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Paper:

Asset Structure and Solvency of Insurance Companies in China with Path Identification Model

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Based on weighted kernel density estimation and the nonparametric path identification model, this paper explores the impact of asset structure on solvency and risk exposure by insurance companies. To test the differences in solvency and risk exposure of admitted assets under stock and time deposit investment paths, we compared distributions under different investment paths to benchmark distribution. Our results suggest that both stock and time deposit investment impact positively on solvency, meaning that, all other things being equal, solvency increases when investment assets are expanded but risk increases simultaneously. The impact of stock investment is also greater than that of time deposit investment. The extent of these differences increased gradually over the year under the stock investment path, but reduced under the time deposit investment. Under the stock investment path, the value of the high quantiles of the distribution are likely to shift from that of low quantiles. Expected value and risk exposure under time deposit investment are not necessarily reduced, so regulators should both emphasize solvency indicators in daily supervision and also take into account changes in the investment structure, improve how admissible assets are calculated in case the insurance company increases the solvency margin by expanding high-risk investment.

Keywords: path identification, distribution shift, weighted-kernel density, risk exposure, solvency

1. Introduction

Insurance funds in China are mainly invested in bank deposits, stocks and bonds, etc. Monetary policy transmission time to insurance under these investment paths is shortened and risk is increased. As a largest burgeoning capital market, China's stock market has high systemic risk with high volatility in share prices, which impacts directly on insurance company solvency. Given that stock investment return and risk exposure obviously differ from those of time deposit investment, we treat the former as high-risk investment and the latter as low-risk. It is undoubtedly considerably realistically significant for the stability and sustainable development of the insurance market to study distribution shift and risk exposure of admitted assets under different investment paths.

Solvency is the key to an insurance market developing in a healthy and sustainable manner. The scarcity of solvency affects both a company's survival and development, and the market's economic order and hinders the development of society. The solvency margin is the core of regulation, defined as the difference between admitted assets and liabilities. Admitted assets equal real assets multiplied by different fixed ratios that measure the risks of corresponding assets. We focus on the impact of admissible assets by different investment assets. In the overall investment structure of nonlife insurance companies in China, time deposit investment accounted for 9.35% and stock investment for 5.25% in 2011. In 2012, time deposit investment accounted for 8.95% and stock investment accounted for 4.21%. The proportion of time deposit investment is nearly twice that of stock investment, and the risk of time deposit investment was relatively small in 2011 and 2012. On the one hand, ratios do not reflect the time-varying characteristics of risks, specifically with risk growing in the Chinese capital market and current fixed ratios very high. On the other hand, admitted assets are calculated simply by the summation of admitted values of specified assets, which does not take into account the different effects of different assets and different investment structures for all insurance companies. The admitted value of every investment asset contributes the same to admitted assets and obviously does not reflect the risk caused by different assets.

Section 2 of this paper summarizes related literature. Section 3 describes our dataset and presents the weighted density estimation and different path models. Section 4 reviews empirical results and Section 5 presents conclusions.

2. Literature Review

2.1. Research on Solvency

In the 1960s, scholars began studying solvency of insurance companies. Based on data from 18 P&C insurance companies, Campagne [1] studied solvency with a ratio model. Li [2] estimated parameters of the minimum solvency margin and obtained the timeliest capital standard of the minimum solvency margin based on with the data of the non-life insurance market data in China. The only financial index in such a single variable model does not necessarily reflect a company's financial characteristics adequately. Trieschmann [3] studied solvency using the multivariate linear model – an approach requiring normally distributed independent variables and covariances of the two groups must be equal, which limits the model's usable range. Using the multivariate nonlinear regression model, Harrington [4], Cummins and Sommer [5] studied solvency and proved that the linear relationship between independent and dependent variable is very weak. Using multivariate linear and multivariate logical models, Lu [6] studied insurance companies without adequate solvency, finding that the multivariate logical model is better than the multivariate linear model. Given the shortcomings of parametric models, nonparametric models are introduced. Using the neural network method, Brockett et al. [7] predicted insurance company solvency and found that neural networks were superior to the multivariate linear models in predicting solvency. Hsiao and Whang [8] assessed financial soundness by adopting CAMEL rating and the risk-based capital model, also proving that the artificial neural network is better than conventional identification by building an effective nonsolvency prediction model. Using PAM clustering and later some Bayesian tools, Albarran et al. [9] pointed out that it is inappropriate for all companies to use a general model to estimate solvency because not all companies operating in a specific market had the same risk profile.

2.2. Research on Solvency Risk

Initial studies on solvency risk particularly emphasized insuring risks. When the capital market and liberalization of investment restrictions improved, the focus shifted to investment risk. The Markowitz model was introduced to study solvency risk. Using the simultaneous equation model, Cummins and Sommer [5] studied capital and portfolio risks of noninsurance companies, showing that risks increased with an increase in the concentration of insurance types or company scale. Grace et al. [10] studied American Association of Insurance Supervisors RBC and found that predicting the insolvency of an insurance company was statistically significant. Wang et al. [11] designed admitted coefficients of various assets, suggesting that admitted levels should be reduced if the proportion of insurance fund applications exceeded the specified level. Su [12] qualitatively analysed risks of various assets and suggested that company scale was the most important influence on solvency. Eling et al. [13] indicated that the risk-based capital regulatory approach was not successful. Empirical results based on U.S. data showed that the effect of regulation was not proportional to model complexity (Cummins et al. [14]; Pottier and Sommer [15]). Du [16] used the DFA to determine that equity investments such as stocks were high-risk even though they contributed more to total net profits of companies, since solvency of insurance companies would be reduced if the proportion of equity investment increased.

Given the above, research on solvency and its risk are mainly descriptive statistical analyses of the risk of insurance companies, or based on financial data. Studies on investment structures with inferential statistical analysis are fewer, and there are few studies on distribution shift and risk exposure of admitted assets under different investment paths with inferential statistical analysis. By studying the different effects on admitted assets brought about by different investment assets under different investment paths, we may find out which assets carried higher risk. Insurance companies could adjust investment structures based on expected returns and risk exposure of different investment assets. At the same time, regulators could decide on which investment asset regulations should emphasize in this study.

Using a weighted kernel density estimation model and studying the distribution of nonlife insurance companies' admissible assets under the impact of different investment assets, we found that expected values of admissible assets and risks both increased. We also showed that different investment assets had different effects. At present, the approach used to calculate admissible assets does not work well because it only sums several evaluations on all kinds of assets. Hence, we must take into account impacts on admissible assets raised from different assets.

Based on nonparametric path models, we were concerned with the distribution shift and risk exposure of admitted assets of the whole insurance market and companies whose admitted assets ranked in the top three in the market under high-risk stock investment and low-risk time deposit investment paths with data from Chinese nonlife insurance companies. We also compared distribution and risk exposure of admitted assets under different investment paths in 2011 and 2012, to project suggestions on solvency regulation from a new angle.

3. Data and Methodology

Considering that stock investment is more risky than time deposit investment, we selected 28 Chinese nonlife insurance companies that invested in stocks and time deposits in 2011 and 2012 and set the quarterly values of admitted assets, with stock and time deposit investment assets as objects of study. Our study standardizes quarterly admitted values of stock and time deposit investment for all insurance companies to show their significance. $\omega_1 \ldots \omega_n$, satisfying $\sum_{i=1}^{n} \omega_i = 1$, as standardized weights of observations $x_1 \ldots x_n$. Data came from http://www.circ.gov.cn.

3.1. Weighted Kernel Density Estimation Model

Given admissible assets values of insurance companies in 2011 and 2012, we defined the standard kernel density estimation of admissible assets as

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right) \quad (1)$$

where $K(\cdot)$ is a kernel function, which is usually a symmetrical probability density function and h is bandwidth, which controls the trade-off between estimator bias and variance.

Model (1) investigates admissible assets with standard kernel density estimation but does not take into account the different effects of separate assets and assumes that each observation makes the same contribution to admissible assets. The neglect of investment assets impacts on admissible assets is unreasonable. To overcome such misleading deviations, we put forward stock-weighted and time-deposit-weighted kernel density estimation to measure different investment impacts on admissible assets.

Our study standardized quarterly admitted values of stock and time deposits for every insurance company to show their indibidual significance. $\omega_1 \ldots \omega_n$ satisfying $\sum_{i=1}^{n} \omega_i = 1$ are standardized weights of observations $x_1 \ldots x_n$. Replacing equal weight $1/n$ by, ω_i, $i = 1,\ldots,n$ gives weighted kernel density estimation with some investment assets as follows:

$$\hat{f}_\omega(x) = \frac{1}{h}\sum_{i=1}^{n} \omega_i K\left(\frac{x-x_i}{h}\right) \quad (2)$$

where bandwidth h and kernel function $K(\cdot)$ are the same to those in Eq. (1).

Model (2) involves different messages for each observation. Contribution degree to overall density function of admissible assets is $\omega_i/h, i = 1,\ldots,n$ and the change in ω_i reflects the difference with which the investment assets of each quarter contribute to admissible assets of all nonlife companies. Model (2) is taken as an investment-asset-weighted kernel estimation.

Kernel function choice and bandwidth selection are the premise of nonparametric estimation, so the study obtains them as follows: Gaussian kernel function $K(u) = (2\pi)^{-1/2}\exp(-u^2/2)$ is chosen to estimate $f(x)$ and $\hat{f}_\omega(x)$, while bandwidth h is selected by Silverman's rule, which leads to the minimization of $MISE = E\int (f(x)^2 - f(x))^2\,dx$, that is, $h = 1.06\min\{\hat{\sigma}, R\}n^{-1/5}$, where $\hat{\sigma}$ is the standard deviation of the sample, n is the sample capacity, and $R = X_{[0.75n]} - X_{[0.25n]}$. The calculation of both the selection of bandwidth h_n and the estimation $f(x)$ and $\hat{f}_\omega(x)$ are implemented in Matlab 7.0.

3.2. Nonparametric Path Identification Model

To identify potential distribution and risk exposure of admitted assets, we establish the following nonparametric path models:

Step 1: The Potential Distribution Model

Assume the potential distribution density function to be

$$g(x) = f(x,X) \quad (3)$$

where $X = (X_0, X_1, \ldots, X_i, \ldots)$, X_0 is the admitted assets value, $X_i (i = 1,2\ldots)$ are admitted values of various investment assets. X_1, for example represents the admitted value of the stock investment asset, while X_2 represents the admitted value of the time deposit investment asset

As the estimation of the potential model, Eq. (3) could be revised as Eq. (4).

Step 2: Benchmark Distribution Model

$$g(x) = f(x,X_0) + \varepsilon \quad (4)$$

where, $\varepsilon = f(x,X) - f(x,X_0)$ is standard error. If ε is neglected directlywe may get potential distribution, i.e., an estimation of benchmark distribution $\hat{g}(x) = \hat{f}(x,X_0)$. Using the nonparametric method, the kernel estimator of $f(x,X_0)$ is

$$\hat{f}_n(x,X_0) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_{0j}}{h}\right) \quad (5)$$

Equation (5) is regarded as a continuous form of discrete percentage density, so we get both the proportion distribution density of admitted assets and also the corresponding expected value and variance.

People are becoming increasingly interested in both the distribution of admitted assets in changes in the investment structure, together with corresponding changes in admitted assets, the distribution shift, and risk exposure, so we get Eq. (6).

Step 3: Path Identification Model

$$g^*(x) = f(x,X_0|X_i) + \varepsilon \quad (6)$$

The change from to $g^*(x)$ is only the change from $f(x,X_0)$ to $f(x,X_0|X_i)$, the dependent structure between them and do not change. According to the path distribution density function, Eq. (3) is revised by Eq. (7).

$$g(x) = f(x,X_0|X_i) + \varepsilon_1 \quad (7)$$

where $\varepsilon_1 = f(x,X) - f(x,X_0|X_i)$ is path error. According to Eqs. (4) and (7), we get

$$f(x,X_0) + \varepsilon = f(x,X_0|X_i) + \varepsilon_1 \quad (8)$$

Due to increased information X_i, we have more reason to believe that path error is smaller than benchmark error, so we neglect path error in Eq. (8), where path error and benchmark error both appear, i.e.,

$$\begin{aligned}\hat{\varepsilon} &= \hat{f}(x,X_0|X_i) - \hat{f}(x,X_0) + \hat{\varepsilon}_1 \\ &\approx \hat{f}(x,X_0|X_i) - \hat{f}(x,X_0)\end{aligned}$$

As a result, the estimation of the distribution of admitted assets under X_i path is:

$$\begin{aligned}\hat{g}^*(x) &= \hat{f}(x,X_0|X_i) + \hat{\varepsilon} \\ &\approx 2\hat{f}(x,X_0|X_i) - \hat{f}(x,X_0). \end{aligned} \quad (9)$$

Using the nonparametric method, we get the estimation of Eq. (9) and get kernel estimation of $f(x,X_0)$ and

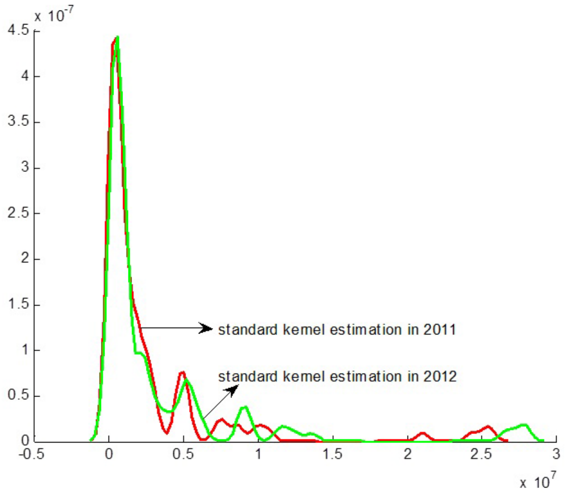

Fig. 1. Standard kernel density estimations of admissible assets in 2011 and in 2012.

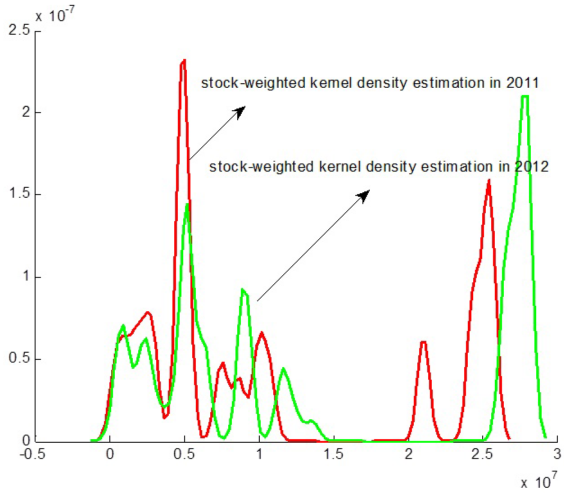

Fig. 2. Stock-weighted kernel density estimation of admissible assets in 2011 and 2012.

$f(x,X_0|X_i)$:

$$\hat{f}_n(x,X_0) = \frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x-x_{0j}}{h}\right)$$

and

$$\hat{f}_n(x,X_0|X_i) = \frac{1}{h}\sum_{j=1}^{n} \omega_{ij} K\left(\frac{x-x_{0j}}{h}\right)$$

where $K(\cdot)$ is a kernel function, which is usually a symmetrical probability density function. Gaussian kernel function $K(u) = (2\pi)^{-1/2}\exp(-u^2/2)$ is chosen in this paper. h is bandwidth, which minimizes $MISE = E\int(f^2(x) - f(x))^2 dx$, that is $h = 1.06\min\{\hat{\sigma}, R\}n^{-1/5}$, where $\hat{\sigma}$ is the standard deviation of the sample, n is sample capacity, and $R = X_{[0.75n]} - X_{[0.25n]}$. Calculations $f(x)$ and $\hat{f}_\omega(x)$ are implemented in Matlab 7.0.

We increase information X_1 and X_2 and presume that path error ε_{12} is smaller than benchmark error ε, so in estimation including both ε_{12} and ε, if we neglect ε_{12}, we get

$$\begin{aligned}\hat{\varepsilon} &= \hat{f}(x,X_0|X_1,X_2) - \hat{f}(x,X_0) + \varepsilon_{12}\\ &\approx \hat{f}(x,X_0|X_1,X_2) - \hat{f}(x,X_0)\end{aligned}$$

so the distribution density estimation of the admitted asset under path X_i is:

$$\begin{aligned}\hat{g}^*(x) &= \hat{f}(x,X_0|X_i) + \hat{\varepsilon}\\ &\approx \hat{f}(x,X_0|X_1,X_2) - \hat{f}(x,X_0). \quad \ldots \quad (10)\end{aligned}$$

4. Empirical Results

To show the different impacts of different investment paths on solvency with standard, stock-weighted, and time deposit-weighted kernel density estimation and the distribution shift and risk exposure of the admitted assets of Chinese insurance companies, we also study differences in distribution and risk exposure between 2011 and 2012 for the whole market and some specific insurance companies.

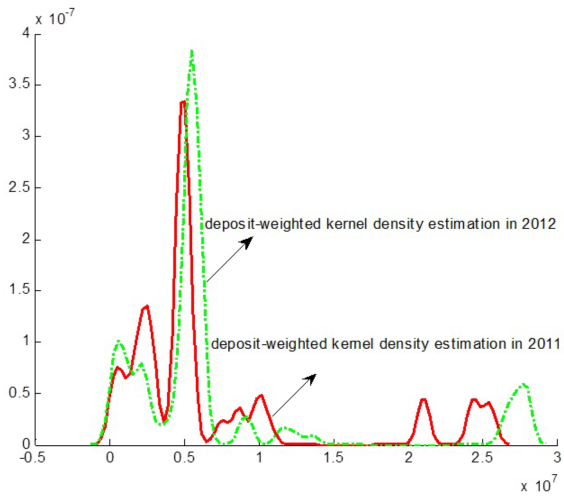

Fig. 3. Deposit-weighted kernel density estimation of admissible assets in 2011 and 2012.

4.1. Stock-Weighted and Time-Deposit-Weighted Kernel Density Estimation

Figure 1 presents standard kernel density estimations of admissible assets in 2011 and in 2012. Expected values for these years are $2.7 * 10^6$ and $3.2 * 10^6$, and variances are $2.29 * 10^{13}$ and $3.05 * 10^{13}$. Note that expected values in 2012 are bigger than that in 2011, and admissible assets of nonlife companies in 2012 involve higher risk. **Figs. 2** and **3** give weighted kernel density estimations of admissible assets in 2011 and in 2012. Taking the stock investment into account, expected values increase to $1.14 * 10^7$ and $1.42 * 10^7$ with relative increases by 320% and 350%.

Taking time deposit investments into account, expectations increase to $7 * 10^6$ and $7.25 * 10^6$, with relative in-

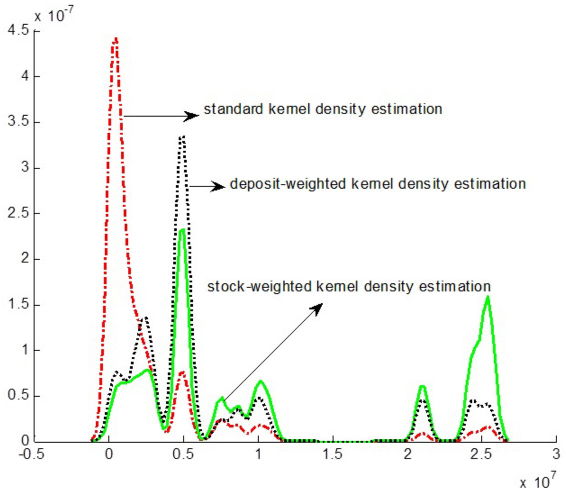

Fig. 4. Standard, stock-weighted and deposit-weighted kernel density estimation of nonlife insurance companies' admissible assets in 2011.

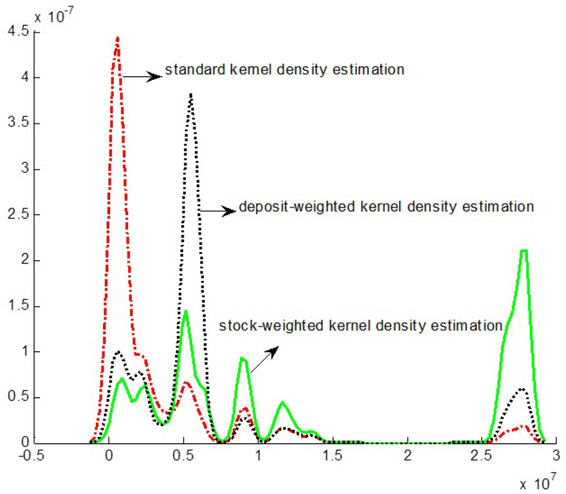

Fig. 5. Standard, stock-weighted and deposit-weighted kernel density estimation of nonlife insurance companies' admissible assets in 2012.

crease by 160% and 130%. On the one hand, the distribution of admissible assets undergoes a big change under the impact of investment assets. On the other hand, stock investment assets had a bigger impact on admissible assets in 2011 than in 2012, while deposit investment assets had a smaller impact on admissible assets in 2011 than in 2012. In addition to comparing standard estimations and investment assets of weighted estimations in 2011 and in 2012, **Figs. 4** and **5** present comparisons of standard, stock-weighted and deposit-weighted estimations of admissible assets for each year, which focus on investment asset impact on admissible assets during the entire sample interval.

Using the standard kernel density in 2011, we found that the majority of admissible assets fell in an interval ranging from 0 to $3.35 * 10^6$, or 69.7%. The remaining four intervals accounted for a relatively small proportion. Under the impact of stock investment assets, the distribution of admissible assets moves to the right, admissible assets in the first interval account for 21.4%, down from 69.7% under the standard kernel estimation. Ratios of admissible assets improve in the remaining four intervals. Specifically, admissible assets account for 20.7%, up from 2.1% in the interval, ranging from $2.29 * 10^7$ to $2.65 * 10^7$. Under the impact of time deposit investment assets, the distribution of admissible assets also moves to the right, admissible assets in the first interval account for 29.8%, down from 69.7% under the standard kernel estimation. Admissible assets in the second increased most, accounting for 42.7%, up from 9.9% in the interval, ranging from $3.35 * 10^6$ to $6.34 * 10^6$.

In 2012, using the standard kernel density, the majority of admissible assets fell in the interval ranging from to $4.12 * 10^6$, or 68.6%. The remaining four intervals accounted for a relatively small proportion. Under stock investment impact, the distribution of admissible assets moves to the right, so admissible assets in the first interval account for 18.5%, down from 69.7% under the standard kernel estimation. The ratio of admissible assets improves in the remaining four intervals. Specifically, admissible assets account for 29.7%, up from 2.8% in the interval, ranging from $2.5 * 10^7$ to $2.9 * 10^7$. Under the impact of deposit investment assets, admissible assets in the first interval account for 24.7%, down from 68.6% under the standard kernel estimation. The admissible assets ratio, ranging from $4.12 * 10^6$ to $7.47 * 10^6$, account for 55.5%, up from 11.5% in the second interval.

Table 1. Proportion of each interval in the discrete state and its continuous correction in 2011.

Intervals	Proportion in the discrete state	Proportion in the continuous state
$[0, 0.32]$	29%	28.85%
$[0.32, 0.64]$	16%	21.63%
$[0.64, 1.16]$	23%	26.45%
$[2.21, 2.30]$	15%	0.03%
$[2.30, 2.57]$	17%	23.04%

4.2. Path Identification of Admitted Assets

4.2.1. Proportion of Individual Intervals and Their Continuous Correction

As shown in **Table 1**, admitted asset values in the whole nonlife insurance market falling in intervals $[0, 0.32]$, $[0.32, 0.64]$, $[0.64, 1.16]$, $[2.21, 2.30]$ and $[2.30, 2.57]$ account for 29%, 16%, 23%, 15% and 17% under direct calculation – called a discrete state in this paper. We found that most of the value falls in $[0, 0.32]$ and $[0.64, 1.16]$. Revising the discrete state continuously, namely, when we estimate the proportions with the nonparametric kernel density function, proportions change. Under benchmark distribution, the expected value and variance are 0.271 and 0.229 million. Similarly, in 2012, as **Table 2** shows, the value falling in intervals $[0, 0.41]$, $[0.41, 0.73]$, $[0.73, 1.07]$, $[1.07, 1.36]$ and $[2.45, 2.85]$ ac-

Table 2. Proportion of each interval in the discrete state and its continuous correction in 2012.

Intervals	Proportion in the discrete state	Proportion in the continuous state
[0,0.41]	23.8%	24.63%
[0.41,0.73]	19.2%	21.98%
[0.73,1.07]	12.7%	14.9%
[1.07,1.36]	13.8%	10.97%
[2.45,2.85]	30.5%	27.52%

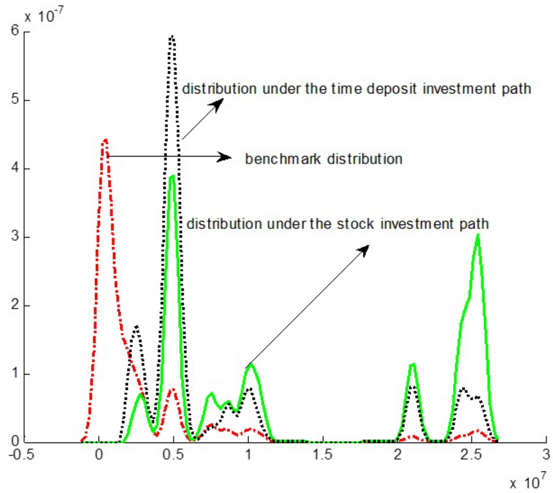

Fig. 6. Distributions under different density functions in 2011 (unit: one yuan).

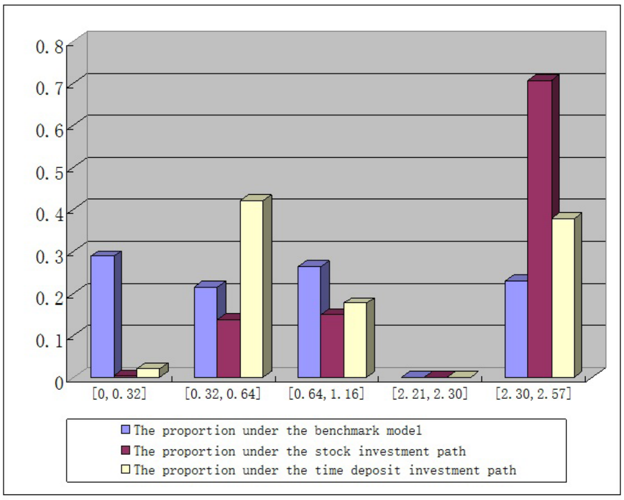

Fig. 7. Proportions under different density functions in 2011.

Table 3. Proportions under time deposit and stock investment paths in 2011.

Intervals	Proportions under the time deposit investment path	Proportions under the stock investment path
[0,0.32]	2.19%	0.32%
[0.32,0.64]	42.21%	13.96%
[0.64,1.16]	17.71%	14.97%
[2.21,2.30]	0.05%	0%
[2.30,2.57]	37.84%	70.75%

counts for 23.8%, 19.2%, 12.7%, 13.8% and 30.5% in a discrete state. The value mainly falls in intervals [0,0.41] and [2.45,2.85]. Revising the discrete state continuously, we estimate proportions of the above intervals and calculate the expected value and variance with a nonparametric kernel density function. The expected value and variance under the benchmark model are 0.32 and 0.305 million. The value that falls in the above intervals accounts for 24.63%, 21.98%, 14.9%, 10.97% and 27.52%.

4.2.2. Distribution Shift and Risk Exposure under Different Investment Paths

The value in each interval is taken into account in both discrete and continuous states, but we do not take the investment structure into account. Different investment assets have different returns and risk exposures. Specifically, there exists an obviously difference between the risky stock investment asset and the time deposit investment asset with less risk. This makes it necessary to study distributions under stock and time deposit investment. How do the different asset allocations change solvency and risk exposure? Specifically, when a company solves the problem of insufficient solvency by changing the investment portfolio, how do we identify corresponding risks?

Figure 6 shows that, compared to benchmark distribution, distributions under time deposit and stock investment paths shift to the right. The value falling in intervals [0,0.32], [0.32,0.64], [0.64,1.16], [2.21,2.30] and [2.30,2.57] accounts for 2.19%, 42.21%, 17.71%, 0.05%, 37.84% and 0.32%, 13.96%, 14.97%, 0%, 70.75%. Expected values are 0.835 and 1.423, and variances are 0.519 million and 0.839 million. Note from **Fig. 7** and **Table 3** that the main distribution is in [0,0.32] and [0.64,1.16] under the benchmark model, which shifts to [0.32,0.64] and [0.64,1.16] under the time deposit investment path, then shifts to [0.64,1.16] and [2.30,2.57] under the stock investment path. The expected value shifts from 0.271 to 0.835, then to 1.423. Specifically, risk exposure shifts from 0.229 million under the benchmark model to 0.519 million under the time deposit investment path, then to 0.839 million under the stock investment path. Both expected values and risk exposure differ under different paths. These results suggest that time deposit and stock investment make the expected value shift to the right 208.39% and 425.87% and risk exposure expand 1.27 and 2.67 times.

Similarly, in 2012 as **Fig. 8** shows, compared with the benchmark distribution of admitted assets, distributions under the time deposit and stock investment paths shift to the right. The value falling in intervals [0,0.41], [0.41,0.73], [0.73,1.07], [1.07,1.36] and [2.45,2.85] accounts for 0.59%, 58.29%, 2.18%, 2.56%, 36.38% and 2.08%, 10.64%, 9.75%, 4.88%, 74.53%. Expected val-

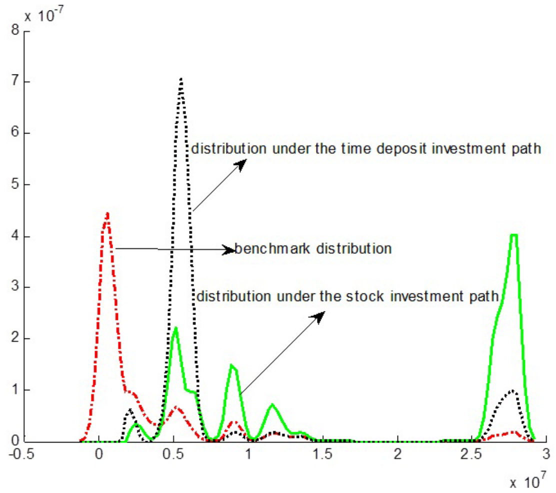

Fig. 8. Distributions under the different density functions in 2012 (unit: one yuan).

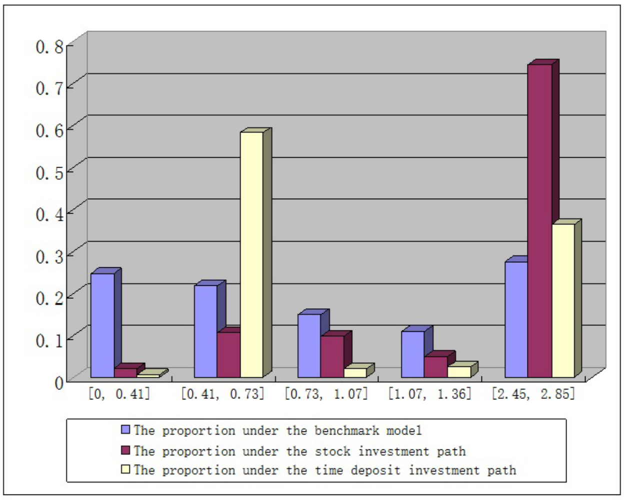

Fig. 9. Proportions under different density functions in 2012.

ues are 0.881 and 1.788 and variances are 0.603 million and 1.041 million. As **Fig. 9** and **Table 4** show, the main distribution is in $[0, 0.41]$ and $[2.45, 2.85]$ under the benchmark model, which shifts to $[0.41, 0.73]$ and $[2.45, 2.85]$ under the time deposit investment path, then shifts to $[2.45, 2.85]$ under the stock investment path. The expected value shifts from 0.32 to 0.881, then to 1.788. Specifically, risk exposure shifts from 0.305 million under the benchmark model to 0.603 million under the time deposit investment path, then to 1.041 million under the stock investment path. Both expected values and risk exposures differ under different paths. These results suggest that the time deposit and stock investment make the expected value shift to the right 175.31% and 458.75% and risk exposure expand 0.98 and 2.41 times. The above analysis shows that due to the time deposit, investment is less risky, so we may regard the distribution shift and the risk exposure under the time deposit investment path as permissible. The distribution shift and risk exposure under the stock investment path are relatively large, which

Table 4. Proportions under time deposit and stock investment paths in 2012.

Intervals	Proportions under the time deposit Investment path	Proportions under the stock Investment path
$[0, 0.41]$	0.59%	2.08%
$[0.41, 0.73]$	58.29%	10.64%
$[0.73, 1.07]$	2.18%	9.75%
$[1.07, 1.36]$	2.56%	4.88%
$[2.45, 2.85]$	36.38%	74.53%

may somewhat influence judgment on the distribution of the insurance market's admitted assets of regulators.

4.2.3. Path Identification of Admitted Assets Values of Some Specific Insurance Companies

Judging from the whole nonlife insurance market, stock and time deposit investment make expected value under the benchmark model shift to the right, and risk exposure increased to different degrees in 2011 and 2012. Yet specific to some companies, the situation differs, such as PICC, Ping An and CPIC, whose admitted assets values rank in the top three of the nonlife insurance market.

Under the benchmark model, the time deposit and stock investment path, expected values of admitted assets of PICC in 2011 are $7.52 * 10^{-3}$, $3.65 * 10^{-2}$, $1.21 * 10^{-1}$, and risk exposures are $1.87 * 10^5$, $8.89 * 10^5$ and $2.75 * 10^6$. In 2012, expected values are $1.17 * 10^{-2}$, $5.1 * 10^{-2}$, $1.99 * 10^{-1}$, and risk exposures are $3.18 * 10^5$, $1.35 * 10^6$ and $4.68 * 10^6$. Time deposit and stock investment all make benchmark expectation shift right and risk exposure increased. In 2011 and 2012, time deposit investment makes the benchmark expectation shift to the right 385.71% and 335.79%, and risk exposure expand 3.75 and 3.23 times. The degree of the expected value shift to the right and risk exposure of admitted assets under the time deposit investment path in 2012 are slightly below that in 2011. Stock investment makes the expected value shift to the right 1508.48% and 1599.63%, and risk exposure expands 13.66 and 13.74 times. The extent of the expected value shift to the right and the risk exposure under the stock investment path in 2012 are above those in 2011. Results show that the enlarging degree of risk exposure in 2012 is slightly below than that in 2011 under the time deposit investment path, while the situation is the opposite under the stock investment path.

Ping An had a similar situation with CPIC. In 2011, under the benchmark model, expected values of admitted assets of CPIC and Ping An were $5.39 * 10^{-3}$ and $6.87 * 10^{-3}$, and risk exposures were $4.147 * 10^4$ and $6.74 * 10^4$. Stock and time deposit investment separately make the expected value shift to the right 249.36% and 98.03%, and risk exposure expanded 2.37 and 0.95 times. In 2012, expected values are $6.62 * 10^{-3}$ and $6.94 * 10^{-3}$ and risk exposures are $5.96 * 10^4$ and $8.51 * 10^4$. Stock investment makes expected values shift to the right 215.79% and

179.55%. Risk exposure expanded 2.06 and 1.74 times, while the time deposit investment makes the expected values shift to the left 11.02% and 63.03%, and the exposure reduced 11% and 63%.

Results showed that, the style of the risk exposure are completely changed under the time deposit investment path, and the degree of enlargement of risk exposure in 2012 was slightly below than that in 2011 under the stock investment path.

From solvency reports of PICC, Ping An and CPIC, we found that stock investment assets accounted for 5.46%, 4.98% and 3.31% of admitted assets in 2011, and 5.39%, 0.7% and 2.39% in 2012. Although proportions of stock investment for these three companies declined in 2012 than 2011, we cannot conclude that the investment risk in 2012 is lower than that in 2011. We should, instead, probe the question in depth as to whether the value of high quantiles of distribution shifted from that of low quantiles.

From the above analysis, we found that, in the case where other conditions are unchanged, the expected value of admitted assets will increase with the expanding proportion of stock investment and at the same time, the company will face more risks. To cover up the problem of insufficient solvency or to seek greater returns, the insurance company may expand stock investment, which may also hide more risks. A direct question is whether the value of high quantiles of distribution is shifted by that of low quantiles through the stock investment path. If it is, once a risk event occurs, consequences will be serious. This also means that the current method, in which the admitted asset value is calculated simply by summing admitted values of specified assets, is excessively simple. This method may underestimate the expected value and risk of admitted assets and even underestimate solvency risk to some extent.

5. Conclusions

The insurance industry has accumulated great risk that may cause great hidden problems of insolvency. Guarding against solvency risk is the key problem that the regulator must take into account. This study brings forward investment assets-weighted kernel density estimation to investigate how different assets impact on solvency with data in quarterly solvency reports of nonlife insurance companies in China. Using data on admissible assets, stock investment assets and time deposit investment assets of nonlife insurance companies, we empirically imply that different investment assets have different impacts on solvency. The impact of stock investment is greater than that of time deposit investment. When investing in high-risk assets, the company should guard against adverse effects on solvency. When developing a second-generation solvency regulatory system, insurance regulators should take into account different effects on admissible assets of different assets, and improve the calculation of admissible assets.

The rapid development of the insurance industry in China presents the possibility of increasingly complicated risks, which may cause more potential problems with insolvency. Guarding against solvency risk is both the core of insurance company management and the key problem that regulators must take into account. This study brings forward a nonparametric path identification model to investigate distribution shift and risk exposure of admitted assets under different investment paths. Using data on admitted assets and stock and time deposit investment asset values of nonlife insurance companies in China in 2011 and 2012, we can empirically obtain three conclusions:

(i) In 2011 and 2012, stock and time deposit investment make the expected value under the benchmark model shift right and risk exposure increases. Specific to some insurance companies, the situation differs, such as with Ping An and CPIC. For them, time deposit investment in 2012 makes distribution under the benchmark model shift left and risk exposure decreases.

(ii) Distribution and risk exposure differ under different investment paths, and insurance companies should allocate the investment structure rationally, trying to get the greatest investment return within the scope of risk. When investing a high-risk asset, we must prevent adverse effects on solvency, brought by the external factors.

(iii) The asset value of high quantiles of the distribution of admitted assets may possibly shift from the low quantile through the stock investment path. An insurance company may improve its solvency by increasing the proportion of high-risk investment assets, such as stock investment. In the process of daily supervision, regulators should focus on both changes in the solvency index and also analyze solvency from changes in the investment assets proportion, in case the insurance company improves solvency by increasing the proportion of high-risk investment assets.

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