Efficiency and Profitability in the Global Insurance Industry

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Abstract

We examine the relationship between firm efficiency and profitability (E-P relationship) using a global insurance dataset across 11 years. Consistent with prior studies in banking and insurance, we document a significantly positive correlation between cost efficiency and returns on equity or assets. Beyond the extant evidence, we found significant industry dependency in the E-P relationship driven by industry idiosyncrasies, whereas cost efficiency is more critical to the profitability of life insurers than nonlife insurers. The E-P relationship is also nonlinear: the marginal effects of cost efficiency on profitability diminish as the insurer's cost efficiency approaches to the best practice.

Keywords

Cost efficiency, Data envelopment analysis (DEA), Frontier efficiency, Industry dependency, Industry idiosyncrasy,

1. Introduction

The optimization principle in microeconomics suggests that business firms minimize costs and maximize profits subject to existing technologies and expertise. Firms that are not attaining the optimization are not of interest because competition drives them out of the industry in the long run (Bauer, Berger, Ferrier, and Humphrey, 1998; Cummins and Weiss, 2013). Various theories explain why inefficient firms can also survive in the long run due to insufficient competition and other motivational reasons (see e.g., Leibenstein, 1966). In business practice, managers, regulators, and other decision makers focus on identifying those non-optimized production units by benchmarking them with peers in the industry and continuously investing in improving the efficiency and profitability of non-optimized units (Kaplan and Norton, 2005).

Farrell (1957) develops the modern framework of frontier efficiency analysis following the concept of optimization in microeconomics and aiming to identify firms that do not succeed in optimization (i.e. those not fully efficient) and to measure how far they are from the optimized (fully efficient) firms. Since the methodological contribution of Aigner, Lovell, and Schmidt (1977) and Charnes, Cooper, and Rhodes (1978), the academic studies on the performance of financial institutions have increasingly focused on the frontier efficiency methods (Bauer et al., 1998), first in the banking industry (see Berger and Humphrey, 1997 for reviews), and shortly afterwards in the insurance industry (see Eling and Luhnen, 2010a; Cummins and Weiss, 2013 for reviews). The booming in academic applications of frontier efficiency analysis endorses the power of this method in aggregating multiple inputs and outputs by a single efficiency measure (Farrell, 1957) and its advantages compared to conventional financial measures, such as returns on equity (ROE), returns on assets (ROA), and cost ratios (Kaplan and Norton, 2005; Leverty and Grace, 2010).

In business practice, a huge demand has been seen to use operational measures as an alternative or complementary to conventional financial measures (Kaplan and Norton, 2005). This is particularly true for those organizations focusing on customer services, innovations, and learning, e.g., financial institutions. However, the frontier efficiency measures have not yet been prevalent in business as it is in academia. Bauer et al. (1998) discuss six conditions that may affect the application of frontier efficiency measures by regulators, managers, and other decision makers. One of them is the consistency between frontier efficiency measures and conventional financial measures. This criterion is critical because the financial ratios are the present common language of managers, investors, and regulator, which thus define the “reality”. The frontier efficiency measures, as a relatively new concept, has to prove and demonstrate its consistency with the conventional measures so that it reflects and well connects with the "reality", not just artifacts of the efficiency approach assumptions (Bauer et al., 1998; Laverty and Grace, 2010).

This paper aims to analyze the relationship between efficiency and profitability (E-P relationship) in the global insurance industry. Our analysis is novel and informative in the following aspects: (1) insurance is one of the fastest growing fields of academic applications of frontier efficiency analysis, with over 100 peer-review journal articles published in the past decade (see Eling and Luhnen, 2010a; Cummins and Weiss, 2013 for reviews). However, the evidence on the E-P relationship in the insurance industry is limited to the US life (Cummins and Zi, 1998; Greene and Segal, 2004) and nonlife (Leverty and Grace, 2010) insurance market. We extend the analysis to Non-US markets and demonstrate the global validity of the E-P relationship. (2) We contribute to the understanding of E-P relationship in terms of its nonlinearity and its industry dependency nature. The importance of a firm's efficiency in determining its profitability depends on the level of its own efficiency and on the industry idiosyncrasies. (3) We advance the methods that Cummins and Zi (1998), Greene and Segal (2004), and Leverty and Grace (2010) used to examine the E-P relationship by using the rank-order correlation measures of Spearman's Rho and Kendall's Tau to avoid the linear assumption of Pearson correlation and by using the best and worst practice correspondence analyses. The strength of our analysis also lies with a large sample of over 4,700 insurers and 16,000 firm-year observations across 11 years, which covers over 50% of premium volume outside the North America (Swiss Re, 2014).

By way of preview, we present evidence showing a significantly positive correlation between efficiency and profitability. This E-P correlation is also economically significant and comparable to Greene and Segal's (2004) results from the US life insurance industry and Leverty and Grace's (2010) results from the US nonlife insurance industry. The differences can be mostly explained by the different leverage levels across various insurance markets. The E-P correlation is nonlinear and industry dependent: the positive impact of cost efficiency becomes smaller as the firm approaches to the best practice, and moreover, cost efficiency is more critical to the profitability of life insurers than nonlife insurers.

The remainder of this paper is organized as follows. We first review the extant E-P relationship literature to develop our hypotheses. Then, we introduce our samples, frontier efficiency methodologies, and empirical models, followed by results and robustness tests. Finally, we present our conclusions.

2. Hypotheses development

Berger and Humphrey (1997) summarize three basic usage of frontier efficiency analysis: (1) to address research questions by describing the efficiency of an industry, ranking its firms, or checking how measured efficiency may be related to the different efficiency techniques employed; (2) to improve managerial performance by identifying "best practices" and "worst practices" associated with high and low measured efficiency, respectively, and encouraging the former practices while discouraging the latter; (3) to inform regulators and policy makers by assessing the effects of deregulation, mergers, or market structure on efficiency.

The frontier efficiency measures are superior in many aspects and for most regulatory and managerial purposes to the conventional financial measures (Bauer et al., 1998; Leverty and Grace, 2010). This is because (1) frontier efficiency measures remove the effects of differences in input prices and other exogenous market factors affecting the conventional financial measures, and thus are better estimates of the underlying performance of the managers and operations (Bauer et al., 1998); (2) conventional financial measures fail to consider the value of management actions and investment decisions that will affect the future as opposed to current performance (Sherman and Gold, 1985; Kaplan and Norton, 2005), and thus may not be appropriate to reflect a firm's real performance in the long run (Oral and Yolalan, 1990). Therefore, frontier efficiency measures gradually dominate conventional financial measures in terms of developing meaningful and reliable measures of performance (Cummins and Weiss, 2013). This is particularly true in the insurance academic research.

Efficiency estimated by frontier efficiency analysis and profitability measured by conventional financial ratios are two connected concepts. The efficiency captures a firm's outputs/inputs ratio relative to the "best practice" firms. It integrates multiple inputs and outputs into a single measurement of efficiency and defines a frontier of best practices with firms at different size. The same is true for conventional financial measures, which are also size neutral and reflect the integrated result of various firm activities. Cost efficiency affects profits through the negative effect of wasted resources on earnings and cash flows (Greene and Segal, 2004). More efficient insurers earn higher profit, because they have a lower operating costs for given amount of outputs and thus have a higher profit. These similarities and connections establish the consistency basis between frontier efficiency measures and conventional profitability measures.

The differences of the two concepts are also significant. Firstly, the efficiency is a relative measure against a group of "best practice" firms operating on the efficiency frontier and thus is bounded between 0 and 1[1]; while the profit ratios are absolute ratios that are theoretically not bounded. Secondly, the profitability reflects the results of all activities of a firm including the exogenous price and market fluctuations that managers have little or no control; while the efficiency focuses on the key inputs and outputs and those elements that managers are able to influence operational and/or capital wise. For example, a financial crisis shall result in immediate low financial returns reflecting on profit ratios, but the output or input adjustments take longer time and all firms operating in the market may adjust in the same direction, therefore, the efficiency of a firm may change much less than its profitability, i.e. less sensitive to the exogenous market factors which affects the whole industry. On the flip side, an insurer may have a good overall financial ratio even if it has poor operations (high expense ratio) but a good luck (very low loss ratio).

In the banking performance literature, Sherman and Gold (1985) and Oral and Yolalan (1990) argue that a bank's operating efficiency is one of the determinants of profitability but only a secondary determinant[2]. Bauer et al. (1998) and Eisenbeis, Ferrier, and Kwan (1999) present evidence from the US banking industry showing a low but significantly positive correlation between the bank efficiency and its profitability. The Pearson correlation coefficients between cost efficiency and ROA are mostly 10% to 25% (Bauer et al., 1998). Casu and Molyneux (2003) document similar small magnitude but significantly positive E-P relationship based on evidence from European banks.

In the insurance performance literature, the E-P correlation seems stronger. Cummins and Zi (1998) found that in almost all cases, frontier efficiency measures derived from various techniques have significantly positive correlation with conventional profitability measures. The Pearson correlation coefficients between cost efficiency and returns on equity plus benefits are mostly 12% to 35%. Greene and Segal (2004) reinforce the E-P link in the US life insurance industry by using a regression model controlling for other factors that influence the financial returns. They document a positive and economically significant impact of cost efficiency on returns. Leverty and Grace (2010) confirm this positive E-P relationship in the US nonlife insurance industry.

[1] We adopt Shephard's (1970) efficiency measures that are the reciprocals of Farell's (1957) inefficiency measures. Both measures capture the same information. The former is bounded between 0 and 1 and the latter has a lower bound of 1. Some scholars also use inefficiency scores (Greene and Segal, 2004), which measures how inefficient a firm compared to the best practice and can be defined as one minus our efficiency measure.

[2] Marketing new services to attract new funds may for example be more prominent focus of bank managers (Sherman and Gold, 1985).

Considering the connections and differences in efficiency and profitability, one should expect a positive correlation between frontier efficiency measures and conventional profitability ratios but should not expect correlation is in any sense close to one (Bauer et al., 1998). Consistent with the extant evidence in banking and insurance performance literature, we hypothesize that

- *Efficiency and profitability are positively correlated in the global insurance industry (H1).*

Comparing the two industries within the financial services, i.e. banking vs. insurance, extant evidence suggests that an industry dependency exist in the E-P relationship, which is stronger in the insurance industry than in the banking industry. The management of operations is a secondary concern and less critical to the profitability of the banking industry (Sherman and Gold, 1985; Oral and Yolalan, 1990) but of paramount importance to the profitability of the life insurance industry (Greene and Segal, 2004). Following this line of thought, the industry dependency may also exist within the insurance industry, i.e. between life insurance and nonlife insurance[3]. The insurance industry provides a unique context to investigate the industry dependency of E-P relationships with its two sub-industries—life and nonlife insurance—operated by separate legal entities in most countries.

We compare the idiosyncrasies of the life and nonlife insurance industries and notice that the roles of product innovation and cost management are different. This different operational focus is driven by the different risk nature: life risks are largely homogeneous and predictable but nonlife risks are much more diverse and more difficult to underwrite. Nonlife insurers may generate significant profits on innovative and tailor made solutions to clients; while innovation of a life insurance product is rarely patent and easily copied by other insurers to their clients (Greene and Segal, 2004). In other words, the life insurance industry is closer to a complete competition market, where the products are largely homogeneous; while the nonlife insurance industry shares the nature of monopolistic competition market, where a large portion of products are heterogeneous and differentiable among competitors. Therefore, the competition among life insurers more focuses on cost management (Greene and Segal, 2004) as opposed to nonlife insurers, for whom product differentiation is also important. We thus hypothesize that

- *The impact of efficiency on profitability is stronger for life insurers than that for nonlife insurers (H2).*

[3] For example, in the internationalization-performance relationship, the internationalization strategy works better for nonlife insurers than for life insurers due to industry idiosyncrasies in these two sub-industries (Biener, Eling, and Jia, 2016).

The principle of diminishing marginal returns in microeconomics suggests that holding other factors of production constant, the marginal increase of a single factor yields marginal decreased (though positive) returns (Samuelson and Nordhaus, 2009). Following this line of thought, will firm efficiency have similar effects on profitability? The marginal profit increase may be lower for insurers that are already very efficient and higher for insurers that are far from best practice. In other words, the impact of efficiency on profitability follows the law of diminishing marginal returns. In this case, the correlation between efficiency and profitability is nonlinear with a positive first order derivative and a negative second order derivative. We thus hypothesize that

- *The impact of efficiency on profitability follows the law of diminishing marginal returns (H3).*

3. Data and methodology

3.1. Sample

We use the Non-US Best's Insurance Reports (A. M. Best, 2003–2013), which are a comprehensive source for information on insurance companies widely used in insurance efficiency research (see e.g., Eling and Luhnen, 2010b; Cummins and Weiss, 2014). In order to construct the comparison between life and nonlife insurers, we exclude composite insurers offering both life and nonlife insurance.[4] We only include operating companies and, thus, exclude entities such as branches, special purpose vehicles, captives, and firms that operate insurance as a minor business (e.g., banks, manufacturers, and healthcare providers).

We trim insurers' key ratios at the 1st and 99th percentiles for life and nonlife insurers separately in order to reduce the potential bias driven by extreme values (Olesen and Peterson, 2002; Zelenyuk and Zheka, 2006).[5] The key ratios are those used in the later DEA and regression analyses: return on assets (ROA), return on equity (ROE), life benefits ratio (benefits paid divided by net premiums written), nonlife loss ratio (loss incurred divided by net premiums earned), leverage ratio (total liabilities divided by total capital and surplus), liquidity ratio (liquidity assets divided by total liabilities), premium retention ratio (inverse reinsurance ratio, net premiums written divided by gross premiums written), and yearly real asset growth. Our final sample contains 1,718 life insurers with 8,984 firm-year observations and 3,054 nonlife insurers with 16,078 firm-year observations. The 2012 sample covers 51% of global life premiums and 50% of global nonlife premiums outside North America (Swiss Re, 2014).

Table 1 reports the summary statistics. We observe that the ROAs of life insurers (with a mean of 0.0095) are much lower than the ROAs of nonlife insurers (with a mean of 0.032), though their ROE means are close (0.078 vs. 0.094). This is because life insurers have much higher leverage ratios (with a mean of 22.3) than nonlife insurers (with a mean of 2.72), driven by different business models of life and nonlife insurance. Life insurance is usually long term and a large portion of insurance reserves are booked under the life insurer's liability resulting in high leverage and small ROAs. The different capital structure of life and nonlife insurers may

[4] The group of composite insurers take only 12.6% of all firm-year observations and for some region-years, they have very small number of observations, thus are not enough to perform the bootstrapping DEA. Moreover, some of them might simply be the consolidation of individual life and nonlife insurers' financial results.

[5] Outliers are present in the A. M. Best dataset because of startups that do not yet underwrite business and runoff insurers that are not comparable to and not in competition with regular insurers (Biener, Eling, and Jia, 2016). We alternatively trim the key ratios at the 0.5th and 99.5th percentiles and the 2nd and 98th percentiles. The different trimming methods are consistent in results and do not change our conclusions. The results are available from the authors upon requests. Similar trimming or winserising for outliers is common practice in insurance efficiency research (see. e.g., Leverty and Grace, 2010).

also be driven by that life risk portfolios are more predictable than nonlife, enabling better capitalization and higher leverage.

From the management perspective, ROE can be decomposed into two elements as shown in Equation (1), the operational profitability measured by the ratio of profit over risks (liability) and the capital efficiency measured by the leverage ratio (liability over equity). The ROA (profit over the sum of liability and equity) cannot fully capture the component of capital efficiency. The frontier efficiency analysis captures the operational efficiency and partially the capital efficiency because equity capital and debt capital are used as separate inputs and both premium (or loss) and invested assets are used as outputs (the input of equity with the output of premium or loss share the essence of capital efficiency).

$$ROE = \frac{Profit}{Equity} = \frac{Profit}{Libaility} \times \frac{Liability}{Equity} = Operational\ profitabilty \times Leverage\ ratio \quad (1)$$

Thus, ROE is a better measurement of profitability than ROA, when comparing the profitability and the E-P relationship between life and nonlife insurers. Moreover, as we use a sample across multiple markets with different tax systems, both the ROE after tax is used as the primary profitability measure, while ROE before tax, ROA before tax, and ROA after tax are considered as robustness tests.

The Panel B of Table 1 presents the following firm specific characters: firm size in terms of total assets and net premiums written (inflation adjusted at 2013), yearly real growth of assets and premiums, premium retention ratio (i.e., inverse reinsurance ratio), leverage ratio, liquidity ratio, a dummy variable with 1 indicating a mutual insurer, and a dummy variable with 1 indicating an unaffiliated single firm. The three dummy variables of Emerging, Developed, and EU describe the geographical distribution of our sample in three exclusive regions. Insurance penetration (life or nonlife premium over GDP) captures the maturity of an insurance market. Real GDP growth captures the economic environment in insurers' home markets. Our sample has a great variety to cover both small and large, both high and low growth, and both developing and developed markets.

Table 1 Summary statistics

Sample		Life				Nonlife			
Panel A: Profitability	Unit	N	Mean	Std. Dev.	Median	N	Mean	Std. Dev.	Median
ROE before tax	1	8968[b]	0.10	0.25	0.11	16003[b]	0.12	0.19	0.12
ROE after tax	1	8984	0.078	0.22	0.083	16078	0.094	0.16	0.095
ROA before tax	1	8969[b]	0.012	0.042	0.0058	16016[b]	0.039	0.060	0.036
ROA after tax	1	8984	0.0095	0.040	0.0046	16078	0.032	0.055	0.029
Panel B: Firm- and Country-Specific Characteristics									
Total assets [a]	1,000	8984	7976411.4	29191572.3	1174673.5	16078	927923.1	4102108.6	138459.3
Net premiums written [a]	1,000	8984	843751.9	2558676.3	161952.6	16078	273236.0	704836.3	47454.3
Real asset growth	1	8984	0.16	0.30	0.11	16078	0.11	0.24	0.072
Real premium growth	1	8880[b]	0.19	0.70	0.057	15861[b]	0.13	0.44	0.061
Premium retention ratio (inverse reinsurance ratio)	1	8984	0.93	0.13	0.99	16078	0.75	0.24	0.82
Leverage ratio	1	8984	22.3	31.0	12.6	16078	2.72	2.47	2.05
Liquidity ratio	1	8984	0.97	0.88	0.92	16078	1.38	2.57	0.89
Mutual	Dummy	8984	0.15	0.35	0	16078	0.15	0.36	0
Unaffiliated	Dummy	8984	0.34	0.47	0	16078	0.44	0.50	0
Emerging	Dummy	8984	0.22	0.41	0	16078	0.23	0.42	0
Developed	Dummy	8984	0.11	0.31	0	16078	0.12	0.33	0
EU	Dummy	8984	0.67	0.47	1	16078	0.65	0.48	1
Insurance penetration	1	8984	4.17	2.90	3.39	16078	1.90	0.71	1.99
Real GDP growth	1	8984	0.023	0.033	0.023	16078	0.022	0.032	0.023
Panel C: Input Quantities									
Labor (approximate number of employees)	1	8984	4536.5	11480.2	744.5	16078	1680.6	3797.2	324.4
Equity capital (capital and surplus) a	1,000	8984	499143.3	2012234.9	75342.0	16078	258995.1	1696206.7	43203.2
Debt capital (total liabilities) a	1,000	8984	7477271.6	27668824.4	1061569.7	16078	668927.4	2658292.3	86647.3
Panel D: Input Prices									
Labor price (Wage) a	1	8984	56808.5	30667.4	63179.0	16078	56337.8	30639.6	61092.9
Equity price (MSCI yearly returns)	1	8984	0.13	0.094	0.11	16078	0.13	0.098	0.11
Debt price (IMF long-term govt. bond rates)	1	8984	0.044	0.027	0.040	16078	0.044	0.027	0.041
Panel E: Output Quantities									
Benefits paid plus reserve changes (life) or smoothed loss (nonlife) a	1,000	8984	1453640.2	4672756.6	210296.1	16078	194945.4	530980.3	29208
Total invested assets a	1,000	8984	7338379.1	27964626.0	1059691.8	16078	677063.0	3322358.5	90776.4
Panel F: Cost Efficiency Scores									
Cost efficiency (bootstrap and regional frontiers)	1	8984	0.51	0.25	0.53	16078	0.29	0.16	0.27
Cost efficiency (bootstrap and global frontier)	1	8984	0.48	0.25	0.50	16078	0.25	0.14	0.22

Notes:
[a] In USD and inflation adjusted for 2013.
[b] The smaller number of observations is due to missing values in respective firm-years.

3.2 Frontier efficiency methodology

Two primary approaches have been used to estimate the efficiency frontiers that are the parametric approach, most prominently Stochastic Frontier Analysis (SFA), and the non-parametric approach, most prominently Data Envelopment Analysis (DEA), among others (Bauer et al., 1998; Cummins and Weiss, 2013). In the banking literature, SFA has been shown to have a better consistency with the conventional profit ratios than DEA (Bauer et al., 1998; Eisenbeis, Ferrier, and Kwan, 1999); while in the insurance literature, DEA shows the highest correlation and consistency with the profit ratios (Cummins and Zi, 1998; Leverty and Grace, 2010). This paper does not aim to discriminate or evaluate different frontier efficiency methods (see Leverty and Grace, 2010 for detailed discussion), but to test the E-P relationship. We choose DEA to estimate the efficiency measures because (1) extant evidence suggests DEA efficiencies are superior to other frontier efficiency measures in terms of the consistency with the profitability measures (Cummins and Zi, 1998; Leverty and Grace, 2010)[6]; (2) DEA is the most prevalent frontier efficiency method applying to insurance data in the past two decades, which has a significantly higher proportion of applications than SFA (Eling and Luhnen, 2010a; Cummins and Weiss, 2013); and (3) Greene and Segal (2004) have already documented the positive correlation between SFA efficiency and profitability in a rigorous regression analysis using the US life insurance data.

We follow the state-of-art procedure of DEA in the insurance industry (Eling and Luhnen, 2010a; Cummins and Weiss, 2013) to estimate an insurer's efficiency by their relative cost efficiency scores, which is widely used in finance and insurance studies[7]. DEA cost efficiencies are the representation of firms' distances to the best-practice efficient frontiers and are bounded between 0 and 1 (Shephard, 1970). The best-practice frontier is defined by firms that use the minimum amount of inputs to produce certain amount of outputs. We assume constant returns to scales (CRS) to estimate cost frontiers separately for life and nonlife insurers, for each year between 2003 and 2013, and for each of the three regions: European Union, Other Developed Markets and Other Emerging Markets. One important assumption of DEA efficiency estimates

[6] Cummins and Zi (1998) show that the Pearson correlation coefficient is the highest as 0.35 between DEA cost efficiency and the profitability; while most other correlation coefficients based on other efficiency measures are below 0.15. Leverty and Grace (2010) demonstrate that DEA efficiencies are much more consistent with ROA and ROE than financial intermediation approach (the flow approach).

[7] A detailed discussion about the DEA methodology in the insurance industry can be found in Eling and Luhnen (2010a) and Cummins and Weiss (2013). Here we only briefly summarize the key steps, inputs, and outputs. There are other efficiency measures can be derived from DEA method, e.g. production, technical, revenue, and profit efficiencies. We use cost efficiency because it is always supported by other frontier efficiency methods and is the most prevalent efficiency measure used and analyzed by the existing literature. For comparison purpose with Leverty and Grace (2010), in later part of the discussion, we decompose the cost efficiency into three components as scale, pure technical, and allocative efficiency that capture different aspects of cost efficiency.

is that firms are employing similar technologies. The assumption that all insurers employ similar technologies worldwide is strong. Therefore, we group insurers in our sample into three regions according to their domiciliary countries considering the operational similarities and the balance of observations in each region (Biener, Eling, and Jia, 2016). Cost efficiency estimated relative to a single global frontier are used as a robustness test, the results of which are consistent with our conclusions. Bootstrapped bias-corrected efficiency scores are used to account for the sensitivity of efficiency measures to sampling variation (Simar and Wilson, 2000).

The inputs, outputs, and prices used to obtain the cost efficiency scores follow the common practice of DEA analysis in insurance industry (Eling and Luhnen, 2010a; Cummins and Weiss, 2013). We use three input quantities: labor (i.e., approximated number of employees), equity capital (i.e., capital and surplus, in real values in 2013), and debt capital (i.e., total liabilities, in real values in 2013). Labor is approximated by operating expenses divided by the annual wage for the insurance sector in respective country-years. We use annual wages (in real values in 2013) for the insurance sector in respective country-years as the price for labor. The wage information is obtained from the ILO Main Statistics and October Inquiry databases.[8] We use the 10-year rolling window moving averages of yearly rates of total returns of Morgan Stanley Capital International (MSCI) indices in the respective countries as the price for equity capital.[9] We use the two-year rolling window averages of International Monetary Fund (IMF) long-term government bond yearly interest rates in respective countries as the price for debt capital.[10] The long-term government bond rates are used to match the long duration of life insurers' liabilities. The MSCI indices and IMF interest rates are obtained from the Thomson DataStream database.

We use two output quantities, total invested assets and insurance benefits or losses (all in real values in 2013). The two outputs represent insurers' two major functions— financial intermediation and risk pooling, respectively. For life insurers, the insurance benefits are captured by net benefits paid plus net reserve changes[11], as reserves reflect the accumulation of unpaid cash values of life insurance policies (Cummins and Weiss, 2013). For nonlife insurers,

[8] To impute missing wages, we adjust the nearest available data point of ILO annual wage to the previous or later years by using changes in general price levels represented by the consumer price indices (CPI).

[9] To impute missing values and replace negative values, we use the rolling window two-year averages of realized country-average ROEs in respective country-years (see Cummins and Weiss, 2013, for a discussion of capital price proxies). We use two-year moving average values because we only have the data that date back to 2002. We use country-average ROEs because many firms may have negative ROEs due to the volatile nature of the insurance business. Less than 10% of our sample is affected by this procedure.

[10] To impute missing interest rates, we use the IMF central bank policy rate or deposit rate in respective country-years.

[11] The net benefits paid plus net reserve changes (NBPNRC) could exhibit negative values; therefore, we follow the standard DEA practice of shifting all values by adding the minimum NBPNRC (Cook and Zhu, 2014).

the insurance losses are captured by the smoothed loss, which is calculated following the loss-smoothing procedure in Cummins and Xie (2008) and documented in Appendix A. This procedure is particularly well-suited for the highly volatile losses of nonlife insurance, because it corrects the potential "error in variables" problem due to the randomness nature of losses (Cummins and Xie, 2013).[12]

The DEA inputs, input prices, outputs, and estimated efficiency scores are presented in the Panel C-F of Table 1, respectively. As expected, the life insurers have a much larger size than nonlife insurers in terms of number of employees, equity capital, debt capital, and invested assets. The input prices are at the similar level for both life and nonlife insurers. The efficiency scores estimated based on one global frontiers are lower than that estimated based on three regional frontiers. The average efficiency scores are lower than previous studies (Greene and Segal, 2004; Leverty and Grace, 2010) because the difference in operations across markets within one region (regional frontier) is larger than the difference in operations across states within the U.S. (country frontier); thus the inefficient insurers tend to have lower cost efficiency scores and larger diversities in our global sample than in the U.S. sample.

3.3 Regression models

We follow Greene and Segal (2004) to test the correlation between cost efficiency and profitability with random effects models (Equation 2). We use random effects models, though Hausman test favors the fixed effects, because fixed effects do not allow for time invariant independent variables (e.g., the life insurer dummy) and thus are not able to identify the different impact of cost efficiency on ROE between life and nonlife insurers.[13] We use firm fixed effects models and OLS mean regression (Equation 3) as robustness tests, the results of which are consistent with our conclusions. The mean regression helps to smooth out the year fluctuation in ROE and ROA and thus is expected to have a higher correlation with the efficiency measures (Greene and Segal, 2004).

To allow for the hypothesized nonlinear correlation (H3) between cost efficiency (CE) and ROE,

[12] Leverty and Grace (2010) compare different output measures of the risk pooling function. They show that measures accounting for the volatilities of losses are moderately better than actual losses. From the theoretical perspective, Brokett, Cooper, Golden, Rousseau, and Wang. (2004, 2005) also criticize the use of incurred loss as output because unexpected large losses due to unforeseen catastrophes or other random fluctuations could be artificially efficiency enhancing as measured output is higher. Premiums are sometimes applied as an output to replace the insurance benefits or losses, since premiums capture the business volume generated by insurers. However, the concerns arise as premiums do not only captures the quantity of outputs but also the price; it represents the price times the quantity of outputs (Yuengert, 1993).

[13] It is acknowledged that with panel data, random effects models better captures the cross-sectional effects among firms; while firm fixed effects models better captures the dynamics of one firm over years. Thus, the use of random effects models is also in line with the relative nature of efficiency measures.

we include the square term of cost efficiency scores. A life insurer dummy is included in the regression as well as its interactions with cost efficiency and cost efficiency square to capture the hypothesized different E-P relationship between life and nonlife insurers (H2). X_i is a vector of time invariant control variables including dummy variables of mutual, unaffiliated, emerging, and developed. $Z_{i,t}$ is a vector of time variant control variables including the natural logarithm of firm total assets and its squared term, real asset growth, premium retain ratio (inverse reinsurance ratio), leverage ratio, liquidity ratio, life or nonlife insurance penetration, and GDP growth rate of the firm domiciliary market. The mean values for the OLS mean regression with Equation (3) are calculated by the average of all available year observations of a firm.

Based on our hypotheses, we expect a positive coefficient of cost efficiency (positive β_1), a negative coefficient of cost efficiency square (negative β_2), and a positive coefficient of the interaction term of CE×Life (positive β_3). To further test the robustness of the nonlinear E-P relationship, if any, we further look at the E-P relationship in four subsamples based on cost efficiency quantiles.

$$ROE_{i,t} = \beta_0 + \beta_1 CE_{i,t} + \beta_2 CE_{i,t}^2 + \beta_3 CE_{i,t} \times Life_i + \beta_4 CE_{i,t}^2 \times Life_i + \beta_5 X_i + \beta_6 Z_{i,t} + \beta_7 Year_t + \varepsilon_{i,t} \quad (2)$$

$$MROE_i = \beta_0 + \beta_1 MCE_i + \beta_2 MCE_{i,t}^2 + \beta_3 MCE_i \times Life_i + \beta_4 MCE_{i,t}^2 \times Life_i + \beta_5 X_i + \beta_6 MZ_i + \varepsilon_i \quad (3)$$

3.4 Rank-order correlation and correspondence models

One concern regarding the parametric regression models to identify the E-P relationship lies with the complexity and nonlinearity of this relationship. This is particularly true considering the profit measures are absolute ratios for one firm itself; while the efficiency measures are relative scores to the best practice firms. Therefore, in addition to the quadratic term included in the parametric models, we are interested in examining the rank-order correlation between efficiency and profitability. The rank-order correlation captures whether a firm having a relatively high rank of cost efficiency is associated with its high rank in ROE. It excludes the effects of different scale of efficiency and profit measures, matches with the relative nature of frontier efficiency measurement, and minimizes the model misspecification risk. The rank-order test is new to the frontier efficiency and profitability studies in the insurance industry.[14]

Spearman's Rho and Kendall's Tau rank correlation statistics are calculated. These statistics

[14] Bauer et al. (1998), Eisenbeis et al. (1999), and Weill (2004) apply the rank-order tests in the banking industry. Leverty and Grace (2010) apply it for the comparison of different efficiency measures.

are informative in two aspects: (1) they tell whether the rank of efficiency and the rank of profitability are independent; (2) the values of correlation statistics tell how important the efficiency in determining the relative position of a firm's profitability. As suggested by Bauer et al. (1998), one should expect a positive rank-order correlations between the efficiency measures and the conventional profit ratios, however the correlations should be far from 1 because the conventional profit measures embody not only the efficiencies, but also the effects of differences in input prices and other exogenous variables over which financial institution managers have little or no control.

Moreover, we conduct the best and worst practice correspondence analyses (Leverty and Grace, 2010) for the E-P relationship. The correspondence rate captures the proportion of insurers classified as top (bottom) 25% efficient insurers that also have the top (bottom) 25% ROE. The correspondence test is a more relaxed benchmark than rank-order correlation because even if the ranks of efficiency and profitability for a firm are not the exactly the same, these two measures may still be consistent to the extent that classify the firm to the same best or worst group. [15] The rank-order statistics and correspondence rate have important management implication when managers try to benchmark its peers; they inform the managers, to what extent, focusing on improving operational efficiency can help to change relative profit position of a firm comparing to its peers. The correspondence test is also new to the frontier efficiency and profitability studies in the insurance industry.

[15] Leverty and Grace (2010) suggest that simple rank-order correlation between efficiency and profitability is not sufficient. This is particularly true when we compare the ranks of a large number of firms, because a slight change in rank (e.g. rank as 10 in profit and 20 in efficiency) will be identified as rank mismatch, thus rank-order statistics are expected to be far from 1. In such case, the correspondence tests may be more informative.

4. Results

4.1 Regression analyses

Table 2 reports the results of estimating Equation (2). The results in Columns 1-2 are from the full sample; those in Columns 3-4 are from the life and nonlife subsample, respectively; those in Columns 5-8 are from four subsamples based on the quantiles of cost efficiency scores. The positive coefficients of cost efficiency (β_1) and of the interaction term CE×life (β_3) suggest that the cost efficiency has a significantly positive correlation with the profitability for both life and nonlife insurance industries. The results thus support our Hypothesis 1.

Looking at the difference between life and nonlife insurers, the positive coefficients of the interaction term CE×life (β_3) in Columns 1-2 suggest that the cost efficiency is more important to life insurers' profitability than to nonlife insurers'. If we compare the magnitude of cost efficiency coefficients in life and nonlife subsamples (Columns 3-4), the impact of cost efficiency in the life sample is significantly larger than that in the nonlife sample, subject to the Z test. This is also in line with the positive (though insignificant) coefficients of interaction term in four quantile subsamples (Columns 5-8). The evidence supports our Hypothesis 2.

The negative coefficients of the quadratic cost efficiency term (β_2) indicate that the positive impact of cost efficiency on profitability is smaller for high cost efficiency firms than for low cost efficiency firms. This interpretation is confirmed by the quantile regression results shown in Columns 5-8. Both the magnitude and the significance level of cost efficiency coefficients become smaller as the firm's cost efficiency quantiles increase from 1 to 4. The efficiency gains for low efficiency firms are more likely to realize in profit than firms that are already high efficiency. These results support our Hypothesis 3.

Looking at the magnitude of the E-P correlation, the coefficients in the life sample (Column 3) suggests that in average or at the means of all covariates, the cost efficiency increases by 1 percentage point, the ROE shall increase by 0.17 percentage point; the (semi-) elasticity of cost efficiency at the means of all covariates is 0.75 (0.088), meaning 1% increase in cost efficiency shall increase the ROE by 0.75% or by 0.088 percentage point in absolute term. For nonlife insurers (Column 4), 1 percentage point increase in cost efficiency only corresponds to 0.15 percentage point increase in ROE and the (semi-) elasticity of cost efficiency is 0.36 (0.044), meaning 1% increase in cost efficiency only increases the ROE by 0.36% or by 0.044 percentage point in absolute term. The (semi-)elasticity of cost efficiency for life insurers is significantly larger than that for nonlife insurers at 99% confidence level subject to Z tests.

As the E-P relationship is nonlinear, for the least efficient quarter of insurers (Column 5), if the cost efficiency increases 1 percentage point, then the ROE increases 0.36 percentage point correspondingly; while for the most efficient quarter of firms (Column 8), 1 percentage point increase in cost efficiency corresponds to 0.12 percentage point increase in ROE. However, such nonlinearity are not reflected in the elasticities of cost efficiency-profitability relationship, for those least efficient quarter of insurers the elasticity of cost efficiency is 0.66; while for the most efficient firms, the elasticity of cost efficiency is 0.63. These results indicate that a log transformation may also capture the nonlinear relationship between ROE and cost efficiency.[16] The results using a log transformation of ROE and cost efficiency scores are reported in Appendix B and are consistent with our conclusions.

To compare our life insurer results with those in Greene and Segal (2004), we transform our efficiency measure to their inefficiency measure by one minus the efficiency scores and re-estimate Equation (2). The results are reported in Appendix B. Greene and Segal (2004) describe the semi-elasticity of cost inefficiency on ROE before tax and ROA before tax (i.e. double cost inefficiency corresponds to 4 percentage points decrease in ROE and 1 percentage point decrease in ROA; or in other words, 1% increase in cost inefficiency corresponds to ROE decrease of 0.04 percentage point and to ROA decrease of 0.01 percentage point). We find, in our global insurer sample, a slightly larger impact of cost inefficiency on ROE as 1% increase in cost inefficiency decreases ROE by 0.085 percentage point; and a slightly smaller impact on ROA as 1% increase in cost inefficiency decreases ROA by 0.008 percentage point. We attribute the different scale of impact to the difference in leverage ratios and returns variation of life insurers. In our global sample, the average ROA (0.012) is much smaller than that (0.02) in their US sample, given that the average ROEs are close (0.10 vs. 0.12), suggesting Non-US life insurers have a higher leverage ratio than the US ones and resulting in smaller impact on ROA in our sample. The standard deviation of ROEs in our sample (0.25) is also larger than that in their sample (0.18) resulting in larger magnitude of impact on ROE in our sample.

To compare our nonlife insurer results with those in Leverty and Grace (2010), we further decompose our cost efficiency measure into pure technical, scale, and allocative efficiencies as per standard DEA procedure, and use the three decomposed efficiency measures to replace cost efficiency in Equation (2). We also follow their practice to use fixed effects regression and ROA after tax as independent variable. The results are reported in Appendix B. Leverty and Grace (2010) report the coefficients (elasticity at means of covariates) as 0.022 (0.522) for pure technical efficiency, 0.003 (0.086) for scale efficiency, and 0.006 (0.114) for allocative

[16] We did not choose the log transformation as our core model because ROE involves with many negative values, a shift of these negative values to positive increase the difficulty in coefficient interpretations.

efficiency. Our results suggest larger impact of efficiency on profitability as 0.077 (1.297) for pure technical efficiency, 0.041 (0.958) for scale efficiency, and 0.025 (0.247) for allocative efficiency. These larger impact may partially contribute to the non-US nonlife insurers have a higher leverage than the US nonlife insurers[17], which is consistent to the case in the life insurance industry. These differences may also reflect the real difference in the US and Non-US market, where the latter is more driven by cost efficiencies.

In summary, our results are quite consistent with previous findings in life (Greene and Segal, 2004) and nonlife (Leverty and Grace, 2010) insurance industries. We confirm the positive correlation between frontier efficiency measures and conventional profit measures. Beyond the positive E-P relationship, we provide two novel insights: (1) the E-P relationship is nonlinear and follow the law of diminishing marginal returns. Therefore, a natural logarithm transformation or a quadratic term of cost efficiency should be included in any E-P relationship analyses to capture such nonlinear effects. (2) We argue that the E-P relationship is industry dependent and document the evidence that cost efficiency is more important to life insurers' profitability than that to nonlife insurers' due to the different risk nature and business models in these two sub-industries. It is in line with Greene and Segal's (2004) argument that operations are particularly important to life insurers' profitability due to industry idiosyncrasies.

[17] Leverty and Grace (2010) present the average capital to asset ratio as 0.440 and ours is 0.279, which indicates our global sample has a higher liability to equity leverage ratio.

Table 2 Estimation of equation (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Samples	Full sample		Life sample	Nonlife sample	CE Quantile 1	CE Quantile 2	CE Quantile 3	CE Quantile 4
Variables	ROEaftertax	ROEbeforetax			ROEbeforetax			
CostEfficiency	0.0942***	0.0935***	0.185***	0.0892***	0.296***	0.196***	0.0862*	0.0613
	(0.0142)	(0.0152)	(0.0250)	(0.0156)	(0.0894)	(0.0685)	(0.0521)	(0.0445)
Life×CostEfficiency	0.0556**	0.0743***			0.300	0.195	0.0636	0.0769
	(0.0251)	(0.0275)			(0.241)	(0.270)	(0.128)	(0.0574)
CostEfficiency^2	-0.197***	-0.235***	-0.117	-0.183***				
	(0.0490)	(0.0537)	(0.0727)	(0.0537)				
$\text{Life×CostEfficiency}^2$	0.0592	0.109						
	(0.0819)	(0.0878)						
Life	-0.0401***	-0.0470***			-0.0865**	-0.0972	-0.0926*	-0.0748*
	(0.00779)	(0.00877)			(0.0379)	(0.0730)	(0.0529)	(0.0385)
Mutual	-0.0126**	-0.0243***	-0.0272**	-0.0304***	-0.0109	-0.0346***	-0.0276***	-0.0312***
	(0.00533)	(0.00581)	(0.0119)	(0.00660)	(0.0144)	(0.00780)	(0.00818)	(0.00977)
Unaffiliated	-0.0103**	-0.0126***	-0.0106	-0.0124**	0.00229	-0.0186***	-0.0140*	-0.00730
	(0.00412)	(0.00459)	(0.00861)	(0.00528)	(0.0101)	(0.00709)	(0.00756)	(0.00796)
Emerging	0.00445	0.00771	0.0581***	0.00496	0.0137	-0.0329***	-0.00741	0.0415***
	(0.00699)	(0.00799)	(0.0165)	(0.00933)	(0.0145)	(0.0125)	(0.0135)	(0.0151)
Developed	0.00665	0.00732	0.0159	0.00164	0.00226	0.00449	-0.00661	-0.00832
	(0.00642)	(0.00719)	(0.0156)	(0.00790)	(0.0124)	(0.0102)	(0.0128)	(0.0139)
lnAsset	0.0109***	0.0138***	0.0208***	0.0129***	0.0173***	0.0102***	0.0131***	0.0198***
	(0.00117)	(0.00134)	(0.00250)	(0.00196)	(0.00372)	(0.00227)	(0.00232)	(0.00201)
lnAsset^2	-0.000731**	-0.000919**	-0.00168***	-0.00200***	-0.00101	-0.00101	-0.000198	-0.000659
	(0.000337)	(0.000389)	(0.000647)	(0.000562)	(0.000886)	(0.000679)	(0.000599)	(0.000524)
RealAssetGrowth	-0.000163	-0.00429	-0.0381***	0.0275***	-0.0220	-0.0167	0.0202	0.00862
	(0.00713)	(0.00737)	(0.0136)	(0.00754)	(0.0138)	(0.0131)	(0.0131)	(0.0136)
PremRetainRatio	0.0154	0.0282***	-0.102***	0.0365***	0.0115	0.0292*	0.0219	0.0365*
	(0.00970)	(0.0109)	(0.0322)	(0.0117)	(0.0197)	(0.0160)	(0.0170)	(0.0221)
LeverageRatio	-0.000768***	-0.000719***	-0.000590**	-0.0120***	-0.00904***	-0.00169*	-0.00117	-0.000336
	(0.000209)	(0.000262)	(0.000268)	(0.00163)	(0.00228)	(0.00103)	(0.000944)	(0.000245)
LiquidityRatio	0.000653	0.000349	0.00879**	-0.00191***	0.00438	-0.000610	-0.00156**	-0.000432
	(0.000531)	(0.000573)	(0.00375)	(0.000459)	(0.00320)	(0.000649)	(0.000766)	(0.000897)
InsurancePenetration	-0.00107	-0.00198	-0.00403**	0.0235***	0.0113***	0.000398	-0.00307	-0.00896***
	(0.00146)	(0.00174)	(0.00197)	(0.00479)	(0.00397)	(0.00380)	(0.00327)	(0.00233)
GDPGrowth	-0.0253	-0.0399	-0.191	0.0347	-0.153	-0.101	-0.0364	0.0490
	(0.0684)	(0.0719)	(0.149)	(0.0777)	(0.132)	(0.125)	(0.135)	(0.158)
Constant/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,062	24,971	8,968	16,003	6,243	6,245	6,240	6,243
No. of Firms	4,756	4,748	1,718	3,046	1,937	2,281	2,233	1,641
R^2	0.051	0.056	0.059	0.049	0.086	0.065	0.074	0.080

4.2 Rank-order correlation and correspondence

In order to smooth out the year fluctuation in ROEs of a firm, we take the average cost efficiency score and the average ROE of all available year observations of a firm (Greene and Segal, 2004) and obtain the rank of mean cost efficiency and the rank of mean ROE, respectively.[18] The Spearman's Rho equals 0.136 for life insurers and 0.131 for nonlife insurers. The Kendall's Tau equals 0.092 for life insurers and 0.087 for nonlife insurers. All statistics are significantly different from 0 at 99% confidence level. The results suggest that the rank by cost efficiency and the rank by ROE are not independent, though the magnitude of correlation is small. The results are comparable to those in Bauer et al.'s (1998) banking sample, where the Spearman's Rho equals 0.109.

We also conduct the rank-order correlation tests year by year, the results of which are consistent with our findings above except for a few years, the correlation becomes insignificant, that are 2005 and 2008 for nonlife insurance industry and 2008, 2009, and 2011 for life insurance industry. These changes can be explained by Bauer et al.'s (1998) argument that conventional profit measures capture not only the efficiency but also the exogenous market factors and fluctuations that managers have little or no control, e.g. 2008 financial crisis reduces the ROE of the insurance industry to 0, many firms are far away from their usual ROEs not because of low efficiency but because of exposures to CDS and CDOs. 2005 is the top profitable year in the nonlife insurance industry, partially driven by the hardening price after Hurricane Katrina, and partially driven by the good stock returns (Swiss Re, 2006). 2011 is a very bad year for life insurers due to quick decreasing in interest rate that endanger the investment returns of life insurers but do not affect the efficiency. The results of yearly rank-order tests are presented in Appendix B.

We look at the correspondence rate for the best practice quarter of insurers and the worst practice quarter of insurers. We found that among the top 25% most cost efficient life (nonlife) insurers, 34% (33%) of them also fall into the top quantile of ROEs; among the 25% least cost efficient life (nonlife) insurers, 33% (27%) of them also fall into the bottom quantile of ROEs. All cost efficiency and ROE considered in this test is the mean over all available year observations (Cummins and Zi, 1998) and all proportions are significantly larger than the random distribution of 25%. The correspondence rates confirm our conclusion from the rank-order correlation analyses: the two ranks are not independent but their rank-order correlation and quantile correspondence are far from perfect match.

[18] Here we use the cost efficiency scores against one global frontier so that all firms can be ranked in one list.

Therefore, we put a question mark on the importance of cost efficiency to the profitability in the insurance industry, as which are unlikely to be paramount. The E-P relationship is indeed statistically and economically significant. It should not be ignored by managers particularly for those firms with relatively low cost efficiencies, however, it is probably not as important as it can fundamentally change the relative market position of an insurer. To test the robustness of our conclusions, we also separate our sample to European Union (EU) insurers and Non-EU insurers as the EU insurers take around two thirds of our observations. The results suggest our conclusions apply to both EU and non-EU insurers.

5. Conclusions

We contribute to the understanding of the efficiency and profitability relationship (E-P relationship) in the life and nonlife insurance industries and in general business practice. The E-P relationship is important because of the demand for operational measures from the business practice (Kaplan and Norton, 2005) and because of the wide application of frontier efficiency analyses in the academic research of financial institutions (Berger and Humphrey, 1997; Cummins and Weiss, 2013). The gap between academic application and business usage of efficiency measures partially attributes to the limited evidence showing the relationship between efficiency measures and the conventional profit measures that define the "reality" (Bauer et al., 1998; Leverty and Grace, 2010).

Consistent with previous results, we document a statistically positive and economically significant E-P relationship in both life and nonlife insurance industries. We advance the understanding of this relationship beyond the insurance industry by showing that the E-P relationship should follow the law of diminishing marginal returns and should depend on industry idiosyncrasies. Firms with low efficiency scores can profit more from the marginal improvement of efficiency than firms with high efficiency scores because the marginal productivity of efficiency diminishes. Life insurers can profit more from efficiency improvement than nonlife insurers because nonlife insurance is more differentiable and tailor-made than life insurance and thus the competition among nonlife insurers focus more on product and less on cost management than life insurers.

The magnitude of E-P relationship in our results is largely consistent with the previous evidence from the US life (Grace and Segal, 2004) and nonlife (Leverty and Grace, 2010) insurance markets. However, we conclude in addition that the efficiency is unlikely to be paramount important to an insurer's profitability, rather our rank-order correlation and best/worst practice correspondence tests confirm Bauer et al.'s (1998) finding in the banking industry that is the E-

P relationship is moderate and economically significant.

Our results have important implications to the management and to the academia. The role of efficiency to profitability differs from industry to industry and differs from low efficiency firms to high efficiency firms. Managers should carefully analyze their own industry idiosyncrasies and take corresponding actions on efficiency improvements. Managers of life insurers and of low efficiency firms should pay more attention to their cost management since which are easily translated into profit. We add the first global evidence to the E-P relationship of financial institutions, however, comparing to the large number of efficiency and profitability investigations, the evidence regarding the E-P relationship has the similar amount of questions from the business and regulatory practice, but much less answers from the academia.

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