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Risk Affection and Transmission of News of Conditional Volatility from the Non-Life to Life Insurance Sector

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Abstract

Non- Life and Life Insurance companies are the main expedients of risk transfer and risk management procedure in the economy and the society. This paper examines, in eight worldwide advanced insurance markets, whether there are transmissions of news of conditional volatility from the non-life to life insurance sector. The reason is that, regularly, non-life insurance risks have higher volatility and they are less predictable than life insurance risks. A GJR - GARCH model is used to test these relationships for the period January 1st 1990 to June 28th 2019 using daily trading observations for each listed insurance index. The results suggest that the French and the Australian non-life insurance sectors influence their life insurance sectors to a greater extent than the other countries insurance indices under study. There is also evidence that the leverage effect indicates that bad news concerning the non-life insurance index shows a more intense impact on the volatility of the life insurance index than the good news in the majority of the countries under study. However, bad and good news are symmetrical in French and Australian insurance markets.

JEL classification numbers: G22, G32, D53, C5
Keywords: Insurance risks, Volatility, Non- Life Insurance, Life Insurance, GJR GARCH

1 Introduction

It is well recognized in the economic and academic world that the insurance procedure is a crucial key that plays a significant role in order to keep the society and the economy safe, sustainable and healthy. Insurance companies transfer, through the collection of diversified and homogeneous risks, a risk regarding the income of an individual insured person to a group of individuals exploiting the law of large numbers in probability theory. By acting as a provider of risk transfer and also as an institutional investor, insurance reinforces financial stability, mitigates financial losses and transfers savings into investments efficiently (Arena, 2008).

There are two main insurance entities (business lines), Life and non-Life Insurance. These companies have different business units and insure different and various risks.

Life insurance companies provide protection, in general, against death, illness and retirement and also provide accident and health insurance. At the same time, life insurance companies offer a plethora of investment products, such as annuities, unit links, whole of life, universal life, endowment life, group life, credit life, guaranteed investment contracts, stock mutual funds (Saunders and Cornett, 2018).

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Regarding the risks faced in the asset and liability side, life insurance companies invest in long-term securities (such as bonds over 25-30 years old, stocks or high liquid real estate). Also, life insurance companies buy a lot of mortgages in the secondary market and keep them as investments. Life insurance companies keep a surplus reserve in order to deal with unforeseen future losses. The risk faced by life insurance companies is related to long-term payment obligations, mainly in case of longevity.

In the asset side of the balance sheet of a life insurance company the main risk is the possible lack of liquidity. Therefore, life insurance companies invest in high liquid real estate and stocks. Some take a little currency risk by investing money in domestic currency coming from their liability side in investment schemes abroad. Lastly, interest rate risk is one of the most important risks that a life insurance company faces. Life contracts and annuities provide a guaranteed interest rate. In order to be solvent against this risk, good management is to keep fixed interest rate bonds for the same period of time as the aforementioned annuities.

On the other hand, non-Life or General Insurance companies provide protection against individual and/or professional wealth loss. More specifically, they protect against fire risk, flood risk, theft risk, natural disaster risks, property risks, civil liability, motor risks, marine, aviation and transport risks.

General insurance companies invest the majority of their assets in medium-term securities, due to the fact that assets could better match the medium-term nature of the liabilities. Additionally, non-life insurance claims arising from the insurance policies (contracts) are more uncertain and volatile than the respective claims in the life insurance companies. Consequently, non-life insurance companies keep, in the asset side, many securities with stable returns, which can be easily liquidated (Saunders and Cornett, 2018).

Regarding the risks facing a non-life insurance entity in the asset and liability side of the balance sheet, there are many unexpected high claims that were not taken into account in the technical reserves. This is the greatest problem in the liability side of the balance sheet for a non- life insurance company. The above risk would be well managed through diversified and selective underwriting. Also, the non-life insurance company is reinsuring or purchasing liability swaps and/or alternative risk transfer (ART) and Finite products, such as PCS options and CAT bonds. Risks derived from the asset side of the balance sheet of a non-Life insurance company stem from the volatility of investment returns or the lack of market capitalization that can lead the company to default on some of its claims. This risk can be reduced through a change in investment policy, through using diversified portfolio management or through hedging, taking a long or a short position in interest rates or stocks derivatives. Another important source of asset side risk is the insolvency of the high risk and return investments (i.e. corporate bonds, stocks), which can be reduced again through an appropriate diversification, both on the investment and commercial portfolios. The interest rate risk does not concern general insurance companies, as insurance contracts are not based on interest rates (i.e. Euribor, Libor).

There are several studies in the literature which focus on the dynamics of insurance premium prices or on insurance underwriting cycle and underwriting profits. For instance, Feldblum (2007) notes that the market structure of insurance is in a state of perpetual disequilibrium with high volatile prices of premiums. Tetin (2016) believes that shifts in loss ratios of insurance policies are caused by dynamics of competition in the insurance market. Ligon and Thistle (2007) suggest that insurance profits change should be asymmetrical and displayed as a cycle (Shi-jie Jiang et.al , 2019) .

Many studies have analyzed the insurance profits dynamics worldwide, either in life or in non- life insurance business line. Most studies have focused on short-term determination of insurance profits and denote that insurance profits might be demonstrated as stationary (e.g., Choi et. al, 2002; Harrington and Yu, 2003). However, if insurance profits are stationary, inclusion of any non-stationary independent variables would render an econometric analysis biased. To solve such problems, Shi-jie Jiang et.al (2019) use the ARDL of Assenmacher-Wesche and Pesaran (2008) test for the threshold cointegration approach in order to empirically capture the characteristics of cycles in insurance markets' profits. The above study used data from US non -life and also from the US general liability insurance industry business line. The results are in line with the prediction of Ligon and Thistle (2007), in which the underwriting profits should be cyclical and change asymmetrically. Finally, Eling and Jia (2018) propose two indicators for insurer failure surveillance: a) efficiency, estimated by the data envelopment analysis (Leverty and Grace, 2010, 2012); and b) business volatility. They found that technical efficiency negatively affects and business volatility positively correlates with the probability of failure. They document that firm (insurance) growth has a U-shaped, nonlinear impact on failure probability.

Contrary to previous studies regarding insurance markets and their embodied risks, this paper examines the possible risk affection from non-life insurance to life insurance indices, using data from eight advanced capital markets. To be more specific, this study analyses the volatility transmission dynamics from non-life insurance indices to life insurance indices. The results indicate a major influence of non life on life insurance markets in France and in Australia in comparison with the other countries under study. Furthermore, this paper measures the volatility asymmetry from non-life to life insurance signal. This paper examines the null hypothesis that there is asymmetric volatility impact from non-life insurance index to life insurance index for eight advanced insurance markets (USA, UK, CANADA, GERMANY, JAPAN, AUSTRALIA, FRANCE and ITALY). To be more specific, it is displayed in research hypothesis that no asymmetric volatility difference takes place between life and non-life insurance indices for each country. In particular, we test the null hypothesis *H0: no statistically asymmetric volatility difference takes place between life and non-life indices for each country,*

H1: statistically volatility difference takes place between life and non-life indices for each country.

The results signify that bad news affects more than good news for the majority of the countries. However, there is no leverage effect for French and Australian insurance markets. One reason for that would probably exist due to the fact that many times in France and Australia, the insurance companies combine some products (covered risks) that exist in both non-life and life sectors. Also, the French insurance market is in general more traditional compare to other countries and the big French insurance companies have a non-life as well as a life insurance part.

The scope of this paper is to address the gap in the literature in this area, by conducting an in-depth analysis of non-life insurance market volatility spillovers effects on the life insurance market. This attempt, based on the rationality that non -life insurance business line, is usually the most risky sector, compared to life insurance business line, owing to the fact that reserves in non-life insurance are not easily predictable and manageable.

To the best of my knowledge, this paper is the first study to provide empirical evidence regarding potential volatility clustering, volatility asymmetry and persistence for non- life and life insurance markets risks. An extended literature review paragraph is omitted since there is no similar published research from the past which illustrates interesting results regarding the impact of non-life insurance risk on life insurance risk by using data from capital markets.

2 Data

The empirical analysis was drawn up collecting daily observations of eight advanced listed non-Life Insurance countries' price indices (USA, UK, CANADA, GERMANY, JAPAN, AUSTRALIA, FRANCE and ITALY) as well as eight advanced listed Life Insurance price indices from the aforementioned countries respectively. These data have been obtained through the DataStream database of the Thomson Reuters Company. Trading days natural logarithmic returns for the selected data are calculated as $R_t=100*\ln(P_t/P_{t-1})$ where R_t and P_t are the daily returns and prices respectively.

The sample covers from 1-1-1990 until 28-6-2019 period and incorporates daily trading observations for each index.

3 Methodology

Glosten *et al.* (1993) suggests the GJR-GARCH model as an alternative method to the EGARCH model. Like the EGARCH model, the GJR-GARCH model has also achieved a good empirical record in the literature. This model expresses the conditional variance of a given variable as a nonlinear function of its own past values of standardized innovations. The variance of this model can be written as:

$$\boldsymbol{\sigma_t^2 = w + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \delta S_{t-i}^{-} \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2} \tag{1}$$

Where,

S^-_{t-i} is a dummy variable which takes the value 1 if ε_{t-i} is negative and 0 otherwise.
The formula expresses the impact of the errors ε^2_{t-i} on conditional variance σ^2_t (Brooks, 2014). The above model also confirms that bad news ($\varepsilon_t<0$) and good news ($\varepsilon_t>0$) might have different conditional variance. If the leverage effect exists, δ is expected to be positive. The condition for a non-negative variance requires that $w\geq0$, $\boldsymbol{\beta_j}\geq0$, $\boldsymbol{a_i}\geq0$, $\alpha_i+\delta>0$.
The leverage effect is observed as the impulse ($\alpha_i+\delta$) of negative shocks, which is larger than the impulse (α_i) of positive shocks. In this model, good news and bad news have different effects on the conditional variance: good news has an impact of α_i, while bad news has an impact of ($\alpha_i+\delta$). For $\delta>0$, the leverage effect exists, which means that bad news has a greater effect on conditional volatility. Good news reflects on the coefficient $\boldsymbol{a_i}$ (δ absorbs the effect of the bad news). When $\delta\neq0$, the conclusion is that the effect of news is asymmetrical.
The use of GJR-GARCH model in this study derived from the fact that this model produces best implementation of data and goodness of fit.

4 Empirical Results

This section presents the descriptive statistics of insurance indices returns (life and non-life) for each country and the empirical results of GJR-GARCH.

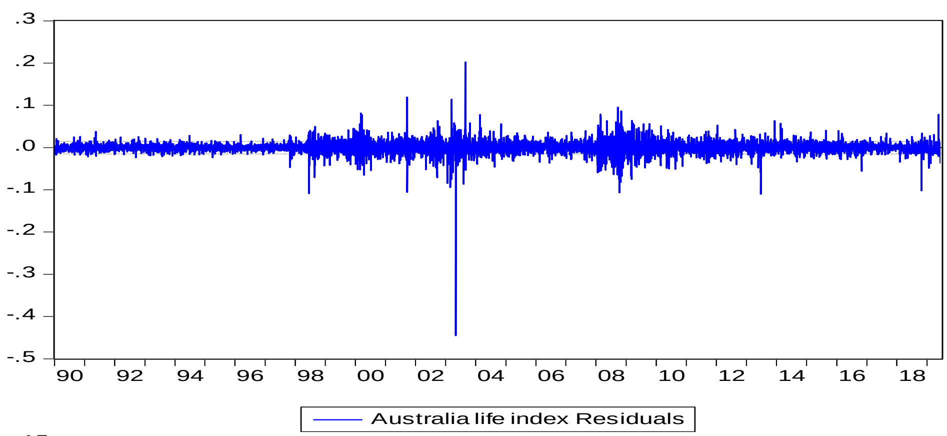
Table 1: Descriptive Statistics for indices returns (life and non-life) per country

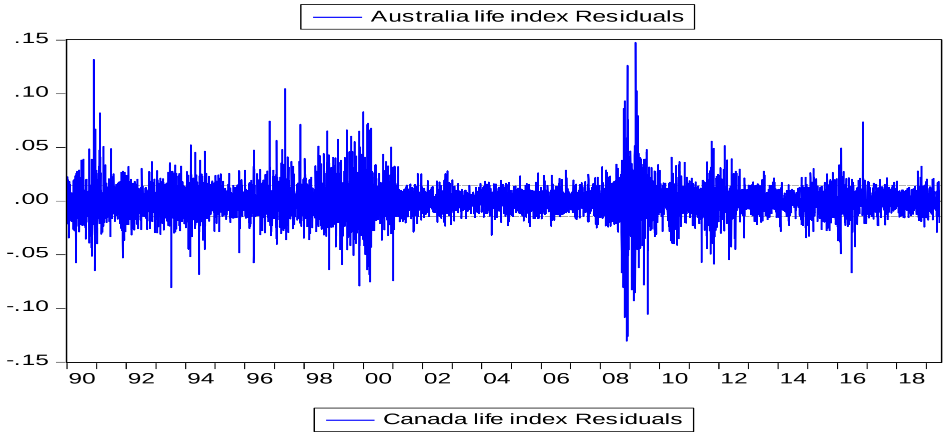
	Mean	**Standard Deviation**	**Median**	**Maximum**	**Minimum**	**Skewness**	**Kurtosis**
Australia life	-0,00013	0,017469	0	0,209026	-0,43736	-2,26916	61,78744
Australia non-life	0,000228	0,016293	0,000444	0,136125	-0,27818	-1,13358	19,6873
Canada life	0,000332	0,01628	0,000177	0,161687	-0,1659	-0,07262	10,97436
Canada non-life	0,000402	0,012112	0,000331	0,075906	-0,10368	-0,26934	4,012485
France life	0,000164	0,016257	0	0,119158	-0,14491	-0,05956	5,915058
France non-life	0,000119	0,020243	0,000268	0,184713	-0,1801	0,104017	10,66941
Japan life	0.000022	0,017469	0	0,154151	-0,16862	-0,12235	10,77847
Japan non-life	-0.00005	0,018856	0	0,127717	-0,15097	0,091055	4,56581
UK life	0,000164	0,019367	0,000345	0,205169	-0,25237	-0,36466	15,10569
UK non-life	0.000008	0,015028	0.000008	0,106402	-0,12896	-0,19154	5,835943
US life	0,000315	0,018395	0,000192	0,20823	-0,18042	-0,19444	23,54075
US non-life	0,000307	0,011599	0,000194	0,101471	-0,10921	-0,01183	9,225011
Germany life	-0.00002	0,015494	0.000005	0,14978	-0,14852	0,599656	10,50546
Germany non-life	0,000176	0,015745	0,000382	0,131131	-0,12496	-0,0753	7,250715
Italy life	0,000108	0,018851	0.000009	0,137088	-0,13263	-0,01181	3,313143
Italy non-life	0,000006	0,017119	0.000004	0,128868	-0,19061	-0,19755	5,703991

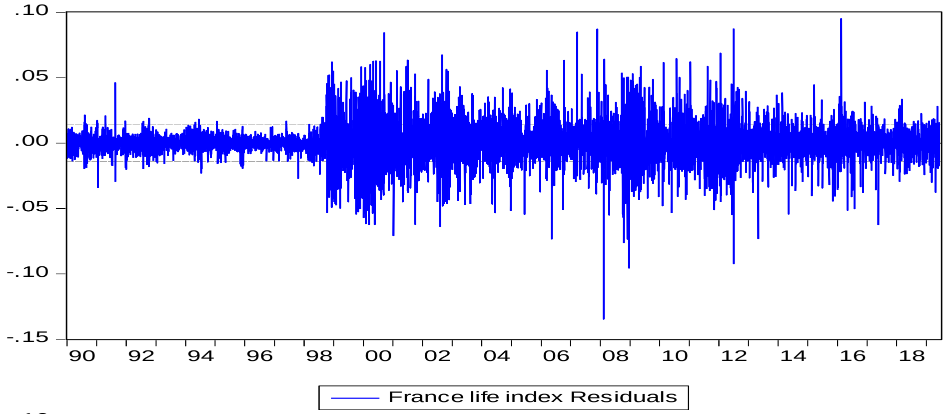
Table 1 presents the descriptive statistics for insurance indices returns (life and non-life) for each country. Australia life insurance index provides the lowest mean (-0,00013), whereas Canada non-life index the highest (0,000402). We observe that most indices have a positive average return value. Also, the standard deviation (volatility) between life and non-life indices shows no significant difference for the majority of indices. However, there are important differences between life and non-life indices returns in the US and the UK, where the volatility of life indices is higher. It is found out that the most of indices returns display negative asymmetry and also, they are leptokurtic.
The skewness is negative for the majority of the sixteen returns series. Only the German Life and the French non-life indices are positively skewed. The sixteen log-return series are leptokurtic. The kurtosis appears to be the largest for the Australian Life index (61,78744), followed by the US Life index (23,54075).

Before implementing a GARCH model, we should test for the presence of volatility clustering phenomenon. Financial time series often exhibit a behavior t known as volatility clustering: volatility changes over time and its degree shows a tendency to persist, i.e., there are periods of low volatility and periods when volatility is high. In order to check for the presence of volatility clustering, we should examine the residuals volatility of the returns in the dependent variable (life insurance indices).

Figure 1 displays the volatility clustering of every Life Insurance index by using the residuals diagnostics.



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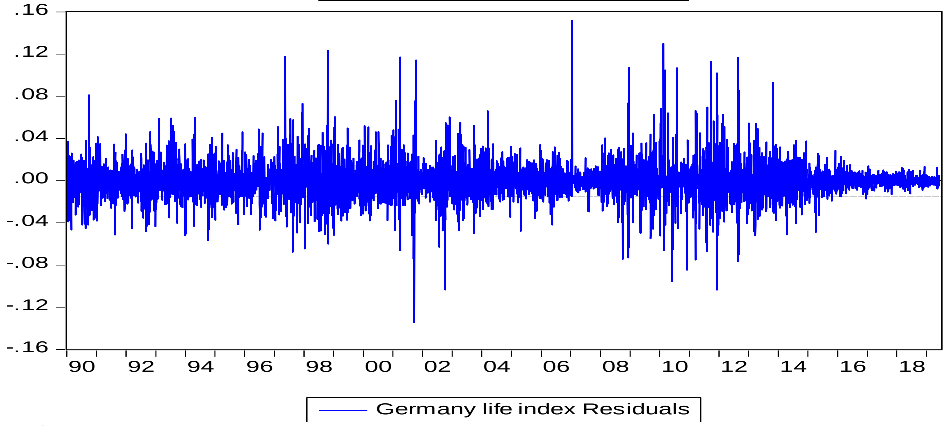
France life index Residuals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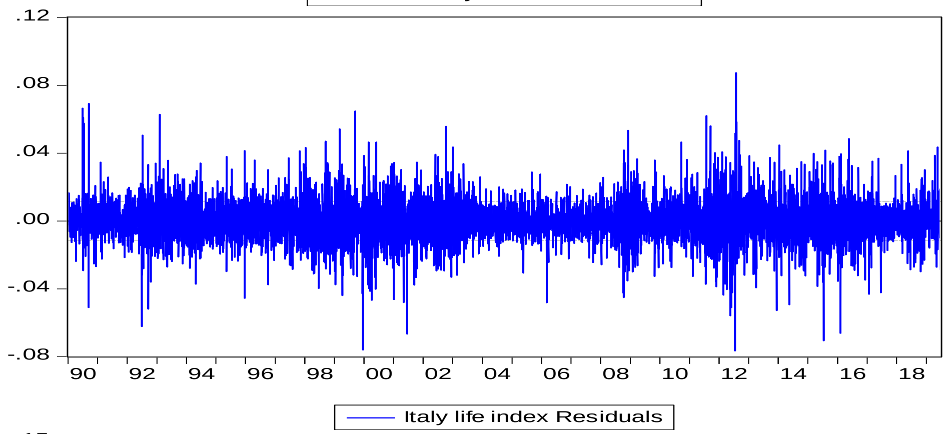
Germany life index Residuals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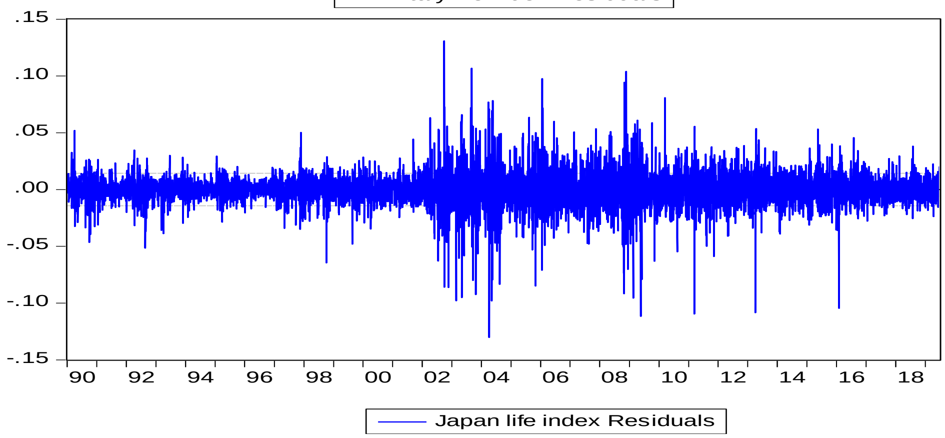
Italy life index Residuals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Japan life index Residuals

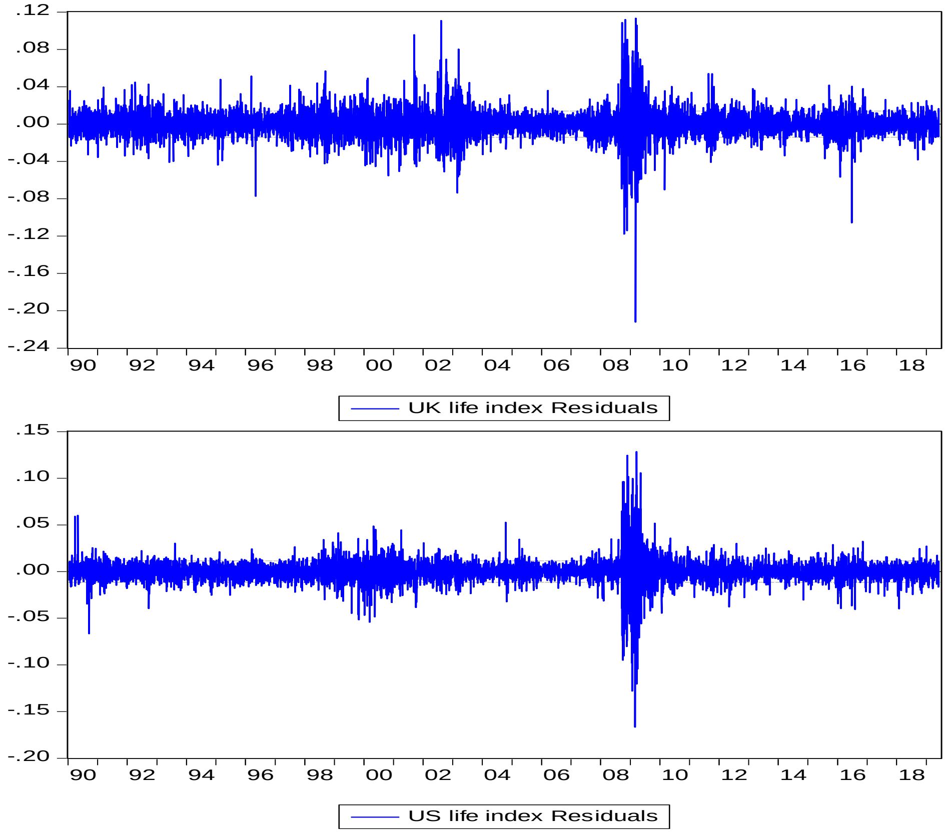

Figure 1: Diagnostics of volatility clustering (residuals) for life insurance indices

The residuals diagnostics figures indicate that volatility clustering is apparent since there are periods with low and high volatility. Therefore, we assume that there is heterogeneity at the conditional variance and the GJR-GARCH can be implemented.

Moreover, the UK and the US life Insurance indices indicate low risk profile for the whole period under study, except the period of the 2008 global financial crisis, which is a rational finding. The above finding eventuates that the UK and the US life insurance markets remain a low risk investment for institutional investors, hedge funds, risk managers and portfolio managers. Also, figures denote that the Canadian life insurance index has had a low risk profile since 2000, apart from the period of the 2008 global financial crisis. The volatility responses results justify that insurers are among the largest institutional investors on the capital markets and thus negative development regarding insurance investments is almost unavoidable (Eling and Schmeiser, 2010). Also, on the liability side, insurers are affected (though less than the asset side) through insurance in the credit market, as well as errors and omissions insurance, or by a reinsurers' default (Eling and Schmeiser, 2010). Moreover, in a period of economic crisis, insurance companies lose the high demand for insurance coverage (Grace and Hotchkiss, 1995).

Table 2 presents the results of White heteroskedasticity test (including White cross-term) in order to test the statistically significant presence of ARCH effect.

Table 2: Empirical Results of White heteroskedasticity test

Country	F-statistic	Prob*
Australia	36.82	0.0000
Canada	183.61	0.0000
France	84.17	0.0000
Germany	23.85	0.0000
Italy	114.44	0.0000
Japan	381.60	0.0000
UK	492.66	0.0000
US	381.55	0.0000

**Statistically significant at 0.05 level*

The probability value is equal to 0% for each country. Therefore, we could assume that an ARCH effect exists in all examined insurance indices. Also, we could implement a GJR-GARCH, since we have found that volatility clustering is apparent, descriptively and inferentially.
Table 3 presents the empirical results of a GJR-GARCH model by using as the dependent variable the daily volatility of each life index and as independent variable, the daily volatility of each non-life index. The use of the GJR-GARCH allows the capture the volatility clustering, the volatility asymmetry, and the long-term component of conditional variance. The current model describes conditional variance (volatility) to react asymmetrically against return shocks. Particularly, we utilized a GJR-GARCH(1,1) including the threshold term (δ). The z-statistic values are in the parenthesis in the tables.

Table 3: Empirical Results of GJR-GARCHlife insurance index vs non-life insurance index

Parameter	Australia	Canada	France	Germany	Italy	Japan	UK	US
Constant	0.0001 (6.24)*	0.0007 (6.94)*	0.0008 (4.68)*	0.0008 (2.19)*	0.0002 (13.14)*	0.0001 (26.12)*	0.0002 (9.33)*	0.0007 (9.44)*
ARCH effect	0.639 (25.95)*	0.033 (11.35)*	0.974 (35.11)*	0.042 (23.55)*	0.032 (11.95)*	0.049 (15.93)*	0.048 (12.19)*	0.042 (14.60)*
δ (leverage effect)	-0.557 (-24.38)*	0.029 (7.29)*	-0.818 (-31.03)*	0.035 (11.21)*	0.027 (6.62)*	0.026 (5.22)*	0.029 (5.18)*	0.001 (2.31)*
GARCH effect	0.826 (173.45)*	0.949 (405.55)*	0.761 (176.08)*	0.948 (1026.94)*	0.942 (338.51)*	0.945 (555.75)*	0.925 (211.62)*	0.946 (356.21)*

**Statistically significant at 0.05 level*

The GARCH parameter shows the time-varying long-term volatility. We observe that the value of this component is approximately equal to unity for all indices, except the French and the Australian Life Insurance indices. For the remaining six countries under study, the long-term volatility memory of Life Insurance indices is highly persistent against the shocks of Non-Life index of the same country.

The α coefficient shows the ARCH effect (volatility clustering), which presents the volatility sensitivity of the Life Insurance index against the shocks of the non-Life insurance index. We expect that the volatility of the Life Insurance index is sensitive to intense shocks of the non-Life insurance index. The above occurs in the majority of the insurance indices under study. However, we observe that the French Life Insurance index is extremely sensitive to major shocks of the Non-Life insurance index. The same condition, though to a lesser extent, takes place in the Australian Insurance market.

Additionally, the δ parameter is the threshold term which shows the leverage effect. The leverage effect is positive for every examined country apart from France and Australia. The leverage effect indicates that the bad news of the non-Life insurance index shows a more acute impact on the volatility of the Life

insurance index than the good news does. For instance, the volatility asymmetry seems to be higher for the German Life Insurance index, indicating the positive German Non-Life Insurance index's signals. Particularly, the bad news of the German non-Life insurance index (stock index fall) shows a 3.5% greater impact than the good news (stock index increase) on the German Life insurance index.
Nevertheless, bad and good news are symmetrical in French and Australian insurance markets. This shows that the leverage effect is not apparent and therefore the good and the bad news of the non-Life insurance index show similar impact on the volatility of the Life insurance index.

5 Conclusions

This paper investigates the influence of non-life insurance on life insurance companies' risk. The study focuses on sixteen advanced insurance markets indices derived from eight countries, i.e. USA, UK, Germany, France, Canada, Japan, Australia and Italy. The volatility of these capital markets indices function as an approximation of the risks incurred in the sixteen non-life and life insurance companies' underwriting and business profits/losses.

The paper examines the conditional volatility news transmission and the leverage effect of non- life on life insurance business lines. The results suggest that indeed there is risk influence of non-life on life insurance companies for all the countries under study. Moreover, this risk (volatility news transmission) influence is very high from non-life to life insurance markets in France and in Australia. Regarding the leverage effect findings, we reject the null hypothesis that there is asymmetric volatility impact of the non-life insurance index on the life insurance index for France and Australia. Looking at the composition of French and Australian non-life and life insurance indices, some findings arise that possible explain the above differences in the results compare to the other countries. Australian life insurance index includes companies that have in their business units non-life products and vice versa (i.e. travel insurance). In France, the insurance market is more traditional compare to other European and American countries and the big French insurance companies often include a non-life as well as a life insurance business entity. For instance, the French non-life insurance index includes major companies (i.e. AXA, SCOR) that have both non-life and life activities. Therefore, according to empirical results we failed to accept the null hypothesis that it is referred to the introduction section.

Also, the majority of the countries under study (except France and Germany) perform time varying low risk (volatility) in the life insurance sector. Nevertheless, in the period of global financial crisis (2008) all the life insurance indices indicate high volatility.

The findings of this paper are very important for risk managers, hedge funds and portfolio managers, taking into account that the insurance sector in general and insurance indices are used as a hedging tool or a low risk investment. Specifically, risk managers which try to diversify their portfolios would not include together in the same portfolio the French non-life and life index or the Australian non-life and life index.

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