# II. INSURANCE ACTIVITY AND ECONOMIC GROWTH NEXUS IN 31 REGIONS OF CHINA: BOOTSTRAP PANEL CAUSALITY TEST[1]

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## Abstract

*This study applies the bootstrap panel Granger causality test to investigate the relationship between insurance activity and economic growth using data from 31 regions of China over the period 1997-2011. Empirical results indicate that the direction of causality seems to be in favor of the neutrality hypothesis in 21 out of 31 regions and a one-way Granger causality running from economic growth to insurance activity in 7 regions. Regarding the direction of insurance activity to economic growth nexus, we find a one-way Granger causality from insurance activity to economic growth for Jiangsu, Zhejiang, and Shandong.*

**Keywords:** insurance activity; economic growth; Bootstrap Panel Granger Causality Test
**JEL classification**: G22; C23; O16

## I. Introduction

Theoretical studies and empirical evidence showed that countries with better-developed financial systems enjoy faster and more stable long-run growth. Well-developed financial markets have a significant positive impact on total factor productivity, which translates into higher growth rate. Therefore, the relationship between financial development and economic growth has long been one of the hotly

[1] This study was presented at 2013 Global Business, Economics, and Finance Conference, Wuhan University, China, 9-11 May 2013.

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debated issues of whether the financial sector actually contributes to the real sector in the process of economic development (Muhsin Kar, 2011).

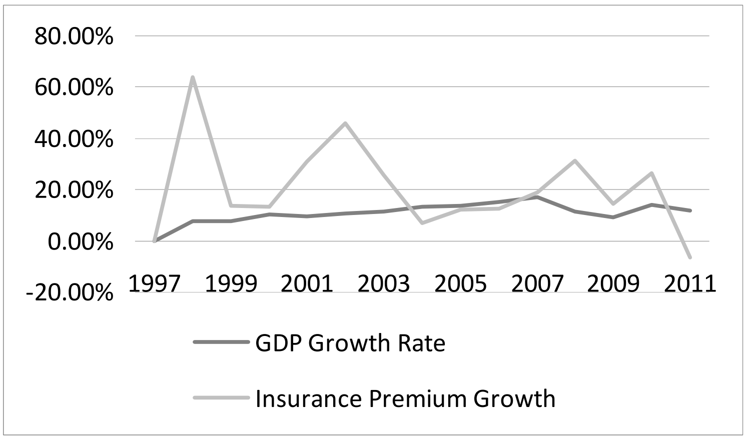
Regarded as the risk management service provider in financial sectors, insurance market activity not only plays a vital role in a myriad of economic transactions through risk transfer and loss compensation, but is also seen to promote financial intermediation, thus contributing to economic growth. According to Outreville (2012), insurance activity contributes to economic growth in several ways:[5] (1) promoting financial stability for both households and firms; (2) mobilizing and channeling savings; (3) supporting trade, commerce, entrepreneurial activity, and social programs; (4) encouraging the accumulation of new capital and fostering a more efficient allocation.

Over the past two decades, we have witnessed an increasing share of insurance sector in the aggregate financial sector in almost every developing and developed country. Insurance companies, together with mutual and pension funds, are one of the biggest institutional investors in the stock, bond and real estate markets, and their possible impact on the economic development will rather grow than decline, due to issues such as ageing societies, widening income disparity, globalization and the increase in risks and uncertainties in most societies. The growing links between the insurance and other financial sectors also emphasize the possible role of insurance activity in economic growth.

Particularly in emerging markets such as China, the insurance industry has grown at a rate of over 10 percent annually in most years since 1997. Figure 1 illustrates the parallel and rapid growth of total insurance premiums relative to GDP growth rate. We can clearly see that the insurance premium growth rate has far exceeded that of economic development, except for the period 2004-2006 and the year 2011.

**Figure1**

**Relationship between GDP Growth Rate and Insurance Premium Growth Rate**




5 See, for example, Das, Davies, and Podpiera (2003), UNCTAD(2005a), USAID(2006), and Haiss and Sumegi (2008).

Despite the potential role that the insurance sector may play in financial and economic development, the assessment of a potential causal relationship between insurance market activity and economic growth has not been as extensively studied as other financial sectors, such as bank or stock market. This situation reflects both data availability and the rather arcane reputation of the insurance sector in economic circles (Marco Arena, 2008).

Previous surveys focus on the relationship between insurance consumption (life and nonlife) and income level (GDP per capita) as well as insurance and financial development. For instance, Beenstock, Dickinson and Khajuria (1986) find that nonlife insurance demand is associated with GDP per capita in a sample of 12 industrialized countries between 1970 and 1981. Outreville (1990), Browne, Chung, and Frees (2000) obtain similar empirical results using the data from 55 developing countries over the period 1983-1984 and the data from OECD countries over the 1986-1993 period. Browne and Kim (1993) find that life insurance consumption per capita is positively associated with GDP per capita for a sample of 45 countries in the period of 1980 to 1987. Outreville (1996) finds that life insurance demand is associated positively with GDP per capita, but not with financial development, in a sample of 48 developing countries for the year 1986.

However, the assessment of a potential causal relationship between insurance market activity and economic growth has not been extensively studied (Marco Arena, 2008). Ward and Zurbruegg (2000) studied the potential causal relationship between economic growth and insurance market activity for nine OECD countries for the period 1961-1996, using annual real GDP as a measure of economic activity and annual real total written premiums as a measure of insurance activity. Long-term relationships for five countries (Australia, Canada, France, Italy and Japan) are found using a vector autoregression error correction model on a country-by-country basis. Webb, Grace and Skipper (2002) study the causal relationship of banks, life and nonlife insurance activity on economic growth in the context of a revised Solow-Swan neoclassical growth model, where the authors include financial activities (including bank, life and nonlife insurance) as additional inputs in the production function, which is assumed to be a Cobb-Douglas type. Marco Arena (2008) uses the generalized method of moments (GMM) for dynamic models of panel data for 55 countries between 1976 and 2004 to test whether there is a causal relationship between insurance market activity and economic development, finding that both life and nonlife insurance have a positive and significant causal effect on economic growth. Chang, TY (2012) applies the bootstrap panel Granger causality test to test whether insurance activity promote output using data from 12 OECD countries between 1979 and 2008. Empirical results indicate a one-way activity for most of these 12 OECD countries, with the exception of Japan, Netherlands, and Sweden, and a feedback between output and insurance activity in both Italy and the UK.

While empirical research already showed that the causal link between insurance development and economic growth is not more prominent, this article investigates the relationship between insurance development and economic growth in a sample of 31 regions[6] over the period 1997-2011 by focusing on region-specific analysis. Because of the principle that the time period (T) needs to be bigger than the cross-section units (N), we break down these 31 regions to 3 sub-areas: the eastern region (i.e., Beijing, Tianjin, Shanghai, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), the central region (i.e., Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan), and the western region (i.e., Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Inner Mongolia, Guangxi, Ningxia, Xinjiang, Tibet). In detecting causal linkages, we apply panel causality approach, which is able to examine both cross-section interrelations and region-specific heterogeneity.

This article is organized as follows. Section II presents the data used in our study and Section III briefly describes the bootstrap panel Granger causality test proposed by Kónya (2006). Section IV presents our empirical results. Section V concludes this article and discusses some economic and policy implications of our empirical findings.

## II. Data

The annual data used in this study cover the period from 1997 to 2011 for 31 regions of China. The variables in this study include per capita real Gross Domestic Product (PRGDP) and real insurance density[7] (RID). The insurance density has been extensively employed as proxy of the insurance markets' activities to investigate the relationship between the insurance market development and macroeconomics in the existing literature (Ward and Zurbruegg, 2000; Arena, 2008, etc.; Chen *et al.*, 2011). Both per capita real GDP and real insurance density are taken from annual Yearbook of China's Insurance, which is a publication from the China Insurance Regulatory Commission (CIRC), and have been transformed into real terms (using CPI 1997=100) in our study.

## III. Methodology

Our empirical methodology is carried out in two steps. First, we devote our attention to preliminary analysis to investigate cross-section dependence and slope homogeneity. In the second step, based on the results from preliminary analysis we apply an appropriate panel causality method, which is able to represent cross-section and slope homogeneity features our panel data set to do the test. In what follows, we briefly outline the econometric methods.

### *III.1. Testing Cross-Section Dependence*

One important issue to be considered in a panel causality analysis is testing for cross-section dependence across the regions. The rationale behind taking into account the cross-section dependence is due to the fact that a shock affecting one region may also affect other regions because all the regions will be influenced by the policies and

[6] *Include provinces, autonomous regions and municipalities directly under the Central Government.*

[7] *Insurance density is equal to (life insurance premium +nonlife insurance premium)/population.*

instructions issued by the Central Government. Besides, with a high degree of economic integration and exchange, other regions will be sensitive to the economic shock of a region. If there is cross-section dependence, estimating sets of equations with Seemingly Unrelated Regressions (SUR) is more efficient than that of equation-by-equation with least-squares (OLS) (Zellner, 1962). It is worthwhile noting here that ignoring cross section dependency leads to substantial bias and size distortions (Pesaran, 2006), which implies that testing for the cross section dependence is an essential step in a panel data analysis.

To test for cross-sectional dependency, the Lagrange Multiplier (LM) test of Breusch and Pagan (1980) has been extensively used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$PRGDP_{it} = \alpha_i + \beta_i' RID_{it} + u_{it} \quad \text{for } i = 1,2,\dots,N; \; t = 1,2,\dots,T \tag{1}$$

where: *i* is the cross section dimension, *t* is the time dimension and $\alpha_i$ and $\beta_i$ are the individual intercepts and slope coefficients that are allowed to vary across regions. In the LM test, the null hypothesis of no cross section dependence - $H_0: Cov(u_{it}, u_{jt}) = 0$ for all *t* and $i \neq j$- is tested against the alternative hypothesis of cross section dependence $H_1: Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the LM test as

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{2}$$

where: $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals from OLS estimation of (1) for each *i*. Under the null hypothesis of no cross-sectional dependency with a fixed N (number of cross-sections) and time period $T \to \infty$, the statistic has chi-square asymptotic distribution with $N(N-1)/2$ degrees of freedom. It is important to note that the LM test is applicable with N relatively small and T sufficiently large. This drawback was attempted to be solved by Pesaran (2004) by the following scaled version of the LM test:

$$\mathrm{CD_{LM}} = \left(\frac{1}{N(N-1)}\right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T\hat{\rho}_{ij}^2 - 1) \tag{3}$$

Under the null hypothesis with $T \to \infty$ and $\to \infty$ , this test statistic has the standard normal distribution. Though $\mathrm{CD_{LM}}$ is applicable even for N and T large, it is likely to exhibit substantial size distortions when N is large relative to T. The shortcomings of the LM and the $\mathrm{CD_{LM}}$ tests clearly show a need for a cross-sectional dependency test that can be applicable with large N and small T. In that respect, Pesaran (2004) proposed the following test for cross-sectional dependence (CD):

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{4}$$

However, in some cases that the population average pair-wise correlations are zero, the CD test is lacking power, although the underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008). Furthermore, when the mean of the factor loadings is zero in the cross-sectional dimension, the CD test can not reject the null hypothesis in stationary dynamic (Sarafisidis et al., 2009). In order to solve this problem, Pesaran et al. (2008) raises a modified version of the LM test based on the exact mean and variance of the LM statistic. This bias-adjusted LM test is:

$$LM_{adj} = \left(\frac{2T}{N(N-1)}\right)^{1/2}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\frac{(T-k)\hat{\rho}_{ij}^2-\mu_{T_{ij}}}{\left(v_{T_{ij}}^2\right)^{1/2}} \tag{5}$$

where: $\mu_{T_{ij}}$ and $v_{T_{ij}}^2$ are the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, respectively, that are provided in Pesaran *et al*. (2008). Under the null hypothesis with first $T \to \infty$ and $N \to \infty$, $LM_{adj}$ test is asymptotically distributed as standard normal.

### *III.2. Testing Slope Homogeneity*

Deciding whether or not the slope coefficients are homogenous is another very important issue. As indicated bt Granger (2003), the causality from one variable to another variable by imposing causality restrictions on estimated coefficients is the strong null hypothesis. Moreover because of region specific characteristics, the homogeneity assumption of the parameters cannot capture the heterogeneity (Breitung, 2005).

Standard F-tesr is the most familiar way to test the null hypothesis of slope homogeneity-$H_0: \beta_i = \beta$ for all *i* against the heterogeneity hypothesis $H_1: \beta_i \neq \beta_j$ for a non-zero fraction of pairwise slopes for $i \neq j$. The *F* test is valid for cases when the cross section dimension (N) is relatively small and the time dimension (T) of panel is large; the explanatory variables are strictly exogenous; and the error variances are homoskedastic. Similarly Swamy (1970) relaxed homoscedasticity assumption of the F test and developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the F and Swamy test require that panel data N is small relative to T. Pesaran and Yamagata (2008) proposed a standardized version of Swamy test (the so-called $\tilde{\Delta}$ test). The $\tilde{\Delta}$ test is valid as $(N,T) \to \infty$ without imposing any restrictions on the relative expansion rates of N and T when the error terms are normally distributed. The first stepof the $\tilde{\Delta}$ test approach, is to compute the following modified version of the Swamy test:

$$\tilde{S} = \sum_{i=1}^{N}(\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2}(\hat{\beta}_i - \tilde{\beta}_{WFE}) \tag{6}$$

where: $\hat{\beta}$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, $M_\tau$ is an identity matrix, the $\tilde{\sigma}_i^2$ is the estimator of error variance $\sigma_i^2$. Then, the standardized dispersion statistic can be written as as:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{7}$$

Under the null hypothesis with the condition of $(N, T) \to \infty$ so long as $\sqrt{N}/T \to \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution (Chang et al.,2013). By using bias-adjusted version, the small sample properties of $\tilde{\Delta}$ test can be improved under the normally distributed errors:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right) \tag{8}$$

where: the mean $E(\tilde{z}_{it}) = k$, and the variance $var(\tilde{z}_{it}) = \frac{2k(T-k-1)}{T+1}$.

### *III.3. Panel Causality Test*

The existence of both cross-section dependency and heterogeneity across these 31 regions indicates that a panel causality method is needed to account for these dynamics. The bootstrap panel causality approach proposed by Kónya (2006) can just account for the two features mentioned above. Seemingly Unrelated Regression (SUR) estimation of the set of equation and the Wald tests with individual specific region bootstrap critical values are the basis of this approach. The using of region-specific bootstrap critical values implies that the variables in the system do not need to be stationary, which means that the variables can be used in level form and panel unit root test and cointegration analyses are not required. In addition, by imposing region specific restrictions, we can also identify in which and how many regions exists Granger causal relation between insurance activity and economic growth.

The system to be estimated in the bootstrap panel causality approach can be written as the follows:

$$y_{1,t} = \alpha_{1,1} + \sum_{l=1}^{ly_1} \beta_{1,1,l} y_{1,t-l} + \sum_{l=1}^{lx_1} \delta_{1,1,l} x_{1,t-l} + \varepsilon_{1,1,t}$$

$$y_{2,t} = \alpha_{1,2} + \sum_{l=1}^{ly_1} \beta_{1,2,l} y_{2,t-l} + \sum_{l=1}^{lx_1} \delta_{1,2,l} x_{2,t-l} + \varepsilon_{1,2,t}$$

$$y_{N,t} = \alpha_{1,N} + \sum_{l=1}^{ly_1} \beta_{1,N,l} y_{N,t-l} + \sum_{l=1}^{lx_1} \delta_{1,N,l} x_{N,t-l} + \varepsilon_{1,N,t} \tag{9}$$

and

$$x_{1,t} = \alpha_{2,1} + \sum_{l=1}^{ly_2} \beta_{2,1,l} y_{1,t-l} + \sum_{l=1}^{lx_2} \delta_{2,1,l} x_{1,t-l} + \varepsilon_{2,1,t}$$

$$x_{2,t} = \alpha_{2,2} + \sum_{l=1}^{ly_2} \beta_{2,2,l} y_{2,t-l} + \sum_{l=1}^{lx_2} \delta_{2,2,l} x_{2,t-l} + \varepsilon_{2,2,t}$$

$$\vdots\; x_{N,t} = \alpha_{2,N} + \sum_{l=1}^{ly_2} \beta_{2,N,l} y_{N,t-l} + \sum_{l=1}^{lx_2} \delta_{2,N,l} x_{N,t-l} + \varepsilon_{2,N,t} \tag{10}$$

where: *y* refers to *PRGDP*, *x* refers to *RID*, *l* is the lag length. Because each equation in this system has different predetermined variables while the error terms might be contemporaneously correlated (i.e., cross-sectional dependency), these sets of equations are the SUR system.

In the bootstrap panel causality approach, there are alternative causal linkages for a region in the system that (i) there is one-way Granger causality from *x* to *y* if not all $\delta_{1,i}$ are zero, but all $\beta_{2,i}$ are zero, (ii) there is one-way Granger causality running from *y* to *x* if all $\delta_{1,i}$ are zero, but not all $\beta_{2,i}$ are zero, (iii) there is two-way Granger causality between *x* and *y* if neither $\delta_{1,i}$ nor $\beta_{2,i}$ are zero, and finally (iv) there is no Granger causality between *x* and *y* if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero (Chang et al.,2013)..

Because the results of the causality test may be sensitive to the lag structure, determining the optimal lag length is crucial for robustness of findings (Tsangyao Chang, 2012). As indicated by Kónya (2006), the selection of optimal lag structure is important because the causality test results may depend critically on the lag structure. In general, both too few and too many lags may cause problems. Too few lags mean that some important variables are omitted from the model and this specification error will usually cause bias in the retained regression coefficients, leading to incorrect conclusions. On the other hand, too many lags waste observations and this specification error will usually increase the standard errors of the estimated coefficients, making the results less precise. For a relatively large panel, equation and variable with varying lag structure would lead to an increase in the computational burden substantially. In determining lag structure we follow Kónya's approach that maximal lags are allowed to differ across variables, but to be same across equations.

We estimate the system for each possible pair of $ly_1$, $lx_1$, $ly_2$, $lx_2$ respectively by assuming from 1 to 4 lags and then choose the combinations which minimize the Schwarz Bayesian Criterion.

## IV. Empirical Results

As outlined earlier, testing for cross-sectional dependency and slope homogeneity in a panel causality study is crucial for selecting the appropriate estimator. Taking into account both cross-sectional dependency and region-specific heterogeneity in empirical analysis is crucial since regions are highly integrated in economic relations. Thereby, our empirical study starts with examining the existence of cross-sectional dependency and heterogeneity across the regions in concern. To investigate the existence of cross-section dependence, we carried out four different test ($CD_{BP}$, $CD_{LM}$, $\mathbf{CD}$, $LM_{adj}$) and illustrate results in Table 3. The results strongly indicate that the null hypothesis of no cross-section dependence is rejected at the conventional level of significance, implying that the SUR method is appropriate rather than region-by-region OLS estimation, as it is assumed in the bootstrap panel causality approach. This finding implies that a shock occurred in one region is easily transmitted to other regions.

Table 3 also reports the results from the slope homogeneity tests of Pesaran and Yamagata (2008). The tests reject the null hypothesis of the slope homogeneity hypothesis in exception of the adjusted delta test. It may be due to the problem of small panel. But in overall, direction of causal linkages between insurance activity and economic growth may differ across the selected regions.

The existence of the cross-sectional dependency and the heterogeneity across 31 regions support evidence on the suitability of the bootstrap panel causality approach. The results of the bootstrap panel Granger causality analysis are reported in Tables 4-9. It is of great interest that the results differ across areas. For the 11 regions in Eastern area, results show one-way Granger causality from insurance activity to economic growth in Jiangsu, Zhejiang, and Shandong. As regards to the direction of Granger causality running from economic growth to insurance, the null hypothesis is rejected only in the case of Beijing. For Central area, the results show one-way Granger causality from economic growth to insurance activity in most of these 8 regions, with the exception of Jiangxi and Henan. As for Western area, there is no causal link between insurance activity and economic growth in all the 12 regions.

## V. Economic and Policy Implications

Even though insurance is of great significance in economic activities, its role in the development process remains difficult to assess. The insurance has been recognized since the early ‘60s by some authors. The insurance is so important in economic development that, as in the first session in 1964, the United Nations Conference on Trade and Development (UNCTAD) formally acknowledged that “a sound national insurance and reinsurance market is an essential characteristic of economic growth.” While insurance plays an important role in the financial sector, it is often ignored in the academic literature. The purpose of this paper is to examine the relationship between insurance and economic growth of China over the period of 1997-2011.

From a theoretical point of view, the relationship between insurance and economic growth may run in either or both directions. The “supply-leading” and “demand-following” views presented by Patrick (1966) represent the two directions, respectively. Based on the “supply-leading” view, financial development enhances economic growth by transferring resources from traditional sectors to modern sectors and by promoting an entrepreneurial response in these modern sectors. In contrast, the “demand-following” view indicates that a lack of financial development or institutions is due to a lack of demand for financial services. Thus, as the growth rate of real income rises, investors’ and savers’ demands for various new financial services materialize, hence leading to the creation of modern financial institutions, the supply of their financial assets and liabilities, and related financial services.

The results differ in the three considered areas. For the Eastern area, we find a one-way Granger causality running from insurance activity to economic growth in Jiangsu, Zhejiang, and Shandong. As regards to the direction of Granger causality running from economic growth to insurance, the null hypothesis is rejected only in the case of Beijing. For the Central area, the results show one-way Granger causality from economic growth to insurance activity in most of the eight regions, with the exception of Jiangxi and Henan. For the Western area, there is no causal link between insurance activity and economic growth in all the regions. Our empirical evidence suggests that economic growth contributes materially to insurance activities in most of regions, especially the regions in Central area of China. Our results show that the insurance-growth nexus varies across regions with different conditions, which is consistent with the finding of Ward and Zurbrugg (2000).

Our empirical findings have four major policy implications, as follows. First, the evidence of a one-way Granger causality running from economic growth to insurance activity in most regions in Central area with the exception of Jiangxi and Henan, implying that economic growth can increase the demand for insurance, and thus leading to the development of insurance markets. This result supports the “demand-following” hypothesis, implying that as real income increases, investors and savers will require various new financial services, thus leading to the creation of modern financial institutions, and related financial services, i.e. insurance services in these regions.

Second, in Jiangsu, Zhejiang and Shandong we find the evidence of a one-way Granger causality running from insurance activity to economic growth, implying that insurance is playing an important role in economic development. Besides, it also supports the “supply-leading” views, indicate that financial markets have a significant positive impact on economic growth, which is consistent with the finding of previous studies (see, Patrick, 1966; Ward and Zurbruegg, 2000; Kugler and Ofogah, 2005; Sumegi and Haiss, 2008).

Third, for most regions in Eastern area (except for Beijing, Jiangsu, Zhejiang, Shandong), Jiangxi and Henan in Central area, and all the regions in Western area, no causal relationship between insurance activities and GDP is found. These results suggest the neutrality hypothesis for the insurance-growth nexus, which indicates that insurance development and economic growth may not mutually influence each other. In these regions, an economic policy may not be effective to insurance market developments, while a financial policy may also have no impact on economic growth, since the results show no evidence of the relationship between all insurance activities and GDP in these regions.

Fourth, we do not find a two-way Granger causality between insurance activity and economic growth, implying that supply-leading and demand-following hypothesis cannot be both supported in all these regions.

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**Table 1**

**Summary Statistics of Per Capita Real GDP**

| Region | Mean | Max. | Min. | Std. Dev. | Skew. | Kurt. | J.-B. |
|---|---|---|---|---|---|---|---|
| Beijing | 38960 | 63867 | 16554 | 17177 | -0.03 | 1.54 | 1.33 |
| Tianjin | 33208 | 66647 | 13270 | 17343 | 0.50 | 2.01 | 1.23 |
| Shanghai | 45183 | 66690 | 23602 | 15785 | 0.01 | 1.44 | 1.52 |
| Liaoning | 19179 | 39701 | 8658 | 9750 | 0.81 | 2.46 | 1.83 |
| Jiangsu | 23446 | 48718 | 9346 | 12930 | 0.61 | 2.08 | 1.45 |
| Zhejiang | 23446 | 48718 | 9346 | 12930 | 0.61 | 2.08 | 1.45 |
| Fujiang | 18775 | 37055 | 8747 | 8832 | 0.77 | 2.38 | 1.72 |
| Shandong | 18639 | 37022 | 7441 | 10018 | 0.51 | 1.86 | 1.46 |
| Guangdong | 22927 | 39737 | 10375 | 10025 | 0.23 | 1.70 | 1.19 |
| Hainan | 11079 | 22602 | 5516 | 5261 | 0.88 | 2.68 | 2.00 |
| Hebei | 13421 | 26568 | 2994 | 6919 | 0.40 | 2.08 | 0.94 |
| Shanxi | 11721 | 24525 | 4699 | 6579 | 0.53 | 2.00 | 1.32 |
| Jilin | 13734 | 30080 | 5572 | 7821 | 0.79 | 2.40 | 1.77 |
| Heilongjiang | 13603 | 25669 | 7111 | 5773 | 0.67 | 2.33 | 1.41 |
| Henan | 10764 | 22416 | 4413 | 6052 | 0.63 | 2.02 | 1.58 |
| Hubei | 12048 | 26746 | 5875 | 6669 | 0.97 | 2.71 | 2.42* |
| Hunan | 10592 | 23370 | 4630 | 6021 | 0.85 | 2.45 | 1.97 |
| Jiangxi | 9368 | 20453 | 3869 | 5200 | 0.78 | 2.46 | 1.72 |
| Anhui | 8955 | 20069 | 3831 | 4949 | 0.99 | 2.85 | 2.44* |
| Chongqing | 11590 | 26983 | 4708 | 7223 | 0.80 | 2.42 | 1.82 |
| Sichuan | 9161 | 20439 | 3938 | 5259 | 0.86 | 2.52 | 1.98 |
| Guizhou | 5498 | 12837 | 2199 | 3317 | 0.93 | 2.73 | 2.23* |
| Yunnan | 7733 | 15068 | 4016 | 3470 | 0.76 | 2.38 | 1.66 |
| Shaanxi | 10853 | 26173 | 3714 | 7159 | 0.85 | 2.53 | 1.93 |
| Gansu | 7298 | 15326 | 3133 | 3792 | 0.75 | 2.45 | 1.60 |
| Qinghai | 10342 | 23090 | 4074 | 5995 | 0.81 | 2.47 | 1.83 |
| Inner Mongolia | 17778 | 45343 | 4959 | 13550 | 0.79 | 2.25 | 1.90 |
| Guangxi | 8767 | 19808 | 4103 | 5011 | 0.95 | 2.73 | 2.28 |
| Ningxia | 10952 | 25844 | 3980 | 6902 | 0.87 | 2.59 | 2.02* |
| Xinjiang | 12184 | 23532 | 6113 | 5425 | 0.66 | 2.36 | 1.35 |
| Tibet | 8352 | 15703 | 3104 | 3957 | 0.38 | 1.94 | 1.07 |

*Note: 1. The sample period is from 1997 to 2011.*

*2. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

Table 2

**Summary Statistics of Real Insurance Density**

| Region | Mean | Max. | Min. | Std. Dev. | Skew. | Kurt. | J.-B. |
|---|---|---|---|---|---|---|---|
| Beijing | 2190.10 | 4184.20 | 747.01 | 1099.80 | 0.03 | 1.88 | 0.79 |
| Tianjin | 766.10 | 1262.50 | 274.50 | 373.10 | -0.07 | 1.55 | 1.33 |
| Shanghai | 2349.80 | 4288.40 | 482.59 | 1313.60 | 0.19 | 1.75 | 1.07 |
| Liaoning | 433.30 | 882.20 | 110.56 | 270.90 | 0.37 | 1.74 | 1.34 |
| Jiangsu | 564.70 | 1217.90 | 117.50 | 370.40 | 0.45 | 2.06 | 1.06 |
| Zhejiang | 612.20 | 1217.80 | 157.30 | 350.10 | 0.22 | 1.86 | 0.94 |
| Fujiang | 455.10 | 1371.20 | 93.48 | 359.60 | 1.13 | 3.71 | 3.49* |
| Shandong | 721.70 | 3362.20 | 74.79 | 1016.30 | 1.96 | 5.26 | 12.76*** |
| Guangdong | 508.10 | 1081.20 | 149.57 | 324.70 | 0.57 | 1.91 | 1.55 |
| Hainan | 205.00 | 479.10 | 78.45 | 131.30 | 0.98 | 2.81 | 2.42* |
| Hebei | 337.60 | 800.30 | 42.04 | 271.30 | 0.62 | 2.00 | 1.60 |
| Shanxi | 360.48 | 822.28 | 57.88 | 274.43 | 0.51 | 1.87 | 1.46 |
| Jilin | 307.96 | 640.72 | 77.71 | 199.01 | 0.49 | 1.91 | 1.35 |
| Heilongjiang | 339.54 | 648.65 | 72.00 | 211.29 | 0.10 | 1.56 | 1.32 |
| Henan | 252.96 | 660.55 | 38.00 | 213.76 | 0.79 | 2.25 | 1.90 |
| Hubei | 277.52 | 682.54 | 71.40 | 211.98 | 0.89 | 2.31 | 2.28* |
| Hunan | 220.17 | 525.95 | 49.40 | 166.50 | 0.76 | 2.17 | 1.87 |
| Jiangxi | 201.00 | 468.25 | 46.33 | 140.69 | 0.65 | 2.19 | 1.46 |
| Anhui | 234.11 | 566.52 | 47.42 | 175.02 | 0.54 | 1.97 | 1.39 |
| Chongqing | 315.27 | 838.23 | 56.41 | 270.05 | 0.85 | 2.17 | 2.23* |
| Sichuan | 281.06 | 757.31 | 54.43 | 246.86 | 0.85 | 2.23 | 2.18* |
| Guizhou | 117.05 | 297.32 | 29.28 | 86.64 | 0.99 | 2.71 | 2.53* |
| Yunnan | 196.07 | 404.78 | 71.60 | 112.44 | 0.71 | 2.15 | 1.73 |
| Shaanxi | 287.82 | 724.11 | 56.66 | 222.28 | 0.78 | 2.29 | 1.85 |
| Gansu | 201.52 | 471.64 | 48.34 | 139.77 | 0.76 | 2.33 | 1.74 |
| Qinghai | 166.53 | 384.00 | 67.56 | 97.04 | 1.13 | 3.11 | 3.21* |
| Inner Mongolia | 289.33 | 724.15 | 62.15 | 228.10 | 0.78 | 2.17 | 1.94 |
| Guangxi | 153.59 | 358.08 | 50.23 | 98.76 | 0.82 | 2.50 | 1.82 |
| Ningxia | 277.13 | 677.01 | 58.54 | 207.44 | 0.73 | 2.25 | 1.68 |
| Xinjiang | 360.29 | 730.19 | 90.35 | 214.71 | 0.33 | 1.85 | 1.08 |
| Tibet | 129.26 | 592.70 | 16.87 | 184.18 | 1.89 | 4.99 | 11.39*** |

*Note: 1. The sample period is from 1997 to 2011.*

*2. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

Table 3

**Cross-sectional Dependence and Homogeneous Tests**

| Test | Estern area | Central area | Western area |
|---|---|---|---|
| $LM$ | 98.25*** | 107.697*** | 223.202*** |
| $CD_{LM}$ | 4.124*** | 10.65*** | 13.77*** |

| Test | Estern area | Central area | Western area |
|---|---|---|---|
| $CD$ | 4.285*** | 8.765*** | 10.569** |
| $LM_{adj}$ | 52.0063*** | 50.2789*** | 69.2669*** |
| $\tilde{\Delta}$ | 32.4131*** | 7.1253*** | 12.9780*** |
| $\tilde{\Delta}_{adj}$ | 2.6044*** | 0.5505 | 1.0204 |
| $\hat{S}$ | 163.0308*** | 36.5011*** | 75.5792*** |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

**Table 4**

## Total Density does not Granger Cause Output in Eastern Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Beijing | 1.56577 | 36.666 | 235.219 | 437.522 | 1398.541 |
| Tianjin | 1.52649 | 6.613 | 122.254 | 217.783 | 1054.552 |
| Shanghai | -1.47866 | 2.181 | 86.796 | 144.178 | 384.532 |
| Hebei | 2.25355 | 37.561 | 136.282 | 229.945 | 641.005 |
| Liaoning | 1.34074 | 3.689 | 69.572 | 131.946 | 430.119 |
| Jiangsu | 4.66578 | 432.021** | 112.516 | 167.841 | 462.407 |
| Zhejiang | 3.34922 | 109.154*** | 4.055 | 5.856 | 10.915 |
| Fujian | 0.07414 | 1.058 | 137.972 | 282.966 | 886.403 |
| Shandong | 0.19203 | 75.655*** | 125.764 | 214.786 | 806.616 |
| Guangdong | -0.20702 | 0.141 | 104.938 | 186.41 | 544.462 |
| Hainan | -1.50096 | 0.39 | 105.415 | 185.561 | 472.589 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. Bootstrap critical values are obtained from 10,000 replication.*

**Table 5**

## Output does not Granger Cause Total Density in Eastern Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Beijing | 0.063946 | 62.201** | 35.9576 | 62.07577 | 172.1948 |
| Tianjin | 0.0046558 | 1.376 | 44.7312 | 74.0693 | 165.6441 |
| Shanghai | 0.038315 | 68.07 | 182.9729 | 257.635 | 606.8858 |
| Hebei | 0.021635 | 43.6193 | 191.7269 | 275.7348 | 577.012 |
| Liaoning | -0.013683 | 12.8133 | 65.1532 | 116.6812 | 265.8286 |
| Jiangsu | 0.01078 | 31.3691 | 160.3771 | 223.1074 | 441.0318 |
| Zhejiang | 0.010509 | 21.4049 | 112.6279 | 167.2084 | 342.1262 |
| Fujian | 0.018381 | 2.8387 | 12.4571 | 20.188 | 56.7905 |

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Shandong | 0.026953 | 0.723 | 8.3786 | 12.1225 | 58.2597 |
| Guangdong | 0.023648 | 64.2006 | 199.4795 | 301.1546 | 711.8807 |
| Hainan | 0.024333 | 54.3684 | 256.5976 | 413.8793 | 922.6613 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. Bootstrap critical values are obtained from 10,000 replication.*

**Table 6**

## Total Density does not Granger Cause Output in Central Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Shanxi | 3.303635 | 2.2524 | 37.9466 | 55.7141 | 131.5666 |
| Jilin | -1.97341 | 2.9923 | 13.0156 | 23.6689 | 56.72 |
| Heilongjiang | 0.49013 | 0.2946 | 18.1808 | 30.323 | 82.6823 |
| Anhui | 1.63866 | 9.8623 | 16.7168 | 29.5413 | 81.5399 |
| Jiangxi | 4.58905 | 11.2928 | 24.3577 | 42.0611 | 94.35676 |
| Henan | -1.06335 | 0.61905 | 30.8476 | 43.9086 | 78.9715 |
| Hubei | 1.9178 | 0.7403 | 19.6075 | 30.1666 | 81.9474 |
| Hunan | 0.14447 | 0.007307 | 17.6946 | 26.44411 | 45.4997 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. critical values are obtained from 10,000 replication.*

**Table 7**

## Output does not Granger Cause Total Density in Central Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Shanxi | 0.024236 | 66.9869** | 39.8221 | 56.4485 | 115.04156 |
| Jilin | 0.021831 | 61.2694** | 29.8221 | 43.6031 | 88.6491 |
| Heilongjiang | 0.028384 | 29.0365** | 18.5768 | 24.8954 | 54.0482 |
| Anhui | 0.037455 | 76.4358** | 22.0813 | 36.3811 | 77.0854 |
| Jiangxi | 0.014183 | 8.8777 | 33.3814 | 48.12821 | 92.4786 |
| Henan | 0.021682 | 35.0329 | 37.5552 | 55.4187 | 114.57272 |
| Hubei | 0.021935 | 33.1804* | 32.5273 | 48.326 | 98.99176 |
| Hunan | 0.019322 | 44.3052* | 43.643 | 60.8986 | 104.77615 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. Bootstrap critical values are obtained from 10,000 replication.*

Table 8

## Total Density does not Granger Cause Output in Western Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Chongqing | 1.5371 | 1.187 | 377.01889 | 690.9795 | 1748.9873 |
| Sichuan | 0.1413 | 0.22547 | 625.57422 | 1117.942 | 2848.7241 |
| Guizhou | 7.4753 | 58.9384 | 745.2319 | 1337.8626 | 2892.4411 |
| Yunnan | 2.7748 | 5.8251 | 772.8089 | 1671.83813 | 6566.1752 |
| Shaanxi | 0.5647 | 0.3333 | 987.2441 | 1764.17566 | 6135.2851 |
| Gansu | 5.6968 | 64.3106 | 809.6784 | 1445.1173 | 4899.2465 |
| Qinghai | 4.6151 | 9.9736 | 988.1901 | 2027.9334 | 8880.248 |
| Inner Mongolia | -20.5639 | 97.9508 | 372.8094 | 731.26599 | 3054.5026 |
| Guangxi | 12.4546 | 219.1193 | 1030.476 | 1773.9771 | 5551.9692 |
| Ningxia | 14.5439 | 58.273 | 1120.20166 | 2442.5871 | 12535.0752 |
| Xinjiang | 1.1704 | 0.8197 | 1217.6108 | 2373.1084 | 15450.3632 |
| Tibet | -0.64112 | 67.26 | 979.0462 | 2078.2321 | 10692.5566 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. Bootstrap critical values are obtained from 10,000 replication.*

Table 9

## Output does not Granger Cause Total Density in Western Region

| Region | coefficient | Wald Statistics | Bootstrap Critical Value | | |
|---|---|---|---|---|---|
| | | | 10% | 5% | 1% |
| Chongqing | 0.027411 | 134.2317 | 1285.286 | 2292.5127 | 7773.4292 |
| Sichuan | 0.034253 | 105.6207 | 427.4969 | 729.35846 | 3500.8979 |
| Guizhou | 0.018843 | 205.045 | 791.3515 | 1479.74805 | 3898.6855 |
| Yunnan | 0.032345 | 120.01777 | 714.7622 | 1344.9146 | 3713.79 |
| Shaanxi | 0.024511 | 190.90554 | 470.44321 | 904.7882 | 3693.3042 |
| Gansu | 0.022381 | 225.85139 | 636.403 | 1295.7421 | 3908.8586 |
| Qinghai | 0.006947 | 110.81922 | 1022.8671 | 1783.3344 | 6733.228 |
| Inner Mongolia | 0.017441 | 385.04502 | 678.07727 | 1081.3575 | 4014.1999 |
| Guangxi | 0.0092324 | 112.29441 | 457.2235 | 806.418 | 2179.6823 |
| Ningxia | 0.021763 | 179.33525 | 533.0735 | 1004.5725 | 3550.2536 |
| Xinjiang | 0.026892 | 44.465705 | 597.093 | 1099.6835 | 3141.2832 |
| Tibet | 0.037157 | 10.080715 | 13.824 | 23.3835 | 46.4206 |

*Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.*

*2. Bootstrap critical values are obtained from 10,000 replication.*