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INSURANCE AND REAL OUTPUT: THE KEY ROLE OF BANKING ACTIVITIES

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This paper applies panel cointegration tests and panel vector error correction models for 17 OECD countries and considers cross-sectional dependence and structural breaks to investigate the interrelationship between an insurance market's development and real output, controlling for banking activities. We first obtain evidence of a fairly strong long-run equilibrium relationship among them. Second, we find that insurance market development has positive effects on real output and that banking activities have an unfavorable, if not negative, effect on real output. In fact, insurance market activity is much more productive than banking sector activity. Finally, there exists bidirectional causality between insurance premiums and economic growth in the long run, suggesting the existence of the feedback hypothesis for the insurance–output nexus.

Keywords: Insurance Premiums, Banking, Real Output, Panel Cointegration, Cross-Sectional Dependence, Structural Breaks, Panel Causality

1. INTRODUCTION

The debate regarding the relationship between financial activities and economic growth has become increasingly intense in recent years, yet the influence of insurance activity on economic growth has not been studied as extensively as the role of the banking sector. The purpose of this article is to provide a systematic assessment of the long-run relationship and causal effect of insurance and banking sector activities on economic growth, taking into account the distinct benefits that life and nonlife insurance provide to households and corporations. To realize this goal, we employ measures of real insurance premiums as proxies of insurance activity (life, nonlife, and total insurance premiums) for a panel data set of 17 selected OECD countries from 1979 to 2006.[1]

Ward and Zurbruegg (2000), Kugler and Ofoghi (2005), and Chen et al. (in press) explore how in offering risk transfer, indemnification for unexpectedly large losses, real services, and financial intermediary services, insurance markets have a crucial productive impact within economies. This view of insurance likely

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helps banks to mitigate credit risk, invest in potentially high yielding projects, and increase corporate and private lending. A more developed banking sector provides fertile ground for the allocation of resources, better monitoring, and fewer information asymmetries, thus stimulating economic growth. Grace and Rebello (1993) argue that insurance promotes greater corporate bank borrowing by reducing companies' market cost of capital, which in turn affects economic growth by stimulating demand for financial services.

The current paper seeks to make up for the familiar disadvantage of neglecting some important endogenous factors, i.e., banking activities, when investigating the relationships between insurance markets and economic growth. The limited empirical studies of the linkage among insurance, banking, and economic growth of which we are aware include one single-country study on Sweden [Adams et al. (2009)] and two static panel data literature [Webb et al. (2002); Haiss and Sümegi (2008)]. Webb et al. (2002) suggest that the independent contribution of insurance is robust to the inclusion of the banking sector, and insurance and banking activities jointly have a larger impact on economic growth than their individual contributions combined. Adams et al. (2009) indicate that domestic banking development preceded economic growth in Sweden during the 19th century, whereas Granger causality was reversed in the 20th century. Sümegi and Haiss (2008) argue that the neglect of the insurance sector may be the reason that the finance–growth nexus seems to be less robust.

Although insurance and banking are closely related, insurance carries out economic functions somewhat different from those of other financial services, and in turn it requires different conditions to flourish and to make a complete economic contribution [Brainard (2008)]. In the last three decades, the interconnection between banking and insurance activities has increased substantially, because of risk transfer. Given that banks and insurers have mutual disclosures in many areas, banks have unbundled their credit risks to insurance providers mainly through the securitization of both credit portfolios and derivatives. On the insurance side, insurers have transferred credit risk to banks through liquidity facilities and letters of credit [Rule (2001)].

The motivations behind and objectives of this paper are as follows. First, it is well known that insurance market activity may contribute to economic growth not only by itself, but also through complementarities with banking sector activities [Impavido et al. (2003); Brainard (2008); Chen et al. (in press)]. Thus, we consider the multivariate model of insurance premiums, banking sector activities, and real output, as well as attempting to jointly analyze the insurance–output hypothesis and the effect of the banking–output nexus.[2] The trivariate model allows an additional channel of causality to be examined and is less likely to suffer from the problem of omitted variable bias, which leads to model misspecification.[3]

Second, it is well recognized that neglecting the presence of cross-sectional dependence in a panel framework may bias the estimated results [Breitung and Pesaran (2008); Banerjee and Wagner (2009)].[4] To the best of our knowledge, none of the existing literature on the insurance–banking–output nexus considers

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the impact of cross-sectional dependence. To fill this gap, we employ the panel cointegration approaches with cross-sectional dependence to examine the cointegrating (long-run) relationship among variables.

Third and finally, we apply a panel vector error-correction model (VECM) to distinguish between short- and long-run causalities. The direction, strength, and stability of the linkage among insurance and banking activities and real output play a pivotal role in the implementation of financial policy.

The direction of the causal (predicted) relation among banking, insurance, and economic growth remains an undetermined empirical topic [Levine et al. (2000)].[5] Does economic growth cause insurance (or banking) development or do insurance market (or banking) activities lead to an increase in economic growth? As for policy implications, if there is clear-cut unidirectional causality from finance development to economic growth, then making strides in financial development (finance-led economic growth) is the most practical approach. If the outcome shows the opposite direction of causality, then every effort should be made to attain overall output increases, as this, in turn, results in the expansion of the finance market. Finally, if the relationship is bidirectional, and insurance market (banking) development and economic growth have a reciprocal causal relationship, then a push in both areas will benefit both.

The remainder of this paper is organized as follows. Section 2 discusses the econometric methods. Section 3 provides the empirical results, and Section 4 reviews the conclusions we draw, and outlines some of the implications.

2. METHODOLOGY

2.1. Panel Unit-Root Tests with Cross-Sectional Dependence

We first apply the cross-sectional dependence (CD) statistics of Pesaran (2004) to collect the ADF(p) regression residuals (for lag lengths $p = 1$, 2, and 3) and calculate the pairwise cross-sectional correlation coefficients of the residuals (denoted by $\hat{\rho}_{ij}$). Next, we calculate a simple average of these correlation coefficients across all the pairs and refer to it as $\bar{\hat{\rho}}$. The test statistic is described as $\mathrm{CD} = \sqrt{2T/[N(N-1)]}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij})$, and the null hypothesis of the CD test assumes no cross-sectional dependence within the sample.

Second, we apply a one-factor model with heterogeneous loading factors for residuals proposed by Pesaran (2007), who augments the standard ADF regressions with the cross-sectional average of lagged levels and first differences of the individual series. A cross-sectionally augmented IPS (CIPS) test can be expressed as $\mathrm{CIPS}(N, T) = N^{-1}\sum_{i=1}^{N} t_i(N, T)$, where $t_i(N, T)$ is the t-ratio given by the ADF regression on cross-country i. We reject the null hypothesis of a unit root if the statistic CIPS*(N,T)* is lower than the critical values tabulated in Pesaran (2007).

2.2. Panel Cointegration Tests with Cross-Sectional Dependence

We introduce three panel cointegration tests after considering cross-sectional dependence, proposed by Westerlund and Edgerton (2007), Westerlund (2008), and Westerlund and Costantini (2009), respectively. For the first method, Westerlund and Edgerton (2007) propose a bootstrap test in panel data and consider the equation

$$y_{it} = \alpha_i + x'_{it}\beta_i + z_{it}, \quad t = 1, 2, \ldots, T \quad \text{and} \quad i = 1, 2, \ldots, N, \tag{1}$$

where x_{it} is a k-dimensional vector containing the regressors and assumed to be pure random walk processes. The disturbance z_{it} is defined as

$$z_{it} = u_{it} + v_{it} \text{ with } v_{it} = \sum_{j=1}^{t} \eta_{ij}, \tag{2}$$

where η_{ij} follows an independent and identically distributed process with $E(\eta_{ij}) = 0$ and $\text{var}(\eta_{ij}) = \sigma_i^2$. The null hypothesis of cointegration is $H_0 : \sigma_i^2 = 0$ for all i, whereas the alternative of no cointegration is $H_0 : \sigma_i^2 > 0$ for some i.

As noted by McCoskey and Kao (1998), in the case of cross-sectional independence the hypothesis can be tested using the Lagrange multiplier (LM) test statistic

$$\text{LM}_N^+ = \frac{1}{NT^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\omega}_i^{-2} S_{it}^2, \tag{3}$$

where S_{it} is the partial sum process of $\hat{z}_{it}$, which is the fully modified estimate of z_{it}, and $\hat{\omega}_i^2$ is the estimated long-run variance of u_{it} conditional on Δx_{it}. To maintain the cross-sectional dependence, the bootstrap draws are made from the joint empirical distribution of the regression errors.

For the second method, Westerlund (2008) sets up the equation

$$y_{it} = \alpha_i + \beta_i x_{it} + z_{it}, \tag{4}$$

where $x_{it} = x_{it-1} + w_{it}$ is a k-dimensional vector containing the regressors and follows a pure random walk process. The disturbance z_{it} is assumed to follow a data-generating process that permits cross-sectional dependence and is expressed as the equations

$$z_{it} = \lambda'_i F_t + e_{it}, \tag{5}$$

$$e_{it} = \phi_i e_{it-1} + v_{it}, \tag{6}$$

where F_t is a k-dimensional vector of unobservable common factors $F_{jt} = \rho_j F_{jt-1} + u_{jt}$ with $j = 1, 2, \ldots, k$, and λ_i is a conformable vector of loading parameters. Assuming that $\rho_j < 1$ for all j, F_t is strictly stationary. Thus, the variables are cointegrated if $\phi_i < 1$ and the relationship between variables is spurious if $\phi_i = 1$.

The Durbin–Hausman test statistics are expressed as

$$\mathrm{DH}_g = \sum_{i=1}^{n} \hat{S}_i(\tilde{\phi}_i - \hat{\phi}_i)^2 \quad \text{and} \quad \mathrm{DH}_p = \hat{S}_n(\tilde{\phi} - \hat{\phi})^2 \sum_{i=1}^{n}\sum_{t=2}^{T} \hat{e}_{it-1}^2, \tag{7}$$

where DH_g is the group mean statistic and DH_p is the panel statistic. Their null hypothesis is $H_0 : \phi_i = 1$ for all i, whereas the alternative hypotheses of DH_g and DH_p are $H_1^g : \phi_i < 1$ for at least some i and $H_1^p : \phi_i = \phi$ and $\phi_i < 1$ for all i.

For the third method, Westerlund and Costantini (2009) consider the panel model as follows:

$$\alpha_{yi}(L)\,\Delta y_{it} = \delta_i' d_t + \phi_{yi}(y_{it-1} - \beta_i x_{it-1}) + \gamma_{yi}(L)\,\Delta x_{it} + e_{yit}. \tag{8}$$

In constructing the new tests, and rewriting equation (8), we now can obtain the estimated proxy equation as follows:

$$\Delta y_{it} = \delta_i' d_t + \hat{\phi}_{yi}\Delta y_{it-1} + \sum_{j=2}^{p_i} \hat{\alpha}_{yij}\Delta y_{it-j} + \sum_{j=1}^{p_i} \hat{\gamma}_{yij}\Delta x_{it-j} + \hat{\gamma}_{yi}\Delta x_{it} + \text{error}. \tag{9}$$

To consider the effect of cross-sectional dependence, Westerlund and Costantini (2009) assume the dependence can be described in terms of a common correlation between the individual statistics as $\mathrm{Cov}(\tau_i \tau_j) = \rho$ for $i \neq j$. Here, $-1/(N-1) < \rho < 1$ and τ is the individual t-statistic for testing the hypothesis $\phi_{yi} = 0$ in equation (9) and the null hypothesis of no cointegration.

The test statistic recommended by Hartung (1999) can hence be written as

$$\tilde{\tau}_N = \left[\frac{1}{N + N(N-1)(\omega\sqrt{\mathrm{var}(\hat{\rho})} + \hat{\rho})}\right]^{-1/2} \sum_{i=1}^{N} \tau_i, \tag{10}$$

where $\omega > 0$ is a weight parameter and $\mathrm{var}(\hat{\rho}) = 2(1-\hat{\rho})^2/(N+1)$ is an estimated variance of $\hat{\rho}$. Because the tests are asymptotically normal, there is no need for a special table of critical values.

2.3. Panel Cointegration Tests with Structural Breaks

We employ two panel cointegration tests with structural breaks developed by Westerlund (2006) and Westerlund and Edgerton (2008), respectively. First, Westerlund (2006) proposes a LM test for the null hypothesis of cointegration that allows multiple structural breaks in both the level and trend for a cointegrated panel regression. Following Westerlund (2006), we adopt the equation

$$y_{i,t} = \alpha_{ij} + \beta_i X_{i,t} + e_{i,t}, \quad j = 1, \ldots, M_{i+1}, \tag{11}$$

where $e_{i,t} = r_{i,t} + \mu_{i,t}$, $r_{i,t} = r_{i,t-1} + \phi_i \mu_{i,t}$, β_i is a country-specific slope that is assumed to be constant over time, and α_{ij} is a country-specific intercept that

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is subject to M_i structural breaks. The null hypothesis is formulated so that all countries in the panel are cointegrated, whereas the alternative is formulated so that there is at least one country for which cointegration does not hold. The panel LM test statistic is defined as

$$Z(M) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M_i+1} \sum_{t=T_{ij-1}+1}^{T_{ij}} \hat{S}_{i,t}^2 \big/ (T_{ij} - T_{ij-1}) \hat{\sigma}_i^2 \to N(0, 1), \qquad \textbf{(12)}$$

where $\hat{S}_{i,t} = \sum_{s=T_{ij-1}+1}^{t} \hat{e}_{i,s}$ and $\hat{e}_{i,t}$ are the regression-estimated residuals obtained from any efficient estimator of the cointegration vector.

Second, Westerlund and Edgerton (2008) propose two test versions, which are derived from the LM-based unit-root tests, for the null hypothesis of no cointegration. Both versions allow heteroskedastic and serially correlated errors, individual-specific intercepts and time trends, cross-sectional dependence, and unknown structural breaks in both the intercept and slope of the cointegrating regression, which may be located at different dates for different countries. They consider the equation

$$y_{it} = \alpha_i + \eta_i t + \delta_i D_{it} + \chi_{it}^{'} \beta_i + (D_{it} \chi_{it})^{'} \gamma_i + z_{it}, \qquad \textbf{(13)}$$

where $x_{it} = x_{it-1} + w_{it}$ is a k-dimensional vector containing the regressors and follows a pure random walk process, and D_{it} is a scalar break dummy such that $D_{it} = 1$ if $t > T_i$ and zero otherwise.

The disturbance z_{it} is assumed to follow a data-generating process that permits cross-sectional dependence and is expressed as the equations

$$z_{it} = \lambda' F_t + v_{it}, \qquad \textbf{(14)}$$

$$\phi_i(L) \Delta v_{it} = \phi_i v_{it-1} + e_{it}, \qquad \textbf{(15)}$$

where F_t are r-dimensional vector unobservable common factors $F_{jt} = \rho_j F_{jt-1} + u_{jt}$ with $j = 1, 2, \ldots, r$, $\phi_i(L) := 1 - \sum_{j=1}^{p_i} \phi_{ij} L^j$ is a scalar polynomial, and λ_i is a conformable vector of loading parameters. Assuming that $\rho_j < 1$ for all j, F_t is strictly stationary. Thus, the relationship in equation (13) is cointegrated if $\phi_i < 0$ and it is spurious if $\phi_i = 0$.

As $N, T \to \infty$ with $N/T \to 0$, the asymptotical normalized test statistics are defined as follows:

$$Z_j(N) = \sqrt{N}[\overline{\mathrm{LM}}_j(N) - E(B_j)] \to N[0, \mathrm{var}(B_j)], \quad j = \phi, \tau. \qquad \textbf{(16)}$$

Here, $\overline{\mathrm{LM}}_j(N)$ is the average of $\mathrm{LM}_j(i)$, and B_j is the integration of a standard Brownian bridge. They are defined in Westerlund and Edgerton (2008).

3. EMPIRICAL RESULTS

3.1. The Data and Panel Unit-Root Test Results

This study uses panel data covering 17 selected OECD countries for the period 1979–2006. The data for the insurance market (real life, nonlife, and total insurance premiums) are taken from various issues of *Sigma*, a publication of the Swiss Reinsurance Company [Swiss Re (various years)].[6] The premium income of insurance companies directly depicts the interest of the economy in insurance coverage, may be a fairly accurate measure for payouts to clients, and can resend an influx of capital into the insurers' assets [Haiss and Sümegi (2008)]. We obtain annual data for real GDP from the World Development Indicators [WDI (2007)]. Real GDP is expressed in U.S. dollars. The bank development proxies, domestic credit provided by the banking sector to the private sector (% of GDP),[7] are taken from the Financial Structure and Economic Development Database.[8]

The empirical period is dependent on the availability of data. All the variables are log-transformed to reduce heteroskedasticity, except bank credit and the relationship between real GDP (LRY), bank credit (LRPC), and real insurance premiums (LIP) (LRF, life insurance; LRNF, nonlife insurance; and LRTF, total insurance), which may have a trend showing long-run comovement. For the sample averages of LRY, LRPC, and LIP (LRF, LRNF, and LRTF), the top three countries for LRY are the United States, Japan, and Mexico. For LRPC, Japan, the United Kingdom, and Spain have highest bank credit. Finally, the top three countries for LRF and LRTF are the United States, Japan, and the United Kingdom.

The properties of the variables need to be investigated to avoid the possibility of spurious regressions. In order to provide an analysis of sensitivity and robustness, this paper employs a broad array of panel unit-root tests: Levin et al. (2002), Breitung's (2000) t-statistic, the Im et al. (2003) W-statistic, the ADF-Fisher χ^2 and the PP-Fisher χ^2 of Maddala and Wu (1999), and Hadri's (2000) Z-statistic. All panel unit-root tests assume nonstationarity under the null hypothesis, except for the one used by Hadri based on the heteroskedastic Z-statistic, which assumes stationarity under the null. As tabulated in Table 1, the statistics significantly confirm that the level values of all series are nonstationary and that all variables are stationary at the 5% significance level of the first difference.

If the data contain cross-sectional dependence across countries, then it is well recognized that the previous five panel unit-root tests will show large size distortions [Banerjee et al. (2005)]. We thus apply the cross-sectional dependence (CD) statistics of Pesaran (2004) to innovations in the five series. Table 2 shows that the null hypothesis—that variable innovations are cross-sectionally independent—is strongly rejected at the 5% level. Finally, Table 3 reports the cross-sectionally dependent panel unit-root tests. The CIPS test results of Pesaran (2007) suggest that the 10% level, real insurance premiums, bank credit, and real GDP contain a panel unit root at different lags. Thus, we suggest that it is reasonable to suggest all investigated variables follow $I(1)$ processes.

TABLE 1. Panel unit-root test results

	Variables	LRY	LRF	LRNF	LRTF	LRPC
LLC (2002)	Level	−0.713	1.266	−0.173	0.224	2.161
		(0.237)	(0.897)	(0.431)	(0.588)	(0.984)
	First difference	−5.972**	−5.059**	−9.268**	−9.770**	−3.238**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Breitung (2000) t-stat	Level	2.031	2.694	−0.971	−0.033	1.863
		(0.978)	(0.996)	(0.165)	(0.486)	(0.968)
	First difference	−5.298**	−3.014**	−5.817**	−8.324**	−1.781**
		(0.000)	(0.001)	(0.000)	(0.000)	(0.037)
IPS (2003) W-stat	Level	0.107	−0.667	−0.591	−0.121	1.961
		(0.542)	(0.252)	(0.277)	(0.451)	(0.975)
	First difference	−8.386**	−10.557**	−13.691**	−15.452**	−4.131**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF-Fisher χ^2	Level	22.575	36.258	41.100	31.802	41.724
		(0.932)	(0.363)	(0.187)	(0.575)	(0.171)
	First difference	127.031**	165.655**	217.735**	242.284**	76.235**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP-Fisher χ^2	Level	38.541	29.918	59.974**	43.831	7.474
		(0.271)	(0.668)	(0.004)	(0.121)	(0.999)
	First difference	117.406**	272.317**	663.261**	381.599**	54.330**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.014)
Hadri (2000) heteroskedastic consistent Z-stat	Level	9.030**	8.329**	3.812**	7.622**	8.311**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	First difference	0.922	0.011	0.035	0.366	2.399**
		(0.178)	(0.495)	(0.485)	(0.356)	(0.008)

Notes: All variables are in natural logarithms. The null hypothesis is that the series is a unit-root process except for the Hadri heteroskedastic consistent Z-stat. p-values are given in parentheses. Probabilities for the Fisher-type tests are computed using an asymptotic χ^2 distribution. All other tests assume asymptotic normality. The lag length is selected using the modified Schwarz information Criteria.
**Parameters are significant at the 5% level.

TABLE 2. Cross-sectional correlation of the errors in the ADF(p) regression

Level	Statistics	LRY	LRF	LRNF	LRTF	LRPC
	$\bar{\hat{\rho}}$					
$P = 1$		0.384	0.081	0.209	0.106	0.052
$P = 2$		0.373	0.065	0.186	0.102	0.051
$P = 3$		0.378	0.055	0.171	0.090	0.048
	CD					
$P = 1$		22.62**	4.76**	12.31**	6.25**	3.05**
$P = 2$		21.98**	3.86**	10.98**	6.01**	3.03**
$P = 3$		22.29**	3.25**	10.06**	5.30**	2.85**

Notes: The CD test statistics are proposed in Pesaran (2004) to test for cross-sectional dependence in panels. $\bar{\hat{\rho}}$ is the simple average of the correlation coefficients across all the pairs. The CD statistic tests for the null of cross-sectional independence and is distributed as a two-tailed standard normal distribution.
**Parameters are significant at the 5% level.

3.2. The Panel Cointegration Test Results

To determine whether the regressions are spurious, the results of the panel cointegration tests must be examined. First, the following equation is implemented:

$$\mathrm{LRY}_{i,t} = \alpha_i + \delta_i t + \beta_i \mathrm{LIP}_{i,t} + \phi_i \mathrm{LRPC}_{i,t} + e_{it}, \qquad (17)$$

where LIP represents the different types of log-transformed real insurance premiums and includes life insurance (LRF), nonlife insurance (LRNF), and total insurance (LRTF) premiums; subscripts i ($i = 1, 2, \ldots, N$) and t ($t = 1, 2, \ldots, T$) indicate respectively the individual country and the time period; LRY is log-transformed real GDP; and LRPC is domestic credit provided by the banking sector to the private sector. Fixed country (α_i) and unit-specific trend effects (δ_i)

TABLE 3. Pesaran's (2007) CIPS test statistics

	Variable	LRY	LRF	LRNF	LRTF	LRPC
$P = 1$		−2.498	−1.702	−2.491	−2.099	−1.858
$P = 2$		−2.282	−1.444	−2.507	−1.859	−1.349
$P = 3$		−2.233	−1.247	−2.093	−1.566	−1.623
	First difference					
$P = 1$		−3.578**	−3.622**	−3.688**	−3.451**	−3.043**
$P = 2$		−2.767*	−2.872**	−2.823*	−2.929**	−2.480
$P = 3$		−3.257**	−2.315	−2.569	−2.799**	−2.379

Note: All variables are in natural logarithms. The null hypothesis is that the panel has a unit root. The 10% and 5% critical values for case 3 (with intercept and linear trend) with $T = 30$, $N = 10$ for Pesaran (2007) are −2.73 and −2.86, respectively.
** and * Parameters are significant at the 5% and 10% levels, respectively.

Table 4. Pedroni residual cointegration test results (LRY as dependent variable)

	Test statistic	Prob.
Model 1: (LRY, LRF, LRPC)		
Panel *v*-stat	0.853	0.277
Panel *r*-stat	−3.669**	0.001
Panel *PP*-stat	−3.554**	0.001
Panel *ADF*-stat	−4.847**	0.000
Group *r*-stat	−2.656**	0.011
Group *PP*-stat	−0.324	0.378
Group *ADF*-stat	−2.192**	0.036
Model 2: (LRY, LRNF, LRPC)		
Panel *v*-stat	0.826	0.283
Panel *r*-stat	−3.800**	0.000
Panel *PP*-stat	−3.624**	0.001
Panel *ADF*-stat	−1.256	0.181
Group *r*-stat	−2.700**	0.010
Group *PP*-stat	−0.330	0.377
Group *ADF*-stat	−4.339**	0.000
Model 3: (LRY, LRTF, LRPC)		
Panel *v*-stat	0.694	0.313
Panel *r*-stat	−2.706**	0.010
Panel *PP*-stat	−2.618**	0.012
Panel *ADF*-stat	−1.149	0.206
Group *r*-stat	−4.069**	0.000
Group *PP*-stat	−3.640**	0.000
Group *ADF*-stat	−0.354	0.374

Notes: The null hypothesis is that the variables are not cointegrated. Under the null tests, all the statistics are distributed as normal (0, 1).
**Parameters are significant at the 5% level.

are assumed. The deterministic trend effect is used to control for the common effects.

Table 4 contains the estimates from Pedroni's (1999, 2004) panel cointegration tests, in which the dependent variable is the measure of LRY, though they are different from the insurance activity indicators. First, for the models with LRY, LRF, and LRPC (Model 1) in Table 4, except for the panel variance and the group PP statistics, the other statistics significantly reject the null of no cointegration at the 5% level. For the nonlife insurance models with LRY, LRNF, and LRPC (Model 2), except for the panel variance, the panel ADF, and the group PP statistics, the results are similar, because all other statistics also significantly reject the null of no cointegration. Finally, for the total insurance premiums models with LRY, LRTF, and LRPC (Model 3), except for the panel variance, the panel ADF, and

TABLE 5. Panel ADF test results of Pedroni (1999, 2004) using asymptotic critical values and bootstrap critical values

	ADF stat.	Bootstrap critical values 1%	5%	10%
Model 1: (LRY, LRF, LRPC)				
Model with a constant	−5.82	−3.89	−2.65	−2.04
Model with a time trend	−5.94	−6.56	−5.48	−4.91
Model 2: (LRY, LRNF, LRPC)				
Model with a constant	−5.44	−6.10	−5.07	−4.52
Model with a time trend	−3.99	−6.60	−5.64	−5.11
Model 3: (LRY, LRTF, LRPC)				
Model with a constant	−4.46	−6.43	−5.23	−4.60
Model with a time trend	−6.80	−6.04	−5.41	−4.88

Notes: The bootstrap is based on 2000 replications. When an ADF statistic is smaller than the critical value, the null hypothesis of no cointegration can be rejected.

the group ADF statistics, the other statistics significantly reject the null of no cointegration.

Following Afonso and Rault (2010), we also calculate the bootstrap critical values of Pedroni's panel ADF tests, which consider the cross-sectional dependence, described in Banerjee and Carrion-i-Silvestre (2006), and the results are reported in Table 5. Based on the bootstrap critical values (between-dimension test), except for Model 2 with a time trend and Model 3 with a constant, the other panel ADF statistics reject the null hypothesis of no cointegration at the 5% significant level. Thus, it can be seen that the three variables for the three models respectively move together in the long run.

Table 6 reports the results of Kao's (1999) residual panel cointegration tests, which reject the null of no cointegration for the three models at the 5% significance level. The results of the Johansen Fisher panel cointegration test, reported in Table 7, are fairly conclusive: Fisher's tests (no matter whether trace test statistics or max-eigen test statistics) support the presence of a cointegrated relation among the three variables for the three models at the 1% significance level.[9]

To deal with the endogeneity bias in regressors, we further consider the bias-corrected estimation methods. Table 8 provides the results of the country-by-country and the panel dynamic ordinary least squares [DOLS; Kao and Chiang (2000)] for the three cointegrated models of equation (17). As shown at the bottom of Table 8, the panel parameters of insurance premiums are 0.139, 0.705, and 0.181 for life (Model 1), nonlife (Model 2), and total insurance (Model 3) premiums, respectively, and as the cointegrating coefficients are statistically significant at the 5% level, the effect is positive. This shows that a 1% increase in real insurance premiums raises real output by around 0.14–0.705%.

TABLE 6. Kao's residual cointegration test results (LRY as dependent variable)

Model	t-Statistic	Prob.
Model 1: (LRY, LRF, LRPC)	−2.568**	0.005
Model 2: (LRY, LRNF, LRPC)	−2.579**	0.004
Model 3: (LRY, LRTF, LRPC)	−1.738**	0.041

Notes: The ADF is the residual-based ADF statistic (Kao, 1999), and the numbers in parentheses are critical probabilities of the null of no panel cointegration.
**Parameters are significant at the 5% level.

On a per-country basis for Model 1, LRF has a significantly positive impact on LRY in 6 of the 17 OECD countries. In 4 of the 17 countries, LRPC has a significantly positive effect on LRY at the 10% level. However, when the insurance development variable is LRNF, as shown in the middle (Model 2) of Table 8, in 8 of the 17 countries the null—that real nonlife insurance premiums have no positive effect on real income—must be rejected. Furthermore, in 6 of the 17 countries, LRPC has a significantly positive effect on LRY at the 10% level. Finally, for the total insurance model (Model 3), LRTF has a significantly positive impact on LRY in 7 of the 17 OECD countries. In 6 of the 17 countries, LRPC has a significantly positive effect on LRY at the 10% level.

The DOLS estimates of the coefficient of the insurance market with respect to real GDP range from 0.090 (the United Kingdom, total premiums) to 11.11

TABLE 7. Panel cointegration test results of a Fisher-type test using an underlying Johansen (1988) methodology

Model	Fisher stat. (from trace test)	Prob.	Fisher stat. (from max-eigen test)	Probability
		Model 1: (LRY, LRF, LRPC)		
None	108.20***	0.000	90.69***	0.000
At most 1	51.50	0.027	45.23	0.094
At most 2	37.12	0.327	37.12	0.327
		Model 2: (LRY, LRNF, LRPC)		
None	89.55***	0.000	73.47***	0.000
At most 1	47.18	0.065	43.29	0.132
At most 2	32.60	0.536	32.60	0.536
		Model 3: (LRY, LRTF, LRPC)		
None	90.62***	0.000	75.80***	0.000
At most 1	44.93	0.101	42.47	0.151
At most 2	32.00	0.565	32.00	0.566

Notes: Asymptotic p-values are computed using a χ^2 distribution. Fisher's test applies regardless of the dependent variable.
***Parameters are significant at the 1% level.

TABLE 8. Dynamic OLS estimates (LRY as dependent variable)

	Model 1		Model 2		Model 3	
Country	LRF	LRPC	LRNF	LRPC	LRTF	LRPC
Australia	−0.036	0.003	0.141	0.005**	−0.066	0.003*
	(−0.583)	(0.968)	(1.417)	(2.548)	(−1.351)	(1.709)
Canada	−0.105**	0.002	−0.045	−0.002	−0.113**	0.008**
	(−5.361)	(0.692)	(−0.495)	(−0.290)	(−6.358)	(2.191)
Denmark	−0.430**	0.002	−0.775**	0.001	−0.538**	0.003**
	(−3.468)	(0.986)	(−5.143)	(0.067)	(−8.617)	(2.883)
Finland	0.133	0.001	−1.161**	0.017**	0.254**	−0.002
	(1.436)	(0.268)	(−3.035)	(3.391)	(2.349)	(−1.588)
Greece	0.214**	0.022**	1.181**	0.012	0.196**	0.019**
	(8.843)	(15.602)	(3.080)	(1.501)	(13.835)	(19.658)
Ireland	0.244**	−0.014**	0.839**	−0.001	0.187**	−0.009**
	(22.481)	(−10.275)	(5.869)	(−0.139)	(17.776)	(−5.822)
Italy	−0.095	−0.016**	−1.221**	−0.017**	0.027	−0.020**
	(−0.982)	(−2.469)	(−9.314)	(−7.418)	(0.417)	(−4.273)
Japan	0.402**	−0.003	1.021**	0.018**	0.417**	−0.004
	(6.396)	(−0.761)	(2.464)	(6.016)	(9.668)	(−1.345)
Mexico	2.186**	−0.014	11.110**	−0.008	2.221**	−0.046**
	(5.928)	(−0.522)	(8.853)	(−0.635)	(10.412)	(−2.838)
New	−0.037**	−0.002**	0.291**	−0.007**	0.004	0.001
Zealand	(−5.898)	(−5.441)	(8.680)	(−6.817)	(0.298)	(1.510)
Norway	−0.222**	0.006**	−0.526**	0.019**	−0.170**	0.011**
	(−24.629)	(5.695)	(−13.565)	(7.190)	(−24.392)	(8.383)
Portugal	−0.024	0.002	−0.463*	0.003**	−0.066	0.003**
	(−0.255)	(1.149)	(−1.732)	(2.947)	(−1.013)	(2.118)
Spain	−0.212	−0.015**	0.656**	−0.002	0.308	−0.004
	(−0.786)	(−3.352)	(4.740)	(−0.776)	(1.444)	(−0.571)
Sweden	0.478**	−0.021**	0.441**	−0.015**	0.288**	−0.021**
	(3.254)	(−3.333)	(2.878)	(−3.636)	(2.846)	(−3.089)
Switzerland	−0.116	0.014**	0.187	0.018**	0.049	0.017**
	(−0.973)	(4.244)	(0.994)	(4.025)	(0.342)	(4.615)
United	0.098**	0.001**	0.356**	0.002	0.090**	0.001
Kingdom	(11.597)	(2.211)	(3.688)	(1.083)	(13.563)	(0.531)
United States	−0.111	−0.004*	−0.048	−0.006**	−0.006	−0.007**
	(−1.565)	(−1.842)	(−0.293)	(−2.328)	(−0.156)	(−3.407)
Panel	0.139**	−0.002	0.705**	0.002	0.181**	−0.002**
	(3.743)	(1.006)	(2.203)	(1.612)	(7.534)	(5.011)

Notes: t-values are in parentheses. Asymptotic distribution of the t-statistic is standard normal as T and N go to infinity.
** and * Parameters are significant at the 5% and 10% levels, respectively.

TABLE 9. Panel cointegration tests allowing cross-sectional dependence

Method	Westerlund and Edgerton (2007)		Westerlund (2008)		Westerlund and Costantini (2009)	
Model	*LM* test with constant	*LM* test with constant and trend	DH_g	DH_p	$\tilde{\tau}_N$ test with intercept	$\tilde{\tau}_N$ test with intercept break
1	0.592	3.835	10.525	5.515	10.319	11.287
	[0.898]	[0.948]	[0.000]	[0.000]	[0.000]	[0.000]
2	3.797	3.840	8.361	5.752	9.854	11.026
	[0.130]	[0.420]	[0.000]	[0.000]	[0.000]	[0.000]
3	0.590	3.262	9.948	5.769	10.371	11.190
	[0.650]	[0.870]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: *P*-values are in parentheses. The null hypothesis is that the variables are not cointegrated in panel data except for the *LM* tests of Westerlund and Edgerton (2007).

(Mexico, nonlife insurance). For Model 1 and Model 2, this shows that a 1% increase in life insurance premiums raises real GDP by around 0.139%, and the corresponding rise from a 1% increase in nonlife insurance premiums is around 0.705%. In addition, Table 8 illustrates that the nonlife insurance market indicators have a greater impact on real GDP than does life insurance.

The coefficients of LRPC are found to be insignificant, except for Model 3, in which the effect is significantly negative. In other words, increasing lending to the private sector decreases real GDP. This counterintuitive result is particularly surprising, because other studies have typically found a positive nexus between banking depth and real GDP. However, as mentioned in the existing literature, banking development may stymie economic development [Arestis et al. (2001), Levine (2002), Khan and Senhadji (2003), Shen and Lee (2006)].[10]

3.3. Stability Test for Considering Cross-Sectional Dependence

It is well recognized that when the presence of cross-sectional dependence in a panel framework is neglectted, the estimated results may be biased. The results are reported in Table 9 and indicate that based on the LM test of Westerlund and Edgerton (2007), the null hypothesis of a cointegrating relationship among real insurance premiums, bank credit, and real GDP cannot be rejected. As to the Durbin–Hausman tests (DH_g and DH_p statistics) of Westerlund (2008) and two $\tilde{\tau}_N$ statistics of Westerlund and Costantini (2009), the results show the rejection of the null hypothesis of no cointegration among variables. Thus, when we consider cross-sectional dependence in the panel cointegration test, there is still a long-run relationship among real insurance premiums, bank credit, and real GDP.

TABLE 10. The results of cointegration in dependent panels with structural breaks

	$Z_\tau(N)$			$Z_\phi(N)$		
Model	1	2	3	1	2	3
No break	−2.254***	−1.963**	−1.954**	−1.845**	−1.516*	−1.514*
	[0.007]	[0.025]	[0.025]	[0.032]	[0.065]	[0.066]
Level break	−2.014**	−2.464***	−2.081**	−2.273**	−2.010**	−1.992**
	[0.022]	[0.007]	[0.019]	[0.012]	[0.022]	[0.023]
Regime shift	−4.891***	−5.794***	−4.964***	−3.810***	−4.390***	−3.804***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: The null hypothesis is that the variables are not cointegrated in panel data. The p-values are for a one-sided test based on the normal distribution. The no-break model does not include any break. The level-break model includes a break only in intercept, whereas the regime-shift model refers to the model with a break in both intercept and slope. We employ the Campbell and Perron (1991) automatic procedure to select the lag length.
***, **, and *Parameters are significant at the 1%, 5%, and 10% levels, respectively.

3.4. Stability Test for Considering Multiple Breaks

Three factors are important in performing tests that allow structural breaks. First, structural breaks may be associated with atypical events (domestic and international, financial market liberalization, integration, regulations, and globalization). Second, considering structural breaks allows one to obtain more detailed information on the behavior of the insurance markets. Such external factors aside, there is the eventual, if not inevitable, possibility that we will heed the call for even greater environmental concern. Third and finally, the economic system's instability may unfortunately in fact be reflected in the parameters of the estimated models that, when used for inference or forecasting, can induce misleading results.

Table 10 reports the results of cointegration in dependent panels with structural breaks. Following Westerlund and Edgerton (2008), we examine three models, the no-break model, the level-break model, and the regime-shift model. According to the level-break and regime-shift models, the results indicate that the null hypothesis of no cointegration can be rejected at the 1% level and/or 5% level of significance, implying that real insurance premiums, bank credit, and real GDP can be cointegrated when structural breaks are considered.

Table 11 reports the results of the panel LM statistics of Westerlund (2006), together with the structural breaks for each of the countries. The estimated breakpoints are obtained from the Bai and Perron (2003) procedure. It is seen that there is at least one break for each country, which is indicative of structural instability during 1982–2002. It can be overlooked that some critical insurance or economic events have occurred in the past. The earliest periods of breaks are mostly found around the bankruptcy crisis of American insurance companies from 1982 to 1985, which impacted the global insurance market heavily. Similar arguments are also reported in Leng et al. (2002) and Meier (2006). The period 1985–1995 was marked by the beginning of globalization and the breakdown of the Soviet Union. The

TABLE 11. The results of panel cointegration with multiple structural breaks

Country	Model 1		Model 2		Model 3	
	Estimated no. of breaks	Breakpoints (year)	Estimated no. of breaks	Breakpoints (year)	Estimated no. of breaks	Breakpoints (year)
Australia	3	1982, 1997, 2002	3	1982, 1987, 2002	3	1982, 1987, 2002
Canada	4	1983, 1987, 1992, 2002	2	1987, 2002	3	1987, 1991, 2002
Denmark	4	1982, 1986,1998, 2002	4	1982, 1986, 1993, 2002	2	1982, 1986
Finland	4	1982, 1986, 1991, 2002	2	1986, 2002	4	1982, 1986, 1991, 2002
Greece	3	1982, 1992, 2002	3	1982, 1992, 2002	3	1982, 1992, 2002
Ireland	1	1989	2	1986, 2002	1	1994
Italy	3	1982, 1986, 2002	2	1982, 1992	3	1982, 1986, 2001
Japan	2	1985, 1990	2	1985, 1991	2	1985, 1992
Mexico	4	1982, 1986, 1994, 1998	3	1982, 1986, 1994	4	1982, 1986, 1994, 2000
New Zealand	3	1982, 1993, 2002	3	1982, 1993, 2002	3	1982, 1993, 2002
Norway	3	1982, 1994, 2002	3	1982, 1994, 2002	3	1982, 1994, 2002
Portugal	2	1982, 1986	2	1982, 1986	2	1982, 1986
Spain	3	1982, 1986, 2002	3	1982, 1986, 2002	3	1982, 1986, 2002
Sweden	4	1982, 1986, 1992, 2002	4	1982, 1986, 1992, 2002	4	1982, 1986, 1992, 2002
Switzerland	3	1986, 1993, 2002	3	1986, 1993, 2002	3	1986, 1993, 2002
United Kingdom	3	1982, 1986, 1995	3	1982, 1986, 1995	3	1982, 1986, 1995
United States	4	1983, 1993, 1997, 2002	4	1983, 1993, 1997, 2002	4	1983, 1993, 1997, 2002

Notes: The breaks are estimated using the Bai and Perron (2003) procedure with a maximum of five breaks.

structural break occurs later, mainly in 1997–2002, which surrounded the Asian financial crisis. The year 2001 was a landmark due to international terrorism, starting with the attack on the World Trade Center towers in New York [Contador and Ferraz (2007)]. The test results suggest that multiple structural changes in panel cointegration relations are important and need to be taken into account in the specifications for the relationships among real insurance premiums, bank credit, and real GDP. Hence, the specifications, comprising changing economic and financial events, do raise some important questions concerning the long-run relationships of these variables.

3.5. Panel Causality Results

A panel-based vector error correction model (VECM) followed by the two-step procedure of Engle and Granger (1987) is employed to account for the long-run and short-run dynamic relationships.[11] The first step estimates the long-run parameters in equation (17) in order to obtain the residuals corresponding to the deviation from equilibrium. The second step estimates the parameters related to the short-run adjustment. The resulting equations are used in conjunction with panel Granger causality testing:

$$\Delta \mathrm{LRY}_{i,t} = \theta_{1i} + \lambda_1 \mathrm{ECT}_{i,t-1} + \sum_{k=1}^{m} \theta_{11k} \Delta \mathrm{LRY}_{i,t-k} + \sum_{k=1}^{m} \theta_{12k} \Delta \mathrm{LIP}_{i,t-k} + \sum_{k=1}^{m} \theta_{13k} \Delta \mathrm{LRPC}_{i,t-k} + u_{1i,t}, \tag{18}$$

$$\Delta \mathrm{LIP}_{i,t} = \theta_{2i} + \lambda_2 \mathrm{ECT}_{i,t-1} + \sum_{k=1}^{m} \theta_{21k} \Delta \mathrm{LRY}_{i,t-k} + \sum_{k=1}^{m} \theta_{22k} \Delta \mathrm{LIP}_{i,t-k} + \sum_{k=1}^{m} \theta_{23k} \Delta \mathrm{LRPC}_{i,t-k} + u_{2i,t}, \tag{19}$$

$$\Delta \mathrm{LRPC}_{i,t} = \theta_{3i} + \lambda_3 \mathrm{ECT}_{i,t-1} + \sum_{k=1}^{m} \theta_{31k} \Delta \mathrm{LRY}_{i,t-k} + \sum_{k=1}^{m} \theta_{32k} \Delta \mathrm{LIP}_{i,t-k} + \sum_{k=1}^{m} \theta_{33k} \Delta \mathrm{LRPC}_{i,t-k} + u_{3i,t}. \tag{20}$$

Here, θ_{ji} $(j = 1, 2, 3)$ represents the fixed country effect, k $(k = 1, \ldots, m)$ is the optimal lag length determined by the Schwarz information criterion, and ECT_{it-1} is the lagged error correction term derived from the long-run cointegrating relationship, in which $\mathrm{ECT}_{i,t} = \mathrm{LRY}_{i,t} - \hat{\beta}_i \mathrm{LIP}_{i,t} - \hat{\phi}_i \mathrm{LRPC}_{i,t}$. The term λ_j $(j = 1,\ 2,\ 3)$

is the adjustment coefficient and u_j is the disturbance term assumed to be uncorrelated with mean zero. The short-run adjustment coefficients are constrained to be the same for all countries [Christopoulos and Tsionas (2004)].[12]

A widely used estimator for the system in equations (18)–(20) is the dynamic panel generalized method of moments (GMM) estimator proposed by Arellano and Bond (1991). This method has been shown to be more efficient than other procedures. We take the first differences of equations (18)–(20) to eliminate the country-specific effects. However, differencing introduces a simultaneity problem, because lagged endogenous variables on the right-hand side are correlated with the new differenced error term. In addition, heteroskedasticity is expected to be present in the genuine errors across countries. To deal with these problems, an instrumental variable estimator must be used to deal with the correlation between the error terms and the lagged dependent variables [Christopoulos and Tsionas (2004)]. To address this issue, we consider the Sargan test of overidentifying restrictions, which examines the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process [Edison et al. (2002)].

The directions of causality can be identified by testing the significance of the coefficient estimate of each of the dependent variables in equations (18)–(20). First, for short-run causality, the null hypotheses $H_0 : \theta_{lmk} = 0$ for $l, m = 1, 2, 3$ and all k mean that one variable does not short-run Granger cause another variable. For instance, $H_0 : \theta_{12k} = 0$ or ΔLIP in equation (18) implies no short-run causality running from insurance activity to economic growth. Next, long-run causality is evaluated by looking at the estimate of the speed of adjustment parameter λ_j, which is the coefficient of the error correction terms ECT_{it-1}. The coefficients of the significance of ECT_{it-1} represent how fast deviations from the long-run equilibrium are eliminated following changes in each variable. For long-run causality, the null hypotheses $H_0 : \lambda_j = 0$ for $j = 1, 2, 3$ mean that all explanatory variables do not Granger cause the dependent variable. For instance, $H_0 : \lambda_1 = 0$ in equation (18) implies no long-run causality from insurance activity and bank sector activity to economic growth.

It is worth investigating whether the two sources of causation are jointly significant. We conduct a joint test of ECT_{it-1} and the respective interactive terms in order to check for strong causality. The joint test shows which variable(s) bears the burden of a short-run adjustment to reestablish long-run equilibrium after a shock to the system. If there is no causality in either direction, then the neutrality hypothesis is supported.

Table 12 shows the F-test results of the panel causality tests for Models 1–3 in both the long run and the short run. Here, we first discuss the direct and indirect short-run causalities among insurance premiums, bank credits, and economic growth, and then analyze the long-run causality among them.

According to Table 12, in the short run there is a unidirectional causality running from life and total insurance premiums to economic growth, whereas there is bidirectional causality between nonlife insurance premiums and economic growth.

TABLE 12. Panel causality test results

Dependent variable	Source of causation (independent variable)						
	Short run			Long run	Joint (short run/long run)		
	Model 1						
	ΔLRY	ΔLRF	$\Delta LRPC$	ECT	$\Delta LRY, ECT$	$\Delta LRF, ECT$	$\Delta LRPC, ECT$
ΔLRY	—	3.501*	1.595	24.673**	—	12.425**	12.902**
		(0.062)	(0.207)	(0.000)		(0.000)	(0.000)
ΔLRF	1.268	—	0.287	2.859*	1.432	—	1.683
	(0.261)		(0.592)	(0.092)	(0.241)		(0.187)
$\Delta LRPC$	8.256**	4.226**	—	0.330	9.025**	2.876**	—
	(0.004)	(0.015)		(0.566)	(0.000)	(0.036)	
	Model 2						
	ΔLRY	$\Delta LRNF$	$\Delta LRPC$	ECT	$\Delta LRY, ECT$	$\Delta LRNF, ECT$	$\Delta LRPC, ECT$
ΔLRY	—	3.204*	1.523	23.451**	—	11.799**	12.287**
		(0.074)	(0.218)	(0.000)		(0.000)	(0.000)
$\Delta LRNF$	5.137**	—	3.321*	3.028*	2.602*	—	2.939*
	(0.024)		(0.069)	(0.082)	(0.075)		(0.054)
$\Delta LRPC$	8.285**	4.246**	—	0.370	8.813**	2.912**	—
	(0.004)	(0.015)		(0.543)	(0.001)	(0.034)	
	Model 3						
	ΔLRY	$\Delta LRTF$	$\Delta LRPC$	ECT	$\Delta LRY, ECT$	$\Delta LRTF, ECT$	$\Delta LRPC, ECT$
ΔLRY	—	3.833*	1.549	24.738**	—	12.545**	12.807**
		(0.051)	(0.214)	(0.000)		(0.000)	(0.000)
$\Delta LRTF$	1.019	—	1.283	0.113	1.160	—	0.821
	(0.313)		(0.258)	(0.736)	(0.315)		(0.441)
$\Delta LRPC$	7.695**	4.380**	—	0.145	9.082**	2.978**	—
	(0.001)	(0.013)		(0.704)	(0.000)	(0.031)	

Notes: Numbers denote F-statistic values. P-values are in parentheses. ECT indicates the estimated error-correction terms.
** and *Parameters are significant at the 5% and 10% levels, respectively.

This implies that insurance activities can have a significant impact on economic growth. However, countries' economic development may only influence their nonlife insurance rather than life insurance in the short run, perhaps because people with more property need more nonlife insurance to reduce their losses if their property is damaged, but they may not increase the volume of life insurance. As to the short-run causal relationship between economic growth and bank activities, the results indicate evidence of unidirectional causality running from economic growth to bank credits, suggesting that countries' economic growth has a short-run impact on bank credits.

We further find unidirectional causality running from life, nonlife, and total insurance premiums to bank credits, but reverse causality running from bank credits to nonlife insurance premiums. This may be because in order to transfer the risks, banks need more nonlife insurance rather than life insurance, and thus banking sector activity has an impact on nonlife insurance premiums. As to indirect short-run causality, we also find indirect causality running from insurance premiums to bank credits by way of economic growth, because causality runs from insurance premiums to economic growth and causality runs from economic growth to bank credits—that is, an increase in insurance premiums enhances economic growth, thus leading to an increase in bank credits.

In the long run overall, there are bidirectional causal relationships between insurance markets (life and nonlife) and real output, showing that both the insurance market and real GDP are endogenous variables, meaning that these variables mutually influence each other. This indicates that a high level of real output leads to a high level of real insurance premiums and vice versa. At the same time this indicates that, in the long run, real output must be based on an effective insurance policy that should be carried out and can facilitate contiguous development in insurance activities.

The unidirectional causal relationship from bank credits to insurance premiums (and real output) in the long run—which may be due to bank sectors having an earlier and more mature development than insurance sectors—is indicative of a truly complementary relationship between the two financial sectors. Thus, we find a meaningful relationship between insurance premiums and banking development. There are some reasons that this complementary relationship between banking and insurance markets might hold: through the contingency that the occurrence of property casualty insurance escapes inefficiently high levels of bankruptcy, as well as supportings the assistance of credit transactions for houses, consumer durables, and small and medium-sized businesses [Brainard (2008)].

The findings suggest that if policy makers want to encourage economic growth, then they should expand their insurance industries as much as possible and focus their attention on long-run policies. Additionally, the government should try to upgrade, develop, and enhance the domestic insurance economy by implementing strategies to alleviate initial risks and provide capital needs for private insurance firms. This will stimulate private investment in the insurance industry by lowering costs to acquire capital, including loan guarantees, tax exemptions, and lower tax rates.

The healthy development of insurance activity is a drawing force for banking sectors. In fact, it could be easier in the long run to attract even more insurance premiums if a well-developed banking sector were supplemented with an active financial policy. With reference to previous studies on financial development, there is strong supporting evidence that a well-developed banking sector represents a source of countless comparative advantages for a country, and that these advantages make it much easier for the country to absorb the impact of insurance activities, which in turn stimulate overall economic performance.

4. CONCLUSIONS

The importance of the insurance–output relationship is expanding due to the increasing share of the insurance sector within the financial sector. Previous studies, however, have largely ignored the role played by banking development in examining the long-run relationship and causality between insurance and real output. The purpose of this paper is to empirically examine the long-run comovement and the causal relationship between real insurance premiums, banking development, and real GDP in a trivariate model in order to jointly analyze the insurance–output hypothesis and the banking–output nexus, using updated data for G17 countries for the years 1979–2006.

In this context, the other tasks assess whether the measures of insurance market activity are complementary or not in order to test whether banks and insurers complement each other. Aside from this, previous studies with time series data may yield unreliable and inconsistent results due to the short time spans of typical data sets. In contrast, we use panel unit-root tests, heterogeneous panel cointegration tests, and a panel-based error correction model. It is well recognized that when the presence of cross-sectional dependence in a panel framework is neglected, the estimated results may be biased. For robust checking, we also take cross-sectional dependence into account for when we employ panel unit-root tests and panel cointegration tests.

By and large, the panel cointegration test results provide substantive evidence that there is a fairly strong long-run cointegrating relationship among real GDP, bank credit, and real insurance premiums. Apart from this, we find interesting evidence that only insurance market development has a positive effect on real output and that banking development has an unfavorable, if not negative, effect on real output. We also find that insurance market activity is more productive than banking sector activity. Finally, a 1% real premium increase raises real GDP by 0.139–0.705%, and nonlife insurance premiums have a greater impact on real GDP than life insurance premiums. Equally important, the unidirectional causal relationship from bank credit to insurance premiums in the long run is indicative of a truly complementary relationship between the two financial sectors.

Based on our empirical results, we conclude that there is fairly strong evidence in favor of the hypothesis of long-run bidirectional causal relationships between insurance premiums (life and nonlife) and economic growth, taking into account the critical channel of banking development. More specifically, the results signify a positive bicausal relationship in the long run between the level of economic activity and insurance markets. In this sense, a high level of real output leads to a high level of insurance premiums and vice versa—that is, the higher the level of real output is, the higher the level will be for insurance premiums, whereas the higher the level of insurance premiums is, the higher real output will be. This explains the fact that in OECD countries, there seems to be a tendency to depend on insurance markets, and sufficiently high insurance activity seems to ensure a higher level of economic real output. The results also suggest that insurance market activity and real output are endogenous, and therefore any single-equation forecast of one or the other could be misleading.

Achieving broad financial reform is admittedly not an easy task, as it depends on regulatory capacity, legal history, investment culture, and cooperation through various governments' policies. All the while, there must be a committed effort to dissolve resistance to reforms, to establish good trade statues, and to advance human capital. In the medium term, it could well be easier for a country to attract more insurance activities if the banking sector were supplemented with an effective financial policy. As a result, an increase in insurance activity will likely produce a rise in domestic credit, and once this banking sector development has crystallized to a desired level, the favorable effects of insurance development on investment efficiency and real output should be realized.

NOTES

1. To cite an example, though Ward and Zurbruegg (2000), Kugler and Ofoghi (2005), and Adams et al. (2009) adopt a time series model, their empirical results conceivably also suffer from the small sample problem. Campbell and Perron (1991) indicate that short-time spans of individual data sets lessen the power of the unit root, cointegration, and causality tests.

2. Although our model is intuitively appealing, empirical work correctly involving the use of the variables in this area has several important gaps.

3. Limited by the desirability of the data length, we do not take into account other financial variables in the stock and bond markets.

4. Some possible cross-country dependence can be conceived in the presence of similar policy measures, or cross-country spillovers in financial markets. Breitung and Pesaran (2008) also provide a theoretical basis that attempts to take into account the residual cross-sectional dependence in panel data.

5. To our knowledge, there are no theoretical works modeling the links among insurance, banking, and economic growth in a unified framework. Rousseau and Wachtel (1998), Levine et al. (2000), Ward and Zurbruegg (2000), Chen et al. (in press), and Lee (2011), among others, designate that either economic growth can be supply-led as a result of development in financial intermediaries such as banks and insurance sectors, or alternatively, economic growth can boost public demand for financial services.

6. We use aggregate as well as various disaggregate data on real premiums, including life and nonlife insurance premiums, which are an important feature that is different from the studies of

Ward and Zurbruegg (2000), Haiss and Sümegi (2008), Adams et al. (2009), and Chen et al. (in press).

7. This measure of financial development is more than simply a measure of the size of the financial sector. Bank credit isolates the credit issued to the private sector as opposed to the credit issued to governments, governmental agencies, and public enterprises [King and Levine (1993); Shen and Lee (2006)].

8. See Levine's Web site, http://www.econ.brown.edu/fac/Ross_Levine/Publications.htm.

9. The results of Table 7 from testing for the number of cointegrating vectors are based on the maximum eigenvalue, and the trace of the stochastic matrix in the multivariate framework that is presented there has 1% critical values, which are limited due to the small sample size.

10. Levine (2002) puts forth three reasons to account for the fact that banking development may hinder real output (or economic growth).

11. To consider the presence of cross-sectional dependence in panel VECM for robustness, we also employ the bootstrapped panel error correction–based cointegration test of Westerlund (2007) to examine the cointegrating relationship among variables. The results are reported in the Appendix and indicate that based on statistics of G_τ, P_τ, and P_α, variables can be cointegrated in Models 1 and 3 with a constant and in Model 2 with a constant and trend.

12. If the short-run adjustment coefficients are assumed to be different for all countries, then the panel cointegration approach of Canning and Pedroni (2008) can be employed. Moreover, Pesaran et al. (1999) also provide a pooled mean group estimate to allow for the heterogeneous short-run dynamics.

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APPENDIX

TABLE A1. The bootstrapped panel error-correction based cointegration test of Westerlund (2007)

	1	2	3	1	2	3
Model	With constant			With constant and trend		
G_τ	−9.282*	−8.787	−9.388*	−11.847	−12.846**	−12.695
	[0.094]	[0.128]	[0.078]	[0.164]	[0.035]	[0.140]
G_α	−0.822	−0.216	−0.991	1.336	0.709	0.453
	[0.772]	[0.792]	[0.740]	[0.972]	[0.920]	[0.922]
P_τ	−5.405*	−7.978**	−5.939*	−12.310***	−11.347***	−11.837**
	[0.088]	[0.024]	[0.062]	[0.007]	[0.000]	[0.013]
P_α	−4.027*	−3.183	−4.303*	−1.895	−1.344***	−1.034
	[0.066]	[0.156]	[0.058]	[0.696]	[0.001]	[0.772]

Notes: The null hypothesis is of no cointegration. Bootstrap tests are also proposed to handle applications with cross-sectional dependence. We use 1000 bootstrap replications. The bootstrapped P-values are in parentheses. The group mean statistics are $G_\tau = \frac{1}{N}\sum_{i=1}^{N}\hat{\alpha}_i/\mathrm{SE}(\hat{\alpha}_i)$ and $G_\alpha = \frac{1}{N}\sum_{i=1}^{N}T\hat{\alpha}_i/\hat{\alpha}_i(1)$. The panel statistics are $P_\tau = \hat{\alpha}/\mathrm{SE}(\hat{\alpha})$ and $P_\alpha = T\hat{\alpha}$, where $\mathrm{SE}(\hat{\alpha})$ is the conventional standard error of the lagged dependent variable's estimators $\hat{\alpha}$.

***, **, and *Parameters significant at the 1%, 5%, and 10% levels, respectively.

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