The Financial Stability Index of the Early Warning System for Taiwan's Life Insurers

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Abstract

We propose a new measure of the financial stability index (FSI) for the early warning system, while applying different quantiles analyses of the financial conditions of life insurers in Taiwan. Instead of the mean-based method in the previous literature, we use the median-based approach to select the FSI. Moreover, we adjust and make the index the risk-adjusted FSI, thereby enhancing the index's ability to provide an early warning. Furthermore, firm size, changes in product portfolios, the risk-based capital (RBC) system's implementation, and whether or not the insurer is credit-rated each have a significantly positive effect on the insurer's financial stability.

Key words: Early warning index, financial stability index, life insurer

I. Introduction

Life insurers' soundness affects financial markets' stability. Furthermore, insurance operations' effective supervision positively impacts on insurers' solvency.[1] Therefore, the supervisory authorities hope to develop an early warning system to adopt remedial actions to reduce overall losses[2] before any insurers' financial structure markedly deteriorates. To measure Taiwan's life insurers' financial stability, we construct an index that will practically serve as an early warning instrument and further analyze related factors that influence this index.

As for financial early warning systems related to life insurers, in the past there were two kinds of systems, the U.S.'s Insurance Regulatory Information System (IRIS) and the Financial Analysis and Solvency Tracking (FAST) system. Chen and

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1 Pasiouras and Gaganis (2013) find that there is a significantly positive relationship between the implementation of a strong insurance supervision system and the solvency of insurers.

2 McShane, Cox, and Butler (2010) discover that a positive correlation exists between supervision and company profits.

Wong (2004) state that these systems were by nature based on ex post supervision and thus unable to instantly reflect a company's financial situation. Therefore, beginning in 1994, the U.S. moved away from ex post supervision to risk-based capital (RBC). Cummins and Phillips (2009) point out that the previous approaches have significant shortcomings in terms of RBC to predict the problem insurers. Therefore, dynamic financial analysis (DFA) and other supervisory instruments have been subsequently developed. However, in terms of practical application, there still has been considerable scope for further development of an effective financial early warning index for insurers.

As for past literature on insurers' solvency, many researchers use the insurer's financial index as a predictive factor (e.g., BarNiv (1990), BarNiv and McDonald (1992), and BarNiv and Smith (1987)). Regarding life insurers, the majority of researchers also analyze the factors that impact on the insurer's solvency (e.g., Baranoff, Papadopoulos, and Sager (2007)). Hollman, Hayes, and Murrey (1993) compare changes in the values of items in the financial statements of insurers with those for the industry in order to predict life insurers' solvency. Following Hollman, Hayes, and Murrey (1993), Chen and Wong (2004) perform an analysis of insurers in Japan and Asian developing countries. Despite these studies, the literature on the analysis of financial stability remains very limited.

The Taiwan insurance supervisory authorities have attempted to develop systems similar to the IRIS and FAST used in the U.S. The currently established "Early warning index" is based on the same concept as the IRIS's, with its main focus on setting up standard warning criteria for each financial index in the insurance industry.[3] However, the system similar to the FAST was only used in research and was not implemented in practice. In 2004, the supervisory authorities introduced an RBC system, and it became the most important tool for supervising insurers. However, Cummins and Phillips (2009) state that the RBC is far from ideal to predict the failures of life insurers. For the insurance supervisory authorities to control changes in the market more effectively, it is necessary in practice to establish various kinds of early warning mechanisms.

Hollman, Hayes, and Murrey (1993) suggest that before insurers encounter a "problem," they are likely to adopt a series of "changes" to try to turn things round. More precisely, such changes predict and further help detect major operating problems hidden within the insurers. Regarding the need for a financial early warning system for life insurers, we follow the approach developed by Hollman, Hayes, and Murrey (1993; henceforth HHM index) and propose an appropriate financial stability index (henceforth FSI) for life insurers. We also take into consideration the risk associated with each investment asset in order to calculate the risk-adjusted FSI (henceforth RFSI). Furthermore, by using the data from 1997 to 2012, we test the FSI's ability to provide an early warning regarding the

[3] Of the financial early warning indices currently adopted, 18 are adopted by property and casualty insurers, and 12 by life insurers. Each index has specific early warning criteria, and based on such characteristics, upper and lower limits are set.

financial soundness of Taiwan's life insurers. Our research results can furnish the supervisory authorities with an early warning instrument that can enable them to determine whether life insurers are encountering a financial distress.

In addition, to provide more information, we further analyze principal factors that affect the FSI by using quantile regression. Recent studies using quantile regression analyses in finance have increased significantly.[4] For example, Born, Viscusi, and Baker (2009) assess the relationships between various tort reform measures and insurer losses. They suggest that any restraining effect of the reforms appears to be largely concentrated between the 75th and 90th percentiles. Klomp and De Haan (2012) suggest that banking regulation and supervision has an effect on the risks of high-risk banks, but not on low-risk banks. Chang and Tsai (2014) find that leverage has the opposite effects on insurers' liquidity in the lower and higher quantile groups. Therefore, besides using the ordinary least squares method to analyze the related factors influencing the financial stability and in order to understand the changes in the tail distributions of the index, we also use the quantile regression approach proposed by Koenker and Bassett (1978).

Comparing our results with the past literature using the mean as the basis of comparison, we find that the median as a criterion for choosing the FSI has a better forecasting ability. In this study, we use the proposed FSI to forecast whether life insurers would experience technical insolvency[5] in 2005. The accuracy of our prediction is 100.00%, and the Type II error is 40.00%. In terms of forecasting which life insurer would be likely to experience a financial distress due to the financial crisis in 2008, our newly proposed RFSI better predict financial difficulties, and its accuracy of prediction is 71.43% with a Type II error of 22.22%. In addition, from the results of the quantile regression analysis, we find that firm size, changes in the product portfolio, the implementation of the RBC system, and whether or not the company is credit-rated each have a significantly positive effect on financial stability, whereas the insurance leverage of life insurers, the share of unit-linked products, and the interest rate level each have a significantly negative impact.

The main contributions of this paper are as follows. First of all, instead of the mean-based method in the previous literature, we use the median-based approach to select the FSI.[6] In addition, we adjust the index to become the RFSI, thereby

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4 For example, the investment of mutual funds (Bassett and Chen (2001)), the application of value-at-risk (Engle and Manganelli (2004) and Bassett and Chen (2001)), hedge fund investment strategies (Meligkotsidou, Vrontos, and Vrontos (2009)), the prediction of bankruptcies among enterprises and banks (Schaeck (2008) and Li and Miu (2010)), the impact of different legal systems or supervisory environments on the financial performance of insurers (Born (2001) and Born, Viscusi, and Baker (2009)), the impact of interest rate controls on the loss provisions of insurers (Grace and Leverty (2010)), the impact of a diversification strategy on business performance and risk (Lee and Li (2012)), the impact of the government's monitoring system on bank risk (Klomp and De Haan (2012)), and the effect of liquidity on property and casualty insurers (Chang and Tsai (2014)).

5 Technical insolvency means that the company's assets are smaller than its liabilities. That is, the value of net assets is negative.

6 Sharpe and Stadnik (2007) point out that the HHM index is susceptible to the effect of extreme values due to the dichotomous nature of the mean.

enhancing the index's ability to provide an early warning. Secondly, we analyze the factors that affect the life insurers' financial stability by using the quantile regression approach, which is more suitable for Taiwan where there are only a small number of life insurers as well as for the markets where there are relatively large variations in assets and liabilities. We believe that the proposed FSI in this paper can serve as a valuable early warning tool and help the supervisory authorities to monitor life insurers.

The remainder of this paper is organized as follows. In Section II, we discuss the literature and present our hypotheses. In Section III, we describe the data and our research method. Section IV consists of our analysis and empirical results. Finally, we conclude this study in Section V.

II. Literature Review and Hypothesis Development

Hollman, Hayes, and Murrey (1993) propose the HHM index to measure the changes in the financial conditions of life insurers. This index transforms the financial data of these insurers into an index of financial stability. It also serves as a basis for predicting whether the insurers will become insolvent. Their empirical results indicate that the HHM index had an accuracy of prediction of 85.70% in the case of U.S. life insurers that subsequently became insolvent. Chen and Wong (2004) suggest that the HHM index can eliminate the problem of data insufficiency and can be applied to either a period or a specific date. The HHM index can avoid the interference that might arise from different sizes.

As for the factors affecting the solvency of insurers, many studies analyze the causes of operating losses and bankruptcies of insurers. BarNiv and Hershbarger (1990) consider that the size of an insurer has an important impact on its insolvency. They also find that the net operating profit of life insurers has a significant influence on their solvency. Kim et al. (1995) analyze U.S. life insurers that went bankrupt between 1987 and 1990 and find that the firm size, investment performance, and net operating income have a significant impact on the solvency. Grace, Harrington, and Klein (1998) point out that the life insurers' sizes and ages are negatively related to the probabilities of their bankruptcies. Das, Davies, and Podpiera (2003) discover that the relaxation of the restrictions on the investment portfolios of insurers would increase their risk of bankruptcy. Baranoff, Papadopoulos, and Sager (2007) suggest that a negative relationship exists between the asset risk and capital ratios of life insurers and that there are differences according to the firm size. In addition, BarNiv and Hershbarger (1990) and Ambrose and Carroll (1994) show that changes in asset portfolios are significantly related to whether or not life insurers would go bankrupt. Carson and Hoyt (1995) find that changes in life insurers' asset portfolios are positively related to insolvency. For this reason, we take the view that some variables have a significant impact on the financial stability index used to measure life insurers' asset changes. We, therefore, propose the following hypothesis:

Hypothesis 1:

The financial stability of life insurers is positively related to firm size, investment performance, and net operating profit.

Life insurers sell a variety of different products, including life, accident, health, and annuity insurance. Chen and Wong (2004) state that product portfolio has a different impact on life insurers' financial stability. BarNiv and Hershbarger (1990) find that for relatively small companies, the greater changes in product portfolios are, the more negative the impact on the companies' financial stability is. Baranoff and Sager (2003) show that different product portfolios have a significant impact on life insurers' assets and capital structures. Moreover, a company's value increases as its leverage ratio increases. After the optimal ratio is exceeded, the increasing leverage ratio instead leads to an increase in the probability of bankruptcy. Carson and Hoyt (1995) find that if the ratio of the reserves to owners' equity exceeds the optimal ratio, this causes life insurers' value to decline and the risk of bankruptcy increases. Zhang and Nielson (2013) suggest that the likelihood of insurers becoming insolvent increases during soft markets. However, a low leverage ratio can reduce the probability of an insurer going bankrupt. Thus, based on the past literature, we propose the following hypothesis:

Hypothesis 2:

The financial stability of life insurers is negatively related to their product portfolio changes and insurance leverage.

Ambrose and Carroll (1994) find that for those companies with poor credit ratings, the probability of bankruptcy has not increased.[7] However, Pottier (1998) discovers that using both financial ratios and the company's credit rating provides better predictions of the bankruptcy probability than merely using financial ratios. Adams, Burton, and Hardwick (2003) likewise emphasize the importance of a credit rating. In addition, Chang and Lin (2007) and Chang-Chien (2009) suggest that the share of unit-linked products has a positive impact on the life insurers' performance. Moreover, according to the experiences of implementing the RBC system in other countries, Cheng and Weiss (2012) find that the RBC and the FAST have different effects on the probability of insurers going bankrupt. De Haan and Kakes (2010) then use a dataset of about 350 Dutch insurers over the period from 1995 to 2005 and find that the insurers' solvency is related to the companies' risk characteristics, not to regulatory solvency requirements. In addition, Lin, Lai, and Powers (2014) show that there is a threshold effect of regulatory pressure on insurer risk taking. Therefore, in accordance with the above literature, we propose the following hypothesis:

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[7] In 2002, Taiwan started to implement a system whereby the information regarding life insurers was publicly disclosed. According to the regulation, life insurers should publicly disclose the results of their credit ratings or the fact of not entrusting the ratings organization with this task. However, current regulations on the supervision of insurers do not make it mandatory for those companies to be credit-rated.

Hypothesis 3:

The financial stability of life insurers is positively related to whether they are credit-rated, the share of unit-linked products, and the implementation of the RBC system.

III. Data and Methodology

A. Data

We focus on Taiwanese life insurers over a 15-year period from 1997 to 2012.[8] The data on the financial statements of these life insurers are obtained from the annual report of life insurance jointly provided by the Life Insurance Association of the R.O.C. and the Taiwan Insurance Institution (TII). Our final sample in this study includes 25 life insurers with a total of 419 observations. The basic statistical data for these life insurers are presented in Table I.

In Table I, the mean, median (50th percentile), and standard error of the FSI calculated based on assets are 38.415, 22.196, and 57.528 respectively, and the coefficients of skewness and kurtosis are 4.935 and 35.300, indicating that the distribution is skewed to the right and leptokurtic. Furthermore, both the FSI and the RFSI have the same type of distribution, as depicted in Figure 1.

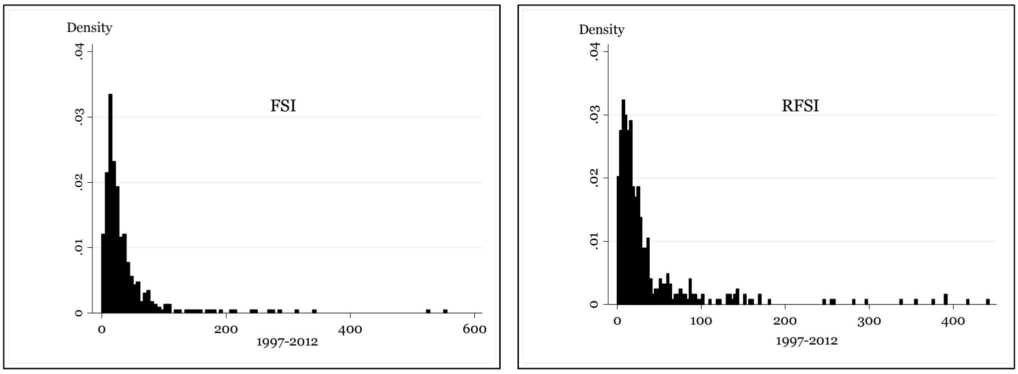

Figure 1. Distributions of the Asset-Based FSI and RFSI

B. Methodology

We calculate the FSI for all life insurers based on the methods proposed by Hollman, Hayes, and Murrey (1993), using Equation (1):

$$\mathrm{FSI_k} = \sum\nolimits_{\mathrm{i=1}}^{\mathrm{n}} x_i \left[\ln x_i / y_i\right] \times 100\,, \tag{1}$$

8 Taiwan announced a complete deregulation of the insurance market in 1994. The period of our analysis is from the year 1997 because we consider the data consistency. Furthermore, we exclude the newly established life insurers with relatively large adjustments during the first three years.

Table I
Summarized Characteristics of Sampled Taiwan Life Insurers (1997-2012)

		Mean	S.D.	Min.	Max.	p10	p25	p50	p75	p90	Skewed	Kurtosis	Obs.
Financial Stability Indices (FSI)													
Asset-Based FSI	FSI_A	38.415	57.528	0.000	556.040	7.874	12.471	22.196	40.004	76.100	4.935	35.300	419
Risk-Adjusted FSI_A	$RFSI_A$	38.226	62.263	0.000	442.747	4.476	9.273	18.068	36.069	86.732	3.870	20.281	419
Liabilities-Based FSI	FSI_L	10.398	17.597	0.277	176.361	1.327	2.467	5.092	11.568	22.356	5.440	42.356	419
Explanatory Variables													
Firm Size	SIZE	17.532	2.093	11.982	22.014	14.774	16.049	17.673	19.036	20.379	-0.141	2.546	419
Investment Performance	INVEST	0.069	0.231	-4.375	0.278	0.012	0.041	0.079	0.118	0.155	-17.272	330.231	419
Net Operating Profit	OPERATE	-0.030	0.139	-0.817	0.431	-0.162	-0.116	-0.033	0.043	0.139	-0.519	6.969	419
Changes in Product Portfolio	ΔPRODUCT	2.217	27.824	-0.535	564.726	-0.030	0.083	0.214	0.493	1.337	19.818	400.659	419
Insurance Leverage	LEVERAGE	0.787	0.227	0.024	1.381	0.499	0.751	0.849	0.907	0.945	-1.524	5.982	419
Share of Unit-Linked Product	IORIENT	0.088	0.198	0.000	0.935	0.000	0.000	0.006	0.071	0.249	3.111	12.054	419
Credit-Rating	RATING	0.444	0.497	0.000	1.000	0.000	0.000	0.000	1.000	1.000	0.226	1.051	419
Foreign Insurer	FOREIGN	0.253	0.435	0.000	1.000	0.000	0.000	0.000	1.000	1.000	1.136	2.291	419
Financial Holding Company	FHC	0.146	0.353	0.000	1.000	0.000	0.000	0.000	0.000	1.000	2.010	5.039	419
GDP Growth Rate	GDP%	4.143	3.037	-1.810	10.760	-1.650	3.470	5.260	5.800	6.190	-0.280	3.257	419
10-yr Bond Rate	RATE	3.186	1.790	1.210	6.410	1.370	1.950	2.340	5.180	6.060	0.614	1.773	419

where FSI_k represents the results of measuring the stability of the financial data of the k^{th} insurer, i=1,2,...,n, with n representing the number of financial statement items. The higher the FSI value, the more unstable the company's financial situation. x_i stands for the specific number within the items in the financial statements as well as the weights attached to those specific items, while y_i represents the corresponding number for x_i in the previous period. Because the changes in the assets are mainly caused by the changes of investment portfolios, we focus attention on eight items contained within the investment statement, namely, risk-free asset, stock, corporate bond, mutual fund, short-term investment, real estate investment, loan, and overseas investment.[9] Each of these items is included within x_i, and the numerical values of the corresponding items in the previous year's investment statement are included as y_i. By incorporating these items in Equation (1), we calculate the asset-based FSI (FSI_A). We deal with the liability items in the same way, selecting the following seven items to perform the calculation, namely, life insurance benefit payment, other accounts payable, life insurance reserve, reserve for unearned premium, claims reserve, special reserve, and other liabilities. We then calculate the liability-based FSI (FSI_L).[10]

Differences in risk for each investment asset in the life insurance industry are extremely large. If changes take place among those low-risk assets as well as among those high-risk assets, what these two types of assets signify is quite different. Furthermore, since Taiwan started to implement its RBC system in 2004, the risk coefficient for each of the assets in the insurance sector has had explicit measures and standards. Therefore, we not only refer to the method proposed by Hollman, Hayes, and Murrey (1993) to calculate the FSI, but also take into consideration the risk associated with each of the investment assets of Taiwan's life insurers to calculate the risk-adjusted FSI (RFSI) for comparison with the early warning effect of the FSI calculated based on relatively early studies. The equation used in the calculation is as follows:

$$\mathrm{RFSI_k} = \sum_{i=1}^{n} RiskAdj\_Factor_i \cdot x_i \left(\ln x_i / y_i\right) \times 100, \tag{2}$$

where $RFSI_k$ represents the risk-adjusted FSI for the k^{th} insurer, and the weight after adjusted for risk (*RiskAdj_Factor*$_i$) is the risk adjustor for each different asset for each company. These weights are displayed in Table II. The data on the risk-adjusted weights in the first column of Table II are mostly obtained from the TII. Apart from those for risk-free assets, short-term investments, and loans which are given values of zero,[11] the data on the risk-adjusted weights for

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9 Because bank deposits and government bonds (or Treasury bills) are both regarded as risk-free assets, we lump these two kinds of assets together when performing the calculation. The calculation of the loans item includes life insurance policy loans and collateralized loans. During the calculation of Equation (1), if x_i or y_i equals zero, then we use 0.0000001 instead.

10 According to the calculation method provided in Hollman, Hayes, and Murrey (1993), we ought to calculate the FSI for the owners' equity. However, the owners' equity for some life insurers in Taiwan is negative, so we refer to the approach proposed by Chen and Wong (2004) and use both assets and liabilities to calculate the FSI.

11 Because the insurance policy loans risk coefficient is 0.000 and the collateralized loans risk coefficient is also an extremely low (0.003), we set both of them as 0.000.

the RFSI in the second column are based on the RBC risk coefficient for real estate investment (with 0.078 being set as 1.000) in order to calculate their respective risk-adjusted weights. To illustrate, the weight attached to common stock is based on the RBC risk-adjusted coefficient of the common stock (=0.241), while the corresponding RFSI risk-adjusted coefficient is 3.087(=0.241/0.078). By using the risk coefficients after adjustment to calculate the RFSI, we can correct for differences in the changes of different risk assets.

Table II
Risk Adjustment Factors of the RBC and the FSI

The data on the risk-adjusted weights in the first column of the RBC are mostly obtained from the TII. Based on the RBC risk coefficients for real estate investments (with 0.078 being set as 1.000), we calculate their respective risk-adjusted weights. For example, the weight attached to stocks is based on the RBC risk-adjusted coefficients of the common shares of stock exchange-listed life insurers (=0.241), while the corresponding FSI risk-adjusted coefficient is 3.087 (=0.241/0.078).

Asset Item	Risk Adjusted Weight of RBC	Asset Item	Risk Adjusted Weight of FSI
Bank Deposit	0.000	Risk-Free Asset	0.000
Treasury Bill	0.000		
Common Stock	0.241	Common Stock	3.087
Corporate Bond	0.114	Corporate Bond	1.462
Mutual Fund	0.241	Mutual Fund	3.087
Short-Term Investment	0.000	Short-Term Investment	0.000
Real Estate Investment	0.078	Real Estate Investment	1.000
Policy Loan	0.000	Loan	0.000
Loan	0.004		
Overseas Investment	0.108	Overseas Investment	1.382

After calculating the FSI and the RFSI, we then ascertain whether the companies' financial situation is able to provide an early warning. According to Hollman, Hayes, and Murrey (1993) and Chen and Wong (2004), the mean of the FSI for all insurers in the current year (FSI_{Mean}) can serve as a reference standard as to whether or not a particular company is financially stable. If for an insurer the value of the FSI is higher than that of the FSI_{Mean}, then they suggest that the financial situation of that company is relatively unstable (thereby providing an early warning). Conversely, if the value of the FSI is lower than that of the FSI_{Mean}, the financial situation of the insurer is relatively stable (and thus an early warning is not provided). However, because the value of the FSI_{Mean} is easily affected by extreme values in the data (Sharpe and Stadnik (2007)), it is likely to create forecasting errors if the insurer's financial stability is based on the average of these extreme values.

Therefore, we go further to examine the forecasting accuracy of the FSI and RFSI values for different quantiles. When a life insurer's FSI or RFSI values are higher than the mean, 50th percentile (median), or 75th percentile for all life insurers in that same year,[12] we test the company's FSI for its early warning effect. Equations (3) and (4) used to determine whether the FSI provides an early warning are expressed as follows:

$$(S_t = 1) \text{ if FSI} \geq \text{FSI}_q,\ q\text{=Mean, Median, } 75^{th} \text{ percentile} \quad (3)$$

$$(S_t = 0) \text{ if FSI} < \text{FSI}_q,\ q\text{=Mean, Median, } 75^{th} \text{ percentile} \quad (4)$$

According to these two equations, when $S_t = 1$, the life insurer provides an early warning. When $S_t = 0$, the life insurer does not provide any early warning.

In Taiwan, apart from the winding up of Kuo Kuang Life Insurance Company in 1969, only Kuo Hua Life Insurance Company has withdrawn from the market so far. Therefore, unlike the approach adopted in the literature, we are unable to regard whether or not an insurer has actually "gone bankrupt" as an event point in our analysis due to very few insurers' failure cases. We then consider whether there have occurred events that have seriously threatened the solvency of the insurance industry as the event point to test the FSI's forecasting ability. In this study, we test two event points, namely, (a) whether or not life insurers have been affected by technical insolvency (where their net worth has turned from positive to negative),[13] and (b) whether the RBC ratio based on statutory criteria has been insufficient due to a major economic event (such as the 2008 financial crisis).[14]

In terms of selecting the length of the forecasting period prior to the occurrence of the event, we use the probability that $S_t = 1$ in 1 year, 3 years, or 5 years prior to the forecasted event point for that company, since the higher this probability is, the more unstable the company's financial situation is. We assume that when this probability is greater than 50% (i.e., not including 50%), an early warning is given in relation to such life insurers. Furthermore, in order to measure the forecasting method and the effect of this FSI on the future events involving these life insurers, we follow the approaches proposed by Kaminsky and Reinhart (1999), Edison (2003), and Alessi and Detken (2011). We first construct the null hypothesis, H_0, that a company's financial situation is worsening, and the alternative hypothesis, H_1, that a company's financial situation has not deteriorated. From Table III, H_0 is equal to A+C, and H_1 is equal to B+D. The Type I error occurs when H_0 is true but H_0 is rejected, indicating that even though a

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12 Because of the limitation of the sample size, we mostly only take into consideration the 50th and 75th percentiles in this study.

13 Five life insurers include Prudential Life Insurance Co., Ltd, Global Life Insurance Co., Ltd., Chaoyang Life Insurance Co., Ltd., Singfor Life Insurance Co., Ltd., and Hontai Life Insurance Co., Ltd. Kuo Hua Life Insurance Co., Ltd. is excluded from our study because it refused to provide its financial statements in 2001 and 2002.

14 This event relates to the financial crisis in 2008, when life insurers were therefore found to have insufficient capital (as evidenced by their failure to reach the legally required RBC ratio of 200.00% that year). According to the data released by life insurers in December 2008, seven life insurers' RBC levels were less than 200.00%.

company's financial situation is worsening, the index does not provide an early warning. The probability of this Type I error is C/(A+C). Based on the same reasoning, the Type II error occurs when H_0 is not true but H_0 is not rejected. This indicates that when a company's financial situation has not deteriorated, the index provides an early warning. The probability of this Type II error is B/(B+D).

Table III
Performances of the FSI and the RFSI

We first construct the null hypothesis, H_0, that the company's financial situation is worsening, and the alternative hypothesis, H_1, that the company's financial situation has not deteriorated. H_0 is equal to A+C, and H_1 is equal to B+D. The Type I error occurs when H_0 is true but H_0 is rejected, indicating that even though the company's financial situation is worsening, the index does not provide an early warning. The probability of this Type I error is C/(A+C). Based on the same reasoning, the Type II error occurs when H_0 is not true but H_0 is not rejected. This indicates that when the company's financial situation has not deteriorated, the index provides an early warning. The probability of this Type II error is B/(B+D).

	Technical Insolvency	No Technical Insolvency
Signal Issued	A	B
No Signal Issued	C	D

For example, we use the FSI to make predictions prior to any events occurring due to technical insolvency. If we use the median value of the FSI for industry assets from 2002 to 2004 as the basis of comparison, the data show that of the 25 life insurers, 11 have probabilities of $S_t=1$ occurring that exceed 50% over the last three years. That is, in at least two of the three years the FSI exceeds the median value for the industry as a whole, indicating that for these 11 companies, an early warning should be given. Moreover, for 8 of the companies, $S_t=1$ for each of the three years. We consider such companies to have a high degree of early warning. According to Equation (3), when the probability of $S_t=1$ exceeds 50% in each of the three years, an early warning in respect of these life insurers should be triggered. Because of back forecasting, we can use whether or not the event actually occurs to judge the accuracy of the forecast, the Type I error, and the Type II error.

Besides the ordinary least squares regression (OLS) used to test each hypothesis influencing the FSI and the RFSI, we also use the quantile regression (QR) proposed by Koenker and Bassett (1978) to further analyze the changes in the distribution tails for the FSI and the RFSI and discuss the relevant factors influencing life insurers' financial stability. Koenker and Bassett (1978) mainly discuss the effect of the conditional distribution of explanatory variables for each different quantile. The OLS method uses the least squared error to calculate parameters, whereas the QR model corrects for the OLS method which only describes the conditional mean of the explained variable under the influence of explanatory variables. Under different conditional quantiles, the QR model describes situations regarding the overall conditional distribution, and therefore can fully explain the statistical relationship between the distribution tails of the explanatory variables and the explained variable. In addition, when there are relatively large outliers in the sample, the QR model can reduce the bias that results from the OLS estimation. If y_i is the explained variable, x_i is a vector of explanatory variables, and $0<\theta<1$, then we can express the relationship by means of the objective function of minimizing the residuals in absolute value terms in the following equation:

$$\text{Min}\left[\theta \cdot \sum_{y_i \ge x_i'\beta} |\, y_i - x_i'\beta \,| + \sum_{y_i < x_i'\beta} (1-\theta) \cdot |\, y_i - x_i'\beta \,|\right], \tag{5}$$

where the coefficient $\widehat{\beta_\theta}$ indicates how many $\widehat{\beta_\theta}$ units the estimated explained variable can be expected to change in the θ^{th} quantile when the explanatory factor, X_t, is changed by one unit, indicating that the QR model provides different weights in the estimation. To illustrate, during the estimation of the 75$^{\text{th}}$ percentile (θ=0.75), the observed value that satisfies the $y_i \ge x_i'\beta$ condition is accorded a weight of 75%, while all other observed values that satisfy the $y_i \ge x_i'\beta$ condition are given a weight of 25%. In this study, we use the bootstrap method to estimate the value of the population parameter in the estimated equation and then construct the confidence interval for the estimation coefficients in order to test Hypotheses 1, 2, and 3. The estimated equation is expressed as follows:

$$\begin{aligned} Q_{it}(\text{FSI}_{it} \text{ or } \text{RFSI}_{it} \mid x_{it}) \\ = \beta_0 &+ \beta_1 \text{SIZE}_{it} + \beta_2 \text{INVEST}_{it} + \beta_3 \text{OPERATE}_{it} + \beta_4 \Delta\text{PRODUCT}_{it} \\ &+ \beta_5 \text{LEVERGE}_{it} + \beta_6 \text{RATING}_{it} + \beta_7 \text{IORIENT}_{it} + \beta_8 \text{FOREIGN}_{it} \\ &+ \beta_9 \text{FHC}_{it} + \beta_{10} \text{GDP\%}_t + \beta_{11} \text{RATE}_t + \beta_{12} \text{RBC}_t + \beta_{13} \text{CRISIS}_t \\ &+ \varepsilon_{it}\,, \end{aligned} \tag{6}$$

where FSI is the financial stability index estimated from Equation (1); RFSI is the risk-adjusted FSI value estimated from Equation (2); SIZE is the natural logarithm of firm size; INVEST is the investment performance; OPERATE is the net operating profit; △PRODUCT is the change in the product portfolio; LEVERAGE is the insurance leverage;[15] RATING is the dummy variable, indicating whether or not the company has been credit-rated; IORIENT is the proportion of the share of unit-linked products; FOREIGN is the dummy variable, indicating whether the company is a subsidiary of a foreign insurer; FHC is the dummy variable, indicating whether the life insurer is a subsidiary of a financial holding company; and RBC is the dummy variable, indicating whether the RBC system has been implemented in the year under consideration. To control for the impact of external environmental factors on the FSI, we establish a dummy variable (CRISIS) for the year 2008, when most insurers were seriously impacted by the financial crisis. GDP% is the growth rate of gross domestic product in the year under consideration, and RATE is the 10-year interest rate on government bonds. The definitions of the data for explanatory variables are presented in Table IV.

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[15] Chen and Wong (2004) define the insurance leverage ratio as reserves to owners' equity. However, the owners' equity of some life insurers in Taiwan remains a negative value after 2005 and, therefore, the statistics obtained from the calculation have no substantial meaning. For this reason, we use the ratio of reserves to assets as a substitute variable for insurance leverage.

Table IV
Definitions of Independent Variables

Variable		Definition
SIZE	Firm Size	Natural logarithm of firm total net assets.
INVEST	Investment Performance	Ratio of (financial income-financial expenditure) to total income.
OPERATE	Net Operating Profit	Ratio of (operating income-operating expenditure) to premium.
ΔPRODUCT	Changes in Product Portfolio	sum of $\beta_i\left(\frac{\text{PRODUCT - PRODUCT}_{-1}}{\text{PRODUCT}_{-1}}\right)\times 100$, where PRODUCT represents the premium for the *i*th kind of insurance product; PRODUCT_{-1} represents the premium in the previous year for the *i*th kind of insurance; β_i is the ratio of the premium for this product to total premium. The main insurance products included in the calculation are life, accident, health, and annuity insurance.
LEVERAGE	Insurance Leverage	Ratio of reserves to total assets.
IORIENT	Share of Unit-Linked Product	Ratio of unit-linked product assets to total assets.
RATING	Credit-Rating	If the life insurer has been credit-rated, then RATING=1; otherwise 0.
FOREIGN	Foreign Insurer	If the life insurer is a foreign company, then FOREIGN=1; otherwise 0.
FHC	Financial Holding Company	If the life insurer is a subsidiary of a financial holding company, then FHC=1; otherwise 0.
GDP%	GDP Growth Rate	Annual GDP growth rate.
RATE	10-yr Bond Rate	10-year interest rate on government bond.
CRISIS	Financial Crisis of 2008	After 2008, CRISIS=1; otherwise 0.
RBC	Risk-Based Capital	For the period after the RBC system was implemented (2004-2012), the variable equals one. For the period before the RBC system was implemented (1997-2003), then it equals 0.

IV. Empirical Results

A. Analysis of FSI's Early Warning Ability

Table V presents the results of tests on the FSI's early warning ability by the predictions of the occurrence of events over three different time periods. When life insurers encounter deterioration in their financial situations and the FSI in the previous year is higher than the baseline value (the median, mean, or 75^{th} percentile), the FSI provides an early warning. When the event occurs and the probability of the FSI in the previous three years being higher than the baseline value exceeds 50% (i.e., the standard is reached in two or all of these three years), the index can be considered to provide an early warning. When the event occurs and the probability of the FSI in these five years being higher than the baseline value exceeds 50% (i.e., the standard is reached in three or more of these five years), an early warning is also provided.[16]

We first conduct tests at the first event point. The results show that to test whether or not the life insurers will face technical insolvency (i.e., their net worth turns from positive to negative), the previous year's FSI that is greater than the median value for all of the life insurers performs superior predictability and the forecasting accuracy is 100.00% (i.e., the Type II error is 40.00%). When compared with the mean used as the basis of comparison in the previous literature, the median has better ability to predict problem insurers.[17] Using the RFSI as an early warning index, we find that over the period from 2000 to 2004 (the five years prior to the event), the RFSI that is greater than the median value for all the life insurers reflects better predictability. The accuracy of prediction is 80.00%, and the Type II error is 45.00%. This indicates that using the median as the basis of judgment can make up for the shortcomings of using the mean as the basis for the HHM index (Hollman, Hayes, and Murrey (1993) and Chen and Wong (2004)).

When we use the FSI value to test whether the financial crisis in 2008 resulted in a corresponding deterioration in life insurers' financial situations, both the FSI for the previous year using the median as the standard and the RFSI for the previous five years provide more accurate predictions The accuracy is 71.43%.

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[16] We attempt to use the FSI that is calculated based on liabilities or the FSI where both assets and liabilities (which we refer as the paired indicator) are taken into consideration. When the values of the FSI based on either assets or liabilities are higher than those of the selected percentiles, a warning is given in regard to that particular life insurer's solvency in the future. The probability of a Type I error occurring is thereby reduced. The results show that for the accuracy of prediction and the Type I error, the FSI calculated based on assets (or on both assets and liabilities) is better than the FSI calculated based on liabilities only. To save space, we only display the relevant results for the FSI calculated based on assets.

[17] The identification method whereby the FSI for the previous year is found to be greater than the mean for all of the life insurers in the current year similarly has an accuracy of prediction of 100.00%, but the Type II error is relatively large (45.00%). If the 75^{th} percentile is used as the criterion, the accuracy of prediction is 20.00%. In addition, the accuracy of prediction for the FSI indices based on forecasts over the previous three and five years is also relatively low.

Table V
Results of Testing the Early Warning Abilities of the FSI and the RFSI

The RFSI is the FSI after adjusted for asset risk. The 1-year prediction indicates that for those life insurers that encounter deterioration in their financial situations, the FSI in the previous year will be higher than the baseline value (the median, the mean, or the 75th percentile). The same explanation is for the 3-year and 5-year predictions. The Type II error indicates that when the insurers do not experience deterioration in their financial situations, the FSI will erroneously provide an early warning. For the relevant explanation, please refer to Table III.

Panel A. Testing for the Life Insurers' Technical Insolvency (Negative Net Worth)

Reference Value	Median			Mean			75th Percentile		
	Accuracy	Type I Error	Type II Error	Accuracy	Type I Error	Type II Error	Accuracy	Type I Error	Type II Error
FSI (1-Year Prediction)	**100.00%**	**0.00%**	**40.00%**	100.00%	0.00%	45.00%	20.00%	80.00%	0.00%
FSI (3-Year Prediction)	60.00%	40.00%	40.00%	60.00%	40.00%	35.00%	20.00%	80.00%	15.00%
FSI (5-Year Prediction)	60.00%	40.00%	40.00%	80.00%	20.00%	45.00%	40.00%	60.00%	0.00%
RFSI (1-Year Prediction)	60.00%	40.00%	50.00%	60.00%	40.00%	31.71%	60.00%	40.00%	20.00%
RFSI (3-Year Prediction)	60.00%	40.00%	50.00%	40.00%	60.00%	26.35%	20.00%	80.00%	20.00%
RFSI (5-Year Prediction)	**80.00%**	**20.00%**	**45.00%**	40.00%	60.00%	15.83%	40.00%	60.00%	10.00%

Panel B. Testing for the Deterioration in the Financial Situation of the Life Insurers during the 2008 Financial Crisis (The RBC is less than 200.00%.)

Reference Value	Median			Mean			75th Percentile		
	Accuracy	Type I Error	Type II Error	Accuracy	Type I Error	Type II Error	Accuracy	Type I Error	Type II Error
FSI (1-Year Prediction)	57.14%	42.86%	33.33%	14.28%	85.72%	16.67%	28.57%	71.43%	22.22%
FSI (3-Year Prediction)	57.14%	42.86%	38.89%	28.57%	71.43%	11.11%	28.57%	71.43%	5.56%
FSI (5-Year Prediction)	**71.43%**	**28.57%**	**44.44%**	57.14%	42.86%	5.56%	16.67%	85.72%	0.00%
RFSI (1-Year Prediction)	42.85%	57.15%	44.44%	42.89%	57.11%	22.22%	42.89%	57.11%	16.67%
RFSI (3-Year Prediction)	57.14%	42.86%	38.89%	42.89%	57.11%	22.22%	28.57%	71.43%	16.67%
RFSI (5-Year Prediction)	**71.43%**	**28.57%**	**22.22%**	42.89%	57.11%	11.11%	42.85%	57.11%	11.11%

However, the Type II error for the FSI is 44.44%, while the Type II error for the RFSI is 22.22%, indicating that the RFSI is superior to the FSI.

To sum up, we find that the FSI and the RFSI with the median value as the basis of comparison can provide an early warning with a high degree of accuracy to identify the possible solvency life insurers.

B. Factors Influencing the FSI and the RFSI

In this section, we explain the relevant statistical tests applied to the model and the results of these tests.

To test whether the correlation among the explanatory variables in Equation (6) may have an offsetting effect, we use the OLS method to analyze the variance inflationary factor (VIF) for each explanatory variable and thereby test for multicollinearity. Our results show that the VIF for each explanatory variable is less than 5.03, indicating that no significant degree of multicollinearity exists among the explanatory variables included in the regression model. In addition, considering the possible problem of heteroskedasticity, we use the Breusch-Pagan (BP) statistic to ascertain whether this problem exists. The results show that the BP statistic is always greater than the Chi-squared statistic, indicating that heteroskedasticity does exist. Therefore, we adopt the heteroskedasticity robust standard error to resolve the problem of heteroskedasticity.

The results of the early warning tests in Section A suggest that the FSI and the RFSI calculated based on assets, both larger than the basis of comparison using the median value (or the 75th percentile) for all of the companies in the same year, provide a certain degree of early warning for those life insurers experiencing a major event impacting their solvency. Therefore, we further analyze the relevant factors influencing the FSI and the RFSI calculated on the basis of assets.[18]

Table VI presents the results of the OLS method. The empirical results indicate that firm size is significantly negatively related (at the 5% significance level) to the FSI and the RFSI. For those companies that have been credit-rated, there is a significantly negative relation (at the 5% and 10% significance levels) with the FSI and the RFSI. These results that larger companies and having been credit-rated can significantly reduce the FSI and the RFSI (i.e., increase the degree of financial stability) partly support Hypotheses 1 and 3. As for the relationship between insurance leverage and the value of the RFSI, there is a positive relationship (at the 10% significance level), which partially supports Hypothesis 2. The relationship between the changes in the product portfolio and the FSI is significantly negative (at the 10% significance level), which does not conform to Hypothesis 2. The higher the share accounted for by the unit-linked product, the higher the value of the FSI, which is also different from Hypothesis 3. In addition, the empirical results show that there is a significant positive relationship between

[18] This study distinguishes between the FSI and the RFSI that are based on assets and liabilities for one-year and two-year periods, and the empirical results obtained are by and large the same. We only present the results for the FSI based on assets for the one-year period. If other results are needed, they can be obtained from the authors upon request.

the interest rate and the FSI and RFSI, indicating that as the interest rate rises, the life insurers' financial situations change. Because the OLS method is only able to explain the extent of the impact of the explanatory variables on the FSI, we once again use the results of estimating the quantile regression to analyze the impact of the explanatory variables on the FSI and the RFSI for each different quantile.

Table VI
Ordinary Least Square Results on the FSI and the RFSI

Standard deviations are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Variable	FSI	FSI	RFSI	RFSI
SIZE	**-5.308****	**-4.995****	**-6.899****	**-6.667****
	(2.451)	(2.488)	(3.015)	(3.088)
INVEST	0.256	0.089	8.880	9.776
	(6.697)	(6.644)	(9.053)	(8.871)
OPERATE	-15.757	-17.536	-27.163	-31.658
	(23.586)	(24.040)	(40.740)	(40.370)
△PRODUCT	**-0.030***	**-0.030***	-0.027	-0.021
	(0.017)	(0.018)	(0.021)	(0.020)
LEVERAGE	8.693	7.740	**53.419***	51.415
	(31.718)	(31.600)	(30.960)	(31.330)
IORIENT	42.266	44.860	**84.858****	**84.404****
	(31.978)	(32.110)	(36.001)	(35.710)
RATING	**-14.662****	**-15.530****	**-13.898***	**-14.125***
	(6.602)	(6.669)	(7.745)	(7.812)
FOREIGN	-11.090	-11.083	-2.007	-1.136
	(9.241)	(9.343)	(10.720)	(10.680)
FHC	18.341	18.626	12.031	11.605
	(12.341)	(12.210)	(9.756)	(9.562)
GDP%	0.266	0.360	-0.856	-0.749
	(0.664)	(0.665)	(0.923)	(0.956)
RATE	**5.008*****	2.187	**4.367****	2.748
	(1.764)	(2.922)	(2.068)	(3.093)
RBC		-11.283		-9.428
		(8.792)		(9.304)
CRISIS (2008)		-3.514		3.213
		(5.927)		(7.043)
INTERCEPT	**110.102****	**121.124*****	**102.901****	**109.293****
	(49.183)	(47.687)	(49.778)	(48.746)
YEAR Dummies	YES	YES	YES	YES
No. of Obs.	419	419	419	419
Adj R^2	0.083	0.087	0.083	0.085

Tables VII and VIII present the results of the quantile regressions for the FSI and the RFSI respectively. The first column of Table VII lists the estimation results of the impacts of five designated conditional quantiles on the FSI. These quantiles include the three quantiles (q0.25, q0.50, and q0.75) and the left and right tail quantiles (q0.10 and q0.90). The 90% quantile in the tail of the distribution indicates that the financial situation of the life insurer is relatively unstable, while the 10% quantile on the other side of the tail shows that the financial situation of the life insurer is relatively stable. From the empirical results in Tables VII and VIII, we find that for those life insurers with the relatively large FSI and RFSI (e.g., the median and the q0.75 and q0.90 quantiles), increasing the firm size can significantly reduce the values of the indices. The greater the impact of such indices is, the less financially stable the companies are. The larger the life insurers are, the more sound the internal risk management systems tend to be and the more ability they have to ensure their financial stability, according with the results that net operating profit only has a significant impact on the RFSI at the q0.10 quantile (for all the other quantiles, the relationship is negative, but not statistically significant; BarNiv and Hershbarger (1990), Kim et al. (1995), Grace, Harrington, and Klein (1998), Chen and Wong (2004), and Baranoff, Papadopoulos, and Sager (2007)). These results indicate that the larger the net operating profit of the life insurers is, the more likely an interest margin or a premium margin results, thereby making them more financially sound. This finding is consistent with BarNiv and Hershbarger (1990) and Kim et al. (1995). However, investment performance never has a statistically significant impact, and the above analysis indicates that Hypothesis 1 is partially supported empirically.

In addition, the effects of the changes in product portfolios for different quantiles are not consistent. For the more financially stable companies (e.g., the q0.10 and q0.25 quantiles), the changes in the product portfolios are positively related to the FSI (although statistically insignificant). For the less financially stable companies (e.g., the median and the q0.75 and q0.90 quantiles), the corresponding correlation is negative (and statistically insignificant). In general, when quantile regression analysis is performed, the product portfolios do not have a statistically significant impact on the life insurers' financial stability, which is not fully consistent with the results of BarNiv and Hershbarger (1990), Ambrose and Carroll (1994), Carson and Hoyt (1995), and Chen and Wong (2004). As for the impact of the reserve assets ratio (insurance leverage) on the FSI as well as the RFSI, it is significant for the q0.10 and q0.25 quantiles. This result partially supports Carson and Hoyt's (1995) conclusion. The above analysis shows that Hypothesis 2 is empirically supported.

The empirical results also indicate that the decision by life insurers to be credit-rated has a significantly negative impact on the FSI at the q0.10 and q0.25 quantiles and the median, which also accords with the conclusions reached by Ambrose and Carroll (1994) and Adams, Burton, and Hardwick (2003). However, the share of the unit-linked product exhibits a positive relationship with the FSI and the RFSI, having a significantly positive impact on the more financially stable

Table VII
Quantile Regression Results on the FSI_A

Standard deviations are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Variable	q0.10	q0.25	q0.50	q0.75	q0.90	q0.10	q0.25	q0.50	q0.75	q0.90
SIZE	-0.539	-0.141	-2.785**	-5.521***	-11.366**	-0.641	-0.552	-2.018*	-4.434**	-10.874**
	(0.645)	(0.598)	(1.296)	(1.809)	(5.290)	(0.704)	(0.516)	(1.148)	(1.744)	(5.241)
INVEST	2.286	-0.137	1.980	8.325	10.330	4.167	0.047	0.029	4.722	11.437
	(8.995)	(13.054)	(29.644)	(55.838)	(116.101)	(8.887)	(10.760)	(24.980)	(48.700)	(132.800)
OPERATE	-4.518	-7.156	-13.930	-31.360	-53.264	-8.354	-9.543	2.633	-19.517	-59.140
	(5.924)	(7.117)	(14.120)	(24.697)	(59.234)	(6.300)	(6.470)	(13.640)	(23.370)	(79.560)
Δ PRODUCT	0.017	0.009	-0.005	-0.035	-0.091	0.018	0.006	-0.011	-0.035	-0.092
	(0.165)	(0.258)	(0.470)	(1.074)	(1.891)	(0.217)	(0.271)	(0.284)	(1.080)	(1.898)
LEVERAGE	15.362**	13.896**	0.716	13.100	-36.720	15.920**	14.590***	17.564	6.579	-46.024
	(6.310)	(6.025)	(19.430)	(28.594)	(94.827)	(6.726)	(4.752)	(16.420)	(27.080)	(102.801)
IORIENT	13.551**	14.712*	8.272	43.120	80.310	15.554**	18.784***	23.075	34.534	74.044
	(6.245)	(7.981)	(20.560)	(33.781)	(122.405)	(7.113)	(6.959)	(18.410)	(34.520)	(125.407)
RATING	-4.737***	-5.050***	-4.253	-7.905	-8.939	-4.826***	-5.187**	-6.672*	-9.198	-12.340
	(1.556)	(1.844)	(3.607)	(5.698)	(17.081)	(1.758)	(2.055)	(3.661)	(5.830)	(15.750)
FOREIGN	-7.152***	-5.560**	-7.276*	0.620	-5.686	-6.036**	-6.745**	-8.636**	-3.865	-7.147
	(2.702)	(2.353)	(4.301)	(7.665)	(20.857)	(2.892)	(2.667)	(3.678)	(9.029)	(21.950)
FHC	0.421	0.082	-0.136	4.759	18.572	2.018	0.574	0.911	6.199*	15.849
	(2.264)	(1.845)	(2.611)	(3.721)	(24.553)	(2.506)	(1.711)	(2.831)	(3.245)	(26.020)
GDP%	-0.009	-0.053	-0.339	-0.224	-0.737	-0.096	-0.0759	-0.140	-0.415	-0.742
	(0.199)	(0.181)	(0.360)	(0.613)	(1.804)	(0.216)	(0.186)	(0.330)	(0.563)	(2.095)
RATE	0.993**	1.509***	1.353	4.802**	8.252	-0.232	-1.248	-1.158	1.862	6.209
	(0.422)	(0.430)	(1.212)	(2.384)	(5.445)	(0.919)	(0.967)	(1.587)	(2.888)	(11.470)
RBC						-3.574	-7.327**	-6.804	-10.244*	-8.924
						(2.951)	(3.331)	(5.562)	(5.571)	(37.000)
CRISIS (2008)						-1.064	-4.934***	-8.405***	-7.482*	3.465
						(1.776)	(1.848)	(3.028)	(4.535)	(18.050)
INTERCEPT	5.744	2.348	72.401**	112.651**	271.014**	12.530	23.717**	58.864**	118.533***	283.118**
	(10.940)	(9.263)	(31.320)	(45.410)	(112.601)	(13.040)	(9.172)	(25.080)	(42.620)	(134.804)
No. of Obs.	419	419	419	419	419	419	419	419	419	419

Table VIII
Quantile Regression Results on the RFSI

Standard deviations are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Variable	q0.10	q0.25	q0.50	q0.75	q0.90	q0.10	q0.25	q0.50	q0.75	q0.90
SIZE	0.411	0.359	-1.508	**-6.008****	**-13.421****	0.518	0.443	-0.708	**-5.432****	**-13.991****
	(0.512)	(0.731)	(1.217)	(2.381)	(6.160)	(0.485)	(0.728)	(1.138)	(2.726)	(6.304)
INVEST	-3.953	-3.562	-0.073	6.287	19.780	-4.831	-3.746	-0.579	6.614	31.440
	(5.147)	(7.878)	(13.710)	(34.240)	(79.650)	(5.747)	(8.222)	(12.250)	(30.160)	(112.103)
OPERATE	**-8.098***	-1.730	-1.292	-13.830	-79.010	-4.194	-4.131	-3.353	-17.160	-129.704
	(4.431)	(5.551)	(14.260)	(31.920)	(66.910)	(4.133)	(5.766)	(14.810)	(32.590)	(99.310)
ΔPRODUCT	0.027	0.018	0.006	-0.022	-0.114	0.031	0.018	0.005	-0.025	-0.093
	(0.083)	(0.138)	(0.467)	(1.588)	(4.157)	(0.103)	(0.176)	(0.271)	(1.642)	(4.230)
LEVERAGE	**9.830****	**15.701****	**32.624****	38.100	1.123	6.753	10.540	**23.754***	36.360	27.040
	(4.880)	(7.084)	(15.020)	(46.650)	(97.730)	(4.618)	(7.611)	(12.460)	(45.200)	(98.390)
IORIENT	**9.016***	**15.403****	**32.526****	47.557	121.801	2.540	11.900	**24.691***	59.224	160.817
	(5.424)	(7.519)	(15.530)	(50.600)	(139.402)	(5.373)	(7.972)	(13.680)	(48.070)	(140.103)
RATING	**-3.340****	**-4.861*****	-4.520	-7.703	-10.694	**-3.316****	**-4.555****	**-5.579***	-11.711	-9.843
	(1.675)	(1.707)	(2.983)	(8.851)	(21.300)	(1.375)	(1.843)	(2.935)	(9.448)	(19.700)
FOREIGN	-1.672	**-3.815***	-4.379	5.234	1.297	-2.886	**-4.322***	**-6.612***	5.092	13.670
	(2.239)	(2.238)	(4.001)	(10.590)	(30.170)	(1.899)	(2.591)	(3.875)	(10.440)	(25.250)
FHC	0.685	0.376	0.541	2.526	5.491	0.0701	0.338	-0.416	5.366	10.215
	(1.778)	(2.626)	(2.512)	(5.091)	(14.120)	(1.751)	(2.215)	(2.539)	(5.029)	(15.380)
GDP%	**-0.291****	-0.202	-0.494	-0.921	-2.115	-0.180	-0.196	-0.249	-0.974	-3.341
	(0.146)	(0.184)	(0.379)	(0.749)	(1.685)	(0.139)	(0.197)	(0.352)	(0.712)	(2.467)
RATE	0.093	0.922	1.301	3.526	8.908	**-1.109****	-1.402	-2.073	1.151	12.874
	(0.327)	(0.607)	(1.017)	(3.423)	(6.615)	(0.553)	(1.051)	(1.550)	(4.437)	(10.090)
RBC						**-4.885*****	**-7.131****	**-12.582*****	-11.234	-11.610
						(1.829)	(3.111)	(4.196)	(8.416)	(25.690)
CRISIS (2008)						0.272	-2.175	-2.326	-0.262	21.679
						(1.341)	(1.748)	(2.802)	(5.700)	(21.510)
INTERCEPT	-7.353	-8.925	18.020	**107.335***	**291.214****	0.0642	6.189	30.237	**112.817****	**265.691****
	(8.093)	(11.680)	(19.000)	(57.260)	(135.400)	(9.034)	(12.800)	(18.430)	(56.710)	(133.400)
No. of Obs.	419	419	419	419	419	419	419	419	419	419

companies (e.g., in terms of the q0.10 and q0.25 quantiles and the median). The likely reason is that the unit-linked product is greatly affected by economic conditions. Following the financial crisis in 2008, the unit-linked product significantly declined, causing the share of the unit-linked product to decline and in turn the FSI and the RFSI to decrease. After Taiwan implemented its RBC system, the RFSI indices of the better and more financially stable companies declined. If one looks at the FSI, there is a significantly negative impact at the q0.25 and q0.75 quantiles only. The above analysis reveals that being credit-rated or not has an impact on the company's financial stability, as do the implementation of the RBC system and a lower share of the unit-linked product for different quantiles, also resulting in a significant improvement in life insurers' financial stability. Therefore, Hypothesis 3 is partly supported by the empirical results.

With the overall impact of the economic effects taken into consideration, our empirical results indicate that the higher the growth rate of GDP becomes, the more financially stable some of the life insurers will become. However, rising interest rates may cause the FSI and the RFSI to rise, thereby being added to the financial stability of these companies. A likely reason is that as the economic growth rate becomes higher and higher, life insurers continue to maintain their original asset portfolios and rising interest rates cause the prices of fixed-income investments to fall. To pursue higher investment returns, life insurers are likely to start to adjust their asset allocation, with the result of becoming less financially stable. Moreover, after the financial crisis in 2008, for those relatively financially stable companies (e.g., at the q0.10 and q0.25 quantiles), the FSI exhibits a tendency to decline, indicating that life insurers' asset allocation adjustment strategies are inclined to be conservative. As for the RFSI, there are no consistent results.

V. Conclusion

Since the early accounting system in the insurance sector was incomplete and the industry was inexperienced in bankruptcy, supervisors had difficulty developing an early warning system to detect the failures of Taiwan's life insurers. Since Taiwan implemented the RBC system in 2004, the RBC ratio has almost become the only and the most important instrument for monitoring the financial and operational risk of insurers, even though the RBC ratio has certain limitations (Cummins and Phillips (2009)). Therefore, a more effective financial early warning index in the process of monitoring life insurers is needed. We intend to remedy this deficiency.

We propose a new measure of the FSI and adopt quantile regressions to provide more insights into an early warning indicator. Our proposed FSI can upgrade the effectiveness of early warning and avoid interference from extreme values. The empirical results show that the proposed FSI and the RFSI have better forecasting ability than previous testing models. In addition, besides using the OLS regression to analyze the factors influencing the FSI and the RFSI, we also analyze the related factors by using different quantiles. This approach is more suitable for life insurers in Taiwan due to the number of insurers being relatively small and the variance in the assets and liabilities being quite large. This paper shows that the size of life insurers, whether or not they are credit-rated, the implementation of the RBC system, and the changes in product portfolios each have a significantly positive effect on financial stability. However, the life insurers' leverage, the share of unit-linked products, and the market interest rate each have a negative impact on financial stability. The overall empirical results show that the proposed FSI in this study can serve as an alternative early warning indicator of the financial distress insurers in Taiwan.

In terms of policy contribution, our proposed FSI can remedy the deficiencies in the current early warning system. The empirical results can assist the supervisory authorities in constructing more straightforward and accurate early warning indicators. In addition, by increasing the monitoring of the factors influencing the FSI and the RFSI, the supervisory authorities can enhance the control over the problem life insures that are likely to encounter a financial crisis before the event does take place, and the insurers themselves can also use this index to provide more information for further improvement to their risk management system.

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我國壽險業財務預警分析
—財務穩定度指標及其影響因素之探討

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摘 要

本研究利用 1997 至 2012 年臺灣壽險公司財務數據，將其轉換成衡量公司財務穩定度之指標 (Financial Stability Index, FSI)，並以不同分量為基準進行財務狀況預警模擬。實證結果發現，利用中位數衡量之風險調整後 FSI，對公司財務惡化狀況有較佳預測能力。而公司規模、商品組合變動、資本適足率制度實施、與是否接受信用評等，對公司財務穩定度有顯著正向影響。

關鍵詞：早期預警指標、財務穩定度指標、壽險公司

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