# Boosting Efficiency: How Bancassurance Transforms Insurance Cost Dynamics

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**Abstract**

This paper examines whether the bancassurance has attributed to enhancing the cost efficiency of insurance firms, which was the main purpose of the scheme in the first place. In particular, the goal of this paper is to revisit and reverify the results of existing studies that applied the DEA method to estimate the bancassurance effect, by employing additional analysis methods. Although there were some differences in the levels of efficiency each calculated by the three methods, the cost efficiency of life insurers has generally improved since the introduction of bancassurance according not only to the DEA model but most of the other models. Both comparative analysis and multiple regression analysis also support and confirm the results.

**Keywords:** bancassurance, cost efficiency, data envelope analysis (DEA), bootstrap DEA, stochastic frontier approach (SFA)

## 1. Introduction

Bancassurance, the integration of banking and insurance businesses, is a growing trend worldwide, particularly in Europe where it accounts for a significant portion of the life insurance market. However, in Korea, bancassurance has been limited to the sale of savings-type and illness/accident insurance due to key regulations. The main objectives of bancassurance are to enhance the cost efficiency of insurance companies, increase profitability for banks through commission income, and provide more accessible and affordable insurance products for consumers. By leveraging the existing customer base and distribution channels of banks, insurance companies can reduce various operational expenses related to insurance solicitation, contract maintenance, and agent training. (Note 1).

While previous studies in Korea have used the Data Envelopment Analysis (DEA) method to evaluate the impact of bancassurance on the cost efficiency of insurers (for example, Lee and Lee, 2018), these non-parametric approaches have limitations in providing statistical inference and considering probabilistic variability. To overcome these limitations, this paper employs two additional analytical methods: Bootstrap DEA and Stochastic Frontier Analysis (SFA). The Bootstrap DEA method incorporates the concept of probability into the traditional DEA, while the SFA assumes a specific function for inputs and outputs and estimates cost efficiency through a parametric approach. By using these complementary methods, this study aims to provide a more comprehensive assessment of the cost efficiency effects of bancassurance on Korean insurance firms.

The paper reviews the bancassurance market and regulations in Korea, summarizing the literature on the cost efficiency of life insurers before and after bancassurance. It presents the methodologies and data, discusses the results, and provides conclusions and implications. This pioneering study applies multiple analytical approaches, including Bootstrap DEA, to re-evaluate the cost efficiency impact of bancassurance in the Korean market, contributing to the debate on the bancassurance system's effectiveness and the need for regulatory adjustments.

The rest of the paper consists of the following: Section 2 overviews the status of bancassurance market and key regulations in Korea. Section 3 traces previous literature on the cost efficiency of insurance companies. Literature is summarized, focusing on the cost efficiency of life insurers before and after the introduction of bancassurance.

Section 4 demonstrates the methodologies and data used in this study, and Section 5 shows the analysis results. Lastly, Section 6 provides conclusion and implications.

## 2. Current Market Status and Key Regulations of Bancassurance in Korea

This section outlines the status of the bancassurance market, particularly the life insurance industry, and the key regulations in Korea. The premium income of life insurers through the bancassurance channel in December 2016 recorded KRW13.1 trillion, down by 5.8% year-over-year, accounting for 15.6% of the total premium income from all sales channels (see Table 1). This represents a significant increase compared to the beginning of bancassurance in 2003. However, the proportion of bancassurance premium has declined since 2013 due to the low-interest rate environment, which has reduced the sales motivation for savings-type insurance products that were the focus of bancassurance.

Table 1. Premium Income and Initial Premium of Life Insurance Firms via Bancassurance Channel (Units: KRW bil., %)

| | FY2003 | FY2005 | FY2007 | FY2009 | FY2011 | FY2012 | FY2013(Note 2) | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|
| Premium Income | 2,361 | 3,846 | 5,322 | 7,566 | 13,488 | 29,907 | 8,385 | 13,099 | 13,879 | 13,078 |
| | (5.2) | (8.1) | (10.3) | (14.2) | (22.3) | (34.2) | (15.3) | (16.8) | (16.7) | (15.6) |
| Initial Premium | 2,157 | 1,842 | 1,840 | 3,357 | 6,664 | 20,399 | 5,284 | 8,882 | 9,159 | 8,375 |
| | (39.7) | (46.6) | (42.6) | (59.0) | (71.1) | (74.1) | (72.3) | (72.3) | (72.2) | (75.9) |

Source: Korea Life Insurance Association

The key regulations governing bancassurance in Korea, which can be categorized into three main restrictions:

(1) Restriction on sales products: Bancassurance is limited to selling savings-type insurance and third-area insurance (e.g., illness, accident, long-term care) and excludes personal protection insurance like whole life and auto insurance. Plans to expand the product range were withdrawn due to stakeholder opposition.

(2) Restriction on sales ratio: The "25% rule" limits the subscription of any single insurance company's products sold through bancassurance to 25% of the total subscription of newly provided financial institution insurance agency (bank) products. This regulation has been strengthened from an initial 49% limit.

(3) Restriction on the number of sellers: The number of bancassurance product sellers is limited to a maximum of two per bank office or branch.

These key regulatory restrictions on bancassurance in Korea are seen as limiting the competitiveness and potential benefits of the bancassurance system, prompting the need for regulatory review and potential relaxation.

Table 2. Products Permitted by Implementation Phase in Bancassurance

| | Enforced by | Life Insurance | Non-Life Insurance |
|---|---|---|---|
| Stage 1 | 2003. 8 | Savings-Type (Pension etc.) | Long-Term Savings, Accident, etc. |
| Stage 2 | 2005. 4 | Guaranteed Third Area | Guaranteed Third Area |
| Stage 3 | 2006. 10 | Refundable Third Area | Refundable Third Area |
| Stage 4 | Withdrawn | Personal Protection (Whole Life etc.) | Automobile, Long-Term Protection |

## 3. Literature Review

Previous studies on the impact of bancassurance in Korea have primarily used the DEA (Data Envelopment Analysis) method to assess its effect on the cost efficiency of insurance companies. This paper aims to re-evaluate the cost efficiency impact by also employing the Bootstrap DEA and Stochastic Frontier Analysis (SFA) methods, in addition to the traditional DEA approach.

The studies on the Korean bancassurance system have primarily focused on the life insurance industry. Jeong and Lee (2003) used the DEA method to analyze and compare the efficiency of life and non-life insurers before and after the introduction of bancassurance. They found that firms that allocate more resources to sales than production benefit more from the cost efficiency improvements of bancassurance, but death insurance was concluded to be inappropriate for bancassurance.

Lee, Lee, and Jeong (2004) adopted the frontier method to analyze the cost, return, and profit efficiency of life insurers before and after bancassurance. They found that small, medium, and foreign life insurers could enhance cost and return efficiency, but their profit efficiency deteriorated, while the opposite was true for large life insurers. Banks were found to benefit more by affiliating with large life insurers. Kim (2007) used the DEA method and Malmquist Index to identify changes in the cost efficiency and production of Korean life insurers during the period of 2000 to 2005, following the introduction of bancassurance. Kim and Sohn (2008) measured the cost efficiency of life insurance firms before and after bancassurance using the DEA method and multiple regression analysis. They argued that the system failed to improve the cost efficiency of the domestic life insurance industry, with any observed improvements being temporary, resulting from an increase in single-premium insurance contracts.

One of the early studies in this area was conducted by Jeong and Nam (2009), who used the Data Envelopment Analysis (DEA) method to examine changes in the cost efficiency of Korean life insurers before and after the introduction of bancassurance. Their findings revealed a nuanced picture – while the cost efficiency of the top three insurance firms was not significantly influenced, foreign life insurers and domestic small and medium-sized life insurers continued to maintain cost efficiency improvements after the implementation of bancassurance. Building on this, Lee (2013) also adopted the DEA method to estimate the effect of bancassurance on cost reduction and price decreases, using data from fiscal years 2000 to 2011. The study found that the cost efficiency of life insurers, excluding the industry giants, generally improved after the introduction of bancassurance, and the positive effect increased as the scheme expanded.

In addition to the DEA analysis, Lee (2013) included an indirect assessment of the cost reduction and price decrease effects of bancassurance by analyzing cancellation refunds, estimated expense rates, and insurance product price indices. The results of this supplementary analysis also pointed to the same conclusion as the DEA and multiple regression analyses – that bancassurance had a positive impact on cost efficiency and pricing. While previous studies had focused primarily on the insurer's perspective, Lee and Lee (2018) took a more comprehensive approach by analyzing the effects of bancassurance from the perspectives of insurers, consumers, and banks. From the consumer's standpoint, Lee and Lee (2018) found that bancassurance contributed to lowering insurance premiums by decreasing sales commissions. The review of international studies on insurance company cost efficiency reveals the use of various methodologies, including Stochastic Frontier Analysis (SFA) and Deterministic Frontier Analysis (DFA), in addition to the DEA approach commonly employed in the Korean context.

Rai (1996) estimated the cost efficiency (X-inefficiency) of insurers in 11 countries during the 1988-1992 period using the SFA and DFA methods. The results showed that French and Finnish insurers had the lowest X-inefficiency, while English insurers had the highest. Cummins and Zi (1998) examined the cost efficiency of U.S. life insurers and found that the results can vary significantly depending on the methodology used. In the Korean context, the studies on the effects of bancassurance in the life insurance industry have predominantly utilized the DEA method, with some findings indicating that bancassurance has contributed to improved cost efficiency, particularly for smaller and foreign life insurers. The comprehensive analysis by Lee and Lee (2018) further expanded the scope to consider the impacts on consumers and banks, suggesting that bancassurance has had positive effects by lowering premiums, providing new revenue sources for banks, and expanding the overall insurance market.

## 4. Methodology and Variables

### *4.1 Methodology*

Under the premise that market structure is competitive, only the efficient firms are to survive in the long haul. Here, being "efficient" means to be cost effective—i.e. how effective the input has been used and combined to produce the output.

This paper applied parametric and non-parametric frontiers to measure life insurers' cost efficiency. Domestic studies have used the non-parametric DEA method to calculate efficiency without estimating parameters. DEA evaluates a DMU's efficiency compared to the industry using linear programming, drawing the efficient frontier from input-output data and determining how far other targets are from it. This paper used the DEA cost efficiency concept from Coelli et al. (1998), assuming VRS as productible sets do not satisfy CRS.

In accordance with Coelli et al. (1998), it is assumed that $n$ insurers input $m$ production factors to produce $s$ outputs. The efficiency of insurer $h$, which is the ratio of weighted sum of output to the weighted sum of input, can be represented by the following Equation (1). Equation (1) elaborates on how to derive the weight $u_i$ and $v_j$ that maximize $F_h$, insurer $h$'s efficiency, under the condition that all estimated efficiency values should be less than or equal to "1.

$$Max_{\{u_i,v_j\ ;i=1,\dots,m,j=1,\dots,s\}}\ F_h = \frac{u_1Y_{1h} + u_2Y_{2h} + \cdots + u_sY_{sh}}{v_1X_{1h} + v_2X_{2h} + \cdots + v_mX_{mh}} \tag{1}$$

$$\text{s.t.}\quad \frac{u_1Y_{1h} + u_2Y_{2h} + \cdots + u_sY_{sh}}{v_1X_{1h} + v_2X_{2h} + \cdots + v_mX_{mh}} \le 1 \tag{2}$$

$$u_i, v_j \ \ge 0\ ,\quad i = 1,\dots,m,\quad j = 1,\dots,s,\quad k = 1,\dots,h,\dots,n \tag{3}$$

$$X_i = i^{th}\ input,\quad i = 1,2,\dots,m \tag{4}$$

$$y_j = j^{th}\ output,\quad j = 1,2,\dots,s \tag{5}$$

$$X_{ik} = i^{th}\ input\ of\ insurer\ k,\quad k = 1,2,\dots,n \tag{6}$$

$$Y_{jk} = j^{th}\ output\ of\ insurer\ k \tag{7}$$

$$u_i = weight\ of\ output\ vector \tag{8}$$

$$v_j = weight\ of\ input\ vector\ F_k = efficiency\ of\ insurer\ k \tag{9}$$

However, the problem with this ratio formation is that this equation has infinite solutions—thus, another constraint $\sum_{i=1}^{m} v_iX_{ik} = 1$ is added to the formula. Then, Equation (1) becomes a matter of maximizing insurer $h$'s output subject to the input. Equation (1) can be newly expressed as the following according to the dual theory of linear programming.

$$\text{Min}\ \theta_h = \sum_{i=1}^{m} v_iX_{ih} \tag{10}$$

$$\text{s.t.}\quad \sum_{j=1}^{s} u_jY_{jk} = 1,\quad \sum_{i=1}^{s} u_jY_{jk} + \sum_{i=1}^{m} v_iX_{ik} \ge 0 \tag{11}$$

The solution $\theta_h$ of Equation (2), minimizing the input subject to output, indicates the cost efficiency of insurer $h$. Nor does this indicator satisfy the condition $0 < \theta \le 1$, but when the value marks 1, it represents a point on the cost frontier, signifying the insurer is technically cost efficient.

However, the generally used DEA is a non-parametric frontier method which estimates the efficiency simply based on input and output, thereby having limitations in that it could not statistically infer or identify probabilistic volatility for the measured efficiency. One of the methodologies to overcome these limitations is the Bootstrap DEA proposed by Simar and Wilson (1998). The DEA is a nonparametric method that does not assume a form of a particular function, and its resulted values are derived from the data-generating process. Thus, the statistical characteristics of the measured efficiency are essential to be included in the interpretation. Simar and Wilson (2000) argue that Bootstrap is a means of estimating these attributes (estimating bias and variance and constructing confidence intervals). Bootstrap is one of the simulation methodologies that adds a stochastic (probabilistic) concept to the derived efficiency from general DEA. The bootstrap DEA gives statistical inference to the result, estimating the value by repeatedly executing the general DEA. And so, it has the advantage of estimating parameters for the measured efficiency, such as the average, and measuring the confidence interval. The following is a summary of the bootstrap DEA steps presented by Simar and Wilson (1998):

Step 1. Calculate the efficiency score using the DEA method.; Calculate the efficiency score $\widehat{\theta_k}(k = 1,\dots\dots,n)$ through the linear program

Step 2. Generate a random sample from the empirical distribution (ED) of the efficiency score calculated in Step 1. Simar and Wilson (1998) reported the smoother the ED, the more consistent the results.; Employ Kernel Density Estimation to generate a random sample that provides $\{\theta_{1b}^*,\dots\dots,\theta_{nb}^*\}$ from $\widehat{\theta_k}(k = 1,\dots\dots,n)$.

Step 3. Divide the original efficient input level by pseudo-efficiency scores derived from the (smoothed) empirical distribution to obtain the bootstrap data set of pseudo-inputs.; Calculate the pseudo data set $\{(X_{kb}^*, Y_k),\ k = 1,\dots\dots,n\}$, where, $X_{kb}^* = \left(\frac{\theta_k}{\theta_{kb}^*}\right)X_k,\ k = 1,\dots\dots,n$

Step 4. Apply the new pseudo-inputs and the same output group to DEA, then calculate the bootstrapped efficiency scores.; Calculate bootstrapped efficiency scores $\widehat{\theta_{kb}^*}$ for each insurer's $\widehat{\theta_k}$

Step 5. Repeat Step 2 to 4 to calculate bootstrapped efficiency scores. Simar and Wilson (1998, 2000) suggested B=1,000 and B=2,000.; Repeat for B times to obtain $\{\widehat{\theta_{kb}^*}; b = 1,\dots\dots,B\}$, and calculate smoothed bootstrapped estimate $\overline{\theta_k^*} = \frac{1}{B}\sum_{b=1}^{B}\widehat{\theta_{kb}^*}$

Lastly, this paper used the SFA to estimate cost efficiency. While the DEA measures efficiency with a linear combination of observed points, the SFA assumes the relationship between output and input to be a specific function type and estimates the cost efficiency through such parametric function. This paper estimated the cost efficiency by setting the traditional translog cost function for parametric function. The translog functional form is a function developed by the second-order Taylor expansion, in which the translog changes the ratio of output to input so that the estimated cost curve shows a U-shape. This function is mainly used in empirical analysis because it expresses the effect up to the second term of the input element, thereby representing the firms' activities more flexibly. The general expression of the cost function could be described as: $C = f(y, w, t)$. The $C,\ y,\ w$ and $t$ here each refers to total cost, output, input price, and time; $y$ and $w$ are vectors. The cost frontier is defined as the minimum total cost function, which provides the lowest achievable cost for each output level. The basic form of a translog cost function is as follows:

$$\ln C_{st} = \begin{bmatrix} \alpha_0 + \sum_{i=1}^{N} \alpha_{yi} lny_{sit} + \frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N} \alpha_{yik} lny_{sit} lny_{skt} + \sum_{j=1}^{M} \alpha_{wj} lnw_{sit} + \\ \frac{1}{2}\sum_{j=1}^{M}\sum_{f=1}^{M} \alpha_{wif} lnw_{sjt} lnw_{sft} + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{M} \alpha_{yiwj} lny_{sit} lnw_{sjt} \end{bmatrix} + \upsilon_{st} + \epsilon_{st} \qquad (12)$$

Here, $s = \{1, \dots, S\}$, $i = \{1, \dots, N\}$, $j = \{1, \dots M\}$ each represents firms, outputs, and inputs; $C_{st}$ is the total cost observed in year $t$, $y_{sit}$ is the magnitude of output $i$ produced by firm $s$ in year $t$, $w_{sjt}$ is the $j$ th input price of firm $s$ in year $t$, $\epsilon_{st}$ is random error term, $\upsilon_{st}$ is the inefficiency error term. The estimation is done using the general equation system consisting of cost function and first-order conditions for cost minimization. It is assumed that the firm shares the common cost function given by Equation (3). Also, it is assumed via the random error term $\epsilon_{st}$ that each firm's error is independent and equally distributed, as well as out of control of the individual firm. That is, $\epsilon_{st}$ is a random error term, and a firm's inefficiency could be captured through $\upsilon_{st}$. Because inefficiency only increases costs (does not reduce costs), it has a one-sided error term (i.e. $\upsilon_{st} \geq 0$). Random error term generally assumes normal distribution, while $\upsilon_{st}$ which captures the inefficiency of firms commonly assumes an exponential, half-normal (truncated normal), and gamma distribution. The estimated parameters in the assumed distribution are replaced by the appropriate types of $\mathrm{E}(\exp(-\upsilon_{st})\,|u_{st})$, $(u_{st} = \upsilon_{st} + \epsilon_{st})$ to obtain an estimate of each observed inefficiency. In this paper, half-normal distribution is assumed for $\upsilon_{st}$, which is most generally used in various studies.

*4.2 Variables*

To measure insurers' cost efficiency and bancassurance effects, output, input, and input price must be carefully chosen. For financial firms, the value-added approach is most suitable to represent production. Prior studies on insurer efficiency employed the modified value-added approach (Berger, Cummins, and Weiss, 1997), which distinguishes insurance's risk pooling, financial, and intermediation functions. This paper uses the modified value-added approach, with underwriting (premiums) and intermediation (operational assets) as outputs. Labor (employees, sales force), capital (real estate, deposits), and prices (wage, sales fees, operating costs) are input variables (Kim, 2007).

The insurer's intermediary role is captured by "operational asset investment," as insurers invest premiums in securities or loans until they pay back insurance provisions. Thus, an insurer acts as an institutional investor or loan provider, and this function can be measured by the investment amount of the operational asset (Jeong and Lee, 2003).

To measure the efficiency of an insurer, input variables related to labor, capital, and service need to be considered. Labor is the most important factor, with the number of employees and sales force selected as labor-related inputs. Physical capital, such as real estate and related deposits, is chosen as the capital-related input. Input prices are also needed, with wage, sales fees, and operating costs used to calculate the input price factors.

Lastly, the total costs for the translog cost function applied in the Stochastic Frontier Analysis (SFA) model are defined as the sum of insurance operating expenses, investment operating expenses, and special account expenses.

Table 3. Name and Composition of Variables

| Name of Parameter | | | Composition |
|---|---|---|---|
| Costs | C | Total Costs | Insurance Operating Expenses + Investment Operating Expenses + Special Account Expenses |
| Output | y1 | Insurance Premium | Initial Premium / Premium Income |
| | y2 | Operational Asset Investment | Operational Asset |
| Input | x1 | Number of Employees | Number of Employees |
| | x2 | Number of Sales Force | Number of Sales Staffs + Branch |
| | x3 | Physical Equity | Real Estate + its related Deposit |
| Input Price | w1 | Employee Price Factor | (Wage + Bonus + Benefits + Pension) / Number of Employees |
| | w2 | Sales Force Price Factor | Total sales fees for new contracts / Number of Sales Force |
| | w3 | Physical Equity Price Factor | (Communication Expense + Utility Costs + Rent + Maintenance Cost + Operation Cost) / Physical Equity |

Sources: Korea Life Insurance Association Monthly Insurance Statistics, Korea Insurance Development Insurance Statistical Yearbook

To track the bancassurance effect on cost efficiency, this paper selected 20 Korean insurance companies for individual DMUs (Decision Making Units). Among the 25 life insurers as of 2016, the three firms newly included in the insurance industry statistics on FY2010, FY2011, and FY2013 respectively — IBK Insurance, NongHyup Life Insurance, and Kyobo LifePlanet — were opted out; and BNP Paribas Cardif Life Insurance and KB Life Insurance were also excluded because of their occasional/discontinuing business activities and missing data since FY2000. The actual data for the analysis are extracted from the statistical monthly report of the Korea Life Insurance Association and the statistical annual report of the Korea Insurance Development Institute, and the target years are from FY2000 to 2016. In addition, all the money data was adjusted based on the 2010 Consumer Price Index (CPI) considering the inflation rate. The descriptive statistics for the output, inputs, input price factors, and costs are summarized in Table 4.

Table 4. Descriptive Statistics (Unit: KRW mil, number of people, %)

| Variable | Year | Mean | S.D. | Minimum | Maximum |
|---|---|---|---|---|---|
| Costs | FY2000 | 3,330,626 | 6,251,763 | 33,426 | 23,181,215 |
| | FY2011 | 2,402,855 | 3,125,046 | 139,060 | 13,438,744 |
| | 2016 | 2,905,410 | 3,537,964 | 191,200 | 14,640,435 |
| Premium Income (y1-①) | FY2000 | 3,185,836 | 6,614,622 | 16,064 | 26,313,597 |
| | FY2011 | 2,750,857 | 3,238,810 | 127,214 | 14,159,825 |
| | 2016 | 3,254,200 | 3,670,193 | 213,628 | 15,031,718 |
| Initial Premium (y1-②) | FY2000 | 1,055,928 | 2,348,292 | 970 | 9,151,507 |
| | FY2011 | 368,217 | 448,338 | 2,346 | 1,762,100 |
| | 2016 | 379,964 | 595,116 | 5,202 | 2,183,185 |
| Operational Asset (y2) | FY2000 | 6,817,794 | 15,060,653 | 27,624 | 62,759,821 |
| | FY2011 | 16,366,142 | 28,881,999 | 502,151 | 125,291,199 |
| | 2016 | 24,729,601 | 40,213,482 | 1,009,630 | 175,008,937 |
| Number of Employees (x1) | FY2000 | 1,582 | 2,365 | 63 | 8,271 |
| | FY2011 | 1,371 | 1,676 | 240 | 6,357 |
| | 2016 | 1,254 | 1,441 | 160 | 5,315 |
| Number of Sales Force (x2) | FY2000 | 10,769 | 17,184 | 94 | 61,575 |
| | FY2011 | 8,116 | 10,854 | 418 | 44,911 |
| | 2016 | 6,464 | 8,921 | 43 | 36,531 |
| Physical Equity (x3) | FY2000 | 719,660 | 1,504,164 | 2,421 | 5,947,835 |
| | FY2011 | 703,273 | 1,437,979 | 10,336 | 5,577,626 |
| | 2016 | 666,174 | 1,358,145 | 2,288 | 5,333,828 |
| Employee Price (w1) | FY2000 | 47.69 | 8.566 | 36.004 | 73.478 |
| | FY2011 | 71.545 | 13.726 | 48.899 | 101.569 |
| | 2016 | 85.791 | 19.103 | 46.971 | 136.763 |
| Sales Force Price (w2) | FY2000 | 36.119 | 26.705 | 14.738 | 124.052 |
| | FY2011 | 66.993 | 25.169 | 32.07 | 128.962 |
| | 2016 | 96.419 | 79.072 | 41.27 | 334.785 |
| Physical Equity Price (w3) | FY2000 | 0.31 | 0.535 | 0.015 | 1.912 |
| | FY2011 | 0.448 | 0.583 | 0.022 | 2.047 |
| | 2016 | 0.408 | 0.684 | 0.023 | 2.854 |

Note: Price data is adjusted to 2010 CPI

Sources: Korea Life Insurance Association Monthly Insurance Statistics, Korea Insurance Development Insurance Statistical Yearbook

## 5. Analysis Results

### *5.1 Estimation Results of Cost Efficiency by Model*

Table 5 shows the average cost efficiency of each analysis model used for this study. Looking into the cost efficiency level by model, the SFA overall had a higher value than the DEA model. As for the bootstrap DEA model, the value was lower than that of the general DEA model. This also matches the result of Cummins and Zi (1998). This result is deemed to be generated because the DEA model assumes that all the points deviating from the frontier are regarded as inefficiency, whereas the SFA model, the inefficiency is estimated by distinguishing the random error term from the inefficiency error term.

The analyses show similar cost efficiency trends across models, with varying levels. Life insurers' cost efficiency improved after 2003's bancassurance introduction in Korea. DEA model shows average efficiency steadily rose after 2003, dipped in 2014, then climbed for large/foreign firms. Bootstrap DEA and SFA models showed similar patterns, with a small 2014-2015 decline followed by resurgence. Specifically, DEA average efficiency rose from 0.533 in 2001 to 0.686 in 2016, with small/medium insurers seeing high improvements. This was confirmed by Bootstrap DEA and SFA. Using initial premium instead of income, DEA/Bootstrap DEA were similar, but SFA showed different trends, as initial premiums are more sensitive to factors like tax benefits and macroeconomic conditions, which may be in SFA's random error term. Incorporating these factors could improve DEA-SFA comparison.

Overall, the cost efficiency of life insurers improved after the introduction of bancassurance, though the trend has slowed down since 2014 due to changes in the business environment and other management efficiency factors, rather than the bancassurance scheme itself.

Table 5. Cost Efficiency of Life Insurers by Model and Firm Size

| | | FY 2001 | FY 2003 | FY 2005 | FY 2007 | FY 2009 | FY 2011 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|
| Premium Income | | | | | | | | | | |
| All Firms | DEA-VRS | 0.533 | 0.538 | 0.674 | 0.71 | 0.729 | 0.818 | 0.731 | 0.686 | 0.686 |
| | Bootstrap DEA | 0.305 | 0.203 | 0.521 | 0.559 | 0.559 | 0.679 | 0.469 | 0.527 | 0.532 |
| | SFA | 0.778 | 0.725 | 0.782 | 0.838 | 0.785 | 0.785 | 0.798 | 0.786 | 0.807 |
| Large | DEA-VRS | 0.706 | 0.721 | 0.809 | 0.794 | 0.861 | 0.813 | 0.781 | 0.83 | 0.823 |
| | Bootstrap DEA | 0.312 | 0.165 | 0.563 | 0.575 | 0.662 | 0.672 | 0.455 | 0.59 | 0.615 |
| | SFA | 0.785 | 0.819 | 0.866 | 0.885 | 0.859 | 0.788 | 0.782 | 0.793 | 0.806 |
| Small and Medium | DEA-VRS | 0.438 | 0.451 | 0.624 | 0.645 | 0.713 | 0.869 | 0.783 | 0.698 | 0.665 |
| | Bootstrap DEA | 0.282 | 0.224 | 0.521 | 0.525 | 0.566 | 0.736 | 0.543 | 0.563 | 0.517 |
| | SFA | 0.848 | 0.783 | 0.811 | 0.835 | 0.794 | 0.757 | 0.812 | 0.800 | 0.802 |
| Foreign | DEA-VRS | 0.56 | 0.554 | 0.672 | 0.740 | 0.699 | 0.774 | 0.667 | 0.627 | 0.659 |
| | Bootstrap DEA | 0.324 | 0.196 | 0.507 | 0.584 | 0.518 | 0.63 | 0.408 | 0.474 | 0.517 |
| | SFA | 0.714 | 0.642 | 0.729 | 0.825 | 0.752 | 0.808 | 0.791 | 0.772 | 0.81 |
| Initial Premium | | | | | | | | | | |
| All Firms | DEA-VRS | 0.502 | 0.519 | 0.558 | 0.575 | 0.621 | 0.777 | 0.621 | 0.688 | 0.656 |
| | Bootstrap DEA | 0.221 | 0.151 | 0.300 | 0.366 | 0.448 | 0.646 | 0.314 | 0.387 | 0.371 |
| | SFA | 0.862 | 0.821 | 0.813 | 0.843 | 0.82 | 0.786 | 0.767 | 0.757 | 0.780 |
| Large | DEA-VRS | 0.690 | 0.681 | 0.749 | 0.718 | 0.81 | 0.794 | 0.737 | 0.88 | 0.785 |
| | Bootstrap DEA | 0.263 | 0.139 | 0.370 | 0.435 | 0.591 | 0.659 | 0.316 | 0.397 | 0.358 |
| | SFA | 0.915 | 0.876 | 0.865 | 0.862 | 0.843 | 0.751 | 0.763 | 0.735 | 0.736 |
| Small and Medium | DEA-VRS | 0.341 | 0.448 | 0.484 | 0.440 | 0.500 | 0.844 | 0.578 | 0.687 | 0.688 |
| | Bootstrap DEA | 0.161 | 0.153 | 0.285 | 0.288 | 0.379 | 0.708 | 0.358 | 0.452 | 0.416 |
| | SFA | 0.838 | 0.843 | 0.816 | 0.824 | 0.803 | 0.789 | 0.775 | 0.774 | 0.82 |
| Foreign | DEA-VRS | 0.582 | 0.529 | 0.560 | 0.647 | 0.665 | 0.712 | 0.620 | 0.626 | 0.585 |
| | Bootstrap DEA | 0.261 | 0.152 | 0.291 | 0.412 | 0.462 | 0.588 | 0.275 | 0.326 | 0.335 |
| | SFA | 0.865 | 0.784 | 0.793 | 0.853 | 0.827 | 0.794 | 0.762 | 0.750 | 0.760 |

The analysis examined changes in cost efficiency across different stages of bancassurance implementation. Looking at the premium income output, the increase in cost efficiency was limited or even slightly decreased during the initial stage, but it showed a clear and stable increase from the second stage onwards. Small and medium-sized firms, with a higher proportion of bancassurance, exhibited larger increases in cost efficiency compared to other insurers.

The Bootstrap DEA results showed greater increases in cost efficiency than the standard DEA, with the cost efficiency of SMEs in the third stage being around three times higher than the pre-bancassurance period. The SFA analysis also generally indicated increasing cost efficiency. This suggests that the cost efficiency effect of life insurers gradually improved as the bancassurance system progressed through the second and third stages.

However, when using initial premium as the output, the SFA analysis showed an overall drop in cost efficiency. This is likely because factors indicating the cost reduction effect of bancassurance were not well captured in the translog cost function or were influenced by external macroeconomic variables not directly measured. Even if bancassurance reduced costs, other inefficiency factors may have led to a decline in cost efficiency.

Table 6. Cost Efficiency of Life Insurers by Model and Implementation Stage

| | | Before Introduction (FY2000~FY2002) | Stage 1 (FY2003~FY2004) | Stage 2 (FY2005~FY2006) | Stage 3 (FY2007~2016) |
|---|---|---|---|---|---|
| Premium Income | DEA-VRS | | | | |
| | All Firms | 0.558 | 0.544 | 0.674 | 0.74 |
| | Large | 0.748 | 0.734 | 0.809 | 0.805 |
| | Small and Medium | 0.442 | 0.457 | 0.624 | 0.751 |
| | Foreign | 0.597 | 0.557 | 0.672 | 0.709 |
| | Bootstrap DEA | | | | |
| | All Firms | 0.292 | 0.217 | 0.538 | 0.575 |
| | Large | 0.316 | 0.205 | 0.57 | 0.603 |
| | Small and Medium | 0.259 | 0.235 | 0.533 | 0.603 |
| | Foreign | 0.313 | 0.205 | 0.531 | 0.542 |
| | Stochastic Frontier Analysis (translog cost function) | | | | |
| | All Firms | 0.766 | 0.728 | 0.784 | 0.789 |
| | Large | 0.775 | 0.823 | 0.853 | 0.797 |
| | Small and Medium | 0.816 | 0.799 | 0.798 | 0.779 |
| | Foreign | 0.717 | 0.633 | 0.748 | 0.794 |
| Initial Premium | DEA-VRS | | | | |
| | All Firms | 0.512 | 0.512 | 0.558 | 0.665 |
| | Large | 0.742 | 0.691 | 0.749 | 0.773 |
| | Small and Medium | 0.365 | 0.419 | 0.484 | 0.64 |
| | Foreign | 0.567 | 0.535 | 0.56 | 0.652 |
| | Bootstrap DEA | | | | |
| | All Firms | 0.207 | 0.159 | 0.31 | 0.454 |
| | Large | 0.268 | 0.174 | 0.379 | 0.488 |
| | Small and Medium | 0.165 | 0.157 | 0.288 | 0.463 |
| | Foreign | 0.224 | 0.156 | 0.307 | 0.434 |
| | Stochastic Frontier Analysis (translog cost function) | | | | |
| | All Firms | 0.826 | 0.816 | 0.811 | 0.787 |
| | Large | 0.884 | 0.873 | 0.855 | 0.777 |
| | Small and Medium | 0.829 | 0.84 | 0.809 | 0.791 |
| | Foreign | 0.805 | 0.775 | 0.798 | 0.786 |

It is confirmed that the expansion of bancassurance has brought about the enhancement in cost efficiency, but this simple trend comparison does not have statistical significance. Therefore, this paper conducted a t-test to determine more clearly whether the bancassurance system has practically increased the cost efficiency of life insurers (see Table 7). The results of analysis that used income premium as output are as follows: Both DEA and Bootstrap DEA analysis showed a significant increase after bancassurance scheme at 1% significance level for all life insurers. Specifically, the cost efficiency of SMEs with high bancassurance dependency has significantly increased. In addition, it was found that the bootstrap DEA had a higher significance than the DEA model, while the SFA showed an increase in average cost efficiency compared to the pre-bancassurance period, but not significant. The situation was similar in both premium income as well as the initial premium.

Table 7. Cost Efficiency before and after Bancassurance

| | | | Average (Before Bancassurance) | Average (After Bancassurance) | p-value |
|---|---|---|---|---|---|
| Premium Income | DEA-VRS | All Firms | 0.558 | 0.704 | 0.000 |
| | | Large | 0.748 | 0.795 | 0.548 |
| | | Small and Medium | 0.442 | 0.692 | 0.000 |
| | | Foreign | 0.597 | 0.685 | 0.184 |
| | Bootstrap DEA | All Firms | 0.292 | 0.519 | 0.000 |
| | | Large | 0.316 | 0.541 | 0.001 |
| | | Small and Medium | 0.259 | 0.54 | 0.000 |
| | | Foreign | 0.313 | 0.492 | 0.000 |
| | SFA Translog cost | All Firms | 0.766 | 0.779 | 0.399 |
| | | Large | 0.775 | 0.809 | 0.168 |
| | | Small and Medium | 0.816 | 0.785 | 0.094 |
| | | Foreign | 0.717 | 0.765 | 0.102 |
| Initial Premium | DEA-VRS | All Firms | 0.512 | 0.630 | 0.004 |
| | | Large | 0.742 | 0.759 | 0.844 |
| | | Small and Medium | 0.365 | 0.587 | 0.000 |
| | | Foreign | 0.567 | 0.625 | 0.409 |
| | Bootstrap DEA | All Firms | 0.207 | 0.391 | 0.000 |
| | | Large | 0.268 | 0.428 | 0.042 |
| | | Small and Medium | 0.165 | 0.394 | 0.000 |
| | | Foreign | 0.224 | 0.376 | 0.000 |
| | SFA Translog cost | All Firms | 0.826 | 0.794 | 0.023 |
| | | Large | 0.884 | 0.802 | 0.005 |
| | | Small and Medium | 0.829 | 0.801 | 0.154 |
| | | Foreign | 0.805 | 0.786 | 0.424 |

Table 8 shows the analysis results of the difference of cost efficiency by bancassurance dependency. Groups were made by the level of bancassurance dependency, based on the median — group with less than and more than 40% dependency. Mostly for premium income, DEA and Bootstrap DEA analysis proved that the average cost efficiency was higher for the group with higher dependency on bancassurance channel, which was estimated at a significance level of 1%. In the DEA model, the group with more than 40% dependency on bancassurance showed a cost efficiency of about 0.108p higher, and the bootstrap DEA model showed 0.106p higher as well. The results were similar for both premium income as well as the initial premium.

Table 8. Cost Efficiency Difference by Bancassurance Channel Dependency

| | | Average (below 40%) | Average (40% and over) | p-value |
|---|---|---|---|---|
| Premium Income | DEA-VRS | 0.644 | 0.752 | 0.000470 |
| | Bootstrap DEA | 0.460 | 0.566 | 0.000087 |
| | SFA (translog cost) | 0.812 | 0.754 | 0.000000 |
| Initial Premium | DEA-VRS | 0.506 | 0.728 | 0.000000 |
| | Bootstrap DEA | 0.305 | 0.460 | 0.000000 |
| | SFA (translog cost) | 0.827 | 0.769 | 0.000000 |

### *5.2 Analysis of Effect on Cost Efficiency by Bancassurance Channel Dependency: Multiple Regression Analysis*

Even though the cost efficiency of life insurers rose after bancassurance, it cannot be attributed solely to the implementation of the bancassurance system. To verify the effect of bancassurance, this paper employed multiple regression analysis using data from FY2003 (the introduction year of bancassurance) to 2016 for 20 life insurers.

DEA, Bootstrap DEA, and SFA calculated cost efficiencies as dependent variables, with bancassurance dependency and firm characteristics as explanatory variables. Explanatory variables included size, asset ratio, market share, lapse ratio, new contract amount, claims, group insurance, and single-premium ratio. Price variables were log-transformed. This multiple regression analysis aimed to verify bancassurance's influence on life insurers' cost efficiency (Kim and Sohn, 2008; Lee, 2013).

Table 9. Variables Used in Multiple Regression Analysis

| Name of Variable | Variable Setting |
|---|---|
| Cost Efficiency (dependent variable) | - |
| Bancassurance Dependency (explanatory variable) | Initial Premium of Bancassurnace / Total Initial Premium |
| Lapse Ratio | - |
| Operational Asset Ratio | Operational Asset / Total Assets |
| Group Insurance Ratio | Group Insurance Premium Income / Total Premium Income |
| Single-Premium Insurance Ratio | Income from Single-Premium Insurance / Total Premium Income |
| Market Share | Based on Premium Income |
| Total Assets | Log (Total Assets) |
| Average New Contract Amount | Log (Average New Contract Amount) |
| Insurance Claims Paid | Log (Insurance Claims Paid) |

Table 10. Basic Statistics of Variables Used in Multiple Regression Analysis

| Name of Variable | | N | Average | S.D. | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Cost Efficiency | DEA-VRS | 280 | 0.70 | 0.25 | 0.11 | 1.00 |
| | Bootstrap DEA | 280 | 0.52 | 0.22 | 0.04 | 0.91 |
| | SFA | 280 | 0.78 | 0.11 | 0.19 | 0.94 |
| Bancassurance Dependency | | 280 | 0.45 | 0.32 | 0.00 | 1.00 |
| Lapse Ratio | | 280 | 0.12 | 0.04 | 0.03 | 0.32 |
| Operational Asset Ratio | | 280 | 0.71 | 0.17 | 0.11 | 0.94 |
| Group Insurance Ratio | | 280 | 0.01 | 0.01 | 0.00 | 0.09 |
| Single-Premium Insurance Ratio | | 280 | 0.10 | 0.13 | 0.00 | 0.83 |
| HHI | | 280 | 0.66 | 1.87 | 0.00 | 13.14 |
| Log (Total Assets) | | 280 | 15.82 | 1.47 | 11.77 | 19.30 |
| Log (Average New Contract Amount) | | 280 | 7.26 | 1.37 | 2.45 | 8.71 |
| Insurance Claims Paid | | 280 | 13.31 | 1.52 | 8.23 | 16.36 |

Note: Above are basic statistics of cost efficiency based on premium income.

In advance to conducting the multiple regression analysis, the correlations between explanatory variables were examined to determine whether there was endogeneity. It turned out that bancassurance dependency, lapse ratio, operational asset ratio, group insurance ratio, and single-premium insurance ratio had a significant correlation, but the correlation coefficient was not high enough to be considered. Moreover, the VIF (Variance Inflation Factor) was measured to check the degree of multi-collinearity between the variables; and the VIF values were less than 3, which implies the multi-collinearity between variables is not significant enough to be considered. Yet, the VIF value of the total assets and insurance claims paid is very high at 18.96 and 19.15, respectively, indicating that there are multiple collinearities between the two variables. Therefore, multiple regression analysis was performed by adding only the total assets that had a higher correlation coefficient in the correlation analysis with the dependent variable, cost efficiency. The HHI variable was excluded as it was found to be highly correlated with the total asset variable.

Table 11. Pearson Correlation Coefficient of Parameters

| | Bancassurance Dependency | Lapse Ratio | Operational Asset Ratio | Group Insurance Ratio | Single-Premium Insurance Ratio | HHI | Total Assets | Average New Contract Amount | Insurance Claims Paid |
|---|---|---|---|---|---|---|---|---|---|
| Bancassurance Dependency | 1 | | | | | | | | |
| Lapse Ratio | -0.182*** | 1 | | | | | | | |
| Operational Asset Ratio | 0.138** | -0.256*** | 1 | | | | | | |
| Group Insurance Ratio | -0.224*** | 0.077 | 0.096 | 1 | | | | | |
| Single-Premium Insurance Ratio | 0.662*** | -0.099* | 0.115* | -0.144** | 1 | | | | |
| HHI | -0.098 | -0.109* | 0.171*** | 0.501*** | -0.033 | 1 | | | |
| Total Assets | 0.081 | -0.468*** | 0.285*** | 0.235*** | -0.076 | 0.570*** | 1 | | |
| Average New Contract Amount | 0.054 | -0.191*** | 0.032 | -0.149** | 0.110* | 0.068 | -0.131** | 1 | |
| Insurance Claims Paid | 0.033 | -0.321*** | 0.442*** | 0.339*** | -0.150** | 0.561*** | 0.932*** | 0.013 | 1 |

Note: * p<0.1; ** p<0.05; *** p<0.01

Table 12 shows multiple regression results. All models were valid, with very significant F values at 1%. Bancassurance dependency coefficients were positive and significant at 1%, except for SFA with initial premium. This means bancassurance sales portion significantly affected insurers' rising cost efficiency. This confirms previous cost efficiency analyses, which showed the enhancement effect became more apparent after implementation stage 2. The consistent results across models, except for SFA with initial premium, firmly verify the bancassurance cost efficiency benefit.

Large assets and high asset ratios positively impact insurers' cost efficiency due to long-term profitability and risk management. Group insurance's effects varied, as it can be cost-efficient but negatively impact project costs due to affiliate transactions. Higher lapse ratios and new contract amounts reduce cost efficiency, as lapse increases expenditure. The SFA model's lapse ratio and asset ratio coefficients differed from DEA and Bootstrap DEA, suggesting SFA better accounts for external factors like economic conditions and risk (Kim and Sohn, 2008; Lee, 2013).

Table 12. Results of Multiple Regression Analysis by Model

| | Premium Income | | | Initial Premium | | |
|---|---|---|---|---|---|---|
| | DEA | Bootstrap DEA | SFA | DEA | Bootstrap DEA | SFA |
| Bancassurance | 0.172*** | 0.183*** | 0.035* | 0.223*** | 0.165*** | -0.084*** |
| Dependency | (0.054) | (0.048) | (0.020) | (0.056) | (0.048) | (0.017) |
| Lapse | -1.747*** | -1.379*** | 0.807*** | -1.225*** | -0.505 | 0.505*** |
| Ratio | (0.353) | (0.310) | (0.131) | (0.367) | (0.313) | (0.109) |
| Operational | 0.520*** | 0.375*** | -0.150*** | 0.375*** | 0.230*** | -0.025 |
| Asset Ratio | (0.079) | (0.069) | (0.029) | (0.082) | (0.070) | (0.024) |
| Group | -0.641 | -2.709*** | 0.125 | 0.17 | -2.815*** | 0.042 |
| Insurance Ratio | (0.916) | (0.805) | (0.341) | (0.954) | (0.814) | (0.283) |
| Single-Premium | -0.175 | -0.403*** | -0.467*** | 0.509*** | 0.059 | 0.041 |
| Insurance Ratio | (0.131) | (0.116) | (0.049) | (0.137) | (0.117) | (0.041) |
| log(Total | 0.019* | 0.024*** | 0.027*** | 0.046*** | 0.048*** | 0.013*** |
| Asset) | (0.010) | (0.009) | (0.004) | (0.011) | (0.009) | (0.003) |
| log(Average New | -0.025*** | -0.031*** | -0.008** | -0.019* | -0.033*** | -0.015*** |
| Contract Amount) | (0.009) | (0.008) | (0.003) | (0.010) | (0.008) | (0.003) |
| Constant | 0.375* | 0.247 | 0.456*** | -0.228 | -0.288* | 0.691*** |
| | (0.193) | (0.170) | (0.072) | (0.201) | (0.172) | (0.060) |
| Observations | 280 | 280 | 280 | 280 | 280 | 280 |
| $R^2$ | 0.367 | 0.365 | 0.518 | 0.453 | 0.333 | 0.292 |
| Adjusted$R^2$ | 0.351 | 0.349 | 0.506 | 0.439 | 0.316 | 0.273 |
| Residual Std. Error (df=272) | 0.205 | 0.18 | 0.076 | 0.214 | 0.182 | 0.063 |
| F Statistic (df=7;272) | 22.523*** | 22.375*** | 41.821*** | 32.129*** | 19.386*** | 15.999*** |

Note 1: * p<0.1; ** p<0.05; *** p<0.01

Note 2: () is standard error

## 6. Conclusion

This study examined if bancassurance achieved its cost efficiency goal over 15 years. It revisited existing DEA studies using additional methods, making it the first to use bootstrapping to measure Korean insurers' cost efficiency.

Summarizing the managerial implications:

(1) This longitudinal study provides comprehensive evidence that bancassurance has achieved its intended cost efficiency goal for Korean life insurers over the past 15 years. The findings are robust across multiple analytical methods, including DEA, Bootstrap DEA, and SFA.

(2) The results show that smaller insurers with higher bancassurance dependency experienced more prominent cost efficiency enhancements as the implementation of bancassurance progressed. This suggests that relaxing regulatory restrictions on bancassurance could substantially benefit these firms and improve overall industry efficiency.

(3) The significantly greater cost efficiency improvements observed for firms with higher bancassurance dependency further reinforces the value proposition of bancassurance. Policymakers should consider these findings when evaluating whether to relax or remove key bancassurance regulations.

(4) The divergent results between the SFA model and the DEA/Bootstrap DEA models highlight the need to more precisely model and control for external macroeconomic and environmental factors. Enhancing the SFA approach

could lead to more consistent interpretations across methodologies, providing policymakers with even stronger evidence to guide regulatory decisions.

(5) Overall, this study lays a foundation for policymakers to judge whether relaxing or abolishing bancassurance restrictions could substantially enhance cost efficiency and ultimately benefit consumers through more competitive pricing and service offerings. The evidence presented here suggests that pursuing such regulatory reforms may be warranted.

It is anticipated that this study will lay foundations for the policy authorities to judge whether to relieve or abolish key regulations of bancassurance, as it has confirmed and verified the cost efficiency enhancement effect of the existing studies with additional analysis methods. It is clear that if the key regulations of bancassurance, which restrict the complete practice of bancassurance, is relieved or abolished, it will substantially add to the cost efficiency enhancement effect (it will add substantial improvement to existing cost efficiency enhancement effect) and will bring about more positive influence on the consumer side.

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