The Relationship between Insurance Development and Economic Growth: A Cross-Region Study for China

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Abstract: This study applies bootstrap panel Granger causality to test the relationship between development of insurance, including life and non-life insurance, and economic growth using data from 31 provinces of China. We find that patterns of interaction between insurance development and economic growth vary according to different level of income. Empirical results show that demand-following pattern is significant only for provinces of high income in both life and non-life insurance sectors, while supply-leading pattern prevails through most provinces at different developing stage, except for provinces of low income level in life sector. Our investigation also finds that in comparatively developed provinces, both life and non-life insurance interact with economy constructively. Further more, the hypothesis from Pattrick (1966) that supply-leading finance tends to play a more significant role at the beginning of the growth process is empirically proved in insurance sector. These results could be useful for regional governments that seek to improve economic growth as they suggest the need for implementation of simulative policies for the development of insurance industry for China.

Keywords: Life and Non-life insurance, Economic Growth; Demand-following, Supply-leading, Bootstrap Panel Causality Test

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1. Introduction

Insurance market activities may contribute to economic growth, both as financial intermediary and provider of risk transfer and indemnification by allowing different risks to be managed more efficiently and by mobilizing domestic savings (Ward and Zurbruegg, 2000). More specifically, insurance can have effects such as promoting financial stability, mobilizing savings, facilitating trade and commerce, enabling risk to be managed more efficiently, encouraging loss mitigation, fostering efficient capital allocation and also can be a substitute for and complement of government security programs (Skipper, 2001). In fact, economic growth is characterized by the soundness of a national insurance market. On the other hand, insurance development, including life and non-life insurance, are found to be significantly affected by economic growth (Outreville, 1990, 1996; Browne and Kim, 1993; Beck and Webb, 2003; Li *et al*., 2007).

The objective of this study is to examine the causal relationships that potentially exist between life and/or non-life insurance industry and economic growth in China. As a major emerging economy, China is characterized for rapid development in both insurance market and national economy in last three decades. In 1978 China started an economic reform and trade was opened to outside world. Overall, the Chinese economic reform has been a spectacular economic success which has generated rapid economic growth over three decades and the country has moved from a centrally planned economy towards a market economy. Instead of being tightly controlled and centrally planned the economies become market-oriented. Privatization has been at the forefront of the economic transition process when insurance industry is considered. Before the transition process took place "private insurance was neither much needed nor purchased" (Dorfman, 2008) because of the exaggerated use of public funds for coverage of losses, comprehensive social insurance and government ownership of the means of production, which consequence was the fact that state-owned enterprises were insured by state owned insurers. Privatization incentives the development of risk management and growth of insurance demand and at the same time insurance markets became deregulated and liberalized. Although local insurance markets are still modestly developed in terms of insurance density compared to their western counterparts, insurance premium growth in China has outpaced economic growth. Since the reform and opening up especially after the 16th National Congress of Communist Party of China (CPC), China's insurance businesses have increased quickly, which played an active role in improving reform, protecting economy, stabilizing society and benefiting people. The Chinese insurance market had total gross written premiums of $214.3 billion in 2010, representing a compound annual growth rate (CAGR) of 26.7% between 2006 and 2010.

However, the interaction relationship between insurance development and economic growth is not clearly known yet. In this study, we investigate it by using bootstrap panel Granger causality approach and try to indentify the interaction patterns through testing in 31 provinces (municipalities and autonomous regions included, thereafter shortened as "provinces") of different levels of income in China. The panel causality analysis which takes into account cross-sectional dependency (so-called the bootstrap panel causality developed by Kónya (2006). Furthermore, by comparing the results from the panel causality analysis with those from the Toda-Yamamoto time series causality approach, Nazlioglu *et al.* (2011) indicated that the choice of statistical method is of importance in causality analysis. Empirical results of this study show that for both life and non-life insurance, demand-following pattern exists only in provinces of high income, while supply-leading pattern is widespread through provinces of different level of income with the exception of life insurance showing weak impact on economic growth in provinces of low income.

This study contributes to the literature in several aspects. First, it provides further evidences on different effects of life insurance and non-life insurance in a country's economy, to our knowledge, this article is the first to compare the effects of life insurance and non-life insurance on economic growth using province-level data in a country, especially in China. Second, specific patterns of interaction between economic growth and life/nonlife insurance are detected and test results show that the interaction patterns vary across provinces of different level of income. Third, this study is one of the few researches focusing on relationship between insurance development and economic growth in China and has important policy implication for China and other developing countries.

The reminder of this empirical study is organized as follows. Section 2 reviews literatures. Section 3 outlines the methodology of the Bootstrap Panel Granger causality. Section 4 presents the data used and discusses the empirical findings and policy implications. Section 5 concludes the paper.

2.Literature Review

Though the acknowledgment of "a sound national insurance and reinsurance market is an essential characteristic of economic growth" by United Nations Conference on Trade and Development (UNCTAD) in 1964 is largely proved by practices, in view of importance of insurance in the economic literature, one might have expected several researches on relationship between insurance development and economic growth. However, in contrast to the available evidence on the economic importance of banks, typified by the work of Levine and Zervos (1998), little is known about insurance.

The relationship between property-liability insurance premium written and economic and financial development was evaluated with cross-section data of 55 developing countries by Outreville (1990) with OLS method. A positive relationship between logarithm of property-liability premia per capita and GDP per capita was founded. Potential relationship between growth in insurance industry and economic growth was examined by Ward and Zurbruegg(2000) for OECD countries. Real Gross National Product and total written premia were considered as measures for economic and insurance activity, respectively. This study tried to answer issues which had not been considered in Outreville's study, such as causal relationships. It did not accommodate the potential for causal relationships to differ in size and direction across countries. Ward and Zurbruegg (2000) use Johansen cointegration trace test and error-correction models and it was concluded that the causal relationships between economic growth and insurance market development may vary across countries. Kugler and Ofoghi (2005) find the components of insurance premia to find a long run relationship between development in insurance market size and economic growth for most components by using Johansen's λ_{trace} and λ_{max} cointegration tests. Arena (2008) used 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 (life and non-life insurance) and economic growth. Robust evidence was found that both life and non-life insurance have a positive and significant causal effect on economic growth. Specifically, for life insurance, high-income countries drive the results, and for non-life insurance, both high-income and developing countries drive the results.

Though these results are provoking, several aspects of the research on this topic need to be improved. First, causal relationships between insurance development and economic growth is still unclear, results from different researches even contradict with each other. Arestis and Demetriades (1997), Pesaran *et al.* (2000) and Ward and Zurbruegg (2000) have pointed out that it is important to accommodate the potential for causal relationships to differ in size and direction across countries. They suggest that the role of insurance in the economy may be varied across countries. This could happen when the influence of insurance market development, while channeled through indemnification and financial intermediation, is tempered by country-specific factors. However, the evidence on the causal relationships between insurance activities and economic growth is scarce on country level, let alone lower level. In our study, province-level data in China is used and thus country-specific factors such as culture, religion, social security, and inflation etc. which are usually thought to affect the insurance development (Browne and Kim, 1993) are removed or partly mitigated, relationships between insurance development and economic growth are expected to be tested with less disturbance factors. Second, ambiguity of results from using aggregated data should be removed carefully. As Granger (2003) claimed, it is possible to have cointegration at the aggregate level and not at the disaggregate level and vice versa. Cross-sectional aggregation occurs when a number of micro variables are aggregated to get a macro variable, results based on aggregated data are somewhat doubtful. Within the researches on issue about insurance and economic growth, total written insurance premium at country level is usually used to represent insurance activities, thus problem of cointegration seems inevitable. For instances, Ward and Zurbruegg (2000) find no relationship between insurance market size and economic growth for the United Kingdom with country-by-country aggregated data, while Kugler and Ofoghi (2005) decompose the insurance premium data and find a long run relationship between development in insurance market size and economic growth for most categories of insurance in UK. Our research use province-level data and split the data into life and non-life categories to remove the aggregation problem. Third, the difference between relationships of life and non-life insurance to economic growth is not fully understood yet. The characteristics between life and non-life insurance are usually viewed as different (Skipper, 1997; Ward and Zurbruegg, 2000). Outreville (1990) identified links between an economy's economic and financial development and property-liability insurance market development. Besides, Beenstock *et al.* (1986), Truett and Truett (1990), Browne and Kim (1993), Outreville (1996) and Beck and Webb (2003) provided evidences of the positive relationship between life insurance demand and income. However, life and non-life are rarely pared to investigate the difference in their relationship with economic growth. In this study, we use two concepts from Patrick (1966) to compare different effects of life and non-life insurance. Patrick (1966) identifies two possible patterns in the causal relationship between financial development and economic growth. One is "demand-following" pattern of which the creation of modern financial institutions with their financial assets and liabilities, and related financial services are in response to the demand for these services by investors and savers in the real economy. The other pattern is named as "supply-leading" where the expansion of the financial system precedes the demand for its services. These two kinds of patterns are tested in Kugler and Ofoghi (2005) using aggregated insurance data, while our study differs from it by testing cases of life and non-life insurance respectively. Furthermore, conventional time-series data tests not only failed to consider cross-sectional information, but also had lower power. In order to increase the power in testing for relationship, many researchers developed the use of panel data. The existing literature has mainly relied on cross-section and time series analysis. In our study, by utilizing information on both the intertemporal dynamics and the individuality of the insurance market, the efficiency of econometric results is greatly improved. In addition, most of previous studies utilized asymptotic methods in the estimation and testing of parameters. It is well-known that these methods lose power when the probability distributions are non-normal. Since it is well-established that time series are non-normally distributed (Chunchachinda *et al.*, 1997), in contrast with previous studies, we use the bootstrapping approach. It is well-recognized that bootstrapping results in more reliable estimates of parameters (Hacker and Hatemi-J, 2006) and thus our study provides new evidence on the issue of causal effect between insurance activities and economic growth.

3. Methodology

Investigating Granger causality within panel data framework requires a careful treatment. First issue in that respect is to control for a possible cross-sectional dependency across provinces since a shock affecting one province may also affect other provinces because of a high degree of development as well as of regional economic integration. The Monte Carlo experiment carried out by Pesaran (2006) emphasizes the importance of testing for the cross-sectional dependence in a panel data study and also illustrates the substantial bias and size distortions when cross-sectional dependence is ignored (Pesaran, 2006). Second issue is to

estimated parameters. The causality from one variable to another variable by imposing the joint restriction for the panel is the strong null hypothesis (Granger, 2003) and the homogeneity assumption for the parameters is not able to capture heterogeneity due to country specific characteristics (Breitung, 2005). In the insurance and economic growth nexus，as in many economic relationships, while there may be a significant relationship in some provinces vice versa may also be true in some other provinces

Based on above discussion, our empirical analysis starts with testing for cross-sectional dependency, followed by examining slope homogeneity across regions. Then, we decide which panel causality method should be employed to appropriately determine the direction of causality between life insurance/non-life insurance and economic growth in China across different economic regions. In what follows, we outline the essentials of econometric methods used in this study.

3.1 Cross-sectional dependency tests

The cross-sectional dependency among countries in previous studies implies that a shock affecting one country may spill on other countries. When we consider 31 provinces in China, cross-sectional dependency may play crucial role in detecting causal linkages among economic series since provinces are highly integrated and have a high degree of economic development.

To test for cross-sectional dependency, decide whether the slope coefficients are treated as homogenous and heterogeneous to impose the causality restriction on the

Breusch and Pagan (1980) proposed a Lagrange test. The construction of the test statistic depends upon the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \varepsilon_{it} \quad \text{for} \quad i = 1, 2, ..., N; \quad t = 1, 2, ..., T \qquad (1)$$

where i is the cross section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables. As shown in equation (1), the individual intercepts (α_i) and slope coefficients (β_i) are allowed to vary across countries. The null hypothesis of no-cross sectional dependency and the alternative hypothesis of cross-sectional dependency are described as:

$H_0 : Cov(u_{it}, u_{jt}) = 0$, for all t *and* $i \neq j$

$H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$

In order to test the null hypothesis against the alternative, Breusch and Pagan (1980) developed the Lagrange multiplier statistic as:

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

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of Equation (1) for each i. Under the null hypothesis, *LM* statistic is asymptotically distributed as chi-square with $N(N-1)/2$ degrees of freedom. It is important to note that the LM test is valid for N relatively small and T sufficiently large. This drawback is tried to be solved by Pesaran (2004) by the following scaled version of the *LM* test:

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

Under the null hypothesis with $T \to \infty$ first and then $N \to \infty$, this test statistic has the standard normal distribution. Even though CD_{lm} is applicable even for *N* and *T* large, it is likely to exhibit substantial size distortions when *N* large and *T* small. The shortcomings of the *LM* and the 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 statistic:

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

Under the null hypothesis with $T \to \infty$ and $N \to \infty$ in any order, the CD test has asymptotic standard normal distribution.

Pesaran (2004) indicates that the *CD* test has exactly mean zero for fixed *T* and *N* and is robust to heterogeneous dynamic models including multiple breaks in slope coefficients and/or error variances, as long as the unconditional means of y_{it} and x_{it} are time-invariant and their innovations have symmetric distributions. However, the *CD* test has an important drawback that it will lack power in certain situations in which the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero (Pesaran *et al*., 2008, p.106). Pesaran *et al.* (2008) proposes a bias-adjusted test which is a modified version of the LM by using the exact mean and variance of the LM statistic. The bias-adjusted LM test is constructed as:

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

where μ_{Tij} and v_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran *et al.* (2008, p.108). Under the null hypothesis with first $T \to \infty$ and then $N \to \infty$, LM_{adj} test is asymptotically distributed as standard normal.

3.2 Slope homogeneity tests

Determining whether slope coefficients are homogeneous or heterogeneous is also important in a panel causality analysis by imposing causality restrictions on estimated coefficients. In Equation (1), the null hypothesis of slope homogeneity and the alternative hypothesis of heterogeneity can be described as:

$H_0 : \beta_i = \beta$, for all *i*

$H_1 : \beta_i \neq \beta_j$, for a non-zero fraction of pair-wise slopes for $i \neq j$.

In order to test for the null hypothesis, the familiar approach is to follow the Wald principle. Accordingly, test of slope homogeneity is $H_0 : \beta_1 = ... = \beta_N$ where the Wald statistic is asymptotically distributed as chi-square with N-1 degrees of freedom (see, Mark *et al.*, 2005). The test based on the Wald principle is valid for cases where 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 homoscedastic (Pesaran and Yamagata, 2008).

Similar to the Wald principle, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. Even though Swamy's test is valid for panel with fixed *N* and large *T* just as the Wald test, it allows for cross-section heteroscedasticity (Pesaran and Yamagata, 2008). The Swamy test for slope homogeneity is:

$$S = \sum_{i=1}^{N} \left(\widehat{\beta}_i - \widehat{\beta}_{WFE} \right)' \frac{x_i' M_\tau x_i}{\widehat{\sigma}_i^2} \left(\widehat{\beta}_i - \widehat{\beta}_{WFE} \right) \quad (6)$$

where $\widehat{\beta}_i$ is the pooled OLS estimator, $\widehat{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, $M\tau$ is an identity matrix, and $\widehat{\sigma}_i^2$ is the estimator of σ_i^2. In the case where *N* is fixed and $T \rightarrow \infty$, the *S* test has an asymptotic chi-square distribution with *k(N-1)* degrees of freedom.[1]

3.3 Panel Causality Test

According to Granger (1969), the Granger causality means that the knowledge of past values of one variable (X) helps to improve the forecasts of another variable (*Y*). If there are cross-sectional dependency and heterogeneity across countries, the method utilized should account for these features. Even though different panel causality approaches have been advocated (for a review see Kar *et al.*, 2011), the bootstrap panel causality approach proposed by Kónya (2006) is able to account for both cross-sectional dependency and province-specific heterogeneity. In detecting causal relationships, the bootstrap panel causality approach of Kónya (2006) is based on Seemingly Unrelated Regression (SUR) estimation of the set of equations and the Wald tests with country specific bootstrap critical values. Since province-specific bootstrap critical values are used, the variables in the system do not need to be stationary, implying that the variables are used in level form irrespectively of their unit root and cointegration properties. By imposing country specific restrictions, we can also identify which and how many provinces exists Granger causal relation.

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

[1] We refer an interested reader to Pesaran and Yamagata (2008) for the details of Swamy's test and its extension for panels where *N* and *T* are both large. Since *N* is small relative to T in our study, we used the Swamy test.

$$\begin{aligned} y_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} y_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} x_{1,t-i} + \varepsilon_{1,1,t} \\ y_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} y_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} x_{2,t-i} + \varepsilon_{1,2,t} \\ &\vdots \\ y_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} y_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} x_{1,N,t-i} + \varepsilon_{1,N,t} \end{aligned} \quad (7)$$

$$\begin{aligned} x_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} y_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} x_{1,t-i} + \varepsilon_{2,1,t} \\ x_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} y_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} x_{2,t-i} + \varepsilon_{2,2,t} \\ &\vdots \\ x_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} y_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} x_{N,t-i} + \varepsilon_{2,N,t} \end{aligned} \quad (8)$$

and

where y denotes the real income, x refers to the indicator of insurance premium (life insurance, and non-life insurance*)*, *l* is the lag length. Since 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.

To test for Granger causality in this system, alternative causal relations are likely to be found for a province: (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. (iv) There is no Granger causality between *X* and *Y* if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero.

Since the results from the causality test may be sensitive to the lag structure, determining the optimal lag length(s) is crucial for robustness of findings. Thereby, prior to estimation, we have to specify the number of lags. For a relatively large panel, equation and variable with varying lag structure would lead to an increase in the computational burden substantially. To overcome this problem, following Kónya (2006)

We allow maximal lags to differ across variables, but to be the same across equations. We estimate the system for each possible pair of ly_1, lx_1, ly_2, and lx_2 respectively by assuming from *1* to *4* lags and then choose the combinations which minimize the Schwarz Bayesian Criterion.[2]

4. Data and Empirical Results

In this study, we use quarterly data of 31 provinces in China from 2006 to 2011 to examine the interaction of insurance activities

[2] As indicated by Kónya (2006), this is a crucial step 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.

and economic growth. From 2006, national premium revenues were up to 564.1 billion yuan, ranked the 9th in the world, higher by 7 than that in 2000. This meant the average annual international rank of China insurance industry rose by 1. China insurance industry has entered rapid development period, and operation model of insurance industry is developing toward diversification. The future prospect of China insurance industry development will be very important. Data of life and non-life insurance[3] are published on the official web site of China Insurance Regulation Commission (CIRC), the change of real GDP per capita is used to proxy for the economic growth, and the data is taken from the China Economic Information Network. We follow EnZ (2000) who finds the relationship between life and non-life insurance penetration and GDP per capita, implying varying income. It could be the case that insurance market activity could have different effects on economic growth depending on the measure of the GDP per capita. In order to test this hypothesis, we divide the provinces into three groups according to the real GDP per capita to discover certain interaction patterns between life/non-life insurance at different stages of economic growth. The high-income group contains 10 provinces with real GDP per capita larger than USD2,500, the middle-income group includes 13 provinces with real GDP per capita ranging from USD 1,300 to USD2,500, the low-income group consists of 8 provinces with real GDP per capita less than USD1,300. The provinces of high income group are mainly those located in the coastal area and are pioneers to open to outside, with the advantages of geography and national supporting policies, these provinces are comparatively with high economic and social development. The middle-income group consists of provinces located in inland of China which traditionally focus on agriculture or heavy industries. The provinces of low income group usually locate in mountainous west region of China where productivity is low and a large population is in poverty.

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 cross-sectional dependency and province-specific heterogeneity in empirical analysis is crucial since provinces of different levels of income could be highly integrated and have close economic relations. Thereby, our empirical study starts with examining the existence of cross-sectional dependency and heterogeneity across the provinces in concern. To investigate the existence of cross-section dependence we carried out four different tests (LM, CD_{lm}, CD, LM_{adj}) and illustrated results in Table 1. It is clear that the null of no cross-sectional dependency across the provinces is strongly rejected at the conventional levels of significance, implying that the SUR method is appropriate rather than province-by-province OLS estimation.[4] Table 1 also reports the

[3] Life and non-life business areas are categorized in this study according to standard EU and OECD conventions, where health insurance is counted as part of non-life insurance.

[4] The cross-sectional dependency furthermore implies that examining causal linkages between

results from the two slope homogeneity tests (Wald and S). Both tests reject the null hypothesis of the slope homogeneity, supporting specific heterogeneity of the provinces in China. The rejection of slope homogeneity implies that the panel causality analysis by imposing homogeneity restriction on the variable of interest results in misleading inferences. In this respect, the panel causality analysis based on estimating a panel vector autoregression and/or panel vector error correction model by means of generalized method of moments and of pooled ordinary least square estimator is not an appropriate approach in detecting causal linkages between life and non-life premium and economic growth in China provinces.

<Table 1 is inserted about here>

The existence of the cross-sectional dependency and the heterogeneity across China provinces provides evidence on the suitability of the bootstrap panel causality approach. The results from the bootstrap panel Granger causality analysis[5] are reported in Tables 2-5. Results from Table 2 shows that economic growth is a strong Granger cause of life insurance development in 9 out of 10 provinces in high-income group. The failure to reject the null hypothesis of non causality running from economic growth to life premium prevails in middle-income and low-income groups (exception for Shannxi, Hunan, Henan, Ningxia in former group and Sichuan, Anhui in later group). It means that for most provinces in middle-income and low-income groups' economic growth does not cause life insurance to increase. The results suggest that the interaction between life insurance and economic growth follows demand-following pattern for provinces of high-income economic growth. On the other side, from Table 3 we can find for most provinces (10 out of 13) in middle-income group life insurance market activities are powerful driving force for economic growth. Half provinces in high-income group also show supply-leading pattern in interaction relationship between life insurance and economic growth. Life insurance development does not seem to have significant impacts on local economic growth in low-income group with only two provinces, Sichuan and Guizhou, rejecting the null hypothesis.

<Table 2 and 3 are inserted about here>

Table 4 presents causality test results from economic growth to non-life insurance development for groups of different income level. The results show that only for High-income group economic growth is Granger cause for non-life insurance development with 9 out of 10 provinces rejecting the null hypothesis at at least 10%

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life and non-life premium and economic growth in China requires taking into account this information in estimations of causality regressions. In the presence of cross-sectional dependency, SUR approach is more efficient than province-by-province ordinary least-squares (OLS) method (Zellner, 1962). Therefore, the causality results obtained from SUR estimator developed by Zellner (1962) will be more reliable than those obtained from the country-specific OLS estimations.

[5] We refer to Kónya (2006) for the bootstrap procedure on how the country specific critical values are generated.

significance level. Provinces in middle-income and low-income groups generally fail to show the same feature except for Hebei, Shanxi, Hubei and Hainan.

<Table 4 is inserted about here>

According to the results of Table 5, it is apparent that non-life insurance development tends to drive the economic growth in provinces belonging to middle-income group with 10 out of 13 provinces significantly rejecting the null hypothesis. At the same time, results show that for most provinces in other two groups (6 out of 10 in high-income group and 5 out of 8 in low-income groups) supply-leading pattern are indentified to exist in the relationship between non-life insurance development and economic growth.

<Table 5 is inserted about here>

With the summary of causality test in Table 6, different interaction patterns between cases of life and non-life insurance sectors can be compared. As is shown in Table 6, for both cases of life and non-life insurance, demand-following pattern exist only in provinces of high income, while supply-leading pattern is widespread through different level of income with the exception of life insurance showing weak impact on economic growth in provinces of low income. These results can be justified by checking relative economic theories. Though a lot of evidences showed that economic growth is a strong drive for insurance development (like Outreville, 1990; Browne and Kim, 1993). Thus it is no wonder that at middle and/or low level of income economic growth does not show strong impacts on insurance development. On the contrary, insurance activities, either life insurance or non-life insurance, nearly always can contribute to economic growth at different stages of economic growth through risk transfer, indemnification, and financial intermediation. Whereas, as financial intermediation is a primary aspect of life insurance and the life insurance companies tend to gather premiums from all around the country and invest it mostly to the hot economic area to earn profit, the impact of life insurance on economic growth in economically backward provinces is not significant. We also notice that in group of middle income both life and non-life insurance show strong power to propel the economic growth. This phenomenon might be the result of expansion of insurance company. After years of fierce competition in coastal developed regions, more and more insurance companies open branches and affiliations and shift their focus of operation to middle-income inland provinces in recent years, which greatly promote the economic growth in these regions. Compared with Arena (2008), this study not only discovers causal relations running from economic growth to insurance development, but also differs in some results about causal relationships running from insurance development to economic growth. Our test results suggest that non-life insurance might play a better role at low stage of economic development rather than life insurance. Our results seem more justifiable with economic theories and insurance industries practices.

<Table 6 is inserted about here>

5. Conclusions

China is in the midst of the transition from planned to market economy, from closed economy to open economy. On the other hand, China is also an economy with big regional difference. This study, relying on quarterly data from 31 provinces of China over the period of 2006-2011, examines the interaction relationships between insurance (life and non-life) development and economic growth using bootstrap panel Granger causality approach. The main findings are as follows. First, life insurance and non-life insurance share most features in relationships with economic growth. To be specific, development of both life and non-life insurance can only be driven by economic growth in relatively developed provinces, and conversely can contribute to economic growth in most of provinces at different stages of economic growth. Second, compared to life insurance, non-life insurance tends to have better impacts on economic growth in provinces of low income. Third, in provinces of high income, insurance (including life and non-life insurance) activities and economy form a benign circulation and promote each other. Fourth, hypothesis in Pattrick (1966) stated as "supply-leading finance is likely to play a more significant role at the beginning of the growth process than later" is proved in insurance sector by observing that supply-leading pattern is more common to see in lower stage of economic growth compared to demand-following pattern. These results could be useful for regional governments that seek to improve economic growth as they suggest the need for implementation of simulative policies for the development of insurance industry in China.

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Table 1. Cross-sectional dependency and homogeneity tests

Study	Test	Life Insurance	Non-Life Insurance
Breusch and Pagan (1980)	LM	2913.804***	3110.170***
Pesaran (2004)	CD_{lm}	80.299***	86.739***
	CD	39.780***	43.016***
Pesaran and Yamagata (2008)	LM_{adj}	144.949***	124.074***
Mark *et al.* (2005)	Wald	6.603***	2.861***
Swamy (1970)	S	82.994***	53.531***

Note: *** indicates significance at the 0.01 level.

Table 2. Real GDP Per Capita Growth does not Granger Cause Life Insurance

	Wald Statistics	Bootstrap Critical Value		
		1%	5%	10%
High Income Provinces				
Shanghai	12.952*	31.628	17.701	12.628
Beijing	23.828**	32.962	18.611	13.401
Tianjin	16.847*	30.982	18.141	12.866
Zhejiang	26.825**	37.655	20.139	14.466
Jiangsu	23.582**	36.684	21.465	15.508
Guangdong	29.794**	31.908	17.696	12.725
Shandong	24.582**	33.450	19.389	14.066
Liaoning	14.578*	30.956	17.919	12.703
Fujian	12.918*	30.988	16.954	11.821
Inner Mongolia	5.429	18.701	9.911	6.823
Middle Income Provinces				
Hebei	24.308	91.287	51.987	38.197
Heilongjiang	5.729	141.951	46.539	24.986
Jilin	19.078	51.378	27.929	19.189
Xinjiang	5.304	40.942	22.025	15.065
Shanxi	21.838	87.896	51.368	38.182
Chongqing	26.847	82.254	46.964	37.846
Hubei	18.384	81.517	47.515	34.766
Hainan	18.877	69.479	40.902	29.523
Shaanxi	32.299*	65.442	38.927	28.491
Henan	33.654**	52.675	29.389	20.973
Hunan	28.269*	65.510	37.051	26.783
Ningxia	56.857**	76.475	45.532	32.951
Qinghai	43.664/	77.507	43.337	29.926
Low Income Provinces				
Jiangxi	4.439	21.218	11.674	8.229
Sichuan	20.661***	17.974	9.711	6.694
Tibet	2.315	22.979	12.525	8.585
Guangxi	2.512	22.609	12.076	8.477
Anhui	10.983*	19.219	10.992	7.7401
Gansu	7.086	20.866	10.939	7.682
Yunnan	2.549	26.366	12.829	8.455
Guizhou	6.154	20.769	11.127	7.577

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 replications.

Table 3. Life Insurance does not Granger Cause Real GDP Per Capita Growth

	Wald Statistics	Bootstrap Critical Value		
		1%	5%	10%
High Income Provinces				
Shanghai	8.144	30.043	16.615	11.789
Beijing	10.900*	23.564	13.359	9.187
Tianjin	0.965	20.563	11.287	7.578
Zhejiang	3.302	24.417	13.697	9.534
Jiangsu	6.360	24.494	13.761	9.587
Guangdong	22.927**	29.485	16.531	11.427
Shandong	29.420**	29.449	17.275	12.415
Liaoning	13.058*	30.017	17.268	12.254
Fujian	16.238*	32.222	18.955	13.279
Inner Mongolia	6.691	31.224	17.232	11.973
Middle Income Provinces				
Hebei	19.974	60.300	35.550	26.431
Heilongjiang	0.032	31.678	16.516	10.973
Jilin	32.189*	74.923	40.779	29.121
Xinjiang	2.240	45.119	24.832	18.157
Shanxi	44.462**	67.963	40.343	29.431
Chongqing	41.271**	61.761	65.117	25.133
Hubei	69.846**	74.753	43.441	31.295
Hainan	83.832***	65.839	39.406	27.595
Shaanxi	37.446*	68.248	40.665	30.049
Henan	100.906***	52.582	30.277	21.428
Hunan	56.339**	81.745	48.562	36.258
Ningxia	30.744**	47.299	26.723	18.851
Qinghai	33.324**	35.267	19.662	13.516
Low Income Provinces				
Jiangxi	5.812	19.347	11.017	7.462
Sichuan	17.789**	19.817	11.306	7.916
Tibet	5.465	19.769	10.651	7.297
Guangxi	5.026	17.808	10.147	6.956
Anhui	3.747	20.016	11.133	7.659
Gansu	2.948	19.705	10.734	7.174
Yunnan	1.162	14.543	8.104	5.681
Guizhou	11.618**	17.372	9.560	6.701

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 replications.

Table 4. Real GDP Per Capita Growth does not Granger Cause Non-Life Insurance

	Wald Statistics	Bootstrap Critical Value		
		1%	5%	10%
High Income Provinces				
Shanghai	54.538***	22.602	12.053	8.315
Beijing	5.462	22.202	12.50	8.759
Tianjin	9.154*	21.655	11.869	7.988
Zhejiang	78.269***	39.329	19.766	13.249
Jiangsu	254.465***	29.247	16.062	11.273
Guangdong	62.513***	31.822	17.522	12.819
Shandong	42.598***	22.777	11.952	8.224
Liaoning	16.490**	22.541	12.201	8.289
Fujian	11.328*	22.333	11.888	8.273
Inner Mongolia	96.439***	32.584	17.786	12.613
Middle Income Provinces				
Hebei	50.382***	39.327	21.146	15.159
Heilongjiang	0.398	73.383	31.66.	19.372
Jilin	4.934	34.923	19.016	13.004
Xinjiang	0.389	26.812	13.611	9.332
Shanxi	33.261***	32.956	18.268	12.378
Chongqing	12.657	39.804	22.461	15.559
Hubei	92.406***	47.366	26.473	18.857
Hainan	76.158***	32.922	16.967	11.596
Shaanxi	9.980	43.168	22.798	15.893
Henan	2.342	50.087	26.949	18.716
Hunan	0.029	40.894	23.367	16.117
Ningxia	11.421	44.874	25.068	17.260
Qinghai	0.033	70.956	37.955	25.773
Low Income Provinces				
Jiangxi	0.024	14.859	8.122	5.596
Sichuan	4.543	13.460	9.966	4.776
Tibet	0.554	49.697	17.462	10.866
Guangxi	0.241	13.186	7.263	4.886
Anhui	5.313	12.887	7.393	5.695
Gansu	3.256	13.723	7.3052	4.867
Yunnan	1.030	19.074	8.834	5.797
Guizhou	0.313	16.737	8.333	5.755

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 replications.

Table 5. Non-Life Insurance does not Granger Cause Real GDP Per Capita Growth

	Wald Statistics	Bootstrap Critical Value		
		1%	5%	10%
High Income Provinces				
Shanghai	28.805***	27.009	14.895	10.683
Beijing	28.728**	28.816	15.407	10.323
Tianjin	0.019	24.560	12.358	8.476
Zhejiang	0.447	35.779	14.633	9.331
Jiangsu	12.136*	26.629	14.277	9.921
Guangdong	7.253	27.301	15.061	10.372
Shandong	16.059*	29.952	16.088	11.465
Liaoning	22.860**	28.932	16.222	11.385
Fujian	21.493**	33.339	17.459	12.254
Inner Mongolia	0.437	31.462	14.588	9.881
Middle Income Provinces				
Hebei	36.590*	73.801	41.329	29.968
Heilongjiang	4.136	34.250	16.864	11.411
Jilin	63.529**	66.489	40.704	29.941
Xinjiang	11.477	64.414	32.78	23.313
Shanxi	45.833**	67.444	40.922	29.689
Chongqing	62.406***	59.102	33.100	23.076
Hubei	118.339***	60.395	37.108	27.321
Hainan	53.710**	72.872	41.312	30.175
Shaanxi	0.004	69.900	35.502	24.792
Henan	29.067*	57.964	30.086	20.640
Hunan	68.981**	75.981	40.386	28.919
Ningxia	67.465***	47.408	21.997	18.959
Qinghai	18.662*	51.258	23.126	15.265
Low Income Provinces				
Jiangxi	7.357*	17.992	10.047	6.837
Sichuan	8.647*	22.147	10.935	7.364
Tibet	0.176	26.168	11.181	6.946
Guangxi	39.947***	17.546	10.067	6.964
Anhui	1.540	18.477	9.913	6.739
Gansu	3.050	18.791	9.188	6.227
Yunnan	11.568**	18.299	9.178	6.218
Guizhou	19.322***	18.806	8.437	5.729

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 replications.

Table 6. Summary of Causality Test between Real GDP Growth and Life/Non-life Insurance

Income	GDP → Life insurance	Life insurance → GDP	Effect
High	◎	◎	Bi-direction
Middle		◎	Supply-leading
Low			
Economic Region	GDP→ Non-life insurance	Non-life insurance→ GDP	
High	◎	◎	Bi-direction
Middle		◎	Supply-leading
Low		◎	Supply-leading