Insurance and economic policy uncertainty

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Abstract

Just as the world has witnessed the increased importance of the insurance sector over the past few decades, it has also witnessed a sharp rise in risks and uncertainties. Surprisingly, studies analyzing the relationship between economic policy uncertainty and the insurance sector are almost non-existent. Also, a major limitation of insurance literature is the choice of methodology. Most studies about the insurance sector do not take into consideration issues of heterogeneity and cross-sectional dependence, and are therefore subject to errors. To address the identified gaps, this study investigates the impact of economic policy uncertainty on insurance premiums, controlling for the effect of real income, in a panel of 15 countries over the period 1998-2016 by employing heterogeneous panel estimation techniques with cross-sectional dependence. CADF and CIPS unit root tests conducted show that each of the variables becomes stationary after first difference. The Westerlund (2007) cointegration test results confirm that a long-run relationship exists between the variables. Findings from the error correction based panel estimations show that the insurance sector is not immune to the effects of economic policy uncertainty and real income. Economic policy uncertainty initially raises insurance premiums in the short run but eventually lessens it in the long run whereas real income increases insurance premiums both in the short and long run, although its long run impact is greater than the short run impact. Also, economic policy uncertainty exerts a bigger influence on non-life insurance premium than on life insurance premium.

JEL Codes: C33, G22.

Keywords: Economic policy uncertainty, insurance premium, short- and long-run relationships.

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1. Introduction

The study of economic uncertainty and its resultant effect on economic activities has been on for decades. As far back as almost 100 years ago, in 1921, Frank Knight's 'Risk, Uncertainty and Profit' was already a leading scholarly work in the study of economic uncertainty. Knight (1921) tried to put the concept of uncertainty in proper perspective by defining it as an unknown risk without a known distribution of expected probabilities. Subsequently, many researchers such as Lucas and Prescott (1971), Bernanke (1983), Caballero (1991), Dixit and Pindyck (1994), Caporale and McKiernan (1998), Mason-Jones and Towill (2000), Fountas and Karanasos (2006), Bloom (2009), and Bai, Kehoe and Arellano (2011) also tried to answer the question of how uncertainty matters for various aspects of an economy.

Research and policy interests in the source, spread and persistence of uncertainty led to the need for a reliable and consistent means of measuring it. Facing this same challenge, Baker, Bloom and Davis (2013), while attempting to study the effect of uncertainty of economic activities, constructed a new index of economic policy uncertainty. The index is built on 3 underlying components—the frequency of newspaper reports on policy-related economic uncertainty, number of federal tax code provisions set to expire and disagreement among economic forecasters. The VAR estimates obtained by Baker *et al.* (2013) using this new index showed that rise in economic policy uncertainty post-recession had significant negative impacts on investment, hiring decisions and consumption spending. The overall significance of the study by Baker *et al.* (2013) however far outweighs the original findings as many researchers trying to examine the relationship between policy uncertainty and other economic variables have similarly adopted their index.

Policy-related uncertainties are a major component of overall economic uncertainties within a given society (Istrefi and Piloiu, 2014). While researchers are increasingly adopting the economic policy uncertainty index in studies on policy-related uncertainties, most of such studies, past and present, are focused on the macroeconomic effects of policy uncertainties. Most of the attention has been on the identification of impacts of economic policy uncertainty on macroeconomic variables such as growth, investment, consumption, unemployment, inflation, etc. Kang and Ratti (2013), Istrefi and Piloiu (2014), Karnizova and Li (2014), Balcilar, Modise, Gupta and Muteba Mwamba (2015), Brogaard and Detzel (2015), Leippold and Matthys (2015), Balcilar, Gupta, Kyei and Wohar (2016), and Kido (2016) are a few of such studies, amongst many others, on the effect of economic policy uncertainty on macroeconomic aggregates.

A substantial portion of uncertainty studies have also considered the relationship between uncertainty and different aspects of the financial system. The complex relationship between economic policy uncertainties and the financial system was further exposed by the global financial crisis of 2007-2009. Fiscal, monetary and regulatory policy uncertainties in Europe and the United States were identified as part of the reasons for the crisis and the slow recovery from it (Baker *et al.,* 2016). Studies on the relationship between uncertainty and the financial sector are however mainly focused on the impacts of uncertainty on the banking system and its lending decisions (e.g. Quagliariello, 2009; Baum, Caglayan and Ozkan, 2013; Bordo, Duca and Koch, 2016) and the stock markets (e.g. Antonakakis, Chatziantoniou and Filis, 2013; Arouri, Rault and Teulon, 2014; Liu and Zhang, 2015; Antonakakis and Floros, 2016; Christou and Gupta, 2016).

Studies examining the influence of policy-related uncertainties on insurance premiums in any financial system are almost non-existent. However, the global insurance market, which has grown rapidly at an average of 10% per annum since 1950, with a global insurance premium value close to 5 Trillion USD as at 2016, is arguably the second most important financial institution—after the banks—in the financial system. A crisis in such a huge sector is capable of causing serious loss to stakeholders and serious damage to an economy; there is thus a greater likelihood that insurers will be tempted to act in a risk-averse manner.

Vast majority of insurers factor policy uncertainties into their premium determination as a means of mitigating risk. Premiums collected by insurers are used to fund investments in guaranteed or low-risk securities, and profits are made from interests and returns on these investments. The possibility that actual returns on these investments may differ from expected returns increases as economic policy uncertainty increases. The possibility of such differences means that insurers stand the chance of losing substantial portions of their investment. To keep profit level constant in case of unanticipated, unfavorable economic policy changes, higher premiums will be charged. Also, for assuming higher risks on behalf of policy holders as a result of increased uncertainty, insurers are likely to charge some risk premium. As an example, the policy uncertainty surrounding the repeal and replacement of the affordable care act (ObamaCare) in the United States has caused many insurers to raise premiums while some others have threatened complete withdrawal from the market. There is thus a strong indication that insurance premiums are strongly influenced by economic policy uncertainties.

Empirically, a connection has been established between economic risks and the insurance sector. Lee, Chiu and Chang (2013) show that reduction in economic risks lowers insurance demand elasticity. Since policy uncertainties are a class of economic risks and economic risks influence insurance demand, it is highly likely that economic policy uncertainties may also influence insurance premiums. Also, Gupta, Lahiani, Lee and Lee (2016) posit that since economic policy uncertainties exert some pressure on economic activities, it is logical to assume that it will also have some influence on insurance purchasing behavior.

On the other hand, the resilience shown by the insurance industry during the global financial crisis should make one curious. Even though growth rate of insurance premium is still below pre-crisis levels, the effect of the crisis on insurance premiums was relatively limited. One is thus tempted to assume that the insurance sector is well capable of absorbing shocks and may therefore be relatively immune to the adverse effects of uncertainty.

This study aims to bridge the gap identified by providing a clear and robust perspective on the relatively un-researched impact of economic policy uncertainty on insurance premium growth by applying superior second generation panel model techniques rather than the commonly used first generation panel model techniques to a panel time-series of 15 countries for the period between 1998-2015.

The rest of this study is organized as follows: section (2) gives a description of the econometric model and data used in our analysis, section (3) outlines the empirical methods used, results obtained and their interpretation, and in section (4), key conclusions are presented.

2. Data

Our sample is made up of 15 countries for the period 1998-2016. The countries included are; Australia, Brazil, Canada, Chile, China, France, Germany, Ireland, Italy, Japan, Korea, Russia, Sweden, UK and USA. The choice of countries and time frame was made solely on the basis of data availability. Although data on economic policy uncertainty is available for 20 countries, only the countries with relatively long historical data on economic policy uncertainty were chosen.

The following variables are used in our estimations; economic policy uncertainty index, insurance premiums (life, non-life and total) and real gross domestic product. Economic policy uncertainty is the variable of interest. The economic policy uncertainty index used in our study follows the Baker *et al.* (2016) historical measure of uncertainty. This index uses only the frequency of newspaper reports component, the other two components included in Baker *et al.* (2013) index are dropped in order to extend the economic policy uncertainty measure across time and countries. The index is constructed from monthly newspaper searches for economic and policy uncertainty related issues. The index can be downloaded at https://www.policyuncertainty.com/us_monthly.html. 12-month averages were taken to convert the economic policy uncertainty monthly index into annual values.

Although the apriori expectation is that a positive relationship exists between economic policy uncertainty and insurance premiums, the tendency of insurers to act in a risk-averse manner and raise premiums in order to compensate for uncertainties suggests that the insurance sector is strongly impacted by uncertainties. On the other hand, the insurance sector has shown strong capacity for absorbing shocks, an indication that uncertainties may have little or no significant impact on it. The effect of economic policy uncertainty on insurance premiums is therefore indeterminate.

Insurance premiums (total, life and non-life) are the dependent variables. Insurance premiums refer to the payments made by individuals or businesses for insurance policies and it represents the income received by insurers. Data on insurance premiums was sourced from 'Swiss Re, Sigma database'.

The plots of economic policy uncertainty index for each of the countries included in our sample are presented in Fig 1. Spikes witnessed in the indexes often seem to correspond with periods of major global events like the gulf wars, the 9/11 terrorist attacks, periods of political tensions, financial crises etc.

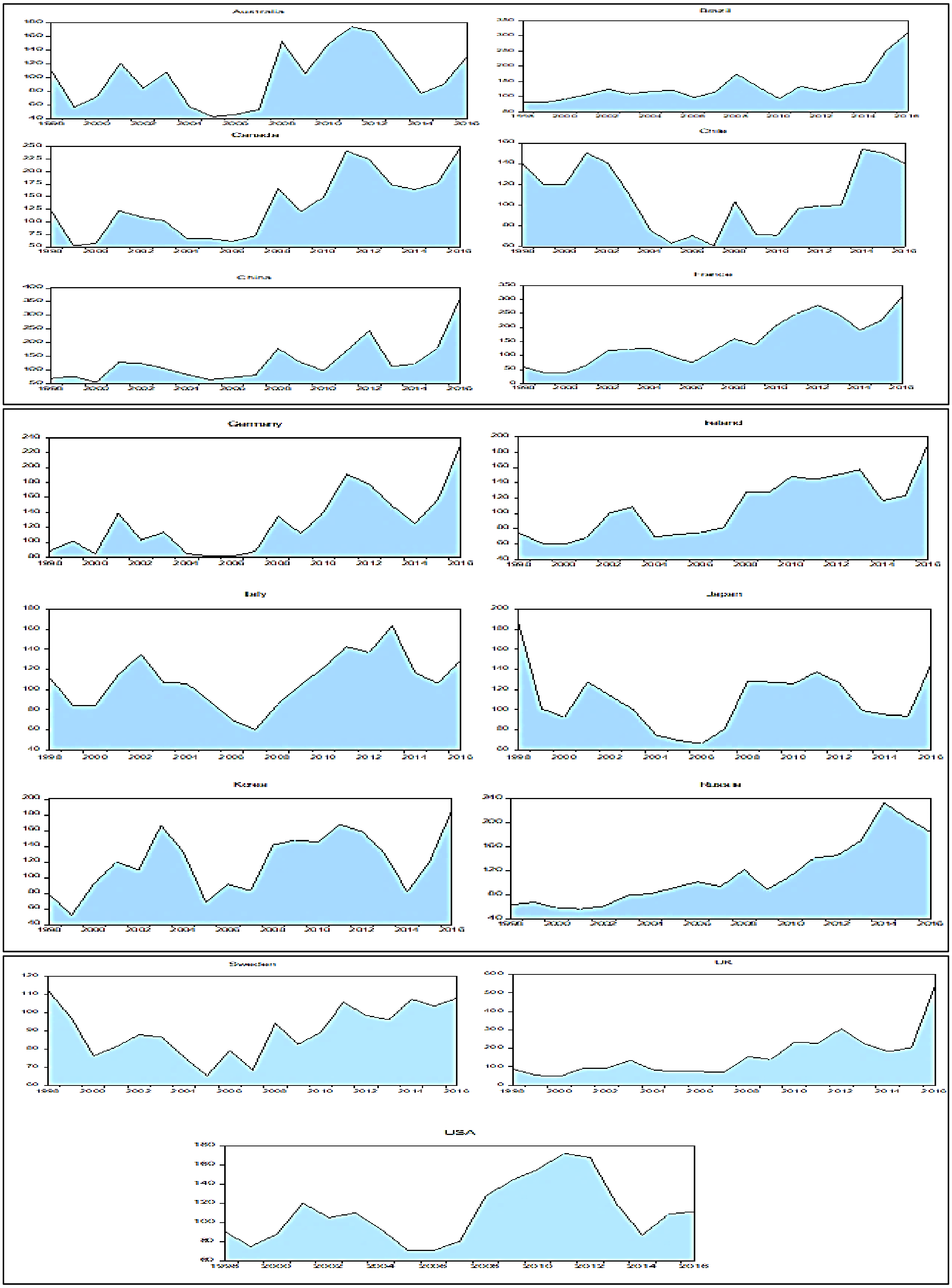

Fig 1. Time series plots of economic policy uncertainty index

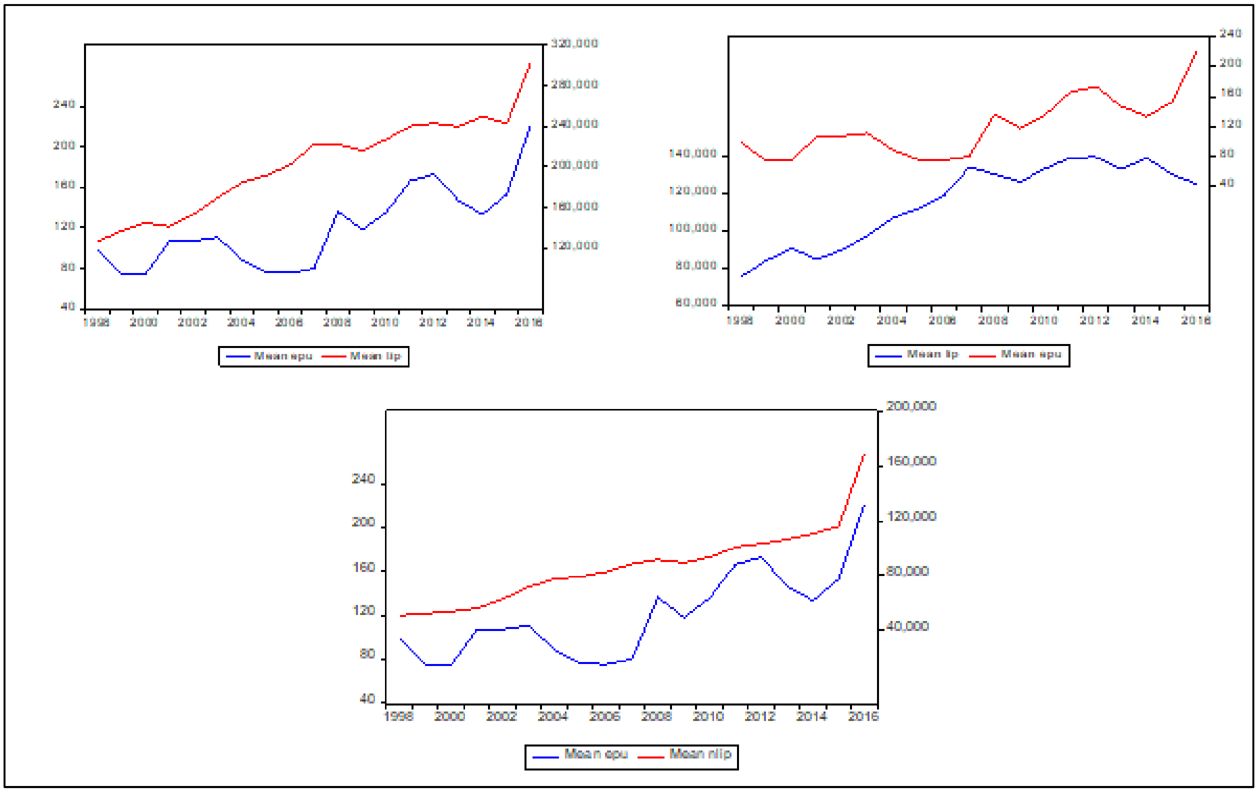

Fig 2. Trend of mean economic policy uncertainty (epu) index and mean total (tip), life (lip) and non-life (nlip) insurance premiums for selected countries

In addition, several studies have identified real income as the most important determinant of the insurance sector performance (Beck and Webb, 2003; Li *et al.*, 2007; Lee *et al.*, 2010). We therefore include real income as a control variable in our analysis. The expected direction of its impact on insurance premiums is indeterminate. While the supply leading theory on the relationship between economic growth and insurance suggests that direction of causality runs from insurance to growth, the demand following theory suggests that the direction of causality runs from growth to insurance. Moreover, the neutrality hypothesis claims there is no significant relationship between both variables and the feedback hypothesis claims the relationship is bi-directional. Data on real income was taken from the World Development Indicator (http://data.worldbank.org).

3. Models, Methods and Results

3.1 Models

The following econometric models are specified in order to determine the extent to which insurance premiums (total, life and non-life) are susceptible to the impact of economic policy uncertainty, controlling for the effect of real income:

$$TIP_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 EPU_{it} + \varepsilon_{it} \tag{1}$$

$$LIP_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 EPU_{it} + \varepsilon_{it} \tag{2}$$

$$NLIP_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 EPU_{it} + \varepsilon_{it} \tag{3}$$

Where TIP_{it}, LIP_{it}, $NLIP_{it}$, GDP_{it}, and EPU_{it}, are the logarithmic forms of total insurance premium, life insurance premium, non-life insurance premium, gross domestic product and economic policy uncertainty respectively. β_k (k=1, 2) are the coefficients on GDP and EPU. ε_{it} is the error term.

3.2 Cross-sectional dependency test

One common issue that often arises in panel estimations is the likelihood that cross-sections included in the panel time-series are interdependent. Cross-sectional dependence could be due to factors such as spatial effects, omitted common effects and socio-economic network interactions (Chudik and Pesaran, 2013). As a matter of fact, the properties of the commonly used first generation panel unit root tests and cointegration tests are based on the assumption of cross-sectional independence. The wrongful relaxation of the cross-sectional dependence assumption has implications on estimates obtained and inferences made, because the variance-covariance matrix will likely increase with the number of cross-sections resulting in unreliable parameter estimates (Cerrato and Sarantis, 2002).

Prior to testing the stationary properties of insurance premiums, economic policy uncertainty and real income, this study first considers whether cross-sectional dependence is present in the panel time-series data. This is to ensure that the appropriate panel unit root and cointegration tests are used. The Pesaran (2004) CD test for cross-sectional dependence was used in our study. The

Pesaran (2004) CD test is designed to test the null of no cross-sectional by taking averages of pairwise correlation coefficients. The test statistic is shown thus:

$$CD_p = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\, \hat{\rho}_{ij} \rightarrow N(0,1) \quad (4)$$

Where $\hat{\rho}_{ij}$ = Pairwise correlation coefficient.

Table 1 reports the Pesaran (2004) CD test results. Ample evidence is provided in support of rejecting the null of no cross-sectional dependence in all 5 variables tested at ($p < 0.01$) significance level. We thus conclude that our panel time-series is plagued by cross-sectional dependence. The implication of this is that the commonly used first generation panel model techniques are unsuitable for our study.

Table 1. Cross-sectional dependence test results

	TIP	LIP	NLIP	EPU	GDP
Statistic	33.120***	20.187***	30.600***	32.451***	34.276***
P-value	0.000	0.000	0.000	0.000	0.000

*Note: *, ** and *** mean statistic relationship significant at 10%, 5%, 1%, respectively.*

3.3 Panel unit root tests

To determine the order of integration of the variables in the panel time-series, we utilize the so-called second generation panel unit root tests that are robust to cross-sectional dependence. Specifically, we employ the Pesaran panel unit root tests—the cross-sectionally augmented Im, Pesaran and Shin (2003) test (CIPS) and the cross-sectional augmented Dickey Fuller test (CADF). These tests have the ability to provide reliable and consistent estimates in the presence of cross-sectional dependence and/or slope heterogeneity.

The CADF unit root test as developed by Pesaran (2007) uses the Dickey Fuller/Augmented Dickey Fuller unit root test as its building block. It is a test for the null of non-stationarity and its test statistic is specified as:

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

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

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

Table 2 presents the results for both CADF and CIPS unit root tests. At levels, all the variables turn out as insignificant in both tests. Therefore unit root is not rejected for any of the panel series. At first difference however, all the variables turn out as significant at (p < 0.01) significance level in both tests, unit root is thus rejected for all the series. We therefore come to the conclusion that all the variables are non-stationary, they are in fact I(1) processes.

Table 2. Results from unit root tests

	CADF		CIPS	
	LEVEL	Δ	LEVEL	Δ
EPU	-1.024	-2.441***	-1.121	-3.589***
TIP	-1.513	-2.574***	-1.563	-2.883***
LIP	-1.773	-2.346***	-1.799	-2.772***
NLIP	-1.475	-2.682***	-1.416	-2.418***
GDP	-0.909	-2.601***	-0.908	-1.697***

*Note: *, ** and *** mean statistic relationship significant at 10%, 5%, 1%, respectively.*

3.4 Error-correction based panel cointegration test

When variables are non-stationary at levels, as the case is in our study, the coefficient estimates obtained are neither economically meaningful nor statistically accurate except in cases where they are cointegrated. The presence of cointegration confirms the existence of a long run relationship between the variables. To test for the presence of cointegration between insurance premiums (total, life and non-life), real income and economic policy uncertainty, we implement the error-correction based Westerlund (2007) cointegration test.

The choice of the Westerlund (2007) cointegration test is due to the fact that commonly used residual-based cointegration tests often fail to reject the null of no cointegration even when cointegration exists; this problem is due to common factor restrictions. This short-coming is well addressed by Westerlund (2007). He came up with 4 structural dynamics based cointegration tests. All 4 tests are designed to test the null of no cointegration by determining whether the error-correction term in a conditional error correction model equals zero. In addition to being superior to residual based cointegration tests, they are also robust to slope heterogeneity and cross-sectional dependence with bootstrapping. The test statistics are:

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

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

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

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

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

All 4 tests share the null of no cointegration $[H_0: \alpha_i = 0 \; for\; all\; i]$. However, specification of the alternative is determined by assumptions made about the homogeneity of α_i. For example, the first 2 tests (group mean statistics) have their alternatives specified as $H_1^g: \alpha_i < 0 \; for\; at\; least\; one\; i$ while the last 2 tests (panel statistics) have their alternatives specified as $H_1^p: \alpha_i = \alpha < 0 \; for\; all\; i$. The decision rule in these tests is that if $\alpha_i < 0$ then error correction exists and cointegration exists as a consequence.

Outcome of the cointegration tests is presented in Table 3. The tests are carried out with three types of deterministic specifications (no constant and no trend, constant only, both constant and trend).

Concerning cointegration between total insurance premium, economic policy uncertainty and real income. When the deterministic specification had no constant and trend, all 4 statistics of Westerlund were significant at ($p < 0.01$), when the specification was changed to constant only, all 4 test statistics were still significant at ($p < 0.01$) and when the specification included both constant and trend, all 4 statistics were again significant at ($p < 0.01$). The null of no cointegration was rejected in all the cases, an indication that a long run relationship exists between the variables involved.

Concerning cointegration between life insurance premium, economic policy uncertainty and real income. With no constant and no trend in the deterministic specification the 4 statistics of Westerlund turn out to be significant ($p < 0.01$), with constant only, all 4 test statistics remain significant at ($p < 0.01$), with both constant and trend the statistics were still found to be significant at ($p < 0.01$). The null of no cointegration are again rejected and the existence of a long run relationship between these variables is confirmed.

Concerning cointegration between non-life insurance premium, economic policy uncertainty and real income. 3 out of the 4 statistics of Westerlund turn out to be significant at ($p < 0.01$) in the case where the deterministic specification had neither constant nor trend. When the specification included constant only, all 4 test statistics were significant at ($p < 0.01$) and when the specification included both constant and trend all the 4 statistics were found to be significant at ($p < 0.01$). The results show that the null of no cointegration is rejected and that there is a long run relationship between the variables involved.

Table 3. Westerlund ECM panel cointegration test results

	TIP, EPU, GDP		LIP, EPU,GDP		NLIP, EPU, GDP	
Statistic	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Deterministic specification: No Constant and Trend						
Gt	-1.026	0.000	-1.133	0.000	-1.400	1.000
Ga	-2.322	0.000	-2.376	0.000	-3.386	0.000
Pt	-6.397	0.000	-5.905	0.000	-6.033	0.000
Pa	-3.905	0.000	-3.700	0.000	-2.548	0.000
Deterministic specification: Constant only						
Gt	-1.749	0.000	-1.525	0.000	-2.209	0.000
Ga	-5.200	0.000	-4.109	0.000	-5.216	0.000
Pt	-7.241	0.000	-6.744	0.000	-11.026	0.000
Pa	-4.550	0.000	-3.900	0.000	-6.145	0.000
Deterministic specification: Constant and Trend						
Gt	-2.001	0.000	-1.802	0.000	-2.494	0.000
Ga	-3.393	0.000	-3.127	0.000	-4.781	0.000
Pt	-6.928	0.000	-5.629	0.000	-10.211	0.000
Pa	-3.253	0.000	-3.013	0.000	-4.240	0.000

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3.5 Error correction based panel estimations

To determine both short and long run impacts of the regressors on total insurance premium, we specify an autoregressive distributive lag (ARDL) dynamic panel model:

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

Where; IP_{it} represents log of insurance premiums (total, life and non-life), i refers to the number of groups (1,2,3,…,N) , t is the number of periods(1,2,3,…,T), X_{it} stands for the vector of explanatory variables (EPU and GDP), δ_{it} represents the vector of coefficients and γ_i stands for the group specific effect.

We thereafter specify an error correction form of the ARDL model as:

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

Where:

$\emptyset_i = -\left(1 - \sum_{j=i}^{p} \lambda_{ij}\right)$ = speed of adjustment, if $\emptyset_i$ = 0, there is no proof of long run 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 $\emptyset_i (IP_{it-1} - \theta'_i X_{it})$ measures the adjustment in insurance premiums to the deviation from its long run relationship with the independent variables and the terms, $\sum_{j=1}^{p-1} \lambda^*_{ij} \Delta LIP_{it-j}$ *and* $\sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{it-j}$ capture the short run dynamics of the model.

We then estimate eq. (12) through estimation techniques designed for non-stationary heterogeneous panels—panel Mean Group (PMG), Mean Group (MG) and Dynamic Fixed Effect (DFE) estimators.

It is noteworthy that while the MG estimator accommodates heterogeneity in the short and long run parameter estimates, the DFE estimator places restrictions on the speed of adjustment, the short run and the long run parameter estimates. The PMG estimator like the MG estimator accommodates heterogeneity in short run parameter estimates and like the DFE estimator imposes restrictions on the long run parameter estimates.

Table 4 presents the estimation results. In all 3 estimations, the reported speeds of adjustment estimates are negative and significant at ($p < 0.01$) significance level. This is an indication that a long run relationship exists between the variables and a confirmation of the cointegration results earlier obtained. The results also indicate that economic policy uncertainty negatively impacts total insurance premium in the long run. 1 percent increase in EPU causes TIP to fall by 0.013 percent, 0.013 percent and 0.016 percent according to PMG, MG and DFE estimations respectively. The PMG estimate is significant at ($p < 0.10$), the MG estimate at ($p < 0.01$) and the DFE estimate at ($p < 0.05$).

The results also hint at the possibility of a positive relationship between economic policy uncertainty and total insurance premium in the short run. However, due to the insignificance of all the short run EPU coefficients, no reliable inference can be made on the short run effect of economic policy uncertainty. Gross domestic product is shown to have a positive and significant impact on total insurance premium in both the short and long run. In the long run, a percentage rise in GDP causes TIP to increase by 2.502 percent, 2 percent and 1.586 percent according to PMG, MG and DFE estimations respectively. In the short run, one period lagged effect of a percentage change in GDP results in 1.522 percent, 1.145 percent and 0.672 percent change in TIP in the following periods according to PMG, MG and DFE estimations respectively. This is in consonance with the findings of Bruneau (2010), Lee and Chiu (2012) and Gupta *et al.* (2016). Our inference is that the long run impact of gross domestic product on total insurance premium is significantly greater than the short run impact.

PMG and DFE estimators which are characterized by varying degrees of slope homogeneity are consistent and more efficient than the MG estimator in cases where slopes are homogeneous. They however become inconsistent in cases where the slopes are heterogeneous rather than homogeneous, whereas the MG estimator remains consistent irrespective of the status of the slope. The Hausman test is employed to determine the differences in the specified models by testing the null of homogeneity restrictions between PMG and MG and between DFE and MG. The Hausman test results are also reported in Table 4. The test statistics fail to reject the null of homogeneity restrictions in both cases. We may therefore conclude that the slope parameters are homogeneous and that the results provided by both PMG and DFE estimators are as consistent and more efficient as the MG results.

Table 4. PMG, MG, and DFE estimates of the ARDL (1, 1) regression equation

	(1)	(2)	(3)
	PMG	MG	DFE
Adjustment coefficient	-0.312***	-0.671***	-0.344***
	(-4.510)	(-6.692)	(-6.051)
Long-run coefficients			
EPU	-0.013*	-0.013***	-0.016**
	(2.202)	(-4.958)	(-2.547)
GDP	2.502***	2.000**	1.586***
	(6.995)	(2.024)	(7.376)
Short-run coefficients			
ΔEPU	0.010	0.024	0.033
	(0.260)	(1.179)	(1.492)
ΔGDP	1.522***	1.145***	0.672***
	(2.884)	(2.769)	(4.310)
Hausman test	MG VS PMG		MG VS DFE
Chi2 (5)	0.332		0.00
Prob>chi2	0.794		1.00

*Notes: (1) *, ** and *** mean statistic relationship significant at 10%, 5%, 1%, respectively (2) t-statistics are reported in parenthesis.*

3.6 Robustness tests

Estimations based on life and non-life insurance premiums

To further examine the effect of uncertainty on insurance premium, we disaggregate total insurance premium into life insurance premium (LIP) and non-life insurance premium (NLIP). Eq. (12) is then re-estimated with the logarithmic forms of life and non-life insurance premiums serving as dependent variables. The superior PMG and DFE estimators are used in the estimations. Results are shown in Table 5. The negative and significant adjustment coefficients once again confirm the existence of a long run relationship between the variables.

The findings also affirm that a significant negative relationship exists between economic policy uncertainty and life insurance premium and also between economic policy uncertainty and non-life insurance premium in the long run. The PMG estimates show that for every percentage increase in EPU, LIP falls by 0.152 percent and NLIP falls by 0.328 percent in the long run. The DFE estimates on the other hand show that a percentage increase in EPU causes LIP to decrease by 0.115 percent and NLIP to decrease by 0.302 percent in the long run.

The findings provide sufficient evidence in support of a short run positive relationship between economic policy uncertainty and non-life insurance premium. From the PMG estimates we may infer that the one period lagged impact of a percentage change in EPU results in 0.183 percent change in NLIP in the following periods. The DFE estimate on the other hand suggests that it changes by 0.044 percent in the following periods. Some evidence is also provided in support of a positive short run impact of economic policy uncertainty on life insurance premium since the PMG estimate suggests that the one period lagged impact of 1 percent change in EPU causes LIP to change by approximately 0.109 percent in the following periods.

The reported coefficients indicate that life insurance premium is positively influenced by GDP in the long run but there is no evidence in support of a short run relationship between them. 1 percent increase in GDP causes LIP to increase approximately by 1.605 percent and 1.621 percent in the long run according to PMG and DFE results respectively. The reported coefficients however show that a positive relationship exists between economic policy uncertainty and non-life insurance premium in both the long and short run. In the long run the PMG results show that 1 percent increase IN GDP leads to 1.422 percent increase in NLIP while the DFE result suggests that it increases by 1.723 percent. In the short run however PMG result suggests that one period lagged effect of 1 percent change in GDP leads to 0.424 percent rise in NLIP in the following periods while DFE result suggests that it changes by 0.811 percent in the following periods.

Table 5. Robustness test for the PMG and DFE estimations with LIP and NLIP

	LIP		NLIP	
	PMG	DFE	PMG	DFE
Adjustment coefficient	-0.294***	-0.363***	-0.266***	-0.207***
	(-5.000)	(-6.153)	(-4.912)	(-6.535)
Long-run coefficients				
EPU	-0.152***	-0.115***	-0.328***	-0.302***
	(-7.452)	(4.924)	(-4.707)	(-4.226)
GDP	1.605***	1.621***	1.422***	1.723***
	(8.000)	(7.651)	(6.790)	(7.019)
Short-run coefficients				
ΔEPU	0.109*	0.026	0.183***	0.044**
	(1.898)	(0.776)	(4.259)	(2.891)
ΔGDP	0.905	0.891	0.424***	0.811***
	(1.134)	(1.225)	(4.073)	(4.269)

*Note: *, ** and *** mean statistic relationship significant at 10%, 5%, 1%, respectively.*

3.7 Panel Granger causality testing

As a means to detect the existence and direction of causal relationships among the variables we employ the Dumitrescu-Hurlin (2012) Granger causality test. It is a test of Granger (1969) non-causality for heterogeneous panel data models obtained by averaging individual Granger non-causality Wald tests across units. The test is based on the following regression model:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} y_{it-k} + \sum_{k=1}^{K} \gamma_{ik} x_{it-k} + \varepsilon_{it} \qquad (13)$$

Where y_{it} and x_{it} are stationary series.

It is assumed that x Granger causes (is a significant predictor) of y if its past values impact the current value of y significantly. Differenced data for the non-stationary variables are used in our bivariate Panel Granger causality tests.

Results for the Dumitrescu-Hurlin tests are reported in Table 6. From the first 2 rows, we find that there is causal effect running both ways, from life insurance premium to economic policy uncertainty and from economic policy uncertainty to life insurance premium.

The 3rd and 4th rows show that causality runs bi-directionally between life insurance premium and gross domestic product. This implies that life insurance premium granger causes gross domestic product and gross domestic product also granger causes life insurance premium.

In the 5th and 6th rows, causality runs from non-life insurance premium to economic policy uncertainty and also from economic policy uncertainty to non-life insurance premium.

The 7th and 8th rows report bi-directional causality between non-life insurance premium and gross domestic product. Non-life insurance premium granger causes gross domestic product and gross domestic product granger causes non-life insurance premium.

From the last 2 rows, we again find causal effects running in both directions. The results show that economic policy uncertainty granger causes gross domestic product and gross domestic product likewise granger causes economic policy uncertainty.

Table 6. Results from Dumitrescu-Hurlin Granger causality tests

Hypothesis	Statistic	P-Value	Conclusion
LIP→EPU	14.426***	0.000	Two-way causality between LIP and EPU
EPU→LIP	3.647***	0.001	
LIP→GDP	4.282***	0.000	Two-way causality between LIP and GDP
GDP→LIP	7.524***	0.000	
NLIP→EPU	7.819***	0.000	Two-way causality between NLIP and EPU
EPU→NLIP	3.010***	0.000	
NLIP→GDP	2.041***	0.000	Two-way causality between NLIP and GDP
GDP→NLIP	4.119***	0.001	
EPU→GDP	2.550**	0.025	Two-way causality between GDP and EPU
GDP→EPU	5.000***	0.000	

*Note: *, ** and *** mean statistic relationship significant at 10%, 5%, 1%, respectively.*

4. Conclusion

Just as the world has witnessed the increased importance of the insurance sector over the past few decades, it has also witnessed a sharp rise in risks and uncertainties. As a result of this increased importance of the insurance sector, the body of literature centered on the interactions between insurance sector performance and real income has risen in recent years, albeit with conflicting findings. Also, apart from the very recent study by Gupta *et al*. (2016), empirical studies addressing the influence of economic policy uncertainty on insurance premium changes is almost non-existent. In order to address these challenges, we apply econometric techniques that are superior to those commonly used in the past.

Our findings lead to the following conclusions:
First, we found out that the insurance sector is not immune to the effects of economic policy uncertainty and real income. Both factors exert influences on insurance premiums although their effects differ. Economic policy uncertainty raises insurance premiums in the short run and lessens it in the long run whereas real income increases insurance premiums both in the short and long run, although its long run impact is greater than the short run impact.
Second, we found out that economic policy uncertainty exerts a bigger influence on non-life insurance premium than on life insurance premium. This supports the view held by Gupta *et al*. (2016).

Third, contrary to the widely held belief that risk and uncertainty lead to increase in premiums, we find this phenomenon only to be true in the short run. Both life and non-life insurance premiums eventually decrease in the long run, in the case of life insurance premium probably because people eventually get priced out of life insurance as premium continues to increase. This in turn leads to a fall in insurance demand, causing premiums to eventually fall. In the case of non-life, this is probably because of uncertainty-induced fall in investments which leads to reduced need for insurance against business risks by investors who dominate the non-life insurance market. This reduction in non-life insurance demand will again consequently result in lower premiums.

Fourth, the positive impact of GDP on insurance premiums may be due to the effects of demand and supply in the insurance market. As wealth increases, demand for insurance will increase and the insurance premiums will also increase. It may also be partly influenced by income-related premium charges. A typical example is income-related monthly adjustment amount (IRMAA) which requires taxpayers with a modified adjusted gross income above certain income brackets to pay a higher premium than others.

Fifth, the failure to reject the null of homogeneous restrictions suggests that despite the differences in economic characteristics of countries included in our study, the long run relationship between insurance premiums, economic policy uncertainty and real income are similar in the chosen countries. This may be related to the fact that most of the countries are members of the Organization for Economic Co-operation and Development (OECD) with broadly similar policy objectives.

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