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Highlights

- **We propose a dynamic network data envelopment analysis model with carry-overs.**
- **Carry-overs are important to the performance evaluation of insurers.**
- **We study investment assets as the carry-over variable in investment efficiency.**
- **Modeling investment assets increases the discriminatory power of performance.**
- **Some insights are derived from regression and multidimensional scaling approaches**

Modeling Investments in the Dynamic Network Performance of Insurance Companies

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Abstract

This study proposes a dynamic two-stage network data envelopment analysis (DEA) model with and without carry-over variables to evaluate corporate performance. Carry-over variables are those continuously held from one term to another, reflecting dynamic components. Apart from considering dynamic aspects, the DEA model called dynamic slacks-based measure with network structure can address various inputs and outputs at both stages and multiple intermediates that link the two stages. We demonstrate the applicability of the proposed model under the assumption of variable returns to scale to the performance evaluation of 30 insurance companies in Malaysia from 2008 to 2016. Specifically, we gauge resource management and investment efficiencies as the two production stages of insurance companies. While investment asset is considered the carry-over variable, investment income is treated as one of the ultimate outputs. Results indicate that the discriminatory power of the overall performance is high when we consider investments, particularly investment assets, as a carry-over variable. Moreover, we employ a multi-criteria decision analysis to compare all insurance companies in a common setting, including each ratio of liquidity, profitability, and leverage. The decision to include these ratios is made after performing regression analyses. This study entails practical implications for insurers and policy makers in terms of resource management and investment after considering investments and relevant performance ratios.

Keywords: Data envelopment analysis; Dynamic network slacks-based measure; Resource-management efficiency; Investment efficiency; Insurance companies

1. Introduction

Measurement of the performance of insurance companies has attracted extensive examinations by researchers. Increasing competition and the recent dynamics in insurance markets have essentially transformed the corporate environment involving insurers. In this fast-moving market, shareholders and managers at insurance companies need accurate, holistic, and credible information regarding the values generated by their business activities. Therefore, the debate over credible methods of performance measurement that enable insurance managers to distinguish superior performance continues. Among modern management techniques, benchmarking methods can be used in various ways to assist firms in evaluating their performance compared with their peers in terms of input minimization and output maximization, as well as technology and scale.

The literature documents that the performance of insurance companies relies on three main services: risk-bearing, financial services, and intermediation [1]. Although risk-bearing and financial services are the fundamental functions of insurance companies, they deposit idle funds due to time differences between obtaining premiums income and paying out claims/benefits for losses in investments to realize the appreciation of insurance funds. The intermediation function involving investments conducted by insurance companies is also the main reason the insurance industry has become an important part of the financial industry. Insurance companies may fail to achieve outstanding performance amid this vibrant corporate world in terms of investments, ultimately affecting their overall performance. This possibility corresponds to the concept of production efficiency[1], which involves relative performance measures.

Since Eling and Luhnen [2] completed their overview of the frontier efficiency of insurance companies, the number of studies [for examples, 3, 4, 5] applying data

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[1] In the literature, efficiency measurement is one of the most rapidly growing streams of studies, with some rapidly growing focuses on the insurance industry since the early 1990s [2].

envelopment analysis (DEA) as the method of frontier efficiency analysis in the insurance industry has increased. However, a crucial but often overlooked factor in the performance of insurance companies is investment assets, which include but is not limited to available-for-sale financial assets, investment securities, and investment properties. These dynamic assets are accumulated and carried forward from one financial term to another on the balance sheet.

When assessing the performance of Malaysian insurance companies, Wu et al. [6] highlight that dynamics should be taken into consideration. Although they include investment assets in the study, they treat it as an intermediate output. As previously argued, the funds collected from premiums income are idle before disbursement and are thus transformed into investment assets that generate returns. This argument is also in line with the accounting convention of going concern, which assumes that, when preparing financial accounts, a firm will continue to operate for the foreseeable future [7]. In other words, the firm's existing resources will remain in operation or permanent accounts in the balance sheet. One of the balance-sheet items is assets such as property, plant, and equipment, as well as investment assets, all of which are carried forward to the next financial term. Therefore, the performance measurement of insurance companies involves not only solving multidimensional problems in various performance indicators but also addressing dynamics in investment assets.

A DEA model that addresses the multidimensional problem and dynamics is the dynamic DEA with network structure from a slacks-based measure perspective. This dynamic slacks-based measure with network structure (DSBMN) is a linear programming-based approach that introduces a "black box" and handles dynamics for performance evaluation and benchmarking. The slacks-based measure is non-radial and non-oriented when dealing directly with input and output slacks. Acknowledging the generally non-proportional nature of noticeable deterioration in performance in the real world is an advantage of DSBMN. Moreover, it is unaffected by statistics over the entire data set.

The main purpose of this study is to investigate the effect of investment assets, which are dynamic in nature, on the performance of insurance companies when the insurance management process is modelled into a dynamic two-stage network process. Stage 1 of efficiency is known as resource management, while that of stage 2 is known as investment efficiency. We interpret investment assets as an inputted carry-over that generates investment income at stage 2 of the two-stage network process. We find that the average investment assets of the 30 sampled insurance companies incorporated in Malaysia increase at a decreasing percentage in the last few years, while those of investment income fluctuate over the sample period of 2008–2016. This inputted carry-over variable of investment assets refreshes the dynamic two-stage network DEA analysis of the performance of insurance companies.

Despite the usefulness of DEA for performance evaluation, the efficiency scores derived from DEA prohibit the comparison of all insurance companies in a common setting because they are evaluated under different weightings of the multiple input and output variables. Following prior research [for an example, 8], we employ regression techniques in the present study to relate performance ratios, such as liquidity, activity, profitability, and leverage. We also conduct cluster analysis and multidimensional scaling to further group the insurance companies in a common setting, similar to Wang et al. [9]. These multicriteria approaches provide insights into the relationship of several performance evaluation criteria of both the two-stage processes and the ratio analyses, all of which are attributes that describe the performance of insurance companies.

This study provides at least two contributions. First, we improve the dynamic two-stage network DEA model proposed in Wu et al. [6] by including investment assets as the carry-over variable in investment efficiency. This inclusion not only considerably explains the dynamic effects of investment assets on overall performance but also increases its discriminatory power because investments are the intermediation function of insurance companies that are carried over from one period to another. This improvement is achieved in the decomposition of overall performance into resource management and investment. Second, addressing the potential effect of the global financial crisis of 2007-2009 by giving a double weight each on the data of years 2008 and 2009 relative to others is another contribution of this study, particularly towards the DEA theory. Besides, it is important to note that investment assets belong to permanent accounts that are carried forward from one financial term to another on the balance sheet, addressing the accounting perspective of going concern. Third, this study contributes to the literature by performing regression analyses, cluster analysis, and multidimensional scaling, all of which evaluate the performance of insurance companies in a common setting. These approaches support the argument of Babalos et al. [10] about the need to consider evaluating decision-making units (DMUs) under a common setting. Given the considerable reliance by insurance companies on not only investments but also liquidity, profitability, and leverage, comprehensively evaluating the performance of insurance companies and providing insightful aspects and key determinants of their performance are crucial.

This paper continues with the following content. The next section provides an overview of studies related to the performance of insurance companies. The third section describes our methodology and data used. The fourth section presents our empirical results with discussions. The last section concludes this paper.

2. Performance Measurement of Insurance Companies

Previous studies use various methods to measure the performance of insurance companies. Financial ratios, such as return on assets, return on equity, and Tobin's Q, are commonly used as the performance measurement of insurance companies [11]. Industry analysts measure profitability according to the considerable proportion of income in the firms. However, Yang [12] indicates that ratio analysis cannot provide accurate information when considering the economies of scale, benchmarking policies, and estimation of overall performance measurement. This situation shows the limitations of using ratio analysis as the performance measurement of insurance companies.

Bikker and Van Leuvensteijn [13] employ stochastic frontier analysis (SFA) to examine the existence of scale economies and the importance of cost X-inefficiency of the Dutch life insurance industry. This approach analyzes several factors that may affect the competitive nature of the said industry. Fenn et al. [14] also use SFA to measure the efficiency of European insurance companies from 1995 to 2001. Their study adopts the one-stage approach on X-efficiency and explores the scale economies of European insurance companies. Meanwhile, Biener et al. [15] examine the efficiency and productivity of Swiss insurance companies by applying state-of-the-art frontier efficiency methodologies from 1997 to 2003.

Recently, DEA has been widely used as an accurate and appropriate tool to measure firm efficiency. Although the SFA and DEA approaches have their respective pros and cons, DEA is the more frequently applied approach in the insurance industry compared with SFA [2]. Biener et al. [15] reveal that the DEA technique is widely accepted for efficiency measurement, particularly in the insurance industry because the production function for this industry is unknown. Furthermore, Yang [12] highlights that DEA can integrate production and investment performances and even compromise both aspects of the Canadian L&H insurance industry. This technique avoids the choice of a specific function form and requires no distributional assumptions. Moreover, DEA is regarded as the best practice tool because it can identify the magnitude of possible inefficiencies and improvements for the inefficient units. Barros et al. [16] further emphasize that DEA allows the use of various inputs and outputs and does not impose any functional form on the data or make distributional assumptions on the inefficiency term. The bootstrapping approach used can resample and recalculate the DEA efficiency score, an ability that solves the criticisms of DEA for being non-statistical or deterministic. DEA is also individual-firm based, which serves as an indicator of efficiency and productivity changes by firms [17]. Banker [18] highlights that DEA is equivalent to a maximum likelihood estimation because its estimators are consistent and converge faster than other frontier methods [19, 20].

In addition, DEA is well known for its acceptance of small samples [21]. Leverty and Grace [22] agree that DEA is appropriately named in that it truly envelops the entire data set that does not accommodate random noise outside the control of the firms. DEA can also solve the optimization problem separately for each sample's DMU. Premachandra et al. [23] agree that DEA is a valuable instrument for performance evaluation and benchmarking because it can handle multiple inputs and outputs without the specification of trade-offs among multiple measures. The authors also develop a new assessment index using an additive super-efficiency DEA for predicting corporate failure. This index permits the firms to explore the dynamic change of corporate failure or success on a time horizon.

This study employs two-stage DEA to investigate efficiency decomposition, where the outputs of the first stage are the inputs of the second stage. Kao and Hwang [24] confirm that the efficiencies calculated from the two-stage DEA approach are meaningful because the series relationship of the two sub-processes provides a precise efficiency level. In other words, more than one stage might be involved to complete a production process. Therefore, by using traditional DEA approaches, we are neglecting the internal linking of activities between different stages or divisions, in which we cannot determine the decomposed inefficiencies of each stage [25].

In the insurance industry, insurers use assets and expenditures to generate premiums.

However, merely stating this as fact is similar to dealing with a black box. Specifically, the incurred claims play a dual role in the entire production process. In the first stage, incurred claims are initially the outputs and then become the inputs in the second stage. The first-stage outputs, which are the second-stage inputs, are the intermediate measures of production processes that link the two stages [26]. Notably, insurance companies deposit idle funds due to time differences between obtaining premiums income and disbursing claims/benefits for losses in investments to realize the appreciation of insurance funds. In this regard, we must also consider the non-static elements of investment assets.

Tone and Tsutsui [27] develop a DSBMN that can handle multiple inputs and outputs at both stages and multiple intermediates that link the two stages. Wu et al. [6] conceptualize the performance of insurance companies as a dynamic two-stage process, which comprises resource management and profitability efficiencies. They consider a case with carry-over variables in their efficiency analysis of the insurance industry. The multistage DEA approaches, or the so-called network DEA, introduce black boxes to provide detailed efficiency measures for what happens inside these boxes [28]. In short, dealing with the inner linking activities within the production process of transforming inputs into outputs can provide a detailed evaluation of the operating efficiency. Meanwhile, rather than emphasizing a single-period static performance measurement, considering the effect of carry-overs between two consecutive periods would provide a more accurate measurement of time-specific dynamic operating efficiency over long-term periods [29]. It is thus also worth noting the same arguments of dynamics and network structure as exemplified in the banking industry; for examples, Fukuyama and Weber [30, 31] develop dynamic network models for Japanese banks.

3. Model Building and Data Collection

3.1 Conceptual Framework

Although a few existing studies [for examples, 16, 32] have incorporated the dynamic aspect of performance in their evaluations, early studies on insurers' performance using DEA consider insurance management activities as a black box [for examples, 3, 4, 33, 34-36]. A major problem of the black-box performance evaluation lies in the ignored internal structure of the insurance management process.

The dynamic two-stage network DEA model proposed in Wu et al. [6] and applied to evaluate insurers' performance is a special case of the general model proposed in the current study. The authors consider investments, particularly investment assets, as an intermediate variable in their study. We propose an improvement of the DEA framework of Wu et al. [6] in this study; that is, we extend the dynamic two-stage network DEA model they proposed by employing investment assets as a carry-over variable in stage 2, given that investment assets are continuously carried over from one period to another. We also add investment income as one of the ultimate outputs to better reflect investment efficiency. Importantly, investment assets represent a large portion of the total assets of insurance companies, and the ratio substantially differs from one insurer to another. Therefore, we develop a modified dynamic two-stage network DEA model as shown in Figure 1.

[Insert Figure 1 about here]

The modeling of Figure 1 and the selection of variables are based not only on prior studies [for examples, 2, 6] but also the following reasoning. Specifically, we apply the production approach (or the value-added approach) in the insurance industry [1, 37]. Insurance companies mainly provide three services, namely, risk-bearing, financial services, and intermediation. To support outlays such as management fees and fixed assets used for productions, insurance managers should be able to accumulate additional reserves, which, in turn, are used to achieve additional premiums earned. In terms of risk-bearing and financial services, insurance companies also incur current losses paid plus additions to reserves. Meanwhile, insurance companies also deal with investments in their intermediation function. An insurance company with high investment assets has high investment income, which will ultimately contribute to its efficiency.

As depicted in the preceding figure, we first consider two variables, namely, *MExp* management expenses (input) and *FAsset* fixed assets (carry-over), both of which are inputted in stage 1. We use one intermediate variable, incurred claims plus additions to reserves (*ICAR)*, to link stages 1 and 2. At stage 2, we perform efficiency analysis with and without investment assets (*IAsset*), which is the inputted carry-over variable, while premiums earned (*PE*) and with and without investment income (*IIncome*) are the output variables. All variables used in the proposed DEA model are deflated according to the 2008 Consumer Price Index to derive their present values. Management expenses refer to the operating expenses used in labor and business services. Fixed assets are the properties, plants, and equipment accumulated from one period to another. Incurred claims are the total claims/benefits disbursed, while reserves are generated funds not intended for claims/benefits. Investment assets are the real value of all financial investments, while investment income is the corresponding returns of investment assets. Premiums earned are advanced premiums earned and thus belong to the insurance companies.

3.1.1 Checking the Model Validity

We test for the (i) homogeneity, (ii) minimum number of DMUs, (iii) isotonicity, and (iv) relevance of variables used in the proposed model to further corroborate its validity.

First, we highlight that insurance companies in this study are homogeneous and have the same objectives, that is, to earn high premiums and investment income. Put differently, the insurance companies are of similar business nature, having characteristics and market conditions alike [38]. Thus, the potential issue of non-homogeneity of DMUs is absent in the current study. The results derived from the proposed model would be reliable, consistent with the arguments presented in Farrell [39], which is the seminal study on DEA. Second, the 30 DMUs are five times that of the total inputs and outputs of six in this study. This ratio is derived after removing three insurance companies that lack the required financial data for DEA and multi-criteria decision analyses. As the minimum required ratio is two in accordance with Golany and Roll [38], we emphasize that the construct validity of the dynamic two-stage network DEA model used in this study is stable and reliable.

Third, the input and output variables used in this study are significantly and positively correlated as evidenced by the correlation matrix in Table 1. In other words, when we increase a proportion of inputs, the proportion of outputs will also increase, thereby suggesting the existence of isotonicity for the choices of input, carry-over, intermediate, and output variables in this study. Although the mixture of variables satisfies the assumption of isotonicity as provided in Golany and Roll [38], we further examine the relevance of variables used in the proposed model.

[Insert Table 1 about here]

Fourth, we assess the sign (direction) and degree of association between the inputs and outputs used in this study. According to Sun [40], such examination can reveal the contributions of the input variables in generating the output variables. Therefore, we conduct a log–log regression analysis. The advantages of a log–log regression model over other models include (i) increasing or decreasing the allowance for variable returns to scale and (ii) coefficients that indicate how a 1% input change would affect change in the output by percentage [41]. The results in Table 2 show that the input variables of stage 1, namely, management expenses and inputted carry-over variable of fixed assets, explain 64.6% of the change in output variables (*ICAR*). Looking at the results individually, an increase in management expenses and fixed assets would result in an increase in *ICAR*. Meanwhile, the input variables of stage 2 indicate the same, in that *ICAR* and inputted carry-over variable of investment assets significantly and positively affect premiums earned (investment income), which have a collective explanatory power of approximately 74.2% (85.5%). These findings validate our model by explaining the contributions of each input variable in generating outputs for the performance evaluation of insurance companies.

[Insert Table 2 about here]

3.2 Measuring Dynamic Two-Stage Network Efficiencies

This study uses the DSBMN for intertemporal performance analysis. DSBMN is a non-parametric approach that refers to the utilization of mathematical programs to cope with productions with multiple inputs, outputs, and carry-over variables [27]. DSBMN deals with the black-box issue within each stage in a network structure, as well as considers the internal connection through linking variables [42, 43].

To analyze the long-term performance of insurance companies in Malaysia from 2008 to 2016, DSBMN is adopted in this study because it can evaluate the operational performance from a multi-period perspective through carry-over variables [27]. DSBMN is a composite of network SBM and dynamic SBM, which confirm the estimation of overall efficiency according to multi-year research and evaluates period efficiency at the divisional level [44]. This measure generates an efficiency score ranging from 0 and 1. An observed DMU is efficient with no input/output slacks if the efficiency is equal to 1.

The non-oriented dynamic two-stage network DEA model under the assumption of variable returns to scale presented in Figure 1 handles *n* insurance companies and comprises $K\left(k=1,\ldots,K\right)$ stages during T terms $\left(t=1,\ldots,T\right)$. The link between stage *k* and *h* is denoted by $\left(k,h\right)_l$. m_k^t and r_k^t are the numbers of inputs and outputs to stage k at time t, respectively. $x_{ijk}^{t}\left(i=1,...,m_{k}^{t}; j=1,...,n; k=1,...,K; t=1,...,T\right)$ is input i to DMU_j for stage k in time t, and $y_{rjk}^{t}\left(r=1,...,r_{k}^{t}; j=1,...,n; k=1,...,K; t=1,...,T\right)$ is output r to DMU_j for stage k in time t. $z_{j(kh)_l}^{t}\left(j=1,...,n; l=1,...,L_{kh}; t=1,...,\mathrm{T}\right)$ links intermediate products of DMU_j from stage k to stage h in time t, where L_{kh} is the number of items in links k to h. $c_{jk_l}^{(t,t+1)}\left(j=1,...,n; l=1,...,L_k; k=1,...,K; t=1,...,T-1\right)$ is the carry-over of DMU_j at stage k from time t to time $t+1$, where L_k is the number of items in the carry-over from stage k.

The overall efficiency of observed DMU_o $\left((o=1,...,n\right)$ is evaluated by the following programs:

$$\theta_o^* = \min \frac{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} w^k \left[1 - \frac{1}{nb_k^t + m_k^t}\left(\sum_{kl=1}^{nb_k^t} \frac{s_{okl\,bad}^{(t,t+1)}}{c_{okl\,bad}^{(t,t+1)}} + \sum_{i=1}^{m_k^t} \frac{s_{iok}^{t-}}{x_{iok}^{t}}\right)\right]\right]}{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} w^k \left[1 + \frac{1}{lino_k^t + r_k^t}\left(\sum_{out=1}^{lino_k^t} \frac{s_{o(k,h)\mathrm{out}}^{t}}{z_{o(k,h)out}^{t}} + \sum_{r=1}^{r_k^t} \frac{s_{rok}^{t+}}{y_{rok}^{t}}\right)\right]\right]}, \tag{1}$$

which are subject to

$$\begin{aligned}
&x_{iok}^{t} = \sum_{j=1}^{n} x_{ijk}^{t}\lambda_{jk}^{t} + s_{iok}^{t-}\left(k=1,...,K; t=1,...,T\right),\\
&y_{rok}^{t} = \sum_{j=1}^{n} y_{rjk}^{t}\lambda_{jk}^{t} - s_{rok}^{t+}\left(k=1,...,K; t=1,...,T\right),\\
&\sum_{j=1}^{n}\lambda_{jk}^{t} = 1\left(k=1,...,K; t=1,...,T\right),
\end{aligned} \tag{2}$$

where x_{ijk}^{t} and y_{rjk}^{t} are inputs and outputs, and s_{iok}^{t-} and s_{rok}^{t+} are input/output slacks, respectively. λ_{jk}^{t} is the intensity of DMU_j corresponding to stage k at time t. Equation (2) represents the input and output constraints.

$$\begin{aligned}
&\sum_{j=1}^{n} z_{j(k,h)out}^{t}\lambda_{jh}^{t} = \sum_{j=1}^{n} z_{j(k,h)out}^{t}\lambda_{jk}^{t}\left(\forall(k,h); t=1,...T\right),\\
&z_{o(k,h)out}^{t} = \sum_{j=1}^{n} z_{j(k,h)out}^{t}\lambda_{jk}^{t} + s_{o(k,h)\mathrm{out}}^{t}, \left(\left(k,h\right)out=1,...,lino_k^t; t=1,...T\right),
\end{aligned} \tag{3}$$

where $s_{o(k,h)\mathrm{out}}^{t}$ is the slacks and free in sign. *ICAR* linking activities are treated as output from the preceding stage, and shortages are accounted for in the output inefficiency in Equation (3).

$$\begin{aligned}&\sum_{j=1}^{n} c_{jk,bad}^{(t,t+1)} \lambda_{jk}^{t} = \sum_{j=1}^{n} c_{jk,bad}^{(t,t+1)} \lambda_{jk}^{t+1} \left(k_l = 1,\ldots,nb_k; k = 1,\ldots,K; t = 1,\ldots,T-1\right),\\ &c_{ok_l bad}^{(t,t+1)} = \sum_{j=1}^{n} c_{jk_l bad}^{(t,t+1)} \lambda_{jk}^{t} + s_{ok_l bad}^{(t,t+1)} \left(k_l = 1,\ldots,nb_k; k = 1,\ldots,K; t = 1,\ldots,T\right),\end{aligned} \tag{4}$$

where $s_{ok_l bad}^{(t,t+1)}$ is the slacks denoting carry-over excess, and nb_k indicates the number of carry-over for each stage k. *FAsset* and *IAsset* carry-overs are treated as inputs in Equation (4), and their values are restricted to avoid exceeding those of the observed ones. Comparative excess in carry-overs in this category is accounted as inefficiency.

$$\begin{aligned}&\sum_{k=1}^{K} w^{k} = 1,\\ &\sum_{t=1}^{T} W^{t} = 1,\end{aligned} \tag{5}$$

where w^k is the weight to stage k and W^t is the weight to time t. λ_{jk}^{t} is the intensity of DMU_j corresponding to stage k at time t.

Then, the observed insurance company's efficiency in each period τ_o^{t*} and period-stage ρ_{ok}^{t*} are respectively assessed by the following expressions:

$$\tau_o^{t*} = \frac{\sum_{k=1}^{K} w^{k}\left[1 - \frac{1}{nb_k^t + m_k^t}\left(\sum_{kl=1}^{nb_k^t} \frac{s_{ok_l bad}^{(t,t+1)}}{c_{ok_l bad}^{(t,t+1)}} + \sum_{i=1}^{m_k^t} \frac{s_{iok}^{t-}}{x_{iok}^{t}}\right)\right]}{\sum_{k=1}^{K} w^{k}\left[1 + \frac{1}{lino_k^t + r_k^t}\left(\sum_{out=1}^{lino_k^t} \frac{s_{o(k,h)\mathrm{out}}^{t}}{z_{o(k,h)out}^{t}} + \sum_{r=1}^{r_k^t} \frac{s_{rok}^{t+}}{y_{rok}^{t}}\right)\right]} \left(t = 1,\ldots,T\right), \tag{6}$$

$$\rho_{ok}^{t*} = \frac{1 - \frac{1}{nb_k^t + m_k^t}\left(\sum_{kl=1}^{nb_k^t} \frac{s_{ok_l bad}^{(t,t+1)}}{c_{ok_l bad}^{(t,t+1)}} + \sum_{i=1}^{m_k^t} \frac{s_{iok}^{t-}}{x_{iok}^{t}}\right)}{1 + \frac{1}{lino_k^t + r_k^t}\left(\sum_{out=1}^{lino_k^t} \frac{s_{o(k,h)\mathrm{out}}^{t}}{z_{o(k,h)out}^{t}} + \sum_{r=1}^{r_k^t} \frac{s_{rok}^{t+}}{y_{rok}^{t}}\right)} \left(k = 1,\ldots,K; t = 1,\ldots,T\right). \tag{7}$$

3.3 Data Collection

The approach described in the preceding subsection is applied to our sample of 30 companies licensed to conduct direct insurance businesses without insurance agents in Malaysia during the period 2008–2016. These sampled companies out of the total 33 insurance companies in Malaysia are those with all required financial data throughout the sample period for our analysis purposes. They are either local or foreign companies, and their focus lies in life, life and general, or general insurance businesses. The source of our input and output variables is the respective corporate annual reports made available on the companies' websites. The usefulness of our proposed DEA model is assessed on the sampled insurers with and without investment assets as the carry-over variable and investment income as one of the outputs in stage 2. We regard each insurance company as a unique DMU and employ the proposed DEA model as shown in Figure 1 to evaluate the overall efficiency, the efficiencies of resource management activities (stage 1), and investment activities (stage 2) of each insurance company. The summary statistics of the variables used in the proposed model are reported in Table 3.

[Insert Table 3 about here]

Table 3 reports the yearly and overall means of all input and output variables, including inputted carry-over variables throughout the sample period. The summary statistics reveal interesting information concerning the behavior of the variables. All variables demonstrate an increasing trend, except for fixed assets (*FAsset*), whose values fluctuate over the sample period. Our attention is drawn to the main carry-over variable in stage 2, namely, *IAsset*, which relatively increased considerably in the first few years; however, the percentages of such increase continued to drop from 2014 to 2016. Another noteworthy information is the corresponding output of the investment assets, *IIncome*, whose increase in percentage has fluctuated over the sample period. These stylized statistics corroborate the need to include investment assets as an inputted carry-over variable that generates investment income in the investment stage. Besides, these observations motivate us to address the potential effect of the global financial crisis of 2007-2009 by giving a double weight each on the data of years 2008 and 2009 relative to others.

4. Findings and Discussion

4.1 Analyses on Dynamic Two-Stage Network Efficiency

The average efficiencies of the two stages, namely, resource management (stage 1) and investment (stage 2), as well as their overall efficiencies with and without investment assets and investment income, are reported in Table 4. The average overall efficiency of those with the investment variables is slightly higher than that of those without the investment variables (0.387 vs. 0.417). An untabulated correlation coefficient between them is 0.829, which is significant at the 1% level. An efficient management of investment assets can thus increase the efficiency of insurance companies. This observation is attributable to the contribution from the investment efficiencies (0.564 vs. 0.467), whereby the majority (except five of them) of the average stage 2 efficiencies with the investment variables is larger than those without. Untabulated t-test (p-value = 0.014) and Mann–Whitney U test (p-value = 0.005) indicate that the stage 2 efficiencies with and without the investment variables are statistically different. By comparing the efficiencies on both sides, we find that insurance companies with high investment efficiency are more likely to perform well in the overall process.

[Insert Table 4 about here]

Further comparisons considering investment variables over the sample period are shown in Figure 2. On average, the investment efficiencies with and without the investment variables increased from 2008 to 2016. The investment efficiencies with the investment variables are all larger than those without the investment variables for every year, except for 2008. The gap between the two trends has been widening since 2013.

[Insert Figure 2 about here]

In summary, the investment efficiency with the investment variables are larger than those without, suggesting that investment assets of the sample insurance companies had considerable impacts on increasing their efficiencies during the sample period. Results for the overall and divisional efficiencies with investment variables and ranks are shown in Appendices A–C. Although the same weight for the two stages of efficiencies is used, the findings show that investment efficiency plays a key role in determining the rankings of insurance companies in terms of their overall performance. These results imply that when evaluating the performance of insurance companies, modeling investment assets as a carry-over variable in a dynamic two-stage network DEA model leads to improved discriminatory power of overall performance, particularly investment efficiency.

4.2 Regression Analyses

The insurance density in Malaysia, which is measured as premiums received divided by gross domestic product, is ranked first among the Association of Southeast Asian Nation countries. Therefore, examining the determinants of the performance of insurance companies in Malaysia is an important agenda. This examination can be a policy suggestion for insurance companies in other countries to learn from. We apply a two-step approach as performed in prior studies [for examples, 6, 8, 45] to examine whether insurance efficiency is also contributed by contextual variables. Specifically, we perform regression analyses by regressing overall efficiency on different types of financial ratios that explain an insurer's liquidity, activity, profitability, and leverage, as written below:

$$EFF_{it} = \alpha + \beta_1 LIQ_{it} + \beta_2 ACT_{it} + \beta_3 PROF_{it} + \beta_4 LEV_{it} + \varepsilon_{it}, \quad (8)$$

where *EFF* is the overall efficiency estimated with investment variables. *LIQ* represents liquidity ratio, which is measured as the ratio of current assets to total assets and is an indicator of whether companies can ensure survival and strengthen development based on solid foundations. *ACT* is the activity ratio, which is measured as the ratio of gross premiums received to total assets; it is an indicator of whether companies have dynamic abilities for survival and development. *PROF* is profitability ratio, which is measured as the ratio of net profits to total assets; it is an indicator of whether companies have adequate earnings for survival and development. *LEV* is leverage ratio, which is measured as the ratio of total liabilities to total assets; it is an indicator of whether companies can service their debt obligations. ε represents the residuals.

Table 5 presents the results of three regression approaches: Tobit, ordinary least squares (OLS), and panel least squares. First, we conduct a Tobit regression analysis based on Sueyoshi et al. [46], who find that this censored regression approach can model unbiased estimated coefficients in situations involving efficiency scores that lie between 0 and 1. Second, Hoff [47] documents that OLS and Tobit regressions work in the second phase of DEA application studies. Therefore, also in line with Banker and Natarajan [48], we rerun Equation (8) using OLS. The OLS results are obtained with heteroskedasticity-consistent standard errors [49]. Third, based on a Breusch–Godfrey serial correlation Lagrange multiplier test (F-statistic = 45.260, p-value = 0.000), we also estimate the regression model using panel least squares. A Hausman test (Chi-Squared Statistic = 7.898, p-value = 0.095) indicates that a fixed-effect model (FEM) should be the choice.

[Insert Table 5 about here]

The testing variables are found to have no potential multicollinearity problem, as indicated by the low values on the diagnostics of variance inflation factors (VIFs) and untabulated correlation analysis. The results obtained using the three techniques consistently reveal that liquidity (LIQ), profitability (PROF), and leverage (LEV) have considerably positive impacts on the performance of insurance companies during the sample period.

However, one of the testing variables, activity (ACT), may not have any direct effect on the overall efficiency because its p-values under the three techniques all exceed the 10% significance level. These results suggest that the sampled insurance companies should focus on improving their LIQ, PROF, and LEV to obtain satisfactory efficiencies.

4.3 Additional Analyses

In addition to efficiency evaluations and regression analyses, we further employ another multivariate analysis for performance evaluation and benchmarking of the insurance companies in a holistic and common setting. Specifically, we use cluster analysis and multidimensional scaling approaches to group the insurance companies based on their respective efficiencies and performance-related ratios. This decision allows us to visualize the main and similar characteristics of insurance companies, a visualization that is achieved in an easy to understand context for non-specialists. The regression analyses presented above provide us with the decision on the number of factors to be used for the clustering estimation. Given that the coefficient of activity ratio is below the conventional significance level, we consider only the resource management and investment efficiencies and the ratios of liquidity, profitability, and leverage in the complete data set, all of which contribute toward the performance of insurance companies. In Figure 3, we illustrate a dendrogram by using Ward's clustering algorithm [50], which maximizes homogeneity within a group and heterogeneity among groups.

[Insert Figure 3 about here]

Figure 3 clearly shows that A20 is the benchmark (Group 1) for companies in the insurance industry in Malaysia. The insurance companies A01, A03, A09, A10, A11, A19, A21, A27, and A30 form a cluster (Group 2), which is shown in the middle of Figure 4. On the top left-hand corner, another group comprises A02, A15, A25, and A28 (Group 3). The identified fourth group (Group 4) comprises A04, A05, A06, A07, A08, A12, A13, A14, A16, A17, A18, A22, A23, A24, A26, and A29.

[Insert Figure 4 about here]

To further verify the classification, we find that Group 1 not only has high efficiencies in both stages but also greater liquidity ratio, which reflects that the insurance company can survive and strengthen development based on solid foundations. Although the profitability ratio of Group 1 is the second lowest, its minimum leverage ratio suggests less pressure on servicing its debt obligations. However, Group 2 has completely utilized the advantages of undertaking debt to operate businesses to the benefit of improved resource management and investment efficiencies. However, the relatively low liquidity level can be an issue. Among these companies, A10, which achieves unity in both stages of efficiencies, can be the peer of reference for others in the group. This finding can also be evidenced by the high resource management efficiency achieved by those in Group 4 (0.513), which has higher leverage ratio (0.733) compared with those in Group 3 (0.236) with an average leverage ratio of 0.637.

[Insert Figure 5 about here]

5. Conclusions

This study proposes a dynamic two-stage network DEA model for evaluating corporate performance. We label inputted variables that are continuously held from one term to another as carry-over variables. These variables bring about a new insight to the two-stage network DEA model because they reflect dynamic components that are crucial for insurance companies' survival and development. We demonstrate the applicability of the proposed model by evaluating the resource management and investment efficiencies of 30 insurance companies in Malaysia from 2008 to 2016. Insurance companies are involved in risk-bearing and financial services and play an intermediation function. Our proposed model is designed to answer why investment assets are regarded as an inputted variable rather than an intermediate variable that links stage 1 to stage 2, as argued by Wu et al. [6].

In our empirical examination, we find that insurance companies with relatively satisfactory investment efficiency have satisfactory overall efficiencies. Our results reveal that modeling investment assets as a carry-over variable in a dynamic two-stage network DEA model brings about the improved discriminatory power of investment efficiency. An important implication of this research result is if insurance companies focus on the dynamics of their investment assets, they are in a better position of building business competitiveness over long-term periods. Specifically, with this model, insurance managers and policy makers can better decide on the importance of investment efficiency and comprehensively understand performance measures from multiple inputs and outputs and multicriteria analyses, all of which will ultimately enhance their competitive edge. The continuous efficiency and success of insurance businesses requires not only rich resources such as managerial inputs, but also the financial dynamics of investment assets. This finding is again evidenced when activity ratio is found to have no impact on the overall efficiency. Activity ratio is an indicator of whether companies possess dynamic abilities for survival and development, that is, the inclusion of carry-over variables has captured the dynamic performance of the sampled insurance companies during the sample period. Specifically, liquidity, profitability, and leverage components are considered key contributors to their corporate performance, particularly resource management and investment. Insurance companies that strive to outperform their counterparts must ensure that all these factors are carefully and thoroughly assessed.

In summary, as pointed out in the introduction, this study considers a carry-over variable from the financial accounting/reporting perspective, particularly the going-concern concept [43], whereby investment assets are accumulated and carried forward from one financial term to another on the balance sheet in this study. We suggest that future studies may take into consideration the final outputs and carry-overs jointly based on Fukuyama and Weber [30, 31] for a dynamic model that could allow decision makers to choose the amount of balance-sheet items to carry forward.

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Table 1. Correlation matrix of input and output variables

	MExp	*FAsset*	*ICAR*	*IAsset*	*PE*	*IIncome*
MExp	1.000					
FAsset	0.508	1.000				
ICAR	0.765	0.669	1.000			
IAsset	0.781	0.668	0.997	1.000		
PE	0.914	0.603	0.911	0.915	1.000	
IIncome	0.781	0.733	0.983	0.986	0.904	1.000

Notes: All the correlation coefficients are significant at the 1% significance level. *MExp* refers to the operating expenses used in labor and business services; *FAsset* is the properties, plants, and equipment accumulated from one period to another; *ICAR* denotes the total claims/benefits disbursed plus generated funds not intended for claims/benefits; *IAsset* is the real value of all financial investments; *PE* is advanced premiums earned and thus belongs to the insurance companies; and *IIncome* is the corresponding returns of investment assets.

Table 2. Regression results on the relevance of variables

Outputs / Inputs	Stage 1: log(*ICAR*)	Stage 2: log(*PE*)	Stage 2: log(*IIncome*)
Constant	−5.945***	7.111***	0.040
	(−4.294)	(13.739)	(0.080)
log(*MExp*)	1.112***		
	(11.322)		
log(*FAsset*)	0.381***		
	(7.025)		
log(*ICAR*)		0.199***	0.229***
		(2.871)	(3.394)
log(*IAsset*)		0.414***	0.630***
		(5.166)	(8.071)
Adj. R^2	0.646	0.742	0.855
F-statistic	246.017***	387.907***	790.956

Notes: *** denotes the 1% significance level. *MExp* refers to the operating expenses used in labor and business services; *FAsset* is the properties, plants, and equipment accumulated from one period to another; *ICAR* refers to the total claims/benefits disbursed plus generated funds not intended for claims/benefits; *IAsset* is the real value of all financial investments; *PE* is advanced premiums earned and thus belongs to the insurance companies; and *IIncome* is the corresponding returns of investment assets.

Table 3. Mean values of input and output variables (MYR millions)

Year	*MExp*	*FAsset*	*ICAR*	*IAsset*	*PE*	*IIncome*
2008	714,453	908,668	33,463,746	28,730,558	5,317,577	1,768,003
2009	848,619	909,157	39,575,517	34,932,086	6,091,674	1,808,561
2010	989,100	620,873	48,881,459	43,972,884	8,415,540	1,898,809
2011	1,076,406	670,348	50,924,413	47,866,474	9,093,036	2,064,076
2012	1,290,965	684,750	55,563,723	54,048,612	10,132,293	2,427,180
2013	1,466,206	660,468	64,070,214	63,915,783	11,458,591	2,766,734
2014	1,618,541	703,878	68,196,832	68,272,799	13,138,506	2,900,782
2015	1,800,193	730,086	71,133,132	71,340,308	13,431,106	3,136,683
2016	1,973,534	805,624	74,575,305	74,377,331	14,176,929	3,305,224
Overall	1,308,669	743,761	56,264,927	54,161,871	10,139,472	2,452,895

Notes: The variables are the present values derived by dividing the respective values by Malaysia's 2008 Consumer Price Index. *MExp* refers to the operating expenses used in labor and business services; *FAsset* is the properties, plants, and equipment accumulated from one period to another; *ICAR* refers to the total claims/benefits disbursed plus generated funds not intended for claims/benefits; *IAsset* is the real value of all financial investments; *PE* is advanced premiums earned and thus belongs to the insurance companies; and *IIncome* is the corresponding returns of investment assets.

Table 4. Overall and divisional efficiencies with and without investment variables

Insurer	Average efficiencies without investment variables			Average efficiencies with investment variables		
	Overall	Stage 1	Stage 2	Overall	Stage 1	Stage 2
A01	0.204	0.676	0.641	0.457	0.777	0.700
A02	0.446	0.379	0.667	0.311	0.171	0.744
A03	0.633	0.399	0.858	0.487	0.528	0.645
A04	0.455	0.747	0.394	0.194	0.437	0.515
A05	0.312	0.471	0.300	0.308	0.357	0.361
A06	0.276	0.825	0.303	0.112	0.694	0.273
A07	0.297	0.795	0.206	0.180	0.283	0.326
A08	0.329	0.484	0.299	0.218	0.326	0.550
A09	0.298	0.406	0.578	0.509	0.683	0.699
A10	1.000	1.000	1.000	1.000	1.000	1.000
A11	0.605	0.631	0.682	0.676	0.647	0.775
A12	0.441	0.516	0.421	0.269	0.371	0.461
A13	0.400	0.739	0.384	0.363	0.851	0.435
A14	0.130	0.531	0.333	0.254	0.316	0.367
A15	0.527	0.333	0.678	0.386	0.268	0.835
A16	0.300	0.729	0.211	0.130	0.480	0.231
A17	0.323	0.756	0.301	0.106	0.584	0.284
A18	0.296	0.706	0.220	0.249	0.440	0.579
A19	0.546	0.999	0.663	0.746	1.000	0.816
A20	0.785	1.000	0.824	0.938	1.000	0.947
A21	0.948	0.913	0.984	0.950	0.901	1.000
A22	0.256	0.918	0.282	0.110	0.809	0.285
A23	0.363	0.781	0.276	0.121	0.541	0.264
A24	0.293	0.656	0.241	0.265	0.316	0.317
A25	0.445	0.350	0.500	0.505	0.245	0.777
A26	0.417	0.617	0.386	0.445	0.469	0.466
A27	0.314	0.964	0.468	0.186	0.967	0.535
A28	0.138	0.585	0.210	0.284	0.260	0.733
A29	0.272	0.538	0.250	0.226	0.475	0.217
A30	0.461	0.574	0.443	0.633	0.476	0.790
Average	0.417	0.667	0.467	0.387	0.556	0.564

Table 5. Determinants of the performance of insurance companies (N = 270)

	Tobit regression		OLS regression		FEM regression		VIF
	Coefficient	z-statistic	Coefficient	t-statistic	Coefficient	t-statistic	
Constant	0.073	0.490	0.107	0.805	0.105	1.038	
LIQ	0.370***	6.101	0.194***	10.232	0.281***	4.265	1.313
ACT	-0.155	-1.107	-0.102	-0.760	0.036	0.419	1.882
PROF	1.402***	2.952	0.935***	3.784	0.641*	1.780	1.442
LEV	0.658***	4.129	0.588***	4.222	0.540***	4.715	1.772
Log likelihood	-91.557						
Adj. R-squared			0.101		0.300		
F-statistic			8.586***		10.591***		

Notes: * and *** denote the 10% and 1% significance levels, respectively. The dependent variable is the overall efficiency estimated with investment variables; *LIQ* represents liquidity ratio, which is measured as the ratio of current assets to total assets; *ACT* refers to activity ratio, which is measured as the ratio of gross premiums received to total assets; *PROF* denotes profitability ratio, which is measured as the ratio of net profits to total assets; and *LEV* is leverage ratio, which is measured as the ratio of total liabilities to total assets.

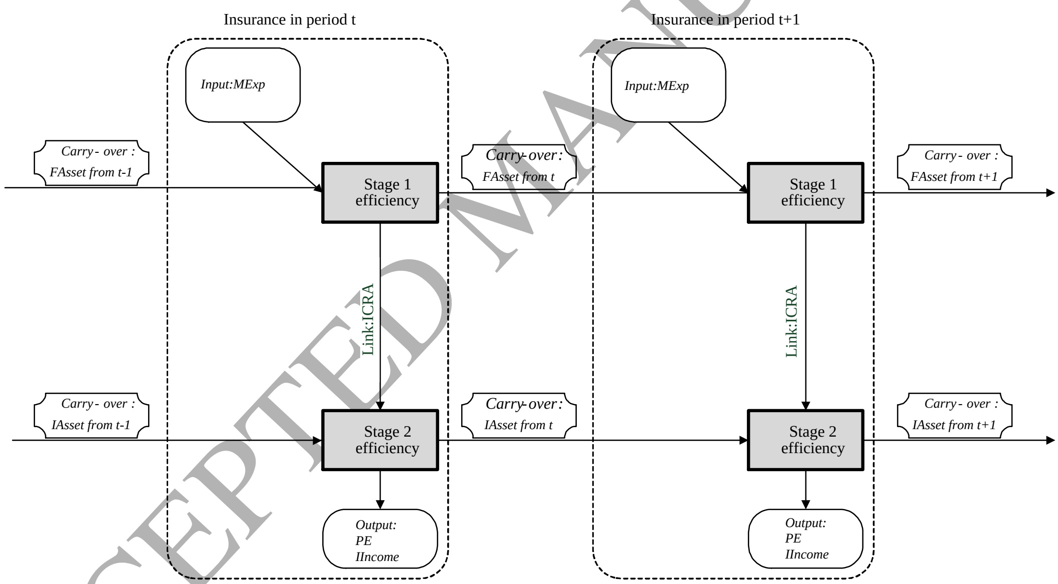
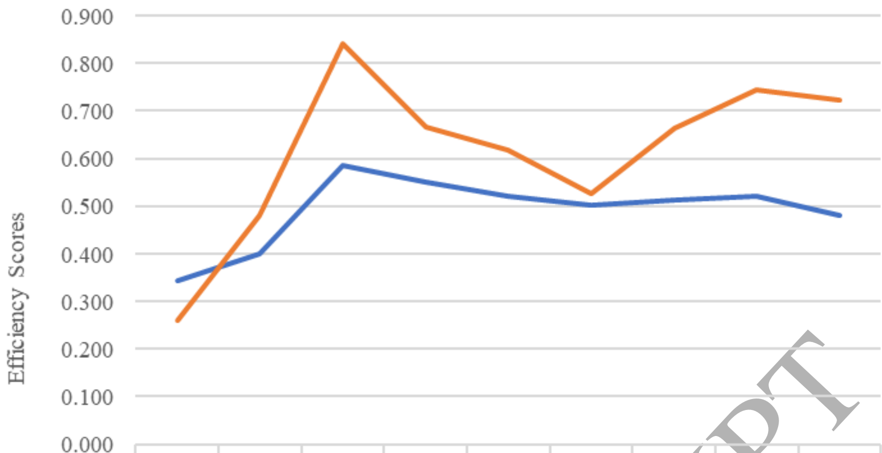


Figure 1. Dynamic two-stage network production process of insurance companies



	2008	2009	2010	2011	2012	2013	2014	2015	2016
Without investment variables	0.343	0.400	0.584	0.549	0.520	0.502	0.514	0.520	0.482
With investment variables	0.259	0.479	0.841	0.667	0.618	0.527	0.662	0.743	0.722

Figure 2. Cumulative investment efficiencies over the sample period

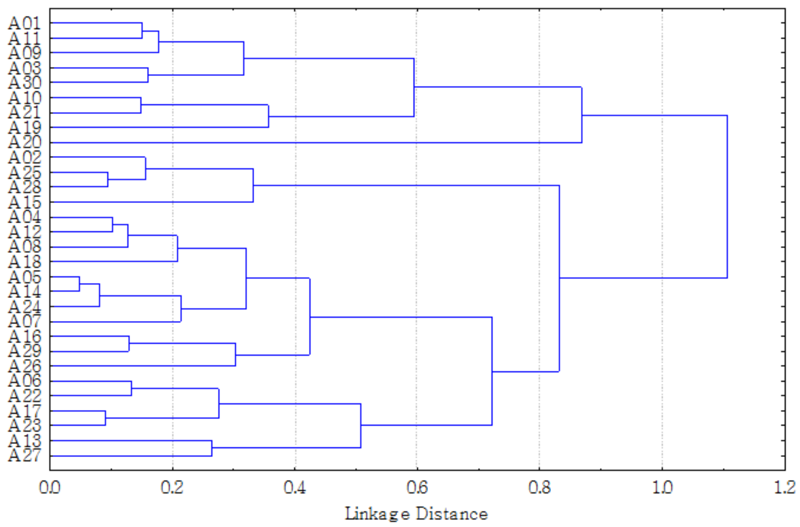


Figure 3. Dendrogram for cluster analysis of insurance companies

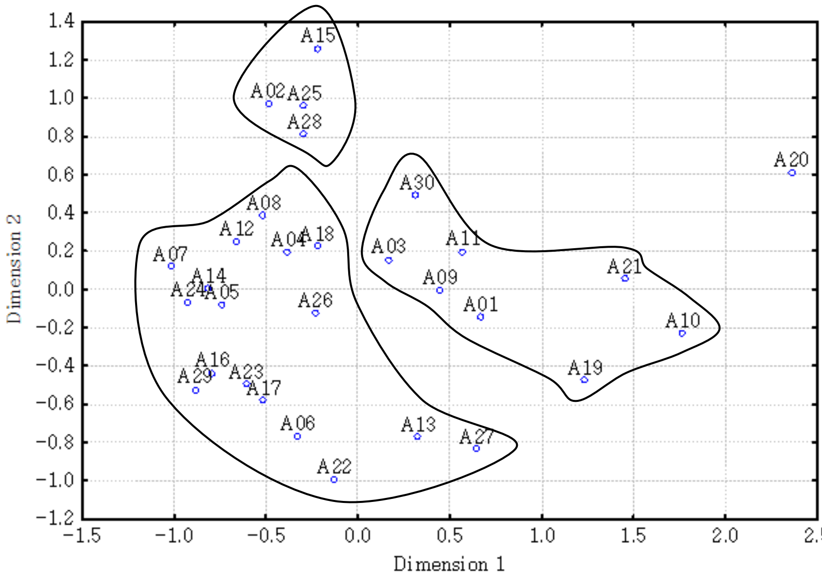
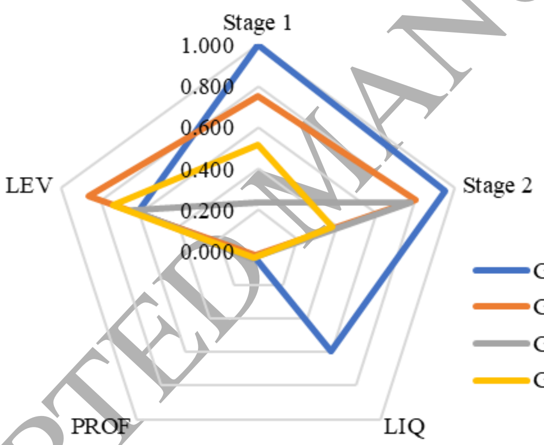


Figure 4. Common map of multidimensional scaling analysis



	Stage 1	Stage 2	*LIQ*	*PROF*	*LEV*
Group 1	1.000	0.947	0.595	0.027	0.610
Group 2	0.751	0.803	0.015	0.022	0.861
Group 3	0.236	0.772	0.022	0.042	0.637
Group 4	0.513	0.380	0.018	0.036	0.733

Figure 5. Radar map of average strengths of the insurance companies

Appendix A. Overall efficiencies

Insurer	2008	2009	2010	2011	2012	2013	2014	2015	2016	Overall	Rank
A01	0.182	0.401	0.989	0.999	0.871	1.000	0.813	0.821	0.737	0.457	10
A02	0.107	0.561	0.550	0.454	0.451	0.589	0.575	0.608	0.597	0.311	14
A03	0.202	0.496	0.752	0.613	0.626	0.775	0.797	0.821	0.709	0.487	9
A04	0.395	0.073	0.643	0.554	0.564	0.190	0.420	0.489	0.485	0.194	23
A05	0.103	0.300	0.638	0.443	0.377	0.349	0.428	0.434	0.397	0.308	15
A06	0.042	0.057	0.653	0.406	0.266	0.282	0.634	0.766	0.710	0.112	28
A07	0.069	0.284	0.454	0.345	0.295	0.164	0.367	0.441	0.414	0.180	25
A08	0.071	0.608	0.638	0.416	0.368	0.204	0.468	0.574	0.618	0.218	22
A09	0.226	0.382	1.000	1.000	0.814	0.776	0.757	0.746	0.748	0.509	7
A10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A11	0.252	0.605	0.898	0.809	0.891	0.792	0.884	0.949	0.947	0.676	5
A12	0.117	0.327	0.760	0.458	0.448	0.274	0.458	0.505	0.556	0.269	17
A13	0.144	0.503	0.819	0.775	0.667	0.519	0.634	0.653	0.574	0.363	13
A14	0.096	0.173	0.549	0.433	0.518	0.430	0.388	0.458	0.438	0.254	19
A15	0.143	0.652	0.632	0.602	0.604	0.653	0.638	0.653	0.630	0.386	12
A16	0.069	0.082	0.484	0.371	0.250	0.168	0.431	0.521	0.465	0.130	26
A17	0.058	0.064	0.738	0.322	0.274	0.193	0.432	0.556	0.546	0.106	30
A18	0.084	0.698	0.709	0.678	0.475	0.173	0.482	0.656	0.459	0.249	20
A19	1.000	1.000	1.000	0.681	0.413	0.338	1.000	1.000	1.000	0.746	4
A20	1.000	1.000	1.000	0.571	1.000	1.000	1.000	1.000	1.000	0.938	3
A21	0.822	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.819	0.950	2
A22	0.056	0.067	1.000	0.260	0.180	0.118	0.435	0.669	0.703	0.110	29
A23	0.063	0.079	0.662	0.383	0.231	0.146	0.478	0.483	0.517	0.121	27
A24	0.139	0.253	0.619	0.346	0.340	0.212	0.330	0.418	0.361	0.265	18
A25	0.623	0.600	0.599	0.437	0.346	0.325	0.564	0.492	0.462	0.505	8
A26	0.217	0.443	0.750	0.555	0.535	0.463	0.512	0.501	0.476	0.445	11
A27	0.064	0.086	0.863	1.000	1.000	1.000	0.461	1.000	0.900	0.186	24
A28	0.087	0.420	0.653	0.615	0.641	0.627	0.640	0.650	0.654	0.284	16
A29	0.136	0.179	0.649	0.335	0.321	0.260	0.246	0.320	0.288	0.226	21
A30	0.331	0.536	0.644	0.624	0.555	0.843	0.766	0.988	1.000	0.633	6
Average	0.263	0.431	0.745	0.583	0.544	0.495	0.601	0.672	0.640	0.387	

Appendix B. Resource-management efficiencies – stage 1

Insurer	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average	Rank
A01	0.854	0.689	0.978	0.999	0.742	1.000	0.626	0.643	0.474	0.777	8
A02	0.104	0.121	0.230	0.181	0.199	0.271	0.150	0.215	0.193	0.171	30
A03	0.302	0.364	0.702	0.448	0.477	0.640	0.757	0.811	0.690	0.528	14
A04	0.620	1.000	0.420	0.107	0.128	0.211	0.150	0.256	0.203	0.437	20
A05	0.233	0.332	0.472	0.371	0.306	0.324	0.503	0.461	0.381	0.357	22
A06	0.610	0.539	0.598	0.518	0.515	0.737	1.000	1.000	1.000	0.694	9
A07	0.248	0.290	0.384	0.258	0.286	0.267	0.261	0.321	0.267	0.283	26
A08	0.279	0.215	0.276	0.299	0.349	0.283	0.401	0.477	0.531	0.326	23
A09	0.614	0.798	1.000	1.000	0.628	0.552	0.515	0.492	0.496	0.683	10
A10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A11	0.357	0.487	0.795	0.617	0.781	0.728	0.768	0.899	0.893	0.647	11
A12	0.399	0.392	0.574	0.272	0.276	0.321	0.363	0.351	0.336	0.371	21
A13	1.000	0.948	0.957	0.888	0.760	0.669	0.753	0.755	0.655	0.851	6
A14	0.123	0.267	0.402	0.345	0.393	0.357	0.295	0.490	0.447	0.316	24
A15	0.259	0.304	0.264	0.204	0.208	0.305	0.277	0.306	0.259	0.268	27
A16	0.535	0.405	0.515	0.360	0.365	0.436	0.536	0.612	0.574	0.480	15
A17	0.764	0.808	0.889	0.311	0.332	0.370	0.430	0.435	0.468	0.584	12
A18	0.380	0.395	0.418	0.356	0.310	0.421	0.463	0.654	0.684	0.440	19
A19	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A20	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A21	0.644	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.638	0.901	5
A22	0.991	1.000	1.000	0.443	0.681	0.657	0.728	0.666	0.690	0.809	7
A23	0.646	0.609	0.718	0.480	0.385	0.436	0.454	0.515	0.430	0.541	13
A24	0.160	0.396	0.421	0.215	0.320	0.262	0.366	0.414	0.374	0.316	25
A25	0.246	0.200	0.311	0.231	0.230	0.265	0.292	0.260	0.216	0.245	29
A26	0.279	0.644	0.771	0.522	0.514	0.400	0.368	0.383	0.358	0.469	18
A27	0.856	0.988	1.000	1.000	1.000	1.000	0.960	1.000	1.000	0.967	4
A28	0.206	0.249	0.306	0.231	0.281	0.254	0.280	0.300	0.308	0.260	28
A29	0.425	0.457	0.664	0.489	0.453	0.450	0.542	0.487	0.380	0.475	17
A30	0.193	0.260	0.289	0.249	0.277	0.773	0.803	1.000	1.000	0.476	16
Average	0.511	0.572	0.645	0.513	0.506	0.546	0.568	0.607	0.565	0.556	

Appendix C. Investment efficiencies – stage 2

Insurer	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average	Rank
A01	0.103	0.311	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.700	11
A02	0.107	1.000	0.825	0.683	0.644	0.862	1.000	1.000	1.000	0.744	9
A03	0.181	0.571	0.801	0.779	0.776	0.909	0.836	0.830	0.727	0.645	13
A04	0.276	0.026	0.828	1.000	1.000	0.184	0.659	0.723	0.760	0.515	17
A05	0.072	0.288	0.803	0.496	0.417	0.362	0.392	0.421	0.404	0.361	22
A06	0.026	0.035	0.701	0.323	0.191	0.184	0.435	0.582	0.524	0.273	27
A07	0.058	0.282	0.500	0.433	0.298	0.144	0.454	0.556	0.555	0.326	23
A08	0.059	1.000	1.000	0.514	0.376	0.187	0.526	0.653	0.676	0.550	15
A09	0.139	0.269	1.000	0.999	1.000	1.000	1.000	1.000	1.000	0.699	12
A10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A11	0.195	0.686	1.000	1.000	1.000	0.847	1.000	1.000	1.000	0.775	8
A12	0.090	0.303	0.945	0.642	0.620	0.254	0.536	0.634	0.724	0.461	19
A13	0.071	0.322	0.709	0.675	0.594	0.433	0.549	0.576	0.516	0.435	20
A14	0.092	0.154	0.673	0.497	0.632	0.483	0.446	0.441	0.433	0.367	21
A15	0.128	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.835	4
A16	0.047	0.060	0.459	0.382	0.217	0.124	0.353	0.444	0.396	0.231	29
A17	0.032	0.033	0.590	0.334	0.250	0.152	0.434	0.677	0.625	0.284	26
A18	0.065	1.000	1.000	1.000	0.596	0.134	0.497	0.659	0.368	0.579	14
A19	1.000	1.000	1.000	0.463	0.259	0.203	1.000	1.000	1.000	0.816	5
A20	1.000	1.000	1.000	0.400	1.000	1.000	1.000	1.000	1.000	0.947	3
A21	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
A22	0.029	0.035	1.000	0.191	0.119	0.076	0.302	0.671	0.714	0.285	25
A23	0.040	0.049	0.613	0.300	0.197	0.109	0.499	0.459	0.602	0.264	28
A24	0.136	0.201	0.781	0.438	0.350	0.198	0.310	0.421	0.354	0.317	24
A25	1.000	1.000	0.872	0.627	0.414	0.356	0.816	0.724	0.679	0.777	7
A26	0.187	0.344	0.732	0.581	0.550	0.502	0.615	0.582	0.557	0.466	18
A27	0.031	0.039	0.759	1.000	1.000	1.000	0.307	1.000	0.802	0.535	16
A28	0.077	0.506	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.733	10
A29	0.097	0.122	0.635	0.245	0.250	0.184	0.154	0.254	0.254	0.217	30
A30	0.431	0.741	1.000	1.000	0.779	0.910	0.738	0.977	1.000	0.790	6
Average	0.259	0.479	0.841	0.667	0.618	0.527	0.662	0.743	0.722	0.564	