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INVESTMENT EFFICIENCY OF LIFE INSURANCE COMPANIES IN GERMANY: APPLICATION OF A TWO-STAGE SBM

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Abstract

Purpose – To prove the robustness of the efficiency-measuring model against potentially system-relevant disturbances to company variables such as SIZE, ROA, solvency and organizational form.
Methodology – In the first stage, the established model is applied using the SBM to measure insurance efficiency. The underlying data sets are from the twenty biggest life insurance companies (2008-2017) in Germany. In the second stage, the established model is examined for its robustness against disturbance variables. Several disturbance variables are introduced individually to the system and examined for their influence by three econometric methods, Tobit regression, OLS and the fixed-effect model. This approach allows a comparative analysis of the results with respect to the systemic relevance of every added variable. In the end, the accuracy of the second stage is compared through the Spearman test.
Findings – The comparative analysis of all three econometric techniques brought ROA as an efficiency-influencing variable. Furthermore, both proved econometric models Tobit and OLS are SBM-suitable with cross-sectional data. Further evidence for SBM compatibility are found for Tobit and the fixed-effect model with panel data.

Keywords: DEA-SBM, Efficiency, Tobit, OLS, Investment, Insurance

JEL classification: C510, C520

Introduction

During the last decade, the life insurance environment in Germany has changed fundamentally. The Third Generation Insurance Direction, the financial crisis of 2007 or the introduction of Solvency II are some examples of events of great significance. Especially, investment management played an important role in the production process of life insurers and the changing environment during this time. Managers of life insurers had to make a fast and accurate decision to avoid a mismatch between assets and liabilities

(Black and Skipper, 2000) or exit from the insurance market – due to bankruptcy or merger. As a consequence, scholars started to investigate the efficiency of insurance companies using different approaches. One of the most relevant models is Data Envelopment Analysis (DEA). DEA is a non-parametric model, which can be used for calculating efficiency scores with multiple input and output variables related to a group of insurers. But only an investigation of efficiency scores was not sufficient enough, therefore scholars started to use two-stage DEA approaches. Although Tobit regression has particular weaknesses in the use with efficiency scores (Hoff, 2007), it is still one of the most applied approaches for the second stage. However, scholars started to compare Tobit regression with other econometric models as Ordinary least square (OLS) in a two-stage DEA approach (McDonald, 2009; Hoff, 2007).

The aim of this article is to investigate efficiency scores of the investment management in the twenty biggest life insurance companies on the German market and to analyze chosen disturbing factors. In order to achieve this aim, a two-stage DEA model is used with a slacks-based measure (SBM) model in the first stage and the Tobit regression, OLS model and the fixed-effect model in the second stage. In addition, the Spearman ranking correlation coefficient is used to compare two second stage models, each in order to find out the accuracy of those models.

This article provides some contributions that have been neglected in the literature so far. First of all, companies from the life insurance market in Germany are investigated. Even though it is the fifth biggest life insurance market in the world, only a few researchers have investigated it, among these Luhnen (2009), Mahlberg and Url (2010). Secondly, instead of the whole insurance company, this article only focuses on the investment management part for more accurate results. Finally, OLS is analyzed, which is rarely used.

This article is structured as follows. After the introduction, a literature review takes place in chapter 1. Chapter 2 includes the research sample, the SBM-approach and the econometric models. The article ends with a comparison and interpretation of the results, including a brief limitation and outlook.

1. Literature Review

DEA, introduced by Charnes *et al.* (1978), is one of the most applied methods in the efficiency area (Eling and Luhnen, 2008). It was used in a wide range of areas such as banking (Wang *et al.*, 2013), fisheries (Hoff, 2007) and insurance markets (Eling and Luhnen, 2008; Yakob *et al.*, 2014, Grmanova and Strunz, 2017). Moreover, it has been developed into a further variant such as BCC, introduced by Banker *et al.* (1984) or the slacks-based measure (SBM) model, introduced by Tone (2001).

However, DEA itself does not investigate any disturbance impacts on the efficiency score. That is why scholars started to use a two-stage DEA model, which leads to more accurate results and the ascertainment of influence of chosen variables with impact on the efficiency (Hoff, 2007; McDonald, 2009; Yakob *et al.*, 2014; Lu *et al.*, 2014; Abidin, Cabanda, 2011).

It is obvious that with the growth of the insurance business, the complexity of the enterprise system is also increasing and is more difficult to handle. Investment efficiency may, thus, depend on the company size. This opinion is shared by some researchers. Eling and Luhnen (2008) found out by using DEA that the efficiency of large insurers is higher than the efficiency of small insurers, but their Tobit regression does not confirm the results of the first stage. Abidin and Cabanda (2011) used DEA without the second stage (i.e. Tobit regression) and ascertained that smaller companies are less efficient than bigger ones. In contrast to the above studies, Yakob *et al.* (2014) proved by using DEA and Tobit, that the company size has no significant impact on investment management efficiency. Other authors like McDonald (2009) investigated the disturbance variable SIZE in another context (size of the estate) and confirmed a significant impact on efficiency. The presented results are thus contrary and inconsistent, so the objective of this article is to prove again the impact on the efficiency.

Another variable used in several studies as disturbance variable is ROA (return on assets). Grmanova and Strunz (2017) found as a result of their investigation that a higher ROA leads to a higher average efficiency of Slovak insurance companies (CCR). Abidin and Cabanda (2011) ascertained a negative relation between ROA and efficiency without statistical significance for non-life-insurances in Indonesia. These contrasting results leave the question open as to how ROA affects efficiency, which is why ROA is being re-examined in our study.

Lu *et al.* (2014) used solvency as a further disturbance and figured out a statistically significant impact on efficiency. Following Lu *et al.* (2014), it is assumed that the variable could have an impact on the efficiency of the investment management, but since Lu *et al.* (2014) had different investigation settings, the impact of the variable will be re-examined.

In Germany, an insurance company can be registered as a public limited company, a mutual insurance association (VVaG), a public insurance company or as a Societas Europaea (SE) (§ 8 (2) VAG). These legal forms allow different operations on the capital market, i.a. the mechanisms for raising capital differ (Breuer and Breuer, 2003; Kürn, 2001). However, Yakob *et al.* (2014) found no statistical significance between the efficiency of the investment management and the organizational form. In contrast, Eling and Luhnen (2008) found out a slightly negative impact of organizational form on DEA efficiency with statistical significance. To resolve this controversy, “Organizational Form” is used as a further disruptive factor.

To conclude SIZE, ROA, solvency and organizational form are taken as disturbance variables in this article. As mentioned above, testing the influence of the selected disturbances requires the use of a second stage after the DEA. For this purpose, the researchers have several available options. For instance, Yakob *et al.* (2014) investigated the risk and investment management efficiency of insurance companies in Malaysia with the two-stage DEA-SBM approach. In the second stage they used the Tobit regression. Other researchers have investigated the efficiency of insurance companies using also the Tobit regression in the second stage, among these Eling and Luhnen (2008) and Grmanova and Strunz (2017). Abidin and Cabanda (2011) and Lu *et al.* (2014) took the Tobit regression for the second stage of the DEA. In these studies, alternatives like OLS have been discussed but discarded due to several aspects. Abidin and Cabanda (2011) argued that OLS cannot account for truncated data, the value of DEA score lies always between 0 and 1. Both Lu *et al.* (2014) and Yakob *et al.* (2014) referred to earlier studies, which complained about biased estimated coefficients in OLS. Furthermore, in their opinion Tobit regression leads, to more precise confidence intervals.

However, before these studies Hoff (2007) compared 4 different second stage models OLS, Tobit, PW and Beta. He concluded that OLS and Tobit deliver the most accurate results after the Spearman ranking correlation, whereas OLS is a bit more precise compared to Tobit. OLS leads after Hoff to reliable but unspecified results. McDonald (2009) also used a two-stage DEA approach and compared the Tobit regression with OLS. In his opinion, the OLS is an adequate approach for the second stage because the efficiency score is fractional and not produced by a censoring process.

Apparently, the researchers are in dispute over the appropriate second-stage model. The research of Hoff (2007) and McDonald (2009), who advocate the OLS, does not focus on insurance companies. As a consequence, in this article, Tobit regression, OLS and the fixed-effect model are used in the second stage compared by the Spearman ranking correlation.

2. Methodology

Research sample and data

The data set of the 20 biggest German life insurers, fundamental for this study form, were measured on the “actuarial reserves” in 2017 over the last ten years 2008-2017 (Bureau van Dijk, 2018). The underlying data is from the Moody’s Analytics InsuranceFocus database of Bureau van Dijk.

For the first stage, the SBM model is used to calculate the investment efficiency scores "CCR" of the 20 mentioned life insurers. This investigation focuses on the insurance market. So far, only a few authors have extensively dealt with efficiency measurement using DEA in the insurance field. Their research subject was the insurance company as a whole but not the investment management separately (for instance, Eling and Luhnen, 2008 used labor and capital as input variables). Unlike many other researchers, Yakob et al. (2014) have used the SBM to investigate life insurance investment management. For his investigation, Yakob et al. (2014) used “return on investment” as output and “actuarial reserves” and “investment assets” as input for the DEA approach. In selecting the input variables for efficiency measurement using SBM, this article follows Yakob et al. (2014) choice to take net actuarial reserves and total investment assets as an input. Investment return is also used as the output variable.

In the second stage, disturbances are investigated as independent variables. These are ”Solvency”, “Return on asset (ROA)”, ”Company size (SIZE)” and “Organization form”.Thereby, Solvency ratio is calculated as total assets⁄net premium written. ROA is calculated as (net investment income⁄ total assets) 100, Size is log (total assets) and for the Organization form 1 is for a stock company and 0 for a mutual company. The panel data consist of 200 observations (n=20, T=10). After the investigation of panel data, a test of result robustness is made with cross-sectional data.

2.1. Slack-based measure (SBM) model

Slacks-based measure (SBM) model first introduced by Tone (2001) is a non-parametric approach to solve a linear program and calculate efficiency scores related to the group of Decision-Making Units (DMUs). SBM model is a variant of the DEA model and differs by non-orientation from the famous CCR model introduced by Charnes *et al.* (1978) and the BCC model introduced by Banker *et al.* (1984). Like the CCR and the BCC model, the SBM model can use multiple input and output variables but the objective function focuses on the maximization of non-zero slacks (input excess and output shortfall).

The SBM considers n different life insurance companies ($j = 1,\cdots,n$), defined $\{x_j \in R^m_+\}$ as observed input and $\{y_j \in R^s_+\}$ as observed output where m and s are the numbers of input and output variables. Furthermore, (s_i^-, $i = 1,\cdots,m$) are the slacks for the input variables and (s^+_i, $i = 1,\cdots,s$) are the slacks for the output variable. The chosen non-oriented SBM model is defined as follows:

$$\text{(SBM)}\ p_0^* = \min \frac{1-\frac{1}{m}\cdot\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s}\cdot\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}}}$$

$$\text{Subject to}\quad x_0 = X\lambda + s^-$$
$$y_0 = Y\lambda - s^+ \qquad (1)$$
$$\lambda \geq O,\ s^- \geq 0,\ s^+ \geq 0$$

where X is the matrix with the input variables x_i $i = 1, \cdots, m$ and Y is the matrix with the output variables y_r $r = 1, \cdots, s$. p_0^* is the efficiency score of the DMU 0.

The SBM model can be transformed into a linear program to use the statistical software R. An appropriate transformation example can be found in Tone (2001).

2.2. Regression Analysis

Hypotheses

Based on the literature review, the following hypotheses have been formulated:

H1: Size of the company has no impact on the investment management efficiency
H2: ROA affects the investment management efficiency positively
H3: Solvency affects efficiency positively
H4: Organizational form has negative impact on efficiency

A two-stage DEA-SBM model is used to prove the hypotheses. In the second stage, the impact of disturbances on the efficiency scores is analyzed. Therefore, the Tobit regression and the fixed-effect model are used with panel data. Afterwards, the robustness of the results is tested with cross-sectional data. Finally, the Spearman ranking correlation coefficient has been applied. For the calculation of the results and to run the statistical test for the panel data, "Gretl" is used as free statistical software.

a) Tobit model

Tobit model is an econometric, censored regression model to analyze limited dependent variables, as in our case the efficiency score lying in the interval [0,1] (Tobin, 1958). The Tobit regression is described by the following model:

$$Y_i = X_i \cdot \beta + \mu_{i;} \qquad \mu_i \sim N(0, \sigma^2),$$

where Y_i is the dependent variable and X_i is the independent variable. The censoring value of the dependent variable is calculated through the next equation:

$$Y_i = \begin{cases} Y_i^* & \text{if } 0 < Y_i^* < 1 \\ 0 & \text{if } Y_i^* \leq 0 \\ 1 & \text{if } Y_i^* \geq 1. \end{cases}$$

b) Ordinary Least Squares (OLS)

The Ordinary least square (OLS) model can be described as follows:

$$Y_i = \beta_0 + x_i \cdot \beta_i + \mu_i$$

Y_i is the dependent variable, β_0 is the intercept term, x_i is the explanatory variable, β_i are the coefficient associated with the variable x and μi is the error term.

c) Panel data

In the case of panel data (n=20, T=10), three statistical tests are to apply. This investigation starts with "First Wald Test", "Breusch-Pegan Test" and "Hausman Test" to decide between a "pooled", "fixed" or "random" effect models, which is consistent with Wooldridge (2012) and Gujarati (2003). After this, the final model will be presented and the β variables as well as the coefficient of determination will be interpreted.

First Wald Test

The null hypothesis in the following test is that the "pooled OLS model" is adequate. In contrary, our alternative hypothesis is that the fixed effect model fits better. Our p-value is 9,513003*e*-006, which is close to zero. This means that the null hypothesis must be rejected and that the fixed effect model is more suitable. It also means that effects are statistically significant when taken individually.

Breusch-Pegan Test

The p-value of 0.000518 is also close to zero. As a consequence, the null hypothesis is also rejected and random effects are preferred over pooled regression.

Hausman Test

Our p-value in this test is 0.00567, which is – as well as the previous test – close to zero. This means that the null hypothesis (model being consistent with random effect) is rejected and the alternative hypothesis (fixed effect model is better) is preferred.

After this three-stage-testing, the fixed-effect model is used.

d) Spearman ranking correlation coefficient

The Spearman ranking correlation coefficient assists in determining whether the fitting values of the second-stage models are more accurate to the actual SBM CCR scores. First, the Spearman correlation will be used for cross-sectional data, where fitting values of the Tobit regression and OLS model are compared. Second, Tobit regression and the fixed-effect model are compared to the actual CCR scores. The calculation is done by ”Gretl”.

3. Research outcomes

The research outcomes of the SBM calculation are listed in table 1 in the appendix. Debeka and Allianz are the insurer, which have been most often efficient within the investigated time period of 10 years, whereby Debeka achieved efficiency in 6 years and Allianz in 4. In addition, the average efficiency of Debeka and Allianz is the highest over the 10 years. The mean of Allianz is 0.906, the mean of Debeka - 0.955. The yearly means of the CRR scores of all 20 insurers are with in the range between 0,73 and 0,88. The lowest values in this range are reached in 2009 and 2016, which can be associated with the financial crisis and the Europe debt crisis. Thus, probably both events have a significant influence on the investment management. In 2009, the year of the financial crisis, DKV is the most efficient life insurer and in the year 2016, Swiss Life AG is the most efficient one. In the same years 2009 and 2016, Provinzial Nordwest Lebensversicherungs AG has the lowest efficiency score. This is also reflected in the standard deviation of the efficiency score, where Provinzial Nordwest Lebensversicherungs AG has the highest value (See table 1 in the appendix).

A summary of statistical data (except of Organization form) for our second stage is listed in table 2.

Table 2: Summary Statistics of the first stage

Variable	Mean	Median	S.D.	Min	Max
CCR	0.81	0.82	0.13	0.29	1.00
Solvency	12.64	11.04	7.38	3.52	46.08
ROA	3.31	3.41	0.57	1.28	4.69
Size	4.45	4.42	0.4	3.54	5.32

Source: the authors' own work.

Tables 3 and 4 in the appendix show the second stage evaluation of the Tobit regression and OLS as well as Tobit regression and the fixed-effect model. These results are then compared and analyzed in a structured way for each examined disturbing variable. After the comparison of results of panel data, the results of cross-sectional have been used for robustness.

For the analysis of panel data (n=20, T=10), Tobit regression and the fixed-effect model are used. The impact of SIZE on efficiency has statistical significance in both models. The coefficient in the fixed-effect model is more than twice as high as in the Tobit model. Also ROA has a highly positive impact on efficiency in both models and is statistically significant. This is unlike the disturbance factor Solvency, which is not statistically significant in either the fixed-effect model or Tobit regression. Finally, the coefficient of the organizational form is in both models low negative and statistically significant.

In the next step, the results of panel data are compared with the results of cross-sectional data to achieve a robust result. Tobit regression and OLS are used for the cross-sectional data analysis.

The impact of SIZE on efficiency has no statistical significance in the OLS model. In contrast to this result, the results in the years 2010, 2012, 2013 and 2014 are statistically significant in the Tobit model. The Tobit model shows a positive low impact on efficiency. Thus, Hypothesis 1 cannot be confirmed.

The influence of ROA is positive after the evaluation in Tobit as well as after OLS. Both models show statistical significance of the results in each year. Furthermore, the ROA coefficients are more positive than solvency and have therefore more influence on the efficiency score CCR. As a consequence, the results confirm our Hypothesis 2.

The statistically significant impact of solvency on efficiency is confirmed by Tobit only in the years 2008 and 2017, in OLS only in 2017. All results show a positive but very low impact. Based on the results of Hypothesis 3 cannot be confirmed.

The evaluation of disturbance to the organizational form gives different results. None of the cross-sectional data is statistically significant in the OLS model and has a slightly negative impact. In contrast to the OLS result, in 2008, 2010, 2011 and 2013 Tobit model delivers statistical significance of the impact. The results differ from the OLS-evaluation and have a slightly negative impact on the efficiency score. However, Hypothesis 4 cannot be confirmed.

Table 5: Results of the Spearman-Test comparing Tobit, OLS and the fixed-effect model*

Year	Tobit		OLS/ the fixed-effect model	
	rho	p-value	rho	p-value
2008	0.86273041	significant at 1%	0.8674771	significant at 1%
2009	098496241	0	0.98496241	0
2010	0.89172932	0.0001	0.89172932	0.0001

2011	.94135338	0	0.94135338	0
2012	0.94126613	significant at 1%	0.92921792	significant at 1%
2013	0.93644234	significant at 1%	0.92365557	significant at 1%
2014	0.94847694	significant at 1%	0.95148559	significant at 1%
2015	0.91989476	significant at 1%	0.91989476	significant at 1%
2016	0.97744361	0	0.98045113	0
2017	0.99511101	significant at 1%	0.99811966	significant at 1%
overall	0.88301382	0	0.91234103	0

*“Significant at 1%” means “Significant at the 1% level (two-tailed)”

Source: oauthors’ own work.

In the last part of the research outcomes, the suitability of the models for the SBM second stage are analyzed. The results of the Spearman ranking correlation coefficients between the actual SBM scores and the fitting value after the Tobit regression, the OLS and the fixed-effect model are listed in Table 5 above. The Spearman coefficients are calculated separately for each year (cross-sectional data) and overall years (panel data). The results are that the Spearman coefficient of the OLS is in the years 2008, 2014, 2016 and 2017 higher than in the Tobit regression. In the years 2012 and 2013 the Spearman coefficient is higher in Tobit. In 2009, 2010, 2011 and 2015, the numbers are equal. The results of both models Tobit and OLS are in the individual years close to each other. All things considered, the fixed-effect model Spearman coefficient is slightly higher than the Tobit regression. A closer look at the results shows that there is only a minimal difference between the numbers. Thus, this article does not confirm the arguments of the other authors cited in this paper. Neither Tobit nor the OLS nor the fixed-effect model are more appropriate or more precise for such Two-stage DEA evaluations.

Conclusions

In addition to the main results, the evaluation makes clear that with a R-squared value between 0.82 and 0.99, the OLS approach might be suitable for the second stage in a two-stage SBM model. Furthermore, our results reveal that ”ROA” has a positive effect on the efficiency of investment management of German life insurers in the years with statistical significance in both models. One of the problems with using OLS for a two-stage SBM model is that the fitting CCR scores can either exceed one or fall below zero. Excluding this problem, OLS is an appropriate option for the second stage.

Limitation

As to the organizational form, three several types of life-insurances exist in Germany. The database used in this article differentiates only between stock and mutual companies. In addition, the results may be more accurate with a larger test sample. This article focuses on investment management efficiency. It is conceivable that the model is also suitable for investigating other areas of the company. Furthermore, instead of chosen disturbances, one can investigate also other impact factors. In this article, the basis for variable selection is primarily the literature review. Nevertheless, further tests could be used to check the interdependencies between variables.

Outlook

Our outcomes do not suggest that the accuracy of one of the econometric models utilized for the second-stage (Tobit, OLS and the fixed-effect model) varies dramatically. Thus, in future, only one of the chosen models can be used for efficiency calculations. For further research, scholars can use another econometric model to compare results with Tobit and OLS. It is also possible for panel data to use the two-way model to consider the temporal evolution over dummy variables. In future, researchers can investigate life or non-life insurance companies by using a larger sample. Other types of SBM, such as the Network SBM, are further options for efficiency measurement (Tone and Tsutsui, 2009).

Appendix

Table 1: CCR efficiency score of 20 biggest life insurer in German market and means and standarf deviation

DMU name	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017		Mean	S.D
Allianz Lebensversicherungs AG	0,671	0,911	0,871	0,874	1,000	1,000	1,000	0,886	0,845	1,000		0,906	0,098
R+V Lebensversicherung AG	0,513	0,798	1,000	1,000	0,939	0,932	0,879	0,957	0,800	0,855		0,867	0,137
Debeka Lebensversicherungsverein auf Gegenseitigkeit	0,486	0,741	1,000	1,000	1,000	1,000	1,000	1,000	0,839	0,980		0,905	0,163
Generali Lebensversicherung AG	0,951	0,472	0,588	0,471	0,936	0,629	0,842	0,779	0,683	0,747		0,710	0,164
AachenMünchener Lebensversicherung AG	0,737	0,671	0,576	0,487	0,640	0,463	0,590	0,578	0,512	0,555		0,581	0,080
Zurich Deutscher Herold Lebensversicherung AG	0,785	0,827	0,818	0,763	0,792	0,757	0,741	0,747	0,606	0,642		0,748	0,068
DKV Deutsche Krankenversicherung AG	1,000	1,000	0,880	0,750	1,000	0,841	0,811	0,855	0,793	0,816		0,875	0,089
Ergo Lebensversicherung AG	0,473	0,788	0,903	0,885	0,944	0,872	0,720	0,954	0,730	0,810		0,808	0,136
AXA Lebensversicherung AG	0,938	0,784	0,769	0,815	0,892	0,945	0,880	0,986	0,769	0,694		0,847	0,090
Württembergische Lebensversicherung AG	0,819	0,830	0,838	0,817	0,818	0,719	0,695	0,733	0,587	0,636		0,749	0,085
Allianz Private Krankenversicherungs AG	0,851	0,864	0,889	0,893	0,891	0,878	0,876	0,930	0,885	0,924		0,888	0,023
BVV Versicherungsverein des Bankgewerbes auf Gegenseitigkeit	0,905	0,843	0,854	0,867	0,790	0,922	0,770	0,877	0,697	1,000		0,853	0,081
Bayern Versicherung Lebensversicherung AG	0,820	0,630	0,789	0,854	0,940	0,749	0,859	0,837	0,672	0,606		0,776	0,104
SV SparkassenVersicherung Lebensversicherung AG	0,902	0,676	0,790	0,826	0,926	0,932	0,797	0,837	0,731	0,770		0,819	0,080
Provinzial NordWest Lebensversicherung AG	0,849	0,293	0,722	0,746	0,893	0,807	0,631	0,779	0,493	0,669		0,688	0,171
Signal Krankenversicherung auf Gegenseitigkeit	0,868	0,813	0,921	0,803	0,919	0,840	0,871	0,985	0,849	0,901		0,877	0,053
AXA Krankenversicherung AG	0,819	0,786	0,695	0,853	0,785	0,762	0,820	0,947	0,763	0,802		0,803	0,063
Gothaer Lebensversicherung AG	0,909	0,779	0,835	0,633	0,883	0,741	0,778	1,000	0,790	0,727		0,808	0,098
Victoria Lebensversicherung AG	0,884	0,688	0,897	0,818	0,686	0,772	0,804	0,896	0,790	0,800		0,803	0,072
Swiss Life AG (Germany Branch)	1,000	0,487	0,786	0,860	0,872	0,746	0,765	0,958	1,000	0,959		0,843	0,149
Mean	0,81	0,73	0,82	0,8	0,88	0,82	0,81	0,88	0,74	0,79			

Source: own illustration.

Table 2: Results of the Tobit regression

Tobit															
	Const.			**Solvency**			**ROA**			**SIZE**			**ORGA**		
Year	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value
2008	0.0706131	0.230423	0.7593	0.00966352	0.00410214	0.0185	0.190549	0.0187369	0.0000	0.00744791	0.0475573	0.8756	-0.0900243	0.0302169	0.0029
2009	-0.189325	0.125638	0.1318	-0.00066316	0.00117943	0.5739	0.228443	0.0105570	0.0000	0.0554565	0.0297876	0.0626	-0.00973676	0.0200001	0.6264
2010	-0.226416	0.182840	0.2156	-0.00142298	0.00153892	0.3551	0.214137	0.0217744	0.0000	0.0852081	0.0399254	0.0328	-0.0543628	0.0275039	0.0481
2011	-0.148900	0.146532	0.3096	-0.00067646	0.00125954	0.5912	0.210923	0.0132800	0.0000	0.0608323	0.0321918	0.0588	-0.0443801	0.0224870	0.0484
2012	-0.346410	0.164383	0.0351	-0.00093051	0.000958761	0.3318	0.231777	0.0179124	0.0000	0.105141	0.0358794	0.0034	-0.0243891	0.0183034	0.1827
2013	-0.396189	0.207974	0.0568	-0.00055570	0.00119362	0.6415	0.214371	0.0158626	0.0000	0.114191	0.0447935	0.0108	-0.0470092	0.0230476	0.0414
2014	-0.338729	0.175747	0.0539	-0.00051420	0.00107245	0.6316	0.223003	0.0197609	0.0000	0.0971517	0.0375445	0.0097	-0.0337502	0.0205851	0.1011
2015	-0.104452	0.129108	0.4185	0.000413091	0.000853833	0.6285	0.270460	0.0163579	0.0000	0.0246528	0.0240416	0.3052	-0.00336280	0.0179593	0.8515
2016	-0.121638	0.0831863	0.1437	0.000336724	0.000579693	0.5613	0.237841	0.00963692	0.0000	0.0291309	0.0167901	0.0827	-0.00793336	0.0137240	0.5632
2017	-0.105690	0.0465231	0.0231	0.00193465	0.000429278	0.0000	0.263837	0.00618614	0.0000	0.0157863	0.0103409	0.1269	0.00765902	0.00828453	0.3552
Overall	-0,266506	0,0789486	0,0007	0,000127952	0,000613211	0,8347	0,216934	0,00752797	0	0,0877555	0,0167755	0	-0,0398348	0,117080	0,0007

Source: authors' own work.

Table 3: Results of the OLS and fixed-effect model

OLS																
	Const.			**Solvency**			**ROA**			**SIZE**			**ORGA**			
Year	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	adjusted R^2
2008	-0.145495	0.285377	0.6176	-0.00123389	0.00242124	0.6177	0.202574	0.0239510	0.0000	0.0681170	0.0556621	0.2399	-0.0669192	0.0380512	0.0990	0.857898
2009	-0.187895	0.139908	0.1992	-0.000573709	0.00131069	0.6678	0.226066	0.0115363	0.0000	0.0564247	0.0331596	0.1095	-0.0103682	0.0222646	0.6481	0.955159
2010	-0.192054	0.202299	0.3575	-0.00131519	0.00172036	0.4564	0.207382	0.0235833	0.0000	0.0824690	0.0446356	0.0845	-0.0569121	0.0307086	0.0836	0.827082
2011	-0.139993	0.160786	0.3976	-0.000615199	0.00138298	0.6628	0.211012	0.0145983	0.0000	0.0578746	0.0352402	0.1213	-0.0410304	0.0244472	0.1140	0.924517
2012	-0.111851	0.128514	0.3978	-0.000810232	-0.00106341	0.4579	0.222355	0.0192238	0.0000	0.0573002	0.0292847	0.0693	-0.0210461	0.0198591	0.3060	0.902878
2013	-0.161666	0.164918	0.3425	-0.000317851	0.00132620	0.8138	0.206591	0.0167741	0.0000	0.0651369	0.0371395	0.0999	-0.0427352	0.0253997	0.1132	0.902816
2014	-0.132499	0.139838	0.3584	-0.000439961	0.00120466	0.7200	0.212326	0.0208803	0.0000	0.0574992	0.0331461	0.1033	-0.0312665	0.0228070	0.1906	0.888256
2015	-0.0977181	0.135023	0.4804	0.000446660	0.000892048	0.6238	0.269281	0.0171144	0.0000	0.0232829	0.0249698	0.3659	-0.00118637	0.0184223	0.9495	0.938910
2016	-0.129718	0.0935436	0.1858	0.000392619	0.000651898	0.5560	0.235096	0.0105917	0.0000	0.0318332	0.0187834	0.1108	-0.00460868	0.0151940	0.7658	0.971398
2017	-0.0573764	0.0546085	0.3100	0.000978459	0.000399713	0.0272	0.260405	0.00810939	0.0000	0.00898079	0.0128592	0.4956	0.0123253	0.0108319	0.2730	0.990575
Overall	-0,823785	0,179045	0	-0,00015683	0,0114937	0,8918	0,211675	0,0077981	0	0,219015	0,039999	0	-0,0513519	0,022289	0,0224	0,815025

Source: authors' own work.

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