INSURANCE-GROWTH NEXUS IN AFRICA

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Abstract

Economic growth may be influenced by insurance-market activity through risk pooling, financial intermediations, indemnification against losses, mobilization of savings and provision of investment opportunities. Over the past few decades, there has been increasing interest in the role of the insurance sector in the economic growth of Africa. This study examines whether there is a causal relationship between the continent's economic growth and insurance-market activity (life, non-life, and total). Applying panel-estimation techniques that are robust to heterogeneity and cross-sectional dependence to a model of panel data for 11 African countries between 1995 and 2016, we find significant evidence in support of such a relationship. Total-insurance penetration has a long-term impact on economic growth, and when disaggregated into its components (life- and non-life-insurance penetration), we find evidence in support of short-term and long-term impacts on economic growth in both cases. Our study also confirms the feedback hypothesis, as we find a positive, bi-directional causality between insurance-market activity and economic growth. We also find that the contribution from non-life-insurance market activity toward economic growth far outweighs that of life-insurance market activity.

JEL Codes: C33, G22.
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1. Introduction

A prominent feature of Africa is its relatively less-developed economy compared with other continents. Based on 2016 gross domestic product (GDP) (purchasing-power parity [PPP]) data, all 10 of the poorest countries in the world are located in Africa. Thus, it is not surprising that much effort currently is being directed toward achieving sustained economic growth and development on the continent.

While trying to address this challenge of tackling underdevelopment, significant research efforts have been directed toward the role of the financial sector in general and the insurance market in particular. (e.g., Olayungbo, 2015; Omoke, 2012; *et al.*).

Particular attention is being paid to concepts that link financial development in general and insurance-market activity in particular to economic growth, such as the demand-following hypothesi, which suggests that economic growth stimulates financial development; the supply-leading hypothesis, which suggests that financial development stimulates economic growth; and the feedback hypothesis, which asserts that there is a bi-directional relationship between financial development and economic growth.

This current interest is tied to the following reasons:

1) Over the past few decades, the global insurance sector has grown rapidly, at an average rate of 10% annually since 1950. In particular, rapid growth in the insurance sector has been observed in developing economies through increased financial integration and liberalization (e.g., Chang, Lee, and Chang, 2014; Outreville, 2011). This huge growth in the sector has drawn increasing global attention.
2) It has been argued that the insurance industry may contribute directly and indirectly to economic growth in several ways. Examples include indemnification against losses, risk pooling, provision of financial intermediation services like those offered by banks, providing investment opportunities for shareholders, etc. (Kugler and Ofoghi, 2005; Rule, 2001; Skipper, 1997; Ward and Zurbruegg, 2000).
3) There is a very low insurance-penetration rate (market size/GDP) in Africa. Developed nations dominate the global insurance industry. According to KPMG's 2014 report on the insurance industry in Africa, roughly 65% of the global insurance market belongs to the

> G7 countries, even though they account for approximately 10% of the world's population. This low insurance-penetration rate in Africa indicates huge potential for growth in the continent's insurance sector.

The argument is that if the insurance sector can drive economic growth, then it is possible for the continent to take advantage of its insurance industry's potential to advance economic growth. Unfortunately, extant literature provides little research on the insurance sector's contributions to African nations' economies.

Our study's contribution to extant literature is three-fold. First, we examine the relationship between insurance-market activity and economic growth across different countries by applying panel-estimation techniques that are robust to heterogeneity and cross-sectional dependence. Thus, we avoided the pitfalls of estimation techniques used mostly by prior studies that simply assume that countries are homogenous and have no cross-sectional dependence among them. Such studies are susceptible to forecasting errors.

Second, our study confirms the feedback hypothesis. The positive, bi-directional causality found between insurance-market activity and economic growth suggests the existence of a mutually beneficial cycle in which insurance-market activity stimulates economic growth and economic growth, in turn, fuels insurance-market activity.

Third, our empirical findings indicate that total insurance market activity makes a long-term impact on economic growth, and when disaggregated into its component parts—life and non-life insurance—we find evidence of both short-term and long-term effects on economic growth. We also discover that non-life-insurance market activity makes a bigger impact on economic growth in Africa than life-insurance market activity.

The rest of this study is organized as follows: Section (2) reviews relevant literature, and Section (3) explains the methodology and data used. In Section (4), we discuss the empirical results. Finally, in Section (5), key conclusions are presented.

2. Literature Review

Despite the recent increased interest in the study of the relationship between insurance-market activity and economic growth, there is no general consensus on the relationship's structure.

There are two major hypotheses concerning the relationship between insurance-market activity and economic growth. The first is the supply-leading hypothesis, which asserts that financial development precedes economic growth. The second is the demand-following hypothesis, which contends that economic growth elicits the need for financial services.

Examples of empirical findings in support of the supply-leading hypothesis are discussed below:

The study by Ward and Zurbruegg (2000) is the first to empirically provide evidence in support of the supply-leading approach. Their work investigates the effect of insurance-sector activity on economic growth in Organization for Economic Cooperation and Development (OECD) countries between 1961 and 1996. Applying Granger causality tests, they find that insurance-market activity causes economic growth in some countries, while others show no significant causality links. They concluded that their study produced weak evidence in support of the supply-leading view.

Webb, Grace, and Skipper (2002) studied the effect of both banking-sector and insurance-sector activities on economic growth in 55 countries (a combination of developed and developing countries) between 1980 and 1996 using simultaneous equation-estimation techniques. Their results indicate that both banking and life-insurance penetration drive growth. They found no relationship between non-life insurance and growth, however.

Similarly, Adams *et al*. (2009) investigated the historical relationship between banking, insurance, and growth in Sweden. Granger causality tests also were used to test long-term series data between 1830 and 1998. Based on their findings, they concluded that the relationship between the aforementioned three variables is supply-leading in nature.

Chen, Lee, and Lee (2012) provide strong evidence in support of the supply-leading approach. The authors analyzed the impact of life insurance on economic growth. Their study covered 60 nations between 1976 and 2005. This research, using dynamic panel estimations, found that life-insurance market activity strongly impacts economic growth.

Other popular studies in support of the supply-leading theory include Han *et al.* (2010), Lee (2011), and Pan and Su (2012).

Examples of empirical findings in support of the demand-following hypothesis are discussed below:

Probably the first empirical study to provide evidence that supports the demand-following approach is that of Beenstock, Dickinson, and Khajuria (1988). Within the framework of a cross-sectional analysis of 45 countries in 1981 and a time-series study of 12 industrialized countries between 1970 and 1981, they report that life-insurance activity depends on GDP per capita.

Outreville (1990), using a cross-sectional sample of 55 developing countries to which multiple regression analyses were applied, discovered a positive relationship between property-liability insurance growth and GDP per capita, i.e., an increase in GDP per capita caused a more-than-proportionate increase in demand for insurance.

Beck and Webb (2003), with the aid of panel-regression estimations, examined the interaction between life insurance and GDP among several other variables within 68 countries between 1961 and 2000. They concluded, on the basis of their estimation results, that income per capita is one of the most robust predictors of life-insurance market activity.

Ching, Kogid, and Furuoka (2010) also assessed the insurance-growth causal nexus in Malaysia from 1997-2008. Using co-integration and Granger causality tests, they found a short-term causal relationship running from economic growth to life-insurance market activity.

Other studies in support of this approach include Browne and Kim (1993), and Pradhan, Bahmani, and Kiran (2014).

While most studies on the insurance-growth nexus support either the supply-leading or demand-following approaches, others have found bi-directional relationships that support the feedback hypothesis. A few such works are reviewed below.

Kugler and Ofoghi (2005) examined the long-term connection between insurance and growth. The paper focused on the United Kingdom and covered the period between 1966 and 2003. By applying co-integration and Granger causality tests, they concluded from the results that the relationship is mainly bi-directional.

A panel study by Lee, Lee, and Chiu (2013) of 41 countries, covering the period between 1979 and 2007, similarly concluded that rather than being strictly supply-leading or demand-following, the relationship between insurance and growth was bi-directional.

Also, Pradhan *et al*. (2016), applying a panel-data study to the Association of South East Asian Nations (ASEAN) between 1988 and 2012, produced results in support of a bi-directional causal relationship between insurance and growth.

A few other studies have discovered differences in the insurance-growth nexus for developed and developing countries. For example, Arena (2008), using generalized method-of-moments (GMM) dynamic panel estimations for 56 countries between 1976 and 2004, in addition to finding results in support of the supply-leading view, also found that life insurance had a greater effect on growth at low levels of development. This suggests that insurance contributes more to growth in developing countries than in developed countries.

Haiss and Sumegi (2008) investigated the role of the insurance sector in economic-growth performance in 29 European countries. The authors applied a cross-country panel-data analysis to life-insurance premium data from the selected nations. The study covers the period between 1992 and 2004. Findings supported a positive, but weak, impact from insurance-sector activity on economic growth. The authors also observed that while life insurance is more important in high-income European Union countries, non-life insurance is more important in developing European Union nations.

Han, Li, Moshirian, and Tian (2010), by applying GMM dynamic panel estimations to 77 nations, also concluded that: 1) The insurance-growth relationship is a supply-leading one, and 2) non-life insurance is of bigger importance to the growth of developing nations.

Some researchers also have suggested that there is no relationship between insurance-market activity and economic growth (Pan and Su, 2012; Pradhan *et al*., 2015).

It is quite evident from reviewed empirical studies that in the past, insurance-growth nexus research was carried out mainly through cross-sectional and time-series analyses (Adams *et al*., 2009; Beenstock *et al*., 1988; Ching *et al*., 2011; Kugler and Ofoghi, 2005; Outreville, 1990; Ward and Zurbruegg, 2000; Webb *et al*., 2002). More recently, the focus has shifted toward panel-data analysis as a means of evaluating related issues (Arena, 2008; Beck and Webb, 2003; Chen *et al*., 2011; Haiss and Sumegi, 2008; Lee *et al*., 2013; Pradhan *et al*., 2016). Still, most of the available related panel studies do not consider cross-sectional dependency and heterogeneity.

3. Methodology and Data

Our study sample consists of 11 African countries (Algeria, Angola, Botswana, Egypt, Kenya, Mauritius, Morocco, Namibia, Nigeria, South Africa, and Tunisia) that jointly account for roughly 93% of the insurance-market activity on the continent, according to Swiss-Re statistics. Annual data for the selected countries during the 1995-2016 period was obtained on eight variables: per-capita growth (PCGR), insurance penetration (IP), investment-to-GDP ratio (INV), inflation (INF), trade openness (OPEN), government expenditures (GEXP), corruption (COR), and population growth (PGR) -- based on data availability.

Since our intention is to examine the impact of insurance activity on economic growth, following Shen and Lee (2006), we specify a typical growth equation that takes the functional form:

GDPPC=f (IP, INV, INF, OPEN, GEXP, COR, PGR) (1)

Equation (1) is re-specified in an econometric form as:

$$GDPPC_{it} = \beta_0 + \beta_1 IP_{it} + \beta_2 INV_{it} + \beta_3 INF_{it} + \beta_4 OPEN_{it} + \beta_5 GEXP_{it} + \beta_6 COR + \beta_7 PGR + \varepsilon_{it} \quad (2)$$

in which all regressors are included in logarithmic form, $\beta_0 =$ constant term, β_k(k = 1, 2, 3, 4, 5, 6, 7) = coefficients on independent variables, ε_{it} = error term.

Per-capita GDP, a measure of the average income per resident of a country, serves as the dependent variable. Insurance penetration is the independent variable of particular interest, since it is a measure of the level of development of the insurance sector. It is computed as the ratio of direct domestic insurance premiums-to-GDP. We also introduce other variables that are generally accepted as determinants of economic growth to serve as control variables (Shen and Lee, 2006; Barro, 1996; Gyimah-Brempong, 2002; Ndoricimpa, 2017). These variables include investment, which accounts for changes in capital stock; inflation rate, which accounts for monetary discipline; trade openness, which is a measure of the degree of economic openness to trade; government expenditures; population growth; and corruption, which accounts for institutional quality. We expect insurance penetration, investment, government expenditures, and trade openness to have a positive effect on per-capita GDP, and we expect inflation and corruption to negatively impact per-capita GDP. The impact of population growth is indeterminate from extant literature.

Data on per-capita GDP, inflation, trade openness, and population growth rate were sourced from the World Development Indicator (http://data.worldbank.org); data on investment-to-GDP ratio and government expenditures were sourced from the World Economic Outlook database (https://www.imf.org); data on corruption were obtained from the Transparency International website (https://www.transparency.org); and insurance-penetration data were acquired from Swiss Re's Sigma database.

Table 1. List of variables used

Variable	Measure (in USD)	Notation	Expected Impact
Dependent Variable			
Real per-capita GDP	Percentage change in real GDP per-capita	GDPPC	
Independent Variables			
Total-insurance penetration	domestic premium as % of GDP	TIP	+
Life-insurance penetration	domestic premium as % of GDP	LIP	+
Non-life-insurance penetration	domestic premium as % of GDP	NLIP	+
Investment-to-GDP ratio	Total investment as % of GDP	INV	+
Inflation	percentage change in CPI	INF	-
Trade openness	Exports + imports as % of GDP	OPEN	+
Government expenditures	total expenses and the net acquisition of nonfinancial assets as % of GDP	GEXP	+
Corruption	Ranked index on a scale from 100 (very clean) to 0 (highly corrupt)	COR	-
Population growth rate	exponential growth rate of midyear population expressed as a percentage	PGR	-+

4. Empirical Results

Preliminary analysis

Two important concerns arise in panel-data estimations. The first was the existence of cross-sectional dependence. A key consideration in panel-data studies is the possibility that individual units are interdependent (Sarafidis and Wansbeek, 2012). Wrongly assuming that there is no cross-correlation between error terms (relaxation of the cross-sectional dependence assumption) means the variance-covariance matrix will likely increase with the number of cross-sections, and the test distributions will be rendered invalid (Cerrato and Sarantis, 2002). The second issue is the existence of heterogeneity in slope parameters, erroneously assuming that slope coefficients are homogeneous across cross-sections when they are, in fact, heterogeneous results in inconsistent parameter estimates.

Therefore, we begin by testing for cross-sectional dependence and slope homogeneity in our data.

Cross-sectional dependence test

The most widely used types of cross-sectional dependence tests are Breusch-Pagan (1980) LM, Pesaran (2004) scaled LM, and Pesaran (2004) CD tests. However, we applied the Pesaran (2004) CD test because it addresses the size-distortion problem present in the other tests. The Pesaran (2004) CD test is developed by averaging pairwise correlation coefficients to test the null of no cross-sectional dependence. The test statistic is given as:

$$\mathrm{CD_p} = \sqrt{\frac{2}{\mathrm{N(N-1)}}} \sum_{\mathrm{i=1}}^{\mathrm{N-1}} \sum_{\mathrm{j=i+1}}^{\mathrm{N}} \mathrm{T_{ij}}\, \hat{\rho}_{\mathrm{ij}} \rightarrow \mathrm{N}(0,1) \tag{3}$$

in which $\hat{\rho}_{\mathrm{ij}}$ = Pairwise correlation coefficient.

Results displayed in Table 2 provide sufficient evidence to reject the null of no cross-sectional dependence in all variables and conclude that cross-sectional dependence exists in the data.

Table 2. Cross-sectional dependence test results

	GDPPC	TIP	INV	INF	OPEN	GEXP	COR	PGR
Statistic	6.98***	5.56***	6.29***	2.55**	4.16***	3.89***	1.82*	5.70***
p-value	0.00	0.00	0.00	0.01	0.00	0.00	0.07	0.00

*Note: ***, **, and * indicate rejection of the null of no cross-sectional dependence at the 1%, 5%, and 10% levels, respectively.*

Homogeneity test

To test whether heterogeneity exists in the slope parameters, we applied the Swamy (1970) test of slope homogeneity. The Swamy (1970) test is deemed suitable since the time dimension is large, relative to cross-sections in our data. The test is based on the dispersion of individual slopes from a suitable pooled estimator (Pesaran and Yamagata, 2008) for a null of slope homogeneity. The test statistic is given as:

$$\hat{S} = \sum_{i=1}^{N}\left(\hat{\beta}_i - \hat{\beta}_{WFE}\right)' \frac{X_i' M_\tau X_i}{\hat{\sigma}_i^2}\left(\hat{\beta}_i - \hat{\beta}_{WFE}\right) \quad (4)$$

in which $\hat{\beta}_{WFE}$= weighted fixed-effect pooled estimator of slope coefficients.

The test results presented in Table 3 also provide enough evidence to reject the null of slope homogeneity in favor of heterogeneous slopes.

Table 3. Swamy (1970) homogeneity test result

Test	Statistic
95.17***	0.0026

*Note: *** indicate rejection of the null of slope homogeneity at the 1%, level.*

Tests for unit roots

Cross-sectional dependence and heterogeneity robust cross-sectional augmented Dickey Fuller (CADF) and cross-sectionally augmented IPS (Im, Pesaran and Shin, 2003) panel unit root tests were applied to test for the presence of panel stationarity. Both tests can deliver reliable and consistent results when both cross-sectional dependence and heterogeneity are present.

Cross-sectional augmented Dickey Fuller (CADF) unit root test

Pesaran (2007), by building on the Dickey Fuller/Augmented Dickey Fuller unit root tests, produced the CADF test for a null of unit root, with the CADF statistic given as:

$$CADF_i = t_i(N,T) = \frac{\left(y_{i,-1}^T \bar{M} y_{i,-1}\right)^{-1}\left(y_{i,-1}^T \bar{M} \Delta y_i\right)}{\sqrt{\sigma_i^2}\left(y_{i,-1}^T \bar{M} y_{i,-1}\right)^{-1}} \quad (5)$$

Cross-sectionally augmented IPS (CIPS) unit root test

Pesaran (2007) generated the CIPS test for a null of unit root against a heterogeneous alternative by averaging CADF test statistics for the entire panel. The CIPS test statistic is given as:

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i\,(N,T) = \frac{\sum_{i=1}^{N} CADF_i}{N} \tag{6}$$

in which $t_i(N,T)$ = the cross-sectionally augmented Dickey-Fuller test statistic for the ith cross section unit from the t-ratio of the coefficient of $y_{i,t-1}$ in the CADF regression.

Results from both tests are presented in Table 4. CADF results show that all variables except for inflation and population growth rate are stationary at first difference. CIPS results similarly indicate that all variables excluding inflation and population growth are stationary after first difference.

Table 4. Results from unit root tests

	CIPS		CADF	
	LEVEL	Δ	LEVEL	Δ
GDPPC	-2.486	-3.990***	-0.781	-4.122***
LIP	-2.608	-4.113***	-0.509	-2.297**
NLIP	-2.614	-4.835***	-0.741	-3.471***
TIP	-2.681	-4.272***	-0.532	-3.002***
INV	-2.317	-3.098 ***	-2.218	-3.205***
INF	-2.573***	-3.839***	-2.913***	-3.247***
OPEN	-1.218	-3.938***	0.879	-2.699***
GEXP	-2.025	-4.096***	2.610	-4.775***
PGR	-2.438**	-4.180***	-2.438***	-2.604***
COR	-1.847	-4.155***	0.513	-2.609***

*Note: ***, **, and * indicate rejection of the null of unit root at the 1%, 5%, and 10% levels, respectively.*

Panel cointegration test

Long-term estimation results can only be non-spurious if non I (0) variables are cointegrated. Thus, we employed the error-correction-based test by Westerlund (2007) to check for the existence of long-term relationships among the variables.

Westerlund (2007) cointegration test

Westerlund (2007) developed four-panel cointegration tests for the null of no cointegration. The tests are constructed to determine whether the error-correction term in a conditional error correction model equals zero. A rejection of the null of no error correction causes a rejection of the null of no cointegration. All four tests can deal with individual specific slope parameters and cross-sectional dependence via bootstrapping. Two out of the four tests (group mean statistics) test the null of no cointegration against an alternative in which at least one section of the panel is cointegrated. The other two tests (panel statistics) test the null of no cointegration against the alternative that the panel is cointegrated as a whole.

The group-mean statistics are computed as:

$$G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \tag{7}$$

and

$$G_\alpha = \frac{1}{N}\sum_{i=1}^{N}\frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \tag{8}$$

in which $\hat{\alpha}_i$ = error correction estimate, and $SE(\hat{\alpha}_i)$ = standard error of $\hat{\alpha}_i$.

The panel statistics are constructed as:

$$P_\tau = \frac{\hat{\alpha}}{SE(\hat{\alpha})} \tag{9}$$

and

$$P_\alpha = T\hat{\alpha} \tag{10}$$

As shown in Table 5, when the long-term relationship between per-capita GDP and the explanatory variables is tested, three out of the four cointegration tests reject the null of no cointegration, i.e., G_t, $P_{t,}$ and P_a test statistics reject the null hypothesis at the 5% significant level.

Table 5. Westerlund ECM panel cointegration test results

Statistic	Value	Z-Value	Robust P-Value
G_τ	-1.330	-1.126**	0.050
G_α	-2.148	1.206	0.550
P_τ	-4.733	-2.605**	0.050
P_α	-1.160	-0.153**	0.020

*Note: ***, **, and * indicate rejection of the null of no cointegration at the 1%, 5%, and 10% levels, respectively.*

Error-correction-based panel estimates

We estimate the relationship between per-capita growth and the explanatory variables using an error-correction form of the ARDL model. Aligning with Pesaran, Shin, and Smith (1999), the following ARDL model is specified as:

$$GDPPC_{it} = \gamma_i + \sum_{j=i}^{p} \lambda_{ij} \, GDPPC_{it-j} + \sum_{j=0}^{q} \delta'_{ij} X_{it-j} + \varepsilon_{it} \qquad (11)$$

in which i = number of groups (1,2,3,…,N) , t = number of periods (1,2,3,…,T), X_{it} = vector of explanatory variables (TIP, INV, INF, OPEN, GEXP, COR, PGR), δ_{it} = vector of coefficients, and γ_i = group specific effect.

We further re-specify eq. (11) as an error-correction equation:

$$\Delta GDPPC_{it} = \emptyset_i (GDPPC_{it-1} - \theta'_i X_{it}) + \sum_{j=i}^{p-1} \lambda^*_{ij} \, \Delta GDPPC_{it-j} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{it-j} + \varepsilon_{it} \qquad (12)$$

in which

$\emptyset_i = -\left(1 - \sum_{j=i}^{p} \lambda_{ij}\right)$ = speed of adjustment. If $\emptyset_i$ = 0, there is no proof of a long-term relationship.

$\Theta_i = \frac{\sum_{j=0}^{q} \delta_{ij}}{1 - \sum_k \lambda_{ik}}$, $\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}$ and $\delta'^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im}$

In eq. (12), the term $\emptyset_i (GDPPC_{it-1} - \theta'_i X_{it})$ measures the adjustment in GDP per-capita to the deviation from its long-term relationship with the independent variables; the terms $\sum_{j=i}^{p-1} \lambda^*_{ij} \, \Delta GDPPC_{it-j}$ and $\sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{it-j}$ capture the short-term dynamics of the model.

The error-correction equation is estimated via three different techniques: Pooled Mean Group (PMG) estimation (Pesaran *et al*., 1999), Mean Group (MG) estimation (Pesaran and Smith, 1995), and Dynamic Fixed Effect (DFE) estimation. While the MG estimator allows heterogeneity in both short- and long-term coefficients, the DFE estimator restricts the short-term, long-term, and speed-of-adjustment coefficients to be equal across cross-sections. The PMG estimator is in between both the MG and DFE. It assumes homogeneity in long-term slope coefficients, but allows heterogeneity in short-term slope coefficients.

Table 6 presents the MG, PMG, and DFE results. Results from Row I of the table reveal that the estimated speed-of-adjustment coefficients are negative and significant at 10%, 5%, and 1% in the MG, PMG, and DFE estimations, respectively, pointing to the existence of a long-term relationship between the variables. The result corroborates the conclusion drawn from the Westerlund (2007) cointegration test: that the variables have a long-term relationship. In absolute terms, the coefficient reported by DFE estimation is the highest (-0.079), followed by PMG (-0.050), then MG (-0.026).

Hausman test

As stated earlier, both PMG and DFE exhibit some degree of slope homogeneity, and they are both consistent and more efficient compared with MG, when homogeneity restrictions hold. However, once the null hypothesis of homogeneous slopes is rejected in favor of heterogeneous slopes, both PMG and DFE estimates become inconsistent, whereas the MG estimates are always consistent irrespective of whether the model is homogeneous or heterogeneous. We apply the Hausman test as a means of determining the difference in the models by performing pairwise comparisons between PMG and MG, and also between DFE and MG.

The Hausman tests' results, reported in Table 6, indicate that the null of homogeneity restrictions is rejected in both cases. Thus, we may conclude that our panel time-series data contain heterogeneous slopes. The result is a reaffirmation of the Swamy (1970) test result, leading to the conclusion that the MG estimates are superior to the others.

Based on the more suitable MG results, insurance penetration has a positive and significant impact on per-capita GDP in the long term, while the short-term effect is insignificant.

Specifically, a percentage increase in total insurance premium results in a roughly 0.31 percent increase in per-capita GDP in the long term. The result is significant at 1%.

Other results show that investment has only a long-term impact on per-capita GDP, and that a 1 percent increase in INV leads to a roughly 1.264% rise in GDPPC. The result is significant at 1%. This conforms with economic theory that says increased investment stimulates economic growth. Our result, however, suggests that the impact of investment on economic growth is not instantaneous.

Inflation is shown to have a significantly negative effect on per-capita GDP, both in the long term and short term. For every percentage-point increase in INF, GDPPC falls by approximately 0.490 percent in the long term. In the short term, one period-lagged effect of a percentage change in INF results in a 0.018 percent change in GDPPC in the following periods. Both results are significant at 5%. This finding is also in line with economic theory suggesting that a negative relationship exists between inflation and economic growth.

Trade openness significantly impacts per-capita GDP positively in the long and short terms. For every percentage-point rise in OPEN, per-capita GDP rises by approximately 1.9 percent in the long term, and in the short term, one period-lagged effect of a percentage increase in OPEN leads to a 0.016 percent increase in GDPPC in the following periods. The results are significant at 1% and 5%, respectively.

Government expenditures have a positive and significant effect on per-capita GDP, both in the long and short terms. If GEXP increases by 1 percent, GDPPC is expected to increase by 1.376 percent in the long term, and one period-lagged effect of a percentage increase in GEXP results in 0.054 percent increase in GDPPC in the following periods. Results are significant at 5% and 1%, respectively. Our findings suggest that government expenditures have the most influence on per-capita GDP for the selected African countries. This outcome aligns with the findings of Barro (1990) and Barro and Sala-i-Martin (1992), which concluded that government expenditures increase GDP.

Corruption, which we use as a proxy for quality of African institutions, has a negative and significant long-term impact on economic performance. A 1% increase in the level of corruption leads to a 1.363 percent decrease in GDPPC. The result is significant at 1%.

The impact of population growth also turns out to be significantly negative in the long term, with each percentage increase in the population growth rate resulting in a 1.823 percent decrease in GDPPC. Our findings suggest that population growth has the largest negative impact on economic performance.

Table 6. PMG, MG, and DFE estimates of the growth equation

	(1)	(2)	(3)
	MG	PMG	DFE
Adjustment coefficient	-0.026 (-1.68*)	-0.0504(-2.61**)	-0.079 (-3.57***)
Long-term coefficients			
TIP	0.31 (2.84***)	0.27 (2.76***)	0.11 (2.42***)
INV	1.264 (5.74***)	1.348 (3.36***)	1.961 (1.86*)
INF	-0.490 (-2.46**)	-1.077 (-3.21***)	-1.056 (-3.36***)
OPEN	1.901 (3.50***)	1.585(2.56**)	2.325 (2.39***)
GEXP	1.376(1.94**)	0.3023(1.58*)	0.607 (2.31**)
COR	-1.363 (-4.78***)	-0.959(-2.50**)	-0.824 (-3.20***)
PGR	-1.823 (-2.19**)	-0.508(-1.46)	-3.334 (-2.60***)
Short-term coefficients			
ΔTIP	0.062(1.09)	0.073 (3.87***)	0.091 (4.74***)
ΔINV	0.053 (1.07)	0.072 (2.47**)	0.00037 (0.02)
ΔINF	-0.018 (-2.37**)	-0.005 (-2.63**)	-0.006 (-1.26)
ΔOPEN	0.016 (2.44**)	0.051 (2.14*)	0.028 (1.07)
ΔGEXP	0.054 (4.61***)	0.073 (1.96**)	0.0098 (4.40***)
ΔCOR	0.002 (1.25)	-.001(-1.78*)	-0.0001 (-0.12)
ΔPGR	2.547 (1.17)	0.885(0.94)	-0.0077(-0.29)
Number of observations	234	234	234
Number of countries	11	11	11
Hausman test	MG VS PMG		MG VS DFE
Chi2 (5)	13.36		22.91
Prob>chi2	0.0639		0.057

*Notes: (1) ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. (2) t-ratios are in parenthesis.*

Estimates based on life- and non-life-insurance penetration

As a form of robustness test, we disaggregate the total insurance-penetration data into its two component parts—life- and non-life-insurance penetration—to examine the different impacts made by each component on per-capita growth. Again, the more-suitable MG estimate is used, and the results are presented in Table 7.

Table 7 results show that the error-correction term remains negative and significant. Impacts from both life- and non-life-insurance penetration were significant and positive in both the long and short terms, and the impact from non-life-insurance penetration (NLIP) was found to be larger than that of life-insurance penetration (LIP). In the long term, for every percentage-point increase in NLIP, per-capita GDP increases by 0.14 percent, and every percentage-point increase in LIP results in a 0.05 percent rise in per-capita GDP. The results are significant at 1% and 5%, respectively. In the short term, one period-lagged effect of NLIP and LIP results in 0.062 and 0.030 percent increases in GDPPC in the following periods, respectively. Both results are significant at 1%. The findings suggest that while long-term effects of insurance are robust in the long term, they are not in the short term, since regardless of whether total insurance penetration or its disaggregated components are used as regressors, the results show that there is a long-term effect. However, the same cannot be said about the short-term estimates that become significant when disaggregated variables are used. Other results are like what was previously obtained in Table 6.

Table 7. Robustness check with life- and non-life-insurance penetration

	MG
Adjustment coefficient	-0.086 (-3.91***)
Long-term coefficients	
NLIP	0.14 (3.07***)
LIP	0.05 (2.25**)
INV	1.924 (1.90*)
INF	-1.004 (-1.43*)
OPEN	2.128 (2.87**)
GEXP	0.654(2.59***)
COR	-0.769 (-3.16***)
PGR	-3.467 (-2.99***)
Short-term coefficients	
ΔNLIP	0.062(3.34***)
ΔLIP	0.030 (3.10***)
ΔINV	0.002 (0.07)
ΔINF	-0.006 (-2.35**)
ΔOPEN	0.031(1.47*)
ΔGEXP	0.018 (2.27**)
ΔCOR	-0.00024 (-0.27)
ΔPGR	-0.0051 (-0.19)
Number of observations	234
Number of countries	11

*Notes: (1) ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.(2) t-ratios are in parenthesis.*

Panel Granger causality tests

Finally, we used the Dumitrescu-Hurlin (2012) Granger causality test to detect causal relationships among the variables for the selected countries. The general form of the multivariate regressions in panel Granger causality testing is specified as:

$$y_{it} = \alpha_{0i} + \alpha_{1i}y_{it-1} + \cdots + \alpha_{li}y_{it-l} + \beta_{1i}X_{it-1} + \cdots + \beta_{li}X_{it-l} + \varepsilon_{it} \quad (13)$$

$$X_{it} = \alpha_{0i} + \alpha_{1i}X_{it-1} + \cdots + \alpha_{li}X_{it-l} + \beta_{1i}y_{it-1} + \cdots + \beta_{li}y_{it-l} + \varepsilon_{it} \quad (14)$$

The Dumitrescu–Hurlin (2012) approach leaves all coefficients free to vary across cross-sections such that:

$$\alpha_{0i} \neq \alpha_{0j,}\alpha_{1i} \neq \alpha_{1j,} \ldots, \alpha_{li} \neq \alpha_{lj}, \forall i, j, \quad (15)$$

$$\beta_{1i} \neq \beta_{1j,} \ldots, \beta_{li} \neq \beta_{lj}, \forall i, j \quad (16)$$

Under the Dumitrescu-Hurlin panel causality test, Granger causality regressions are performed for each of the cross-sections from which test-statistics averages are generated. The differenced data for the non-stationary variables are used in the bivariate Panel Granger causality tests, while the level data are used for the stationary variables.

Results from the Dumitrescu-Hurlin causality tests are reported in Table 8. Bi-directional causality is revealed between total insurance penetration and per-capita GDP, total insurance penetration and corruption, investment and corruption, investment and population growth, inflation and per-capita GDP, trade openness and per-capita GDP, government expenditures and per-capita GDP, government expenditures and corruption, population growth and per-capita GDP, and per-capita GDP and corruption.

One-way causality was revealed running from investment to total insurance penetration, total insurance penetration to trade openness, total insurance penetration to government expenditures, population growth to total insurance penetration, investment to inflation, investment to per-capita GDP, trade openness to investment, investment to government expenditures, trade openness to corruption, trade openness to government expenditures, and government expenditures to population growth.

No causality was found between total insurance penetration and inflation, inflation and trade openness, inflation and government expenditures, inflation and corruption, inflation and population growth, trade openness and population growth, and corruption and population growth.

Table 8. Results from Dumitrescu-Hurlin Granger causality tests

Hypothesis	Statistic	P-Value	Conclusion
ΔTIP→ΔGDPPC	0.2558**	0.0218	Two-way causality between TIP and GDPPC
ΔGDPPC→ΔTIP	0.0796***	0.0046	
ΔTIP→ΔINV	0.7714	0.4810	One-way causality from INV to TIP
ΔINV→ΔTIP	2.4036***	0.0000	
ΔTIP→INF	0.3444	0.1003	No causality between TIP and INF
INF→ΔTIP	0.9891	0.9732	
ΔTIP→ΔOPEN	0.4484*	0.0891	One-way causality from TIP to OPEN
ΔOPEN→ΔTIP	0.5689	0.1839	
ΔTIP→ΔGEXP	0.3678**	0.0413	One-way causality from TIP to GEXP
ΔGEXP→ΔTIP	0.9393	0.8515	
ΔTIP→ΔCOR	0.2722**	0.0249	Two-way causality between TIP and COR
ΔCOR→ΔTIP	2.4572***	0.0000	
ΔTIP→PGR	1.3930	0.2258	One-way causality from PGR to TIP
PGR→ΔTIP	0.1888**	0.0124	
ΔINV→ΔGDPPC	0.1281***	0.0072	One-way causality from INV and GDPPC
ΔGDPPC→ΔINV	1.3611	0.2657	
ΔINV→INF	0.4213*	0.0745	One-way causality from INV and INF
INF→ΔINV	0.5738	0.1889	
ΔINV→ΔOPEN	0.6772	0.4983	One-way causality from OPEN to INV
ΔOPEN→ΔINV	0.4450*	0.0871	
ΔINV→ΔGEXP	0.4138*	0.0708	One-way causality from INV to GEXP
ΔGEXP→ΔINV	0.8338	0.6085	
ΔINV→ΔCOR	0.6132***	0.0000	Two-way causality between INV and COR
ΔCOR→ΔINV	0.5552***	0.0000	
ΔINV→PGR	0.6276***	0.0000	Two-way causality between INV and PGR
PGR→ΔINV	0.1449***	0.0018	
INF→ΔGDPPC	0.1498***	0.0088	Two-way causality between GDPPC and INF
ΔGDPPC→INF	2.5425***	0.0000	
INF→ΔOPEN	1.1841	0.5703	No causality between OPEN and INF
ΔOPEN→INF	1.0137	0.9663	
INF→ΔGEXP	0.6026	0.2206	No causality between INF and GEXP
ΔGEXP→INF	0.7117	0.3742	
INF→ΔCOR	1.3007	0.3540	No causality between COR and INF

ΔCOR→INF	1.0188	0.9537	
INF→PGR	-0.1365	0.7883	No causality between INF and PGR
PGR→INF	0.6972	0.5794	
ΔOPEN→ΔGDPPC	0.4102*	0.0691	Two-way causality between OPEN and GDPPC
ΔGDPPC→ΔOPEN	0.3263**	0.0378	
ΔOPEN→ΔGEXP	1.1254***	0.0000	One-way causality from OPEN to GEXP
ΔGEXP→ΔOPEN	1.8025	0.1500	
ΔOPEN→ΔCOR	0.3120*	0.0548	One-way causality from OPEN to COR
ΔCOR→ΔOPEN	0.6917	0.5230	
ΔOPEN→PGR	1.2354	0.2367	No causality between OPEN and PGR
PGR→ΔOPEN	0.4534	0.1065	
ΔGEXP→ΔGDPPC	0.5890***	0.0000	Two-way causality between GEXP and GDPPC
ΔGDPPC→ΔGEXP	1.5729***	0.0000	
ΔGEXP→ΔCOR	0.6657***	0.0005	Two-way causality between GEXP and COR
ΔCOR→ΔGEXP	0.8114***	0.0000	
ΔGEXP→PGR	2.0647***	0.0000	One-way causality from GEXP to PGR
PGR→ΔGEXP	0.4705	0.2071	
ΔCOR→ΔGDPPC	1.0000***	0.0030	Two-way causality between GDPPC and COR
ΔGDPPC→ΔCOR	1.4114***	0.0040	
ΔCOR→PGR	2.5935	0.2967	No causality between COR and PGR
PGR→ΔCOR	1.4989	0.3972	
PGR→ΔGDPPC	26.8420***	0.0000	Two-way causality between GDPPC and PCR
ΔGDPPC→PGR	3.6642***	0.0002	

*Note: ***, **, and * indicate rejection of the null of no causality at the 1%, 5%, and 10% levels, respectively.*

5. Conclusion

Most extant literature on the relationship between insurance-market activity and economic growth has focused mainly on either time-series analysis of single countries or on panel studies that do not consider cross-sectional dependence and slope heterogeneity. As a result, their findings have been mostly ambiguous and influenced heavily by country-specific factors. We improved on these studies by investigating the insurance-growth nexus in 11 African nations within a panel framework that is robust to these two problems. The econometric techniques adopted in our study provide an improvement on past studies. Thus, our findings are more accurate and very useful for aiding insurance-market policy formulation.

This study adopts the following: Pesaran (2004) CD test, Swamy (1970) slope homogeneity test, CIPS and CADF unit root tests, Westerlund (2007) cointegration test, and the PMG, MG, and DFE estimation techniques to examine the relationship between insurance penetration and per-capita GDP in 11 African countries that jointly account for roughly 93% of the continent's insurance-market activity. A panel time-series data set for the period 1995 to 2016 was used for our analysis.

Results from the panel cointegration test proffer evidence in support of a long-term relationship between total insurance penetration and per-capita GDP. The MG estimates indicate that increases in total insurance penetration cause per-capita GDP to rise only in the long term. However, it is possible to obtain incorrect estimates when an aggregated measure of insurance-market activity is used in regression estimates (Kugler and Ofoghi, 2005). To avoid this problem, we disaggregated total insurance penetration into life- and non-life-insurance penetration, with the results showing that per-capita GDP is, in fact, positively affected by increases in life- and non-life-insurance penetration, both in the short and long terms.

To obtain further details about the patterns of relationships concerning insurance penetration and per-capita GDP (i.e., demand-following hypothesis, supply-leading hypothesis, neutral hypothesis, and feedback hypothesis), we applied panel-causality tests. The outcomes indicated that a positive and bi-directional relationship exists between total insurance penetration and per-capita GDP.

The findings also indicate that non-life-insurance market activity has a bigger effect than life-insurance market activity on economic performance in Africa. Therefore, we reached the following conclusions:

First, our study provides evidence in support of both the supply-leading and demand-following concepts (feedback hypothesis) for Africa. This positive, bi-directional causality found between insurance penetration and per-capita GDP suggests that while insurance-market activity stimulates economic growth, economic growth also induces insurance-market activity. This supports the conclusions reached by Lee, Lee, and Chiu (2013), and Pradhan *et al*. (2016).

Second, our study provides empirical justification for the adoption of policies that strengthen the insurance sector in Africa. For example, policies that address issues said to be limiting insurance penetration on the continent, e.g., lack of trust in financial service providers, challenging business environments, lack of reliable information (especially in assessing creditworthiness), poor legal and judicial systems, and lack of human capital/expertise, should be actively pursued.

Third, policies that drive growth in the real economy should be supported to improve the insurance sector's performance in Africa. According to KPMG's 2014 sector report on insurance in Africa, because most Africans still struggle to meet their daily needs, insurance is not a priority for them. Thus, a major way to boost the insurance sector in Africa is to improve residents' standard of living.

Fourth, the larger impact of non-life-insurance market activity, compared with life-insurance market activity, provides evidence that supports the conclusion reached by Haiss and Sumegi (2008) and Han *et al*. (2010): that the impact of non-life insurance is greater than that of life insurance in developing countries.

Fifth, the fact that our findings suggest that the effect of life insurance is relatively very small is of key interest, especially because several studies have asserted that there is a negative relationship between attitude toward purchasing life insurance and fatalism (proxied mainly by culture and religion), such that people who believe in fate purchase less life insurance. We suspect that fatalism could have an influence on the limited impact of life insurance since Africa is a continent with strong cultural and religious attachments.

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