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Intellectual capital and performance in the Chinese life insurance industry

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ABSTRACT

This study applies the dynamic slack-based measure (DSBM) model to evaluate the performance of 34 Chinese life insurance companies for the period 2006–2010. This study also examines the relationship between intellectual capital and performance using the truncated regression approach. Our findings indicate that over the period of the study, the mean efficiency scores of life insurers are relatively stable, ranging from 0.905 to 0.973. We verify that the efficiency scores of the DSBM model differ significantly from those of the traditional data envelopment analysis (DEA) model, which supports the use of the DSBM model. Our regression analysis reveals that intellectual capitals are significantly positively associated with firm operating efficiency. Our findings corroborate prior studies which show that intellectual capital can make a company rich. In this dynamic business world, life insurers' managers should invest and fully utilize intellectual capital to gain a competitive advantage.

1. Introduction

Since economic reforms were carried out in China, the Chinese insurance industry has grown rapidly. China's fastest-growing economy has grabbed worldwide attention, yet its overall growth rate has been dwarfed by that of the Chinese insurance industry. The Chinese life insurance market experienced particularly strong growth from 2007 to 2010. In 2011, the industry recorded a 6.8% rise in premium income, reaching RMB 969.98 billion (about USD 154 billion) [2], and it is expected to have a value of USD 237.5 billion in 2015, an increase of 66.3% over 2010. The largest segment of the Chinese insurance market is life insurance, accounting for 97.3% of the market's total value [3]. This segment has grown significantly with the number of life insurers increasing from 29 in 2004 to 61 in 2010.[2]

The Chinese insurance industry indeed holds enormous potential and offers opportunities to international insurers equipped with expertise and scale economies [4]. Nevertheless, mounting competition has caused domestic insurers to lose their advantage in efficiency. As a result, the gap between domestic and foreign insurers has narrowed since 2005 [5]. Yao et al. [6] point out that low productivity and low efficiency could stop the Chinese insurance industry from developing further. Many academicians and practitioners have studied whether efficient growth and development exist in the industry. Specifically, a considerable number of extant studies have investigated the performance of the industry by applying the data envelopment analysis (DEA) approach [7–9]. Overall, prior literature suggests that the DEA technique is a valuable addition to traditional methods such as ratio analysis, because DEA is able to compare companies' multiple input–output data [10–17]. For a company that operates in a multidimensional setting, aggregating a set of financial ratios can be complicated and require imagination and experience [10,15,17]. Another advantage of DEA is that it does not require any distributional assumptions.

However, none of the prior studies specifically investigated the operating efficiency of a life insurer using a dynamic production process. In today's dynamic business world, life insurance companies must focus on changes in operating performance over long time periods. The capital[3] allocation and planning processes are of central importance for life insurance companies [18]. Efficient resource allocation can provide a life insurer with a competitive advantage that can sustain its business over time. Several methods such as window analysis [19] and the Malmquist index [20] are effective for evaluating efficiency changes over time. However, to deal with the long-term dynamic process of a company, the dynamic slack-based measure (DSBM) model developed by Tone

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[1] Tel.: +886 3 463 8800x2589; fax: +886 3 463 3845.
[2] We obtained the statistics from the website of China Insurance Regulatory Commission (CIRC).

[3] Capital is a type of resource that is carried over from one term to another.

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and Tsutsui [21] is particularly suitable because it incorporates carry-over activities into the model and enables researchers to measure period-specific efficiency based on long time optimization [20–24]. Thus, this paper aims to examine the operating efficiency of China's insurance companies using the DSBM model in the first stage.

In the Chinese insurance industry, a lot of talent and technical know-how have been outsourced [25]. The industry is a knowledge-intensive industry that has to count on intellectual capital (IC) for continuous growth since insurers equipped with IC are more competitive [4]. IC is the key success factor for a company's success [26–28]. Thus, companies should focus on IC management to maximize long-run corporate wealth [29–31].

While there are various application areas in the insurance industry [7–9], no other published study has reported an association between IC and the operating efficiency of life insurers.[4] In this study, we employ the Value Added Intellectual Coefficient (VAIC™) to measure IC. To further investigate whether Chinese insurance companies are able to improve their efficiency through IC investment, this paper utilizes truncated regression with a bootstrapping procedure introduced by Simar and Wilson [32,33], which better describes the efficiency scores in the second-stage regression analysis.

Although research on insurers' efficiency has been increasing, this is the first paper to employ the DSBM model to evaluate the efficiency performance of Chinese life insurers by using a dynamic process. Furthermore, we are the first to apply Simar and Wilson's [32,33] approach to testing the relationship between intellectual capital and firm operating efficiency for the Chinese life insurance industry. Our analysis is particularly relevant to life insurers' managers, who may be interested in knowing whether investment in intellectual capital serves as a key performance driver.

The study is also significant in that it may provide insights into potential avenues of policy improvement. Since utilizing IC is essential to improve efficiency, policy makers, who are capable of influencing the direction of the Chinese life insurance business environment, may make changes to the existing policies to promote the development of IC in the life insurance industry. Even more significant, policy makers may promote greater understanding of the IC concept to increase investment planning policy at the corporate level. Since the contribution of the life insurance industry to China's economic growth is substantial, continuous investment in IC by Chinese life insurers may have positive consequences.

The remainder of this study proceeds as follows. Section 2 presents a review of the literature, followed by hypotheses development, while Section 3 describes the methodology and procedures adopted for data collection. The empirical results of the various analyses are presented in Section 4. Finally, conclusions are presented and suggestions are made for further research.

2. Literature review

2.1. Efficiency in the insurance industry

Efficiency measurement of the insurance industry is one of the most rapidly growing areas of research [12]. The econometric approaches and the mathematical programming approaches are the two frontier efficiency techniques available for efficiency measurement [7,34]. The DEA approach is a mathematical programming approach, while stochastic frontier analysis (SFA) is an econometric approach. Although both the econometric and mathematical programming approaches have their advantages and disadvantages, Eling and Luhnen [35] find that the results obtained using the DEA approach differs slightly from those obtained using SFA for 6462 insurers in 36 countries. Similarly, Cummins and Zi [34] apply a wide range of econometric and mathematical programming techniques to a sample of US life insurers and found that the results obtained using the DEA and FDH mathematical programming methodologies differ significantly. No conclusive evidence exists to show which assessment approach is superior [34].

Fecher et al. [36] use the DEA approach and SFA to analyze 84 life and 243 non-life insurance companies in France from 1984 to 1989, and their results show a high correlation between the two measurement approaches. Fenn et al. [37] apply a procedure developed by Kumbhakar and Lovell [38] to control for the impact of potential heteroskedasticity in order to overcome the weakness of SFA. Drawing on European insurance company data from 1995 to 2001, Fenn et al. [37] show that most European insurers operate at increasing returns to scale. Yuengert [39] also employs SFA to estimate the efficiency of US life insurance companies.

In addition, contemporary studies on the insurance industry have widely used the DEA model to evaluate firm performance [5,21,40–45]. In 95 surveyed papers focusing on the insurance industry, the DEA approach was most frequently applied, followed by SFA [7]. Using the DEA model, Fukuyama [46] investigates the productive efficiency and productivity changes of Japanese life insurance companies from 1988 to 1993, and finds that mutuals and stocks had identical technology. Barros et al. [47] study the effects of deregulation on the efficiency of the Greek insurance industry using the two-stage procedure of Simar and Wilson [32], wherein the efficiency is estimated using the DEA approach.

The traditional DEA model, nevertheless, cannot be applied to assess long-term efficiency changes because it ignores the effect of carry-over activities[5] between two consecutive terms. As such, the dynamic DEA model,[6] which provides a more accurate measurement of time-specific dynamic efficiencies over long time periods, is more appropriate than a single period static evaluation [21]. In contrast to the radial models that assume proportional changes in inputs or outputs, the DSBM model developed by Tone and Tsutsui [21] is a non-radial dynamic DEA model that can deal individually with inputs, outputs, and carry-overs. Furthermore, the DSBM model allows carry-over activities to be categorized into four types: desirable, undesirable, discretionary, and non-discretionary. Up to this point, no research has used dynamic DEA to evaluate the corporate performance of insurance companies.

2.2. Overview of the Chinese life insurance industry

The Chinese life insurance industry is often described as having experienced rapid expansion over the past decade, with life insurance premiums increasing from RMB 406 billion in 2006 to approximately RMB 1.05 trillion in 2010. Records show that the growth rate was a remarkable 158%. During the same period, the number of life insurance companies increased from 45 to 61. Increasing demand and the immaturity of the industry all explain the strong growth and the potential of the Chinese life insurance industry to help drive China's growing economy.

Since China's accession to the World Trade Organization (WTO) on 11 December 2001 [50], it has experienced an influx of foreign insurance companies. Most restrictions on ownership and

[4] For the other application areas, refer to Eling and Luhnen [7] for an overview.

[5] For example, fixed assets of an insurer are carried forward from one period to another continuously.

[6] Färe and Grosskopf [48] are the first innovative scholars who formally deal with inter-connecting activities. Dynamic DEA has been used to examine efficiency performance in industries other than the insurance industry [22–24,49].

business scope were abolished by the end of 2004. However, foreign life insurers still face huge barriers in terms of ownership, in that they are only allowed to enter the Chinese life insurance industry by setting up a joint venture with a local counterpart or by holding a maximum 50% share in a joint venture. In other words, the Chinese life insurance industry is still dominated by local life insurers, with China Life Insurance Co., Ltd. commanding a market share of around 45% in 2006. The concentration ratio of the top 5 Chinese life insurers in 2006 was approximately 92%. This is supported by the relatively high Herfindahl index in 2006 of 0.254.

Enticed by the great potential of China's life insurance market, foreign life insurers have made significant inroads. Evidently, the concentration ratio of the top 5 Chinese life insurers dropped from 92% in 2006 to about 73% in 2010. The Herfindahl index also dropped from 0.254 in 2006 to 0.154 in 2010. This implies that the competitive environment faced by the Chinese life insurers has intensified. The flood of foreign life insurers into China has also had positive impacts such as inflows of knowledge and skills. Indirectly, the greater level of competition has encouraged innovation and positive development in the industry.

3. Research design

3.1. Dynamic production process for a life insurance company

In today's dynamic business environment, life insurance companies must focus on changes in operating performance over long time periods since capital allocation is the main economic process in an insurance company [18]. According to the going-concern concept in accounting, a business will operate continuously over long time periods. A firm operating on a continuum basis will have not only current periodic inputs and outputs but also carry-over items from one term (t) to the next term ($t+1$). For instance, a company will accumulate and carry forward its fixed assets from one time period to another continuously. In accounting, such items are referred to as permanent accounts [51,52].

Beginning with the accounting cycle, we investigate the dynamic process of a life insurer from the operational point of view. Fig. 1 depicts the dynamic production process of this study. The inputs for each term are labor and business services, debt capital, and equity capital, where both debt capital and equity capital represent the carry-over activities or permanent accounts. Incurred benefits plus additions to reserves and investment profits are the outputs for each term.

As discussed in the study by Eling and Luhnen [7], the three main insurance inputs are labor, business services and materials, and capital. In this study, we use operating expenses to proxy for labor, and business services and materials. Following Eling and Luhnen [35], we maintain that both labor and business services are combined and treated as a single input due to data unavailability. Consistent with prior studies [35,45,53,54], both debt capital and equity capital make up the total capital. For the determination of output variables, we apply the value-added approach (also known as the production approach), in line with prior studies [35,55,56]. Yuengert [39] argues that the real value of real incurred losses is a good proxy for both the risk-pooling/risk-bearing function and financial services. We thus add incurred benefits plus additions to reserves as one of the outputs. The second output included is

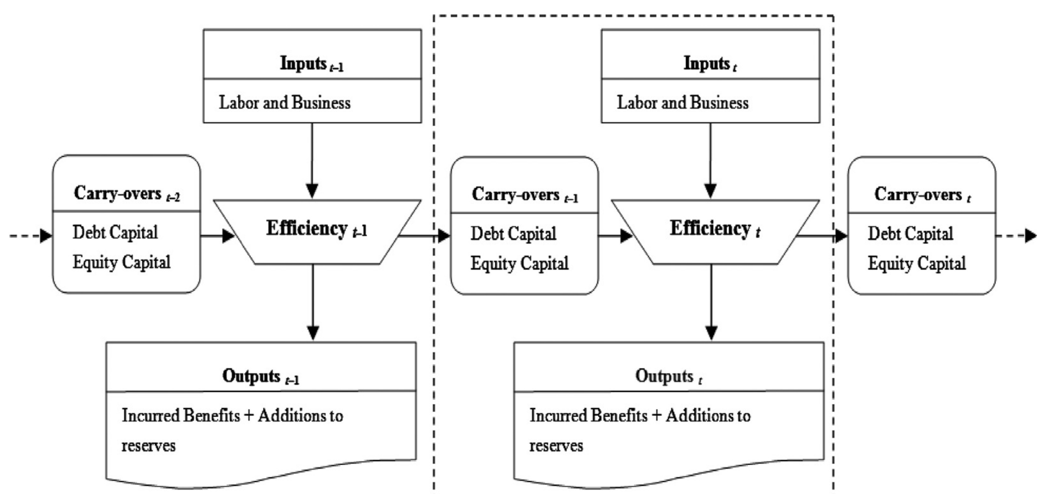

Fig. 1. The dynamic business process.

Table 1
Definitions of inputs and outputs.

Variable	Definition	Carry-over (Y/N)
Inputs		
Labor and business service	The various types of expenses incurred in daily operation	N
Debt capital	The year-end total amount of liabilities from the balance sheet	Y
Equity capital	The year-end total amount of owner's equity from the balance sheet	Y
Outputs		
Incurred benefits plus additions to reserves	Incurred benefits refer to payments received by policyholders in the current year. Additions to reserves are the funds received by insurers not needed for benefit payments and expenses that are added to policy reserves	N
Investment profits	Profits earned from the investment portfolio	N

Note: All variables are measured in RMB million.

investment profit. Following Kao and Hwang [44], we use investment profit to proxy for the intermediation function. Table 1 presents an overview of the inputs, outputs, and carry-overs used in this study.

3.2. Data collection and summary statistics

In this study, we obtain: (i) input and output data, and IC-related data from the Yearbook of China's Insurance published by the Editorial Department of China's Insurance Yearbook [57]; and (ii) public information published on the websites of life insurance companies, including annual income statements, balance sheets, industry segments, and supplemental data. We use balanced panel data, covering the period 2006–2010, of 34 Chinese life insurance companies (170 firm-year observations). We deflate all variables to 2006, using the China's Consumer Price Index (CPI) (2006 = 101.5), which we obtain from the 2007 China Statistical Yearbook.

Table 2 provides the descriptive statistics of the inputs and outputs used for the period 2006–2010. On average, the inputs and outputs increased gradually over these years. The standard deviations of the variables reveal that the sample life insurers do not cluster in any specific operating characteristics. Whether or not the life insurers efficiently utilize their resources to generate maximum outputs is an important issue.

Table 3 summarizes the Pearson correlation coefficients of the input and output variables. The findings show that there are significantly positive relations between the input and output variables, meaning that an increase in the inputs would result in an increase in the outputs, thus fulfilling the assumption for DEA on the characteristics of 'isotonicity' relations. Therefore, the number of sample companies should be at least twice the sum of the input and output variables [58]. This study meets the criterion with five variables and 34 life insurers. Taken together, the validity of the DEA model is established in this study.

Table 2
Summary statistics of inputs and outputs ($N = 34$ life insurers).

Variable	Mean	SD
Year 2006		
Labor and business service	10,562.49	6646.91
Debt capital	22,773.40	80,932.47
Equity capital	2388.26	10,714.18
Incurred benefits plus additions to reserves	7582.14	24,594.15
Investment profits	1531.88	5451.70
Year 2007		
Labor and business service	14,819.26	43,613.26
Debt capital	30,846.70	103,850.49
Equity capital	3789.92	16,884.62
Incurred benefits plus additions to reserves	10,015.11	25,825.00
Investment profits	4617.32	16,089.67
Year 2008		
Labor and business service	19,278.07	58,562.92
Debt capital	40,416.77	129,149.23
Equity capital	6492.01	29,266.71
Incurred benefits plus additions to reserves	12,915.76	41,132.51
Investment profits	2774.38	9514.20
Year 2009		
Labor and business service	18,365.53	53,572.92
Debt capital	50,672.30	152,650.87
Equity capital	5442.59	23,343.38
Incurred benefits plus additions to reserves	1125.03	20,595.46
Investment profits	3431.24	11,118.01
Year 2010		
Labor and business service	24,258.82	63,802.37
Debt capital	60,603.64	180,630.84
Equity capital	8737.65	36,369.83
Incurred benefits plus additions to reserves	18,092.83	47,024.14
Investment profits	3876.75	12,060.58

Note: The variables are all measured in RMB million.

3.3. Efficiency measure—slack-based dynamic data envelopment analysis

The DEA approach, a non-parametric mathematical linear programming technique, is the method that has been most commonly used in extant studies to measure the relative efficiency of insurers or, more broadly, decision-making units (DMUs) [7]. In contrast to the traditional DEA approach, which is radial and takes no account of slacks, the SBM model is a non-radial, non-oriented model that deals directly with the input and output slacks of the DMU of interest. The non-radial feature acknowledges the generally non-proportional nature of noticeable deterioration in performance in the real world. The efficiency measure of the SBM model is between 0 and 1. It reports an efficiency score of unity if and only if the DMU concerned is on the frontier of the production possibility set without any input or output slacks. Other desirable properties of the SBM model are: (i) it is unit invariant and monotone decreasing with respect to input and output slacks, (ii) the efficiency score is determined only by consulting the reference-set of the DMU of interest, and (iii) it is not affected by statistics over the whole dataset.

However, the traditional DEA models, including the SBM model, do not account for the effect of carry-over accounting items between two consecutive terms. To address the dynamic production process of insurers and compute efficiency scores of China's insurers, this study thus applies the DSBM model [21] in the first stage as this improves the DEA approach and overcomes the shortcomings of the traditional DEA models. The DSBM model incorporates carry-over activities and thus enables more accurate measurement of time-specific dynamic efficiencies over long time periods [21].[7] Another advantage of the DSBM model is that it deals with inputs, outputs, and carry-over items individually. This study makes use of the input-oriented DSBM model under variable returns to scale. The choice of input-orientation enhances the relevance of frontier efficiency studies in today's dynamic business world since excesses in both input and carry-over resources are emphasized.

Next, we will outline the formulation of the input-oriented DSBM model under variable returns to scale. Suppose k DMUs ($j = \text{DMU}_1, \text{DMU}_2, \ldots, \text{DMU}_k$) over T terms ($t = 1, 2, \ldots, T$) are observed in the dynamic production process, where each DMU utilizes common d inputs ($i = 1, 2, \ldots, d$) and e carry-over items ($c = 1, 2, \ldots, e$) to produce f outputs ($g = 1, 2, \ldots, f$) at each term. Let x_{ijt} denotes the amount of inputs used by DMU j at term t; let z^{σ}_{cjt} be the amount of carry-over[8] items of DMU j at term t. To evaluate the levels of the observed DMUs' operating efficiency, the input-oriented DSBM model under variable returns to scale in the following fractional program has to be solved:

$$\text{IOE}^{*}_{o} = \min \frac{1}{T}\sum_{t=1}^{T}\left[1 - \frac{1}{d+e}\left(\sum_{i=1}^{d}\frac{s^{-}_{it}}{x_{iot}} + \sum_{c=1}^{e}\frac{s^{\sigma}_{ct}}{z^{\sigma}_{cot}}\right)\right] \quad (1)$$

[7] Even though methods like window analysis [19] and Malmquist productivity indices [20] can measure performance changes over time, they have some limitations: (i) carry-over activities between two consecutive periods are neglected and (ii) independent separate time periods are emphasized such that only local optimization in a single period is achieved.

[8] This study following Tone and Tsutsui [21] treats an undesirable (bad) carry-over item as an input and its value is restricted to not greater than the observed one. The symbol σ is used to denote the term undesirable (bad).

Table 3
Pearson correlation matrix of inputs and outputs.

	(1)	(2)	(3)	(4)	(5)
(1) Labor and business service	1				
(2) Debt capital	0.984***	1			
(3) Equity capital	0.939***	0.952***	1		
(4) Incurred benefits plus additions to reserves	0.942***	0.906***	0.903***	1	
(5) Investment profits	0.939***	0.939***	0.889***	0.858***	1

*** Statistical significance at the 1% level.

subject to:

$$x_{iot} = \sum_{j=1}^{k} x_{ijt}\lambda_{jt} + s_{it}^{-}, \quad (i = 1, 2, \ldots, d;\ t = 1, 2, \ldots, T)$$

$$z_{cot}^{\sigma} = \sum_{j=1}^{k} z_{cjt}^{\sigma}\lambda_{jt} + s_{ct}^{\sigma}, \quad (c = 1, 2, \ldots, e;\ t = 1, 2, \ldots, T)$$

$$\sum_{j=1}^{k} z_{cjt}^{\sigma}\lambda_{j}^{t} = \sum_{j=1}^{k} z_{cjt}^{\sigma}\lambda_{j}^{t+1}, \quad (\forall c;\ t = 1, 2, \ldots, T-1) \tag{2}$$

$$\sum_{j=1}^{k} \lambda_{j}^{t} = 1, \quad (t = 1, 2, \ldots, T)$$

$$\lambda_{jt} \geq 0,\ s_{it}^{-} \geq 0,\ s_{ct}^{\sigma} \geq 0 \tag{3}$$

where, s_{it}^{-}, s_{gt}^{+}, and s_{ct}^{σ} are slack variables denoting input excess, output shortfall, and carry-over excess, respectively. This objective function is based on the input-oriented SBM model [59]. The main targets of evaluation of the objective function are excesses in both input resources and carry-over values. Since carry-over items have similar features as inputs, to be exact, a smaller amount is preferable to a larger amount, and both are accounted for in the objective function in a similar way. As observed from the constraint (2), carry-over items are those that have the role of connecting two consecutive terms. From model (1), it can be inferred that the efficiency of term t is measured by the relative slacks of inputs and carry-over items. Model (1) is thus the weighted average of term efficiencies over the whole terms. Note that this study defines the input-oriented overall efficiency (IOE_o^*) as a ratio ranging between 0 and 1, and that it is equal to 1 when all slacks are zero. Moreover, it is units-invariant.

While the (IOE_o^*) of model (1) is a weighted average of term efficiencies over the whole terms, model (4) is the model for measuring term efficiency. If the optimal solution for (3) satisfies $\mathrm{IOE}_{ot}^* = 1$, then DMU_o is considered input-oriented term efficient because the optimal slacks for term t in model (4), are all zero [more specifically, $s_{iot}^{-*} = 0(\forall i,t)$ and $s_{cot}^{\sigma *} = 0(\forall i,t)$]:

$$\mathrm{IOE}_{ot}^* = \left[1 - \frac{1}{d+e}\left(\sum_{i=1}^{d} \frac{s_{iot}^{-*}}{x_{iot}} + \sum_{c=1}^{e} \frac{s_{cot}^{\sigma *}}{z_{cot}^{\sigma}}\right)\right], \quad (t = 1, 2, \ldots, T) \tag{4}$$

The overall efficiency during the period (IOE_o^*) can be described by replacing model (4) into model (1), which gives the following:

$$\mathrm{IOE}_o^* = \min \frac{1}{T}\sum_{t=1}^{T} \mathrm{IOE}_{ot}^* \tag{5}$$

If $\mathrm{IOE}_{ot}^* = 1$, then DMU_o is considered input-oriented overall efficient. Also interesting is that DMU_o is called input-oriented overall efficient if and only if its $\mathrm{IOE}_{ot}^* = 1$ for all terms.

Table 4
Efficiency scores of the DSBM model and BCC model.

	DSBM model		BCC model		Wilcoxon signed rank test z-stat
	Mean	SD	Mean	SD	
2006	0.963	0.068	0.965	0.054	−0.412
2007	0.973	0.065	0.927	0.081	−2.412**
2008	0.930	0.133	0.841	0.193	−3.385***
2009	0.912	0.131	0.808	0.225	−3.371***
2010	0.905	0.133	0.873	0.125	−2.038**
Total	0.937	0.113	0.883	0.159	−5.179***

** Statistical significance at 5% level.
*** Statistical significance at 1% level.

3.4. *Measure of intellectual capital: value added intellectual coefficient*

Following prior studies [60–63], we apply VAIC™ to measure the IC of the Chinese life insurers. We rely on Pulic [64] to develop our proxies for IC. First, we calculate the life insurers' net worth or value added (VA). VA = total operating income−(total costs incurred−payroll). Next, we calculate how efficiently VA has been created through three types of capital, namely, human capital (HC), structural capital (SC), and capital employed (CE). That is, VAIC™ consists of three components, viz., human capital efficiency (HCE), structural capital efficiency (SCE), and capital employed efficiency (CEE). Algebraically, they can be expressed as follows:

$$\mathrm{CEE} = \mathrm{VA}/\mathrm{CA}$$

$$\mathrm{HCE} = \mathrm{VA}/\mathrm{HC}$$

$$\mathrm{SCE} = \mathrm{SC}/\mathrm{VA}$$

where CA represents capital employed, payroll is the proxy for HC, and SC = VA−HC. A higher value of each indicator, CEE, HCE, and SCE, indicates higher value creation in terms of intellectual capital.

3.4.1. *Hypotheses development*

Employing VAIC™, we develop three hypotheses based on the individual components of IC and the total IC. Based on the resource-based view of firms, a firm's resources are the driver of superior performance [65–67]. From the knowledge-based view of a firm, Yang and Chen [68] further note that knowledge is the most productive resource. To illustrate, human capital is regarded as the main invisible IC asset because it is the central source of IC-created synergies (1 + 1 = 11) [28,30,69,70]. Meanwhile, Bontis [70] labels human capital as individual tacit knowledge of employees. Taken together, human capital embraces the collective knowledge and skills, the ability to be innovative, and the competency to serve customers [28], all of which are important assets for growth and future development of a life insurer [71] or a service industry. As

Table 5
Efficiency scores of the 34 Chinese life insurers.

	2006	2007	2008	2009	2010	Total
Local						
China Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
China Pacific Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
New China Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Taikang Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Taiping Life Insurance Co., Ltd.	0.927	1.000	0.873	0.810	0.751	0.872
Minsheng Life Insurance Co., Ltd.	1.000	1.000	0.819	0.787	0.702	0.862
Sino Life Insurance Co., Ltd.	0.765	0.800	0.617	0.846	1.000	0.806
Union Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Huatai Life Insurance Co., Ltd.	0.986	1.000	1.000	1.000	0.921	0.981
PICC Health Insurance Company Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Greatwall Life Insurance Co., Ltd.	0.971	1.000	1.000	1.000	1.000	0.994
Kunlun Health Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Jiahe Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.973	0.985	0.947	0.957	0.952	0.963
Foreign						
Manulife-Sinochem Life Insurance Co., Ltd.	0.973	0.948	0.916	0.928	1.000	0.953
Pacific-Antai Life Insurance Co., Ltd.	1.000	1.000	1.000	0.907	0.854	0.952
Allianz China Life Insurance Co., Ltd.	1.000	1.000	0.654	0.634	0.594	0.776
AXA-Minmetals Assurance Co., Ltd.	0.981	1.000	1.000	0.889	0.788	0.932
CITIC-Prudential Life Insurance Company Ltd.	0.839	0.886	0.825	0.574	0.616	0.748
China Life-CMG Life Assurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Generali China life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Sun Life Everbright Life Insurance Co., Ltd.	0.871	0.988	1.000	0.726	0.915	0.900
American International Assurance Co., Ltd.	0.827	0.962	1.000	1.000	1.000	0.958
Haier New York Life Insurance Co., Ltd.	1.000	1.000	1.000	0.860	0.885	0.949
Aviva-Cofco Life Insurance Co., Ltd.	1.000	1.000	0.729	0.616	0.631	0.795
AEGON-CNOOC Life Insurance Co., Ltd.	0.777	0.749	0.577	0.662	0.759	0.705
CIGNA & CMC Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Nissay-Greatwall Life Insurance Co., Ltd.	0.996	0.946	0.995	1.000	1.000	0.987
Heng An Standard Life Insurance Co., Ltd.	0.889	0.794	0.619	0.914	0.832	0.810
Skandia-BSAM Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
Sino-US MetLife Insurance Co., Ltd.	0.945	1.000	1.000	1.000	0.740	0.937
Cathay Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
United MetLife Insurance Co., Ltd.	0.985	1.000	1.000	0.846	0.789	0.924
Samsung Air China Life Insurance Co., Ltd.	1.000	1.000	1.000	1.000	1.000	1.000
PICC Life Insurance Company Limited	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.956	0.965	0.920	0.884	0.876	0.920
Difference in the efficiency scores (*p*-value)	0.524	0.242	0.612	0.172	0.108	0.016

for the second component of VAIC™, Ahangar [28] stipulates that structural capital includes organizational ability, processes, data, and patents. More specifically, structural capital consists of two sub-components: innovation capital and process capital [30,72]. Bontis [70] specifies structural capital as the mechanisms and structures that enable employees to utilize their intellectual resources, which further enhances an insurance company's performance. That is, investment in structural capital results in better firm performance. Another resource in VAIC™, capital employed, is also essential capital that contributes to the performance of a company.

As noted earlier, the Chinese life insurance industry is facing mounting competition in this highly competitive era. To cope with the challenges and to sustain growth in this dynamic and knowledge-intensive industry, these life insurers must depend on their resources, that is, both their tangible and intangible assets. In other words, they must recognize and utilize their IC to be more efficient. From either resource-based or knowledge-based theory, there should be a positive relationship between IC and operating efficiency in the life insurance industry. Based on the above discussion, we thus state the hypotheses, in alternate form, as follows:

Hypothesis 1. Human capital increases firm operating efficiency.

Hypothesis 2. Structural capital increases firm operating efficiency.

Hypothesis 3. Capital employed increases firm operating efficiency.

3.5. Regression model

Since the efficiency score lies between 0 and 1, using ordinary least square (OLS) regression in the second stage might lead to estimated coefficients that are biased. As Simar and Wilson [32] point out, direct regression analysis is invalid due to the unknown serial correlation among the efficiency scores. Simar and Wilson [33] confirm that applying OLS in the second-stage estimation is consistent only under very peculiar and unusual assumptions about the data-generating process that limit its applicability. Put differently, truncated regression provides consistent estimation in the second-stage estimation. In the second stage, we thus adopt truncated regression with a bootstrapping approach introduced by Simar and Wilson [32,33] to examine whether exogenous factors, i.e., intellectual capital variables in this study, affect the corporate performance of Chinese insurance companies.

This study assumes and tests the following specification:

$$\mathrm{OE}_j = \alpha + X_j\beta + \varepsilon_j, \quad j = 1, \ldots, n \tag{6}$$

where α is the intercept, ε_j is the error term, and X_j represents a vector of observation-specific variables for firm j that is expected to be related to the firm's efficiency score, OE_j. Instead of using Tobit estimation, Simar and Wilson [32,33] propose an approach based on a truncated regression with a bootstrapping procedure for estimating Eq. (6). The performance of their Monte Carlo experiments is satisfactory.

More specifically, the distribution of ε_j is restricted by the condition $\varepsilon_j \geq 1-\alpha-X_j\beta$ in Eq. (6). Following Simar and Wilson [32,33], this study modifies Eq. (6). The true but unobserved efficiency score, OE_j, in Eq. (6) is replaced by its estimate $\hat{\text{OE}}_j$, and the distribution is assumed to be truncated normal with zero mean (before truncation), unknown variance, and a truncation point, which are determined by different conditions. Accordingly, we estimate the following:

$$\widehat{\text{OE}} \approx \alpha + X_j\beta + \varepsilon_j, \quad j = 1, \ldots, n \tag{7}$$

where $\varepsilon_j \sim N(0, \sigma_\varepsilon^2)$ such that $\varepsilon_j \geq 1-\alpha-X_j\beta$, $j = 1, \ldots, n$. To gain more precise confidence intervals, this study uses the parametric bootstrap for regression process to derive the confidence intervals for the estimates of parameters $(\beta, \sigma_\varepsilon^2)$. For an overall picture and the details of the estimation algorithm, readers are encouraged to refer to Simar and Wilson [32,33].

We perform a simulation test with a total of 3000 experimental observations to confirm the fitness of the truncated regression model, which is specified as follows:

$$\begin{aligned} \text{OE}_{it} = {} & \alpha + \beta_1 \text{HCE}_{it} + \beta_2 \text{SCE}_{it} + \beta_3 \text{CEE}_{it} + \beta_4 \text{DOM}_{it} \\ & + \beta_5 \text{GP}_{it} + \beta_6 \text{DIST}_{it} + \beta_7 \text{SOLV}_{it} \\ & + \beta_8 \text{LEV}_{it} + \beta_9 \text{AGE}_{it} + \beta_{10} \text{SIZE}_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where

- OE_{it} efficiency score derived using the input-oriented DSBM model under variable returns to scale.
- HCE_{it} an indicator of human capital, which is measured as the ratio of value added to human capital.
- SCE_{it} an indicator of structural capital, which is measured as the ratio of structural capital to value added.
- CEE_{it} an indicator of financial capital, which is measured as the ratio of value added to capital employed.
- DOM_{it} a dummy variable equal to 1 if the capital source is local, and equal to zero otherwise.
- GP_{it} a dummy variable equal to 1 if a Chinese life insurer is group-affiliated, and equal to zero otherwise.
- DIST_{it} the ratio of the number of distribution channels used to the total available channels.
- SOLV_{it} the adequacy of solvency or the ability of a Chinese life insurer to repay debt.
- LEV_{it} the ratio of total debt to total assets.
- AGE_{it} the natural logarithm of the number of years since an insurer was established.
- SIZE_{it} the natural logarithm of total assets.

4. Results and discussions

4.1. Dynamic efficiency analysis

To examine the accuracy of the DSBM model, this study first compares the efficiency scores derived using the Banker et al. [73] (BCC) model and those obtained using the DSBM model. Table 4 summarizes the mean efficiency scores of sample life insurers from 2006 to 2010. Under the DSBM model, the results indicate that the range of average efficiency remained between 0.905 and 0.973 during this period. In contrast, the mean efficiency scores obtained using the BCC model decreased monotonically from 2006 to 2009 but increased in 2010. In fact, the mean efficiency scores obtained using the BCC model are consistently lower than those obtained using the DSBM model. The standard deviations under the DSBM model are generally lower than those under the BCC model. This suggests that considering carry-over activities could lead to more accurate efficiency estimation because the continuity of carry-overs from year to year is taken into account. In the life insurance business, life insurers cannot control their debt capital and equity over a short time period. Therefore, it is not practical to independently measure the performance of life insurers on an annual basis [21].

In addition, we apply a Wilcoxon signed rank test to investigate whether the observed differences are significant. The test indicates that significant differences exist between the efficiency scores obtained using the two different models, and that the difference is particularly evident in the total values. These findings further support the use of the DSBM model.

As noted earlier, since the life insurers selected for sampling do not display similar operating characteristics, we need to further determine whether differences exist between the capital sources (foreign or local) for the firm operating efficiency under the DSBM model. Table 5 shows the operating efficiency scores for the 34 Chinese life insurers, classified based on whether the insurers were local or foreign. The results show that approximately 38% of the life insurers with local capital source need to reduce their inputs if they were to become efficient, whereas about 67% of the foreign life insurers are found to be inefficient. This indicates that there is still room for improvement. Using a Mann–Whitney test, we find that the total average efficiency scores of the foreign life insurers are significantly lower than those of the local life insurers (p-value $= 0.016$). However, the tests of difference in the efficiency scores are not significant throughout the period from 2006 to 2010.

Table 6
Descriptive statistics of independent variables ($N = 68$ firm-year observations).

Variable	Mean	Standard deviation	1st Quartile	3rd Quartile
HCE	1.111	1.328	0.144	1.574
SCE	0.350	2.907	−0.171	0.737
CEE	0.567	2.585	0.009	0.211
DOM	0.382	0.490	0.000	1.000
GP	0.382	0.490	0.000	1.000
DIST	0.544	0.302	0.500	0.750
SOLV	3.858	6.232	1.648	2.956
LEV	0.825	0.160	0.787	0.920
AGE	1.942	0.420	1.609	2.197
SIZE	9.337	1.840	8.228	10.164

Note: The variables are all measured in RMB million.

4.2. Descriptive statistics

Using VAIC™ to measure IC, subject to data availability, we concentrate our initial final dataset into a 2-year dataset (2009 and 2010). Table 6 presents the descriptive statistics of the independent variables. The average human capital efficiency (HCE) in our sample is about RMB 1.11 million. The mean structural capital efficiency (SCE) is RMB 0.35 million, and the mean capital employed efficiency (CEE) is about RMB 0.57 million. Among the three aspects of intellectual capital, human capital seems to have created the largest amount of value, followed by CEE. It is also noteworthy that the standard deviations of SCE and CEE are relatively high as compared to that of HCE. The findings suggest that there are large differences in the degree of value created through the investment of structural capital and financial capital in our sample. Of the total sample, approximately 38% are local insurers and are group-affiliated. In general, the Chinese life insurers use at least two types of distribution channels. The average solvency rate of the sample firms reaches approximately 386%, suggesting a great ability of the Chinese life insurers to repay debt. Meanwhile, the mean leverage is approximately 0.825. The average firm age is about 7 years, while the average firm size

Table 7
Pearson correlation matrix.

	OE	HCE	SCE	CEE	DOM	GP	DIST	SOLV	LEV	AGE
HCE	0.190									
SCE	0.225*	−0.059								
CEE	0.161	0.471***	0.019							
DOM	0.435***	0.358***	−0.111	0.229*						
GP	0.323***	0.504***	−0.027	0.249**	0.502***					
DIST	−0.050	−0.174	−0.095	0.033	0.136	−0.217*				
SOLV	0.227*	−0.304**	0.416***	−0.065	−0.119	−0.233*	−0.134			
LEV	−0.065	0.188	0.137	0.059	0.161	0.344***	−0.023	−0.056		
AGE	0.095	0.379***	−0.006	0.100	−0.084	0.202*	−0.225*	−0.194	0.029	
SIZE	0.208*	0.400***	−0.048	−0.031	0.500***	0.509***	0.145	−0.118	0.537***	−0.028

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

is RMB 9.337 million in logged term (equivalent to RMB 11.35 billion).

4.3. The relationship between operating efficiency and intellectual capital

As the data used in this study are drawn mainly from publicly available sources, we have to restrict our sample period to only 2009 and 2010. In other words, we indirectly place an additional restriction on our sample for regression analysis that include our intellectual capital proxies, since data on these proxies are only available from the annual reports of the Chinese life insurers.[9] A strong correlation is expected between the input/output variables and explanatory variables in small samples, indicating that the regression assumption that error terms are independent of explanatory variables is violated [47]. Note, however, that the small sample is unlikely to introduce any bias since this study applies the truncated regression with bootstrapping approach, which could overcome the above problem.

Before conducting the regression analysis, we first perform a test of the possibility of multicollinearity. The results of the Pearson correlation coefficients are reported in Table 7. The correlation coefficients between OE and HCE, SCE, and CEE are positive, with SCE reaching the conventional significance level. Other correlation coefficients are generally lower than 0.5. In addition, the untabulated values on the diagnostics of variance inflation factors (VIF) are all less than 2.8. The findings suggest the non-existence of the potential multicollinearity problem.

Table 8 reports the regression results of the 68 firm-year observations. The second column reports the truncated regression results, while the third and fourth columns present the Tobit regression results and robust cluster regression. The results obtained using the three techniques reveal that human capital efficiency (HCE), structural capital efficiency (SCE), and capital employed efficiency (CEE) have positive impacts on firm operating efficiency. However, almost all of the main testing variables did not reach the conventional significance level under Tobit regression and robust cluster regression. The findings may somewhat corroborate Simar and Wilson's [32,33] argument that direct regression analysis is invalid, and that truncated regression provides consistent results in the second-stage estimation. These findings are sufficiently robust to justify another round of estimation, where we use invested assets as another proxy of the intermediation function of life insurers in the estimation of firm operating efficiency. In untabulated results, all of our main results persist.[10]

Table 8
Regression results.

Variable	Truncated regression	Tobit regression	Robust cluster regression
	Coefficient	Coefficient	Coefficient
Intercept	1.475***	1.009***	0.948
HCE	0.166***	0.062	0.013
SCE	0.044**	0.004	0.009
CEE	0.070***	0.082	0.001
DOM	0.343**	0.170*	0.129
GP	0.101	0.159	0.094
DIST	0.615***	0.040	−0.004
SOLV	0.020**	0.049**	0.008**
LEV	1.354***	−0.438*	−0.232**
AGE	0.104	−0.111	−0.042
SIZE	−0.199***	0.012	0.002
Log likelihood	26.684		
Pseudo R^2		0.600	
R^2			0.364

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

The results of truncated regression reveal that intellectual capital, specifically human capital (HCE), structural capital (SCE), and financial capital (CEE), have significantly positive impacts on firm operating efficiency. The significantly positive coefficients of the three testing variables suggest that the three hypotheses of this study are supported, indicating that the greater the investment in intellectual capital, the better the performance. The results are consistent with prior studies [28,74,75]. All of the control variables are positively associated with firm operating efficiency, with the exception of firm size. The significantly positive coefficient on DOM confirms that domestic Chinese life insurers have greater firm operating efficiency.

4.4. Discussion

The findings imply that firm operating efficiency can be improved by investing in human capital, structural capital, and

[9] Almost all of the sample firms had published only 2010 and 2011 annual reports at the time this study was conducted.

[10] We thank two anonymous referees for suggesting that we use the Tobit regression and robust cluster regression techniques as well as the alternative proxy for output variables as robustness checks.

financial capital. Statistically, human capital is the most significant of the three proxies of IC. If we were to set the statistical significance at the 1% level, structural capital would have no impact on the operating efficiency of the life insurance companies. To be able to provide responsive service to customers in China, life insurers probably need to fully utilize their human capital. Without a large amount of human capital, they might face difficulties in running many branches across China. In addition to training, Chinese life insurers should thus continue to recruit and retain capable employees since they are the most important intangible assets of a firm. According to Ahangar [28], employees are the source of collective knowledge, competency, experience, and skills needed to provide goods or services and solutions to customers. Life insurers should also not overlook structural capital, which is the supporting infrastructure and process of human capital. Efficient spending on administrative needs is essential since the eventual result is better overall efficiency. Life insurers can better serve their customers with great human capital and structural capital, which will ultimately result in more outputs or earnings. In summary, investing in intellectual capital is the key for life insurers to achieve better performance.

5. Conclusions

The academic literature on measuring the performance of the insurance industry has grown significantly. This study has employed the DSBM model, a dynamic DEA model, to analyze the performance of the Chinese life insurance companies, setting this study apart from previous studies that merely apply either SFA or traditional DEA models. We employ a Wilcoxon signed rank test, with a null hypothesis that no differences exist between the efficiency scores of the BCC model and those of the DSBM model. We always reject the null hypothesis. Under the DSBM model, the median values of the Chinese life insurers from 2006 to 2010 are all consistently over 1. Moreover, we regress the operating efficiency scores on the exogenous factors, specifically intellectual capital. The truncated regression results prove that intellectual capital, which includes human capital, structural capital, and financial capital, have positively significant impacts on firm operating efficiency. The outcome confirms the importance of intellectual capital since the dimensions of intellectual capital are complementary.

Although there are advantages to using the DSBM model, it is nevertheless particularly challenging to hand collect the proprietary information of Chinese life insurance companies. When more information becomes available, future research could probably examine the association of other exogenous factors, such as corporate governance, with corporate performance.

References

[2] CapitalVue. China insurance industry posts higher premium income, challenges ahead; 2012.
[3] Life Insurance Industry Profile: China. Datamonitor Plc; 2011.
[4] Wu X, Strange R. The location of foreign insurance companies in China. International Business Review 2000;9:383–98.
[5] Chen B, Powers MR, Qiu J. Life-insurance efficiency in China: a comparison of foreign and domestic firms. China & World Economy 2009;17:43–63.
[6] Yao S, Han Z, Feng G. On technical efficiency of China's insurance industry after WTO accession. China Economic Review 2007;18:66–86.
[7] Eling M, Luhnen M. Frontier efficiency methodologies to measure performance in the insurance industry: overview, systematization, and recent developments. Geneva Papers on Risk & Insurance—Issues & Practice 2010;35:217–65.
[8] Liu JS, Lu LYY, Lu W-M, Lin BJY. A survey of DEA applications. Omega 2013;41:893–902.
[9] Liu JS, Lu LYY, Lu W-M, Lin BJY. Data envelopment analysis 1978–2010: a citation-based literature survey. Omega 2013;41:3–15.
[10] Yeh QJ. The application of data envelopment analysis in conjunction with financial ratios for bank performance evaluation. The Journal of the Operational Research Society 1996;47:980–8.
[11] Homburg C. Using data envelopment analysis to benchmark activities. International Journal of Production Economics 2001;73:51–8.
[12] Biener C, Eling M. The performance of microinsurance programs: a data envelopment analysis. Journal of Risk and Insurance 2011;78:83–115.
[13] Lu W-M, Hung S-W. Exploring the operating efficiency of Technology Development Programs by an intellectual capital perspective—a case study of Taiwan. Technovation 2011;31:374–83.
[14] Premachandra IM, Chen Y, Watson J. DEA as a tool for predicting corporate failure and success: a case of bankruptcy assessment. Omega 2011;39:620–6.
[15] Fang H-H, Lee H-S, Hwang S-N, Chung C-C. A slacks-based measure of super-efficiency in data envelopment analysis: an alternative approach. Omega 2013;41:731–4.
[16] Matthews K. Risk management and managerial efficiency in Chinese banks: a network DEA framework. Omega 2013;41:207–15.
[17] Yang X, Morita H. Efficiency improvement from multiple perspectives: an application to Japanese banking industry. Omega 2013;41:501–9.
[18] Koller M. Life insurance risk management essentials. Key insurance processes and their risks. Berlin Heidelberg: Springerlink; 2011 [chapter 5].
[19] Klopp G. The analysis of the efficiency of productive systems with multiple inputs and outputs [Ph.D.]. Illinois (United States): University of Illinois at Chicago; 1985.
[20] Färe R, Grosskopf S, Norris M, Zhang Z. Productivity growth, technical progress, and efficiency change in industrialized countries. American Economic Review 1994;84:66–83.
[21] Tone K, Tsutsui M. Dynamic DEA: a slacks-based measure approach. Omega 2010;38:145–56.
[22] Nemoto J, Goto M. Measurement of dynamic efficiency in production: an application of data envelopment analysis to Japanese electric utilities. Journal of Productivity Analysis 2003;19:191–210.
[23] Ouellette P, Vierstraete V. Technological change and efficiency in the presence of quasi-fixed inputs: a DEA application to the hospital sector. European Journal of Operational Research 2004;154:755–63.
[24] Ouellette P, Li Y. Investment and dynamic DEA. Journal of Productivity Analysis 2008;29:235–47.
[25] Radwan S. China's Insurance Market: lessons from Taiwan. Bloomberg Businessweek; 2010.
[26] Teece DJ. Capturing value from knowledge assets: the new economy, markets for know-how, and intangible assets. California Management Review 1998;40:55–79.
[27] Gholipour R, Jandaghi G, Hosseinzadeh SAA. Explanation of knowledge management enabler as a latent variable: a case study of SMEs in Iran. African Journal of Business Management 2010;4:1863–72.
[28] Ahangar RG. The relationship between intellectual capital and financial performance: an empirical investigation in an Iranian company. African Journal of Business Management 2011;5:88–95.
[29] Uzzi B. The sources and consequences of embeddedness for the economic performance of organizations: the network effect. American Sociological Review 1996;61:674–98.
[30] Edvinsson L, Malone MS. Intellectual capital: realizing your company's true value by finding its hidden brainpower. New York: Harper Business; 1997.
[31] Lynn B. Intellectual capital: key to value-added success in the next millennium. CMA Magazine 1998;72:10–5.
[32] Simar L, Wilson PW. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics 2007;136:31–64.
[33] Simar L, Wilson P. Two-stage DEA: caveat emptor. Journal of Productivity Analysis 2011;36:205–18.
[34] Cummins JD, Zi H. Comparison of frontier efficiency methods: an application to the U.S. life insurance industry. Journal of Productivity Analysis 1998;10:131–52.
[35] Eling M, Luhnen M. Efficiency in the international insurance industry: a cross-country comparison. Journal of Banking and Finance 2010;34:1497–509.
[36] Fecher F, Kessler D, Perelman S, Pestieau P. Productive performance of the French insurance industry. Journal of Productivity Analysis 1993;4:77–93.
[37] Fenn P, Vencappa D, Diacon S, Klumpes P, O′Brien C. Market structure and the efficiency of European insurance companies: a stochastic frontier analysis. Journal of Banking and Finance 2008;32:86–100.
[38] Kumbhakar SC, Lovell AK. Stochastic Frontier analysis. Cambridge: Cambridge University Press; 2000.
[39] Yuengert AM. The measurement of efficiency in life insurance: estimates of a mixed normal-gamma error model. Journal of Banking and Finance 1993;17:483–96.
[40] Cummins JD, Nini GP. Optimal capital utilization by financial firms: evidence from the property-liability insurance industry. Journal of Financial Services Research 2002;21:15.
[41] Cummins JD, Rubio-Misas M, Zi H. The effect of organizational structure on efficiency: evidence from the Spanish insurance industry. Journal of Banking and Finance 2004;28:3113–50.
[42] Wu D, Yang Z, Vela S, Liang L. Simultaneous analysis of production and investment performance of Canadian life and health insurance companies using data envelopment analysis. Computers and Operations Research 2007;34:180–98.

[43] Cummins JD, Xie X. Mergers and acquisitions in the US property-liability insurance industry: Productivity and efficiency effects. Journal of Banking and Finance 2008;32:30–55.
[44] Kao C, Hwang SN. Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. European Journal of Operational Research 2008;185:418–29.
[45] Cummins JD, Weiss MA, Xie X, Zi H. Economies of scope in financial services: a DEA efficiency analysis of the US insurance industry. Journal of Banking and Finance 2010;34:1525–39.
[46] Fukuyama H. Investigating productive efficiency and productivity changes of Japanese life insurance companies. Pacific-Basin Finance Journal 1997;5:481–509.
[47] Barros CP, Nektarios M, Assaf A. Efficiency in the Greek insurance industry. European Journal of Operational Research 2010;205:431–6.
[48] Färe R, Grosskopf S. Intertemporal production frontiers: with dynamic DEA. Norwell: Kluwer; 1996.
[49] Emrouznejad A. An alternative DEA measure: a case of OECD countries. Applied Economics Letters 2003;10:779–82.
[50] Leverty JT, Lin Y, Zhou H. WTO and the Chinese Insurance Industry. Geneva Papers on Risk & Insurance—Issues & Practice 2009;34:440–65.
[51] Weygandt JJ, Kimmel PD, Keiso DE. Financial accounting: IFRS. Taiwan: Wiley; 2010.
[52] Reeve JM, Warren CS, Duchac JE, Wang W. Principles of financial accounting with conceptual emphasis on IFRS. Taiwan: Cengage Learning; 2011.
[53] Greene WH, Segal D. Profitability and efficiency in the U.S. Life Insurance Industry. Journal of Productivity Analysis 2004;21:229–47.
[54] Tone K, Sahoo BK. Evaluating cost efficiency and returns to scale in the Life Insurance Corporation of India using data envelopment analysis. Socio-Economic Planning Sciences 2005;39:261–85.
[55] Grace MF, Timme SG. An examination of cost economies in the United States Life Insurance Industry. Journal of Risk and Insurance 1992;59:72–103.
[56] Berger AN, Cummins JD, Weiss MA, Zi H. Conglomeration versus strategic focus: evidence from the Insurance Industry. Journal of Financial Intermediation 2000;9:323–62.
[57] Editorial Department of China's Insurance Yearbook. Yearbook of China's Insurance; 2004–2009.
[58] Golany B, Roll Y. An application procedure for DEA. Omega 1989;17:237–50.
[59] Tone K. A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research 2001;130:498–509.
[60] Young CS, Su HY, Fang SC, Fang SR. Cross-country comparison of intellectual capital performance of commercial banks in Asian economies. Service Industries Journal 2009;29:1565–79.
[61] Zéghal D, Maaloul A. Analysing value added as an indicator of intellectual capital and its consequences on company performance. Journal of Intellectual Capital 2010;11:39–60.
[62] Zou X, Huan T-C. A study of the intellectual capital's impact on listed banks' performance in China. African Journal of Business Management 2011;5:5001–9.
[63] Wang M-C. Value relevance on intellectual capital valuation methods: the role of corporate governance. Quality and Quantity 2012:1–11.
[64] Pulic A. VAIC™ an accounting tool for IC management. International Journal of Technology Management 2000;20:702–14.
[65] Wernerfelt B. A resource-based view of the firm. Strategic Management Journal 1984;5:171–80.
[66] Barney J. Firm resources and sustained competitive advantage. Journal of Management 1991;17:99–120.
[67] Galbreath J. Which resources matter the most to firm success? An exploratory study of resource-based theory Technovation 2005;25:979–87.
[68] Yang C, Chen TY. Evaluating the efficiency of intellectual capital management for Taiwan IC design industry. African Journal of Business Management 2010;4:3366–73.
[69] Stewart TA. Intellectual capital: the new wealth of organizations. New York: Double Day; 1997.
[70] Bontis N. Intellectual capital—an exploratory study that develops measures and models. Management Decision 1998;36:63.
[71] Chen YS, Lin JMJ, Chang CH. The influence of intellectual capital on new product development performance—the manufacturing companies of Taiwan as an example. Total Quality Management & Business Excellence 2006;17:1323–39.
[72] Hsu YH, Fang W. Intellectual capital and new product development performance: the mediating role of organizational learning capability. Technological Forecasting and Social Change 2009;76:664–77.
[73] Banker RD, Charnes A, Cooper WW. Some models for the estimation of technical and scale inefficiencies in data envelopment analysis. Management Science 1984;30:1078–92.
[74] Bollen L, Vergauwen P, Schnieders S. Linking intellectual capital and intellectual property to company performance. Management Decision 2005;43:1161–85.
[75] Sharabati AAA, Jawad SN, Bontis N. Intellectual capital and business performance in the pharmaceutical sector of Jordan. Management Decision 2010;48:105–31.