZE, GDPPC, INFL) \qquad (3.2)$$

$$TQ_{it} = f\ (CFP, FSIZE, GDPPC, INFL) \qquad (3.3)$$

One of the independent variables used to define the dynamic panel data model in econometric form is the lag of the dependent variable. To add dynamism to the model, the dependent variable was incorporated as a regressor and lagged by one year. The delayed dependent variable enables the dependent variable to be partially adjusted to its long-run equilibrium (Baltagi, Demetriades and Law, 2009). Additionally, it was added since insurance companies' success frequently depends on their prior realizations. The following is the dynamic panel data model specification:

$$ROA_{it} = \beta_0 + \beta_1 ROA_{it} + \beta_2 CFP_{it} + \beta_3 FSIZE_{it} + \beta_4 GDPPC_{it} + \beta_5 INFL_{it} + \mu_{it} \quad (3.4)$$

$$ROE_{it} = \beta_0 + \beta_1 ROA_{it} + \beta_2 CFP_{it} + \beta_3 FSIZE_{it} + \beta_4 GDPPC_{it} + \beta_5 INFL_{it} + \mu_{it} \quad (3.5)$$

$$TQ_{it} = \beta_0 + \beta_1 ROA_{it} + \beta_2 CFP_{it} + \beta_3 FSIZE_{it} + \beta_4 GDPPC_{it} + \beta_5 INFL_{it} + \mu_{it} \quad (3.6)$$

Where;

β_0 ... β_5 are coefficients of the parameters.

μ_{it} = the stochastic (error) term for insurance firm *i* at time t.

The a *priori* expectation: $\beta_1 > 0, \beta_2 > 0, \beta_3 > 0, \beta_4 > 0, \beta_5 < 0$. According to theory, the performance of insurance businesses should be positively impacted by factors like the previous year's performance, carbon footprint, company size, and economic growth, while negatively impacted by factors like inflation rate.

The subscripts *i* and *t* refer to individual firms or countries (for the macroeconomic variables) and period (2010 - 2019), respectively. ROA_{it-1}, ROE_{it-1} and $\beta_1 TQ_{it-1}$ are lagged dependent variables and their inclusion in the model is meant to take care of the potential endogeneity of the independent variable, which included the likelihood of omitted variables, simultaneity, and variable measurement error in the context of dynamic panel data method.

Table 3.1: Description of variables

Variables	**Definition**	***a priori sign***
ROA_{it}	Return on asset of insurance firm *i* at time *t*	Dependent Variable
R_{ohit}	Return on equity of firm *i* at time *t*	Dependent Variable
TQ_{it}	Tobin’s q of insurance firm *i* at time *t*	Dependent Variable
ROA_{it-1}	Lagged value of the return on asset of insurance firm *i* at time *t*	+
R_{ohit-1}	Lagged value of the return of equity of insurance firm *i* at time *t*	+
TQ_{it-1}	Lagged value of the Tobin’s q of insurance firm *i* at time *t*	+
CFP_{it}	Carbon footprint	+
$FSIZE_{it}$	Size of insurance firm	+
$GDPPC_{it}$	Economic growth	+

$INFL_{it}$	Inflation rate	-

Source: Author's Compilation, (2021).

3.3 Operational Definitions of Variables

The adopted variables are described in Table 3.2, along with information on the prior researchers who used each variable in their work.

Table 3.2: Operational Definitions of the Variables

S/N	**Variable**	**Type of Variable**	**Measurement**	**Sources**
1	Return on Asset (ROA)	Dependent Variable	$ROA = \frac{Profit\ after}{-tax\ total\ Assets}$	Aduloju & Ajemunigbohun (2017)
2	Return on Equity (ROE)	Dependent Variable	$ROE = \frac{Profit\ after}{-tax\ total\ Equity}$	Aduloju & Ajemunigbohun (2017)
3	Tobin's Q (TOQ)	Dependent Variable	$\frac{Market\ capitalization + Total\ liabilities - net\ cash\ flov}{total\ asset}$	Zeitun & Tian (2007)
4	Carbon footprint (CFP)	Independent Variable	measured as the annual tons of CO_2 emission in a country	Grub & Ellis (2007)
5	Firm Size (FSIZE)	Independent Variable	Size is measured as logarithm of total assets of the insurance firm	Kazeem (2015)
6	Economic Growth – GDP per capita (GDPPC)	Independent Variable	measured as real GDP/Population	Above & Uwubanmwen, (2014)
7	Inflation Rate (INFL)	Independent Variable	measured as the annual change in the CPI; (CPIt –CPIt-1) / CPIt-1	Above & Uwubanmwen, (2014)

Source: Author's Compilation, (2021).

3.4 Data Analysis Techniques

The data estimate is carried out in this study using statistical and economic methodologies. Descriptive and correlation analyses are both included in the descriptive statistics. We used the System Generalized Method of Moments (System GMM) estimate approach for dynamic panel data models created by Arellano and Bond (1991) and improved by Arellano and Bover (1995) to calculate the inferential statistic. To verify the validity and trustworthiness of the results from the empirical analysis, the data was exposed to a number of preliminary and diagnostic tests before we moved further with system GMM estimation. The panel unit root and cointegration tests are two examples of these preliminary and diagnostic tests. We used the Econometric View Software (REVIEW) version 10.0 to analyze all of our data.

4.0 EMPIRICAL ANALYSIS

4.1 Description of Data

The pattern of data characteristics is initially highlighted by presenting trends in relevant variables and the related summary statistics. Figure 4.1 shows the trend in carbon footprint in terms of annual changes for the individual countries. Only Zimbabwe had a generally downward trend, indicating that the rate of growth of carbon dioxide (CO_2) and other greenhouse gases emitted in the country is declining over time. Most of the other countries have trends that indicate annual instabilities but a general level trend over the years. This suggests that “carbon dioxide (CO_2) and other greenhouse gases emitted by these countries have remained relatively steady throughout the analysis.

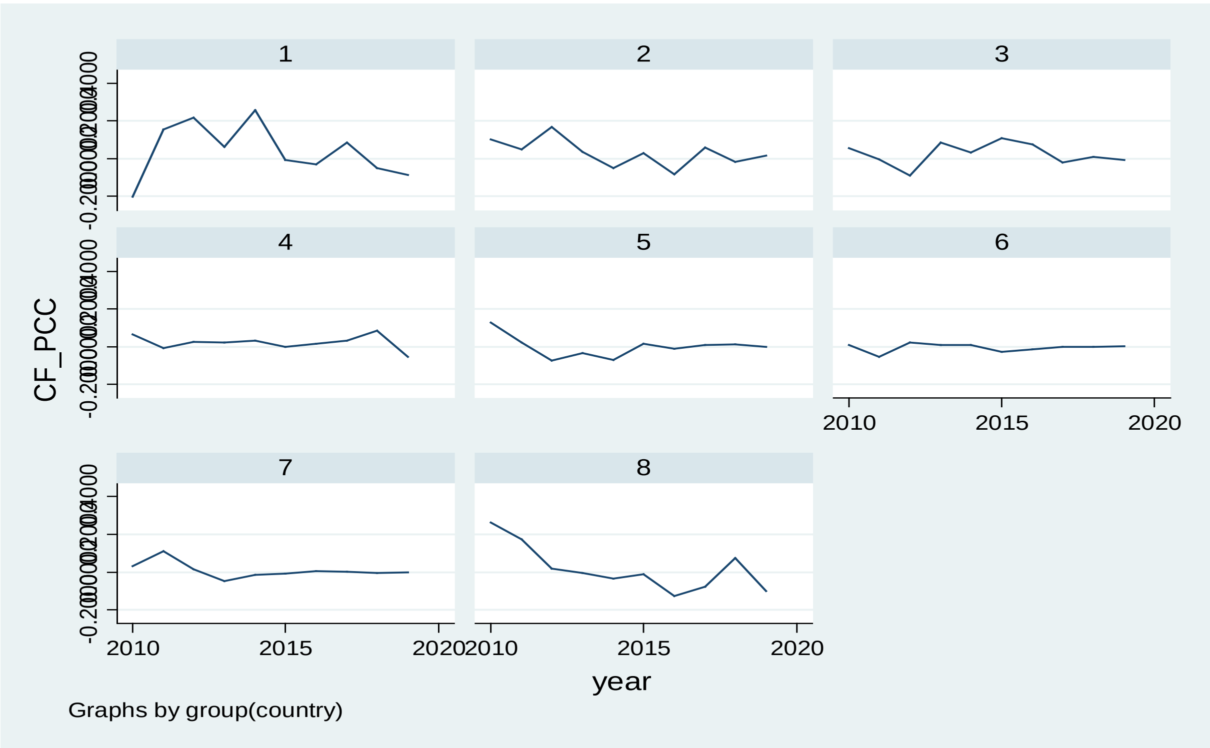

Fig. 4.1: Trends in annual changes in carbon footprint

Source: Author’s computations, (2021) using Eviews 10.0.

4.2 Statistical Analysis

4.2.1 Descriptive Statistics

The basic characterization of the datasets is also performed using descriptive statistics to summarise the data. The annualized summary statistics for all the variables in the study are presented for the sampled companies over ten years. For the performance indicators, the average return on assets (ROA) is 2.60, although there are large extreme patterns for the different companies considering the minimum of -78.32 and a maximum of 21.4. The standard deviation is much higher than the mean value, indicating that ROA across the insurance firms for the countries is exceptionally divergent (this is validated in Figure 4.1a). For return on equity, the average value is 10.08, and the standard deviation is 19.57, again showing that the ROE values are wildly divergent across the countries in the study. The average Tobin Q ratio is 1.46, indicating that insurance firms are performing well in the market in sub-Saharan African (SSA) countries. For each of the performance measures, the minimum values are essentially low (with ROE and ROA having negative minimum values), suggesting that some of the sampled companies did not perform well over the period. The standard deviations for each performance measure are relatively high (compared to the respective mean values). This also indicates that performances across the firms are highly varied, with some performing well and others performing poorly. The J-B values of the variables are also respectively significant at the 1 per cent level, suggesting a high level of heterogeneity among the firms in the sample.

Table 4.1: Descriptive Statistics

	Mean	**Max**	**Min**	**Std. Dev.**	**Skew**	**Kurt.**	**J-B**	**Prob**
ROA	2.60	21.40	-78.32	7.77	-3.66	33.13	1705.46	0.00
ROE	10.08	142.18	-158.00	19.56	-1.28	23.47	7874.25	0.00
TBQ	1.46	34.08	0.02	3.99	6.70	48.39	377.62	0.00
SIZE	5.29	7.81	3.41	0.83	1.07	4.26	103.84	0.00
GDPPC	3.82	15.45	-7.67	5.30	-0.04	2.67	1.89	0.39
INFO	10.09	255.30	-2.40	17.97	12.59	172.07	493.70	0.00
CFP	2.24	9.01	0.11	3.09	1.46	3.37	163.06	0.00
ΔCFP	0.01	0.26	-0.20	0.06	1.01	5.90	233.95	0.00

Source: Author’s computations, (2021) using Eviews 10.0.

The average annual carbon footprint per capita for the countries is 2.24 metric tonnes, while the average growth rate of carbon emission for the countries is low at 0.01. However, given a maximum annual growth rate of 0.26 in the carbon footprint for the countries, it is clear that the sub-Saharan African region does not contribute significantly to global carbon footprints.

For the control variables, the average GDP per capita growth rate among the countries is 3.82 per cent. This is a relatively low growth rate among the economies, given that the growth rate in the economy in the first decade of the 21st century was as high as 6 per cent for the region (African Center for Economic Transformation, 2014). This means that growth in the economies has declined since the middle of 2010. The skewness value of -0.04 for the GDPPC variable suggests that the countries in the study experienced similar growth rates over the period. The average size of the insurance firms is 5.29 per cent. This is relatively low. The average inflation rate is high for the economies at 10.09 per cent, although the high rates in a country like Zimbabwe (reaching 255.3 per cent) may have contributed to the relatively high average value.

All of the variables' Jarque-Bera statistics are significant at the 1% level (except for the rise in GDP per capita), demonstrating the lack of normalcy. This outcome is expected since a pool of different countries and companies was adopted for the datasets.

Hence, the result shows that firm-level characteristics may exert strong heterogeneous influences on the datasets. This is a solid basis for providing a panel-form analysis in the regression process for the study.

4.2.2 Correlation Analysis

The patterns of relationships among the independent variables in the study are evaluated with the correlation analysis shown in Table 4.2. Positive correlations exist between carbon footprint and two control variables (FSIZE and GDPPC), indicating that carbon footprint in the economy moves in the same direction as FSIZE and GDPPC. However, the carbon footprint is shown to be negatively correlated with inflation, suggesting that the carbon footprint moves in the opposite direction of the inflation rate (INFL). Positive relationships also exist between FSIZE and GDPPC, which clearly shows that the size of insurance firms generally thrives better in countries that have high GDPPC. However, the correlation coefficients between FSIZE and the inflation rate are negative. GDPPC is also negatively correlated with the inflation rate.

Table 4.2: Correlation among the explanatory variables

	CF	SIZE	GDPPC	INFO
CF	1.000000			
SIZE	0.130557	1.000000		
GDPPC	0.345859	0.113810	1.000000	-0.194680
INFO	-0.108061	-0.042720	-0.194680	1.000000

Source: Author’s Computation, (2021) using Eview 10.0

4.4 Analysis of the Panel Unit Root, Co-integration and Tests of Panel and Time series Properties of Data

4.4.1 Cross-section Dependence Test

It is necessary to disentangle the relevant variables' cross-sectional features to observe the dependence pattern. This is because the insurance firms in the sample are all SSA companies and may therefore likely exhibit similar responses to overall patterns of macroeconomic (GDPPC and INFL) and firm-specific (FSIZE) factors. This can present certain levels of interdependencies related to spatial autoregressive processes among the variables (Adegboye, 2020). In the dataset, the number of cross-sectional units (45 companies) in this study is more than the time period (10 years). This suggests that the Breusch and Pagan (1980) LM test might not offer the required measurement efficiency. In light of its greater applicability for a high number of cross-sectional units (N) observed across T time periods, Pesaran's (2004) cross-sectional dependency (CD) test is employed. For the Pesaran cross-sectional dependency (CD) approach, the test shown in Table 4.3 is used for the three equations determined in the research.

Table 4.3: Cross-section Dependence Test Results

Model series tested	Pesaran CD	P-value	Abs corr
ROA	0.24	0.81	0.11
ROE	0.82	0.41	0.17
TBQ	1.94	0.11	0.15

Source: Author’s computation, (2021) using Eviews 10.0.

This implies that the LM test by Breusch and Pagan (1980) might not provide the necessary measurement efficiency. Pesaran's (2004) cross-sectional dependence (CD) test is used due to its better applicability for a large number of cross-sectional units (N) observed throughout T time periods. The test presented in Table 4.3 is applied to the three equations discovered in the study for the Pesaran cross-sectional dependence (CD) method.

4.4.2 Panel Unit Root Tests

The data utilized for this analysis reflects the common (homogeneous) qualities of the companies included in the study and the country- and firm-specific characteristics (individual heterogeneity). To prevent the occurrence of "spurious" inference, it is necessary to utilize panel unit root tests to determine whether the data are stationary. In this work, the homogeneous panel's stationarity qualities were investigated using the test created by Levin, Lin, and Chu (LLC) (2002). These tests presuppose that the nations' cointegration vectors are equal. However, it is expected that each of the study's participating nations, along with the enterprises, will demonstrate variations in their economic and financial policies and institutionally unseen traits.

Given that the common unit root assumption may not be sufficiently realistic, the homogeneous unit roots alone may not be adequate to capture the stationarity status of the data sets. Im, Pesaran and Shin - IPS (2003) and the Augmented Dickey-Fuller test (which accounts for heterogeneity in the panel's cross-section and assumes a null hypothesis of no cointegration in the panel data) are also used to circumvent this ostensibly implausible assumption for the chosen datasets. Table 4.4 displays the results of all unit root tests. Because the variables are basically ratios, only the tests for initial differences (Xt-Xt-1) are presented in the findings.

Table 4.4: Panel Data Unit Root Tests Results *in first difference

Variable	Homogenous Unit Root Process	Heterogeneous Unit Root Process		Remarks (order of integration)
	Intercept and Trend			
	LLC	IPS	ADF-Fisher	
	X_t-X_{t-1}	X_t-X_{t-1}	X_t-X_{t-1}	
ROA	-10.24**	-5.51**	196.89	I[1]
ROE	26.69**	-13.52**	353.74**	I[1]
TBQ	-16.63**	-7.85**	252.84**	I[1]
CFP	-18.22	-8.12	234.42**	I[1]
SIZE	-11.66**	-4.66**	174.49**	I[1]
GDPPC	-5.81**	-1.94*	110.98	I[1]
INFO	-637**	-1.33	134.12**	I[1]

*Note: ** and * indicate significant at 1% and 5 % levels respectively; IPS = Im, Pesaran & Shin; LLC = Levin, Lin & Chu*

Source: Author's computation, (2021) using Eviews 10.0.

In the table above, only the test results that vary are shown. The coefficients of the first difference test for all the variables show that they are all stationary, as can be shown (given that the critical test values are higher than the test statistic). Given this circumstance, it is demonstrated that the variables are all integrated into the same order one (i.e., I[1]), allowing for the performance of a co-integrated analysis for the variables with useful results. The unit root findings strongly suggest that the variables are all stationary, with each variable having the value I[1].

4.4.3 Panel Cointegration Test

However, creating the long-term circumstances of the variable interactions is possible to provide a more solid foundation for a dynamic relationship between the variables. The results of the Pedroni and Kao cointegration tests on the panel and group assumptions are shown in Table 4.5, together with the corresponding variance ratios and rho statistics (non-parametric tests).

Table 4.5: Panel Cointegration Test Result

ROA equation	Panel Statistics	Group Statistics	Kao (ADF)
Variance ratio	-3.33		
Rho	7.99**	11.15**	-3.89**
IPS	-13.16**	-21.12**	

ADF	-2.84**	-3.93**	
ROE equation	**Panel Statistics**	**Group Statistics**	**Kao (ADF)**
Variance ratio	-6.10		-5.584**
Rho	8.58**	10.75**	
IPS	-9.34**	-17.74**	
ADF	-2.27**	-4.03**	
Tobin's Q ratio equation	**Panel Statistics**	**Group Statistics**	**Kao (ADF)**
Variance ratio	-1.99		-1.705*
Rho	6.18**	11.20**	
IPS	-4.11**	-20.15**	
ADF	-2.05**	-3.95**	

Note: **, * indicates the rejection of the null hypothesis of no cointegration at the 0.01 and 0.05 levels of significance, respectively

Source: Author's computation, (2021) using Eviews 10.0.

For both the panel and group assumptions, the coefficients of the IPS and Augmented Dickey-Fuller test statistics are significant at the 5% level. In light of this, panel cointegration is well supported by both the ADF-t and non-parametric-t statistics. Another residual-based (Kao) panel cointegration test is used to supplement these findings. The null hypothesis of no cointegration may be rejected at the 5% level for each of the equations based on the Kao residual-based cointegration test presented in Table 4.5. As a result, the cointegration tests' results indicate that the research variables have a significant long-term link. Thus, the empirical study may use the dynamic panel data estimation approach.

4.6 Regression Results for Carbon Footprint and Insurance Firms Performance

In this section, the equations specified in section three are estimated, and the results are presented and interpreted with the goal of drawing relevant policy conclusions. The dynamic panel data (DPD) estimations made with the system GMM provide the foundation for the estimated equations in this section. The results are presented in Table 4.6, where the probability of the Hansen J-statistic has the expected values, and both the first and second-order Arellano and Bond tests also possess the expected coefficients and significance level. The coefficient of carbon footprint per capita is significant at the 1 per cent level and negative. Also, the coefficient of firm size is significant at the 1 per cent level and negative. However, the coefficient of inflation rate and economic growth are significant at the 1 per cent level but positive.

Table 4.6: Results for determination of ROA

Variable	*Carbon footprint*	
	Coefficient	Prob.
ROA_{t-1}	0.127	0.000

CFP	-0.014**	0.000
SIZE	-0.376**	0.000
INFO	0.007**	0.000
LGDPPC	0.579**	0.000
Hansen J (prob)	0.517	
AR(1) (prob)	-2.37*	
AR(2) (prob)	-0.56	

Note: The symbols * and ** denote significance at the 5% and 1% levels, respectively.

Source: Author's calculation, made in 2021 with Eviews 10.0.

Table 4.7 shows the results for the estimates of the ROE equation. The diagnostic tests are all impressive and indicate precise estimation and instrument selection procedures. The coefficients of CFP are also significant at the 1 per cent level and negative, suggesting the carbon footprint has a negative impact on ROE. This further strengthens the result that carbon footprint hurts the performance of insurance firms. Also, the coefficient of firm size is also significant at the 1 per cent level, and it is also negative. However, the coefficient of inflation rate and economic growth are significant at the 1 per cent level but positive.

Table 4.7: Results for determination of ROE

Variable	*Carbon footprint*	
	Coefficient	**Prob.**
ROE_{t-1}	0.010	0.000
CFP	-0.432**	0.000
SIZE	0.836	0.747
INFO	-0.002	0.950
LGDPPC	-22.999**	0.000
Hansen J (prob)	0.336	
AR(1) (prob)	-2.28*	
AR(2) (prob)	-0.87	

Note: The symbols * and ** denote significance at the 5% and 1% levels, respectively.

Source: Author's calculation, made in 2021 with Eviews 10.0.

Table 4.8 lists the findings for Tobins' Q estimations. At the 1% level, the coefficient of carbon footprint per person is considerable and negative. This demonstrates that carbon footprint greatly influences the insurance businesses' Tobin's Q and supports the earlier findings in Tables 4.6 and 4.7. However, the correlation between company size, inflation, and economic growth is considerable but positive at the 1% level.

Table 4.8: Results for determination of Tobin’s Q

Variable	*Carbon footprint*	
	Coefficient	**Prob.**

TOBINQ$_{t-1}$	0.816**	0.000
CF	-0.009**	0.000
SIZE	0.160**	0.000
INFO	0.007**	0.000
LGDPPC	0.331**	0.000
Hansen J (prob)	0.288	
AR(1) (prob)	-1.48	
AR(2) (prob)	-1.63	

Note: The symbols * and ** denote significance at the 5% and 1% levels, respectively.

Source: Author's calculation, made in 2021 with Eviews 10.0.

Finally, we test causality between carbon footprint and performance of insurance firms in order to determine which improved insurance performance has a reverse impact on carbon footprint. This will support the argument that more insurance activities spur economic activities that may promote carbon emissions. The result of the causality test using the Dumitrescu-Hurlin Panel Causality technique is presented in Table 4.9. From the result, it is seen that causality only runs from carbon footprint to performance indicators of the insurance firms. Furthermore, only the W-statistics for the null hypothesis of causality running from CFP to the performance measures (ROA, ROE, and TOBINQ) passed the significance test. Thus, it is seen that while carbon footprint stimulates insurance performance (negatively, as shown in the regression analysis), boosts in insurance performance do not generate responses regarding higher carbon emissions among the economies in the study.

Table 4.9: Causality test between carbon footprint and insurance firm performance

Null Hypothesis:	**W-Stat.**	**Zbar-Stat.**	**Prob.**
CF does not homogeneously cause ROA	3.330	3.570	0.000
ROA does not homogeneously cause CF	2.180	1.317	0.188
CF does not homogeneously cause ROE	3.495	3.712	0.000
ROE does not homogeneously cause CF	2.455	1.755	0.079
CF does not homogeneously cause TOBINQ	2.830	2.590	0.010
TOBIN does not homogeneously cause CF	2.005	0.974	0.330

Source: Author's calculation, made in 2021 with Eviews 10.0.

4.8 Discussion of Findings

An essential outcome in the study is the clear negative impact that carbon footprint was found to exert on all performance indicators. Thus, there is a clear negative effect of the carbon footprint on performance indicators of insurance firms. This result has substantial implications given that, as Grimaldi (2021) noted, the environment plays a significant role in modern insurance companies' activities, especially in developing countries. In particular, investors and regulatory agencies have begun to increase pressure on the industry to provide appropriate mechanisms for responding to risks associated with climate change since more and more segments of society are being affected. This can lead to depletion of premium and profit pools even for more stable market segments since insurance will become challenging to operate by the affected companies.

Furthermore, as Croson and Kunreuther (2000) have noted, increased risks in environmental degradation impose additional moral hazards related to information limitations on the insurance company, thereby increasing costs and reducing efficiency. This has necessitated recent aspects of the insurance industry that focus on environmental liability aimed at reducing the information asymmetry problems generated by environmental demands. Therefore, the outcome contradicts the position of Wagner (2007); Herweijer et al. (2009); Botzen et al. (2010); Carroll et al. (2012); Porrini & Schwarze (2014); Keskitalo et al. (2014); Ahmed et al., (2013) among others who have all argue that carbon footprint exerts a significant and direct impact on insurance firm financial performance.

5.0 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this study, the effect of carbon footprints in an economy on the financial performance of insurance companies was examined in the sub-Saharan African region. Consider that carbon footprint is an externality within the insurance industry. Thus, the study presents the performance of the firms as depending on factors beyond the firms' immediate control (and the firms do not directly generate these factors). Generally, the factors considered tend to intensify the background for risks faced by the insurance operators. Forty-five (45) insurance firms in eight selected countries in the sub-Saharan African region with virile insurance sectors were used in the analysis for the period 2010 to 2019. A dynamic framework was devised for the panel data analysis using the system GMM estimation technique. The results reveal that the patterns of relationships differ in terms of the measurement used for a performance indicator.

5.2 Recommendations

The following policy recommendations are made following the outcomes of this research:

(i) There is a need for insurance companies in Sub-Saharan African countries to adopt revised business models that can provide safety nets both to support customers and enhance business efficiency. This should be done by making climate risks part of their strategic management decisions. In this direction, the strong participation of the companies in the field of risk needs to be combined with climate science to help provide mitigation systems against the influences of climate risks.

(ii) Insurance companies should adopt more innovative means of addressing the risks posed by climate change, either by helping to mitigate the risks or gearing up measures to help activate global climate change minimization.

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