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Disposable Income and Life Insurance Demand in Sub-Sahara Africa

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Abstract: This study examines the effect of disposable income on life insurance demand in Sub-Saharan Africa by taking a sample of 15 selected African countries in the Sub-Sahara region. To achieve this, we selected various countries of our interest that have consistently published their data between 1995 and 2016. The specific objectives are to determine the relative effect of per capita income, as well as major macroeconomic factors and preferences on life insurance demand in the sample countries. A sample of fifteen (15) selected African countries in the Sub-Saharan region formed the sample of this study, this was to ensure adequate observation for statistical testing. We adopted a panel (balanced) data analysis to identify the possible country's specific type of disposable income and how it affects life insurance demand. To this end, we conducted the unit root test analysis to check the level of data stationarity in the specified models. Fixed and random effects panel data techniques were conducted as well as the Hausman test which formed basis for selecting the preferred model between fixed and random effects models. Our results indicate that inflation and real interest rate both exert negative effect on life insurance demand in Sub-Saharan Africa, while gross domestic product per capita shows positive significant impact on life insurance demand in Sub-Saharan Africa. We therefore recommend that efficient management of gross domestic product per capita leading to increased disposable income is crucial if Sub-Saharan is to sustain growth in life insurance demand. The specific objectives are to determine the relative effect of per capita income, as well as major macroeconomic factors, preferences and life insurance demand in the sampled countries. It is argued in this study that the key macroeconomic factors driving demand for life insurance in the case of Sub-Saharan Africa is disposable income captured by GDPPC. Using annual data covering the period 1990 – 2011 (22 years), the study applies the panel data estimation and analytic methodology, which allows for endogenization of individual country characteristics in the analysis. The modeling adopted in this study categorizes all the necessary macroeconomic factors in the study that seek to explain both insurance penetration and insurance density for the sampled countries, which are Nigeria, South Africa, Namibia, Cameroon, Ghana, Cote d'Ivoire, Sudan, Kenya, Uganda, Mozambique, Togo, Benin, Senegal, Cape Verde and Zambia. Analyses and tests were carried out using location.

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1. Introduction

The critical nature of insurance and economies in present times cannot be over emphasized. Additionally, the important role of life insurance in volatile economic scenarios presently calls for serious insurance activity evaluation and analysis. The developing countries are not only consumers but also suppliers of insurance services to a certain degree. In a domestic market, the supply of insurance generally consist of services provided by national companies, with local and/or foreign capital, as well as by foreign companies and agencies or branches.

It is vital that if insurance is critical to economic development of developing nations, then the level of income available to individuals to be able to acquire policies must be investigated. The increased ability to accumulate savings directly affects demand for life insurance (Reddy, Reddy & Naidu, 2019). Their study suggests that an increase in savings rate and public expenditure on social security have a positive effect on life insurance.

The role of insurance has been predominantly to smoothen out consumption over time, make bequests, and repay debts or to ensure a constant income stream after retirement. The ongoing discussion also reveals that individuals' current income and future anticipated consumption expenditure plays a crucial role in determining the amount of insurance to be purchased. Insurance is of primordial importance in domestic economies and internationally. The role of insurance in the development process is difficult to assess, but there is some evidence that the promotion of life insurance programmes might have a particularly significant impact on the level personal savings in many developing countries (UNCTAD, 1982).

Life insurance demand generally has been modeled after the life cycle framework pattern in which households maximize the expected utility of their lifetime consumption. Sen (2008) shows the critical nature of income to insurance density. He states that as household incomes increase, their desire to purchase life insurance also goes up. Feyen, Lester and Rochas (2011) examine determinants of life and non-life insurance premiums for a panel of 90 countries during the period 2000-2008. The results show that premiums are driven by per capita income, the population size and density, demographic structures, income distribution, the size of the public pension system, state ownership of insurance companies, the availability of private credit and religion. The study further points out that the development of the insurance sector can be influenced by a number of policy variables. With the critical nature of life insurance in developing countries, the need for a higher level of disposable income is of utmost for households in such countries. This is so, as the per capita income of households across Africa is amongst the lowest globally and thus necessitates a critical assessment of the nascent life insurance industry is to be developed. Considering the high risk in living in such regions, life insurance ought to be a critical tool to hedge against loss of income yet very minimal studies cover how disposable income enhances this demand. This research seeks to close such gap:

- to investigate the impact of disposable income on life insurance demand in Sub-Sahara Africa;
- to determine the effect of inflation on life insurance demand in Sub-Sahara Africa;
- to evaluate the significance of interest rate on life insurance demand in Sub-Sahara Africa.

2. Litreature Review and Framework

Recent works show that gross domestic product, inflation rate and interest rate are the major macroeconomic factors influencing insurance demand. (Elango & Jones, 2011; Sen, 2008; Christophersen & Jakubik, 2014): others include disposable income, financial development etc..

Income is a central variable in insurance demand models that positively affects life insurance consumption (see Fortune, 1973; Lewis, 1989). In addition to increasing the affordability of life insurance products, a large income results in a greater loss of expected utility for the dependents in the event of the income earner's death. This effect increases the value of life insurance coverage, and therefore contributes to the positive relationship with income. Working on household level data, Fitzgerald (1987) shows that insurance demand increases with the husband's future earnings (and decreases with the wife's future earnings). Most empirical works on cross-country data use nominal GDP per capita as a proxy for disposable income. It is known, in that case, that aggregate demand is biased by positive skewness in the income distribution as individual wealth affects insurance demand. However, this issue should pose fewer problems in our sample of developed countries. Beenstock, Dickinson, and Khajuria (1986), Truett and Truett (1990), Browne and Kim (1993), Outreville (1996), and Beck and Webb (2003) provide evidence of the positive relationship between life insurance demand and income.

Theory of Life Insurance Demand

Cumulative Prospective Theory

Cumulative Prospect Theory (CPT) is a model for descriptive decisions under risk which was introduced by Amos Tversky and Daniel Kahneman in 1992 (Tversky & Kahneman, 1992). It is a further development and variant of prospect theory. The difference that this brings as compared to the original version of prospect theory is that weighting is applied to the cumulative probability distribution function, as in rank-dependent expected utility theory but not applied to the probabilities of individual outcome.

In the 1970s and 1980s, expected utility theory came under increasing question for failing to explain certain irregularities in behavior, and many modifications to the axioms or suggestions for alternate theories were proposed. Prospect theory and its successor, cumulative prospect theory (CPT), are two of the responses that have attracted a good deal of attention. As originally constructed by Kahneman and Tversky (1979) and extended by Tversky and Kahneman (1992), both theories have two component parts, loss-averse utility and a probability weighting function. Together these two features attempt a concise explanation of the major violations of expected utility theory

Cumulative prospect theory assumes that investors display a risk seeking behavior on losses (e.g., payoffs below the reference point): investors are willing to take risk in order to avoid missing their investment goals for sure. This behavior has been documented in several experimental works. Recently, the risk attitude of fund managers has also been related to their contractual incentives. (Dass, Massa, & Patgiri, 2008)

3. Methodology

We adopted a basic methodological approach for such research which is the quantitative research design using secondary data to explain the empirical relationships of the variables.

Using empirical analysis, panel data regression technique is applied on a panel regression model. The framework for the study involves the use of descriptive and inferential techniques to estimate the empirical effect of disposable income on life insurance demand in Sub-Sahara African countries.

The study further draws inference from the works of Gosh (2013) to test the effect of core variables in the work on life insurance demand in Sub-Sahara Africa, measured by insurance penetration and density. This we structured and situated into a Multiple Regression Log-linear model.

Model Specification: The model specified in this study is an extension of the research works of Browne and Kim (1993), Li et al (2007), and Elango and Jones (2011). Since the prospects and utility theories that feed the model show decision making under uncertainty, the basic tenets from the framework show that insurance demand can be decomposed into two observable concepts – risks (uncertainty) and preferences.

Risk: The uncertainties expressed in the models generally presents risk as a negative outcome that occurs with some given probability and implies a given loss with a money equivalent. This basic framework can be extended in various directions by considering some cases where correlated risks have to be considered simultaneously (e.g., an accident). More complex issues arise when utility is state dependent, since the risk then cannot be considered as purely monetary. For instance, the benefits derived from a life insurance contract depend on the current utility, for a person, of a future transfer to the offspring after the person's death. The underlying inter temporal rate of substitution/ altruistic motive may be hard to assess, let alone to distinguish from risk aversion. Hence, factors that generate risk for the policy holders are included in the model developed in this study.

In particular, we draw the model from both the prospects and utility models as effectively combined by Einav (2013) - who devised that insurance demand evolves from a vector of consumer characteristics as well as tendency for market/public sector failure (or macroeconomic uncertainties).

The demand for insurance is therefore hypothesized to depend on both aggregate macroeconomic uncertainties (risks) and individual consumers (or demographic) factors in the economy. Thus, the general form of the model may be specified as:

$$DINS = f\,(MAC) \qquad (3.1.)$$

Where DINS = demand for insurance which may be measured as the number of insurance policy taken by individuals/households

MAC = aggregate macroeconomic factors (representing risks or prospects-based factors).

Since, the price of a product is essential in the demand function, the price of insurance (PRICE) is included in the model. The use of the demand function in the model implies that estimates should report elasticities at the mean (Iyoha, 2004) by which the percentage changes in each of the explanatory variables can explain the percentage changes in insurance demand.

Equation 3.1 is therefore presented as a mathematical demand function as follows:

$$DINS = A \cdot MAC^{\alpha}\, PRICE^{\rho} \qquad (3.2)$$

Where α is the elasticity of insurance demand with respect to changes in macroeconomic factors, and ρ is the price elasticity of demand for insurance. The demand function above is a power function and reports how (after accounting for the price effect) demand for insurance will change when either macroeconomic (policy induced) factors change.

To estimate equation 3.2, there is need to make it linear by taking logarithms of both sides and also include a stochastic term. Thus, equation (3.2) becomes

$$logDINS = logA + \alpha logMAC + \rho logPRICE + u \qquad (3.3)$$

where u is the stochastic error term.

In the general demand function quantity demanded and price of the product are endogenous (at the equilibrium level) and anyone can be used to measure the behavior of demand (see Iyoha, 2004). Indeed, a study like Phelps (1973) used insurance price to model insurance demand while Browne and Kim (1993) and Fitzgerald (1987) use quantity of insurance policy taken as representative of insurance demand. It should however be noted that using insurance quantity is often associated with micro-level studies while the macro-level studies, such as this current one, uses insurance price. Hence, in this study, the price of insurance (insurance premium) is used to represent the size of demand for insurance. MAC in equation (3.3) is a vector of exogenous variables that cover the macroeconomic factors in the model. Hence, following Einav (2013) and Einav, Finkelstein and Levin (2010), the vector

MAC = {GDPPC, INFR, RIR}

Where GDPPC = Gross Domestic Product per Capita

INFR = Inflation Rate

RIR = Real Interest Rate

Note that insurance price has been endogenized in the model and the effects of the exogenous variables on insurance demand are now captured by observing their impacts on the size of the amount of price paid for insurance cover. The relationship between price of insurance (premium) and insurance demand is rather straight forward. A rise in insurance premium received by insurers due to the peculiarity of the African systems, indicates that the level of individual socio/economic development may play a major part in demand for insurance policy. Thus, given that the expanded demand for insurance model is presented as:

DINS = *f* (GDPPC, INFR, RIR)

Where DINS = Demand for insurance coverage (the insurance premium), the apriori relationships between each of the exogenous variables on the endogenous variable may be written as: $f_1, f_2, > 0; f_3 < 0$

where f_i is the partial derivative of DINS with respect to each exogenous variable.

In order to obtain more robust results, we break down insurance demand to the extent of penetration within the economy (*PEN*) and the density of insurance cover (*DEN*). Penetration shows the level of development of insurance industry in the economy while density indicates the extent of individual embrace of the industry.

Hence two models are specified further as:

$$PEN = f\,(GDPPC, INFR, RIR) \tag{3.5}$$

Where PEN = insurance penetration (measured as insurance demand/GDP);

$$DEN = f\,(\,GDPPC, INFR, RIR) \tag{3.6}$$

Where DEN = insurance density (measured as insurance demand/population)

In equations (3.5) and (3.6), it is argued that the same factors that explain development of the insurance industry in terms of demand are also responsible for explaining the level of individual demand for insurance coverage.

Given the function generated in equation (3.3), the two main models specified in this study are presented in logarithmic forms as:

$$logPEN_{it}= \alpha_{it}+ \alpha_2 logGDPPC_{it} + \alpha_3 logINFR_{it} + \alpha_4 logRIR_{it} + \delta_i + \gamma_t+ U_t \tag{3.7}$$

$$logDEN_{it} = \alpha_{it}+ \beta_2 logGDPPC_{it} + \beta_3 logINFR_{it} + \beta_4 logRIR_{it} + \delta_i + \gamma_t+ Ui_t \tag{3.8}$$

Expected Result

Where *i* represents the country, *t* represents time, α represents the general intercept and Ui_t is the general stochastic error term.

It should noted that the model specified above (3.7) and (3.8) is a panel regression model that takes the cross sectional heterogeneity among the data into cognizance. The use of fifteen (15) countries in the sub Sahara Africa sub region would definitely generate within-sample bias when OLS technique is applied in the estimation. Hence, a model that can capture such biases and endogenise them is employed. The panel model also include the random effects (or cross sectional) term (δ) and the fixed effects (or period specific) term (γ). These coefficients account for the variations across countries and over time period (Greene, 2004).

Technique of Estimation

In this study, the panel regression technique is applied in the empirical analysis on a panel regression model. A variety of different models for panel data are used in studies where heterogeneous effects are noticed within time series across space. In the panel regression method, if z_i contains only a constant term, then ordinary least squares provides consistent and efficient estimates of the common α and the slope vector β. In this estimation, two effects are highlighted:

Fixed Effects: If z_i is unobserved, but correlated with x_{it}, then the least squares estimator of β is biased and inconsistent as a consequence of an omitted variable. However, in this instance, the model

$$y_{it} = x'_{it}\beta + \alpha_i + \varepsilon_{it} \qquad (3.9)$$

(where αi = $z'_i\alpha$,) embodies all the observable effects and specifies an estimable conditional mean. This fixed effects approach takes α_i to be a group-specific constant term in the regression model. It should be noted that the term "fixed" as used here signifies the correlation of α_i and x_{it}, note that α_i is non stochastic.

Random Effects: If the unobserved individual heterogeneity, however formulated, can be assumed to be uncorrelated with the included variables, then the model may be formulated as

$$y_{it} = x'_{it}\beta + E[z'_i\alpha] + z'_i\alpha - E[z'_i\alpha]' + \varepsilon it \qquad (3.10)$$

$$= x'_{it}\beta + \alpha + u_i + \varepsilon_{it}$$

that is, as a linear regression model with a compound disturbance that may be consistently, albeit inefficiently, estimated by least squares. This random effects approach specifies that u_i is a group-specific random element, similar to ε_{it} except that for each group, there is but a single draw that enters the regression identically in each period.

The Hausman test of randomness is used to determine the best effects model to be used. The software package used in the analysis of panel data is the EVIEWS 8.0 because asides from taking care of the above mentioned effects, it is user friendly and it makes the task of actually implementing panel data regression quite easy.

Method of Analysis

Panel data was used for the analysis and for test of hypotheses; this is because it has space as well as time dimensions.

The study employs panel data for fifteen African countries for the period of twenty-two years; therefore the conditions for panel unit roots test of times series and cross-sectional observations greater than fifteen years and balanced panel data are met by the pooled observations of the study. In the study, the purposive sampling approach was used to select the fifteen (15) countries in the Sub-Sahara African region; Benin, Cameroon, Cape Verde, Cote d'Voire, Ghana, Kenya, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, Togo, Uganda and Zambia. The selected national economies range from large ones like Nigeria to very small ones like Benin Republic as can be seen from the sample list. The data also ranges across different sub-regional blocks in the region including 7 countries from West Africa, 2 from Central Africa region, 2 from East Africa and 4 from Southern African region.. The data used in study are all sourced from the World Bank. The insurance data were obtained from the World Bank schedule of the Sigma Reports (*Swiss Re*) while the other data were obtained from the World Bank *World Development Report* (2012).

Explanation of Variables is Summarized Below:-

Variable	**Description/Measurement**
GDPPC= Gross Domestic Product Per Capita	GDP/Total Population (rep. disposable income)
INFL= Inflation	% increase in prices of goods per year (average)
RIR = Real Interest Rate	Interest rate adjusted for inflation per year

4. Model I Interpretation

Hausman Test

Ho: Fixed effect model is appropriate

H1: Random effect model is appropriate

From the Hausman test result, the Chi-square statistic is 7.618247. With a probability value of 0.0545.

This shows that the Chi-square statistic is significant at the 10% level. Hence, we reject the null hypothesis that fixed effects model is appropriate. Thus the results of the fixed effects model is reported below in table.

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	7.618247	3	0.0546

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LOG(GDPPC)	2.399961	2.043739	0.017889	0.0077
LOG(INFL)	-0.046635	-0.068431	0.000077	0.0127
LOG(RIR)	-0.009562	-0.024010	0.000034	0.0136

The coefficient of determination (R^2) is approximately 0.26. It shows that about 26% of the systematic variations in the dependent variable Insurance penetration are explained by the independent variables. Similarly, the adjusted R^2 is approximately 0.25. This implies that 26% of the systematic variations in insurance penetration are accounted for by the explanatory variables. While, about 74% of these variations are attributable to disturbance terms.

The F- Statistic is 32.29 with its probability value of 0.0000. This shows that the overall model is highly significant at the 1% level. That is, all the explanatory variables are jointly significant in explaining the dependent variable (Insurance penetration).

All the explanatory variables conform to their expected signs. Gross domestic product per capita was found to be positive. While, inflation and real interest rate were negative. The coefficient of financial development is 2.044. Its t-statistic is 8.923 with a probability value of 0.00. It is highly significant at 1% level of significance. This implies that 10% increase in financial development will result in about 20.4% increase in insurance penetration. Thus gross domestic product per capita has a significant positive effect on insurance penetration in Sub-Saharan Africa.

The coefficient of inflation is -0.068. It has at-statistic of -1.43 with a probability value of 0.154. It is not significant at 10% level of significance. Thus inflation has an insignificant effect on insurance penetration in Sub-Saharan Africa.

Real interest rate has a coefficient of -0.024. Its t-statistic is -0.38. It is not significant at the 10% level. Thus real interest rate has no significant effect on insurance penetration in Sub-Saharan Africa.

Dependent Variable: LOG(PEN)
Method: Panel EGLS (Cross-section random effects)
Date: 02/28/16 Time: 17:41
Sample: 1990-2011
Periods included: 22
Cross-sections included: 15
Total panel (unbalanced) observations: 287
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(GDPPC)	2.043739	0.228909	8.928176	0.0000
LOG(INFL)	-0.068431	0.047978	-1.426305	0.1549
LOG(RIR)	-0.024010	0.063187	-0.379982	0.7042
C	-16.19772	1.756022	-9.224099	0.0000

	Effects Specification			
			S.D.	Rho
Cross-section random			1.464934	0.8190
Idiosyncratic random			0.688764	0.1810

	Weighted Statistics		
R-squared	0.254985	Mean dependent var	-0.166352
Adjusted R-squared	0.247087	S.D. dependent var	0.801318
S.E. of regression	0.694403	Sum squared resid	136.4612
F-statistic	32.28599	Durbin-Watson stat	0.827156
Prob(F-statistic)	0.000000		

	Unweighted Statistics		
R-squared	0.146024	Mean dependent var	-1.536034
Sum squared resid	800.1988	Durbin-Watson stat	0.181408

5. Model II Interpretation

Hausman Test

Ho: Fixed effect model is appropriate

H1: Random effect model is appropriate

From the hausman test result, the Chi-square statistic is 15.578429 with a probability value of 0.0014

This shows that the Chi-square statistic is significant at the 1% (precent) level. Hence, we reject the null hypothesis that fixed effects model is appropriate. Thus the results of the random effects model is reported in the table below.

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	15.578429	3	0.0014

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LOG(GDPPC)	3.594488	3.173217	0.014085	0.0004
LOG(INFL)	-0.048312	-0.075892	0.000063	0.0005
LOG(RIR)	0.043056	0.024524	0.000024	0.0002

The coefficient of determination (R^2) is approximately 0.44. It shows that about 44% of the systematic variations in the dependent variable Insurance density are explained by the independent variables. Similarly the adjusted R^2 is approximately 0.43. This implies that 43% of the systematic variations in Insurance density are accounted for by the explanatory variables. While, about 57% of these variations are attributable to disturbance terms.

The F- Statistic is 72.63 with its probability value of 0.0000. This shows that the overall model is highly significant at the 1% level. Implying that all the variables are jointly significant in explaining the dependent variable (Insurance density).

All the explanatory variables conform to their expected signs. Gross domestic product per capita and real interest rate were found to be positive. While inflation was found negative

The coefficient of (GPPC) Gross domestic product per capita is 3.17. Its t- statistic 13.81 with a probability value of 0.0000. It is highly significant at 1% level. This implies that 10% increase in Gross domestic product per capita will result in about 31.7% increase in Insurance density. Thus Gross domestic product per capita has a significant positive effect on insurance density in Sub-Saharan Africa.

The coefficient of Real interest rate is 0.026. Its t-statistic is 0.40 with a probability value of 0.69. It is not significant at 1% level. Thus real interest rate has a positive insignificant effect on insurance density in Sub-Saharan Africa.

The coefficient of inflation is -0.076. Its t-statistic -1.59 with a probability value of 0.111. It is not significant at 1% level. Thus inflation has a significant negative effect on insurance density in Sub-Saharan Africa.

Dependent Variable: LOG(DEN)
Method: Panel EGLS (Cross-section random effects)
Date: 02/28/16 Time: 17:44
Sample: 1990 2011
Periods included: 22
Cross-sections included: 15
Total panel (unbalanced) observations: 290
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(GDPPC)	3.173217	0.229748	13.81173	0.0000
LOG(INFL)	-0.075892	0.047487	-1.598154	0.1111
LOG(RIR)	0.024524	0.062117	0.394796	0.6933
C	-18.10431	1.769511	-10.23125	0.0000
	Effects Specification			
			S.D.	Rho
Cross-section random			1.623023	0.8504
Idiosyncratic random			0.680772	0.1496
	Weighted Statistics			
R-squared	0.432430	Mean dependent var		0.451758
Adjusted R-squared	0.426476	S.D. dependent var		0.917969
S.E. of regression	0.695685	Sum squared resid		138.4175
F-statistic	72.63416	Durbin-Watson stat		0.725301
Prob(F-statistic)	0.000000			
	Unweighted Statistics			
R-squared	0.191353	Mean dependent var		4.814167

Sum squared resid	1341.690	Durbin-Watson stat	0.106497

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	15.578429	3	0.0014

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LOG(GDPPC)	3.594488	3.173217	0.014085	0.0004
LOG(INFL)	-0.048312	-0.075892	0.000063	0.0005
LOG(RIR)	0.043056	0.024524	0.000024	0.0002

6. Conclusion

It is obvious from the results that amongst key macroeconomic variables affecting life insurance demand in Sub-Sahara Africa that disposable income has the strongest effect.

This paper investigated the impact of disposable income amidst macroeconomic factors on life insurance demand in the Sub-Sahara region of Africa. In the analysis of disposable and major macroeconomic indicators, it was observed that Gross Domestic Product per Capita had the most significant effect on life insurance demand. From the analysis, results showed that financial disposable income, the main variable under investigation has significant and positive effect on life insurance demand in Sub-Sahara Africa. This goes to show that for increased life insurance penetration and demand in this region of Africa, countries in this region must re-engineer their economies to create more opportunities that will directly or indirectly increase incomes across households. The governments can do this by creating the enabling and conducive environments for large scale investors to invest in different sectors of the economy. In addition, it should provide friendly and inducing economic policies like tax holidays for firms with huge investments and others.

Additionally, future research can consider if micro insurance schemes may help deepen insurance penetration across the region.

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