Received: 7 September 2021 | Revised: 4 August 2022 | Accepted: 30 September 2022

DOI: 10.1002/ijfe.2723

RESEARCH ARTICLE

WILEY

Measuring the efficiency and productivity of U.K. insurance market

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Abstract

The U.K. insurance industry has a dominant international presence, suggesting strong competitiveness and performance. Yet, its efficiency and productivity has rarely being investigated. The purpose of this paper is to provide an overview of insurers' performance in the U.K. insurance market from 1996 to 2017, using stochastic frontier analysis to measure efficiency scores and productivity at the firm level. Results show the U.K. insurance industry could improve by about 40% in terms of cost efficiency and by 70% in terms of profit efficiency. In addition, our model reveals a higher cost efficiency score compared to profit efficiency, implying that there are higher inefficiencies on the income side of the insurance industry as measured by our profit function. In terms of total factor productivity (TFP) growth, we report a steady decline over time while on average is negative. By decomposing TFP growth into its underlying components, we reveal that the reported negative trend in TFP growth over time has mainly been driven by the enhanced competition that resulted in a drop in markup, while the scale and cost efficiency has also driven TFP growth down. However, from a positive point of view, we report evidence of both β-convergence and σ-convergence in cost and profit efficiency.

KEYWORDS

convergence, cost efficiency, productivity, profit efficiency, U.K. insurance

1 | INTRODUCTION

The U.K. insurance is ranked as the largest one across the European Union, and the third largest in world. The U.K. insurance was responsible for 24% of total EU premium income that contributed £25bn to the United Kingdom's gross domestic product (GDP), created more than 314,400 job opportunities provided in 2014 (Association of British Insurers, 2014). Given the contribution of the insurance industry to the economy, a study of its underlying performance over time is warranted. We focus on two main questions: how well is the firm

Despite every effort to contact Dr Zhi Cheng Wang to fulfill his authorship duties per journal policy, he could not be reached. The other authors have provided to the editor evidence of Dr Zhi Cheng Wang's commitment to participating as an author during the development of the manuscript. The article in question is therefore published with Dr Zhi Cheng Wang included as an author, and any questions that arise in relation to the manuscript will be dealt with by the other authors.

operating in terms of cost/profit efficiency but also total factor productivity (TFP) growth? and is there convergence in efficiency scores across the U.K. insurance industry? We are addressing these questions by measuring U.K. insurance efficiency and productivity growth with the stochastic frontier approach.

From a methodological point of view, there is a plethora of methods to measure firm efficiency. Two broad categorizations refer to non-parametric and the parametric estimation of efficiency. The non-parametric measure follows the data envelope analysis (DEA) vis a vis parametric estimation that is mainly following the stochastic frontier analysis (SFA). There are advantages and disadvantages associated with both methods. But, the SFA prior evidence shows that it provides the least biased result in principle, because the constructive advantages of SFA allows to identify the two components of composited error terms into the pure random error term and the inefficiency term (Cummins & Weiss, 2011; Eling & Luhnen, 2010a; Hardwick et al., 2011). Therefore, following Cummins and Weiss (2011) who argued that the efficiency analysis is a superior method to identify insurer's performance, this paper opts for SFA to measure both productivity and efficiency of U.K. insurance (see also Cummins & Weiss, 2011; Cummins & Xie, 2008; Eling & Luhnen, 2010a; Hardwick et al., 2011).

In some detail, the purpose of our paper is threefold: first, we undertake a comprehensive analysis of the U.K. insurers' efficiencies and productivity by using SFA to estimate both efficiency and productivity; second, we provide comparisons among types of insurance business, controlling for ownership. Lastly, having derived efficiency and productivity scores we test for convergence in terms of σ-convergence and β-convergence.[1] It is also worth noting that we employ panel dada analysis throughout this paper, because panel data analysis treats for heterogeneity (see Kumbhakar et al., 2015). Therefore, by utilizing panel data analysis, estimating efficiency can be achieved by introducing an individual unobservable effect variable, which are time-invariant and individual-specific, and not interacted with other variables. The database is derived from financial statements of individual insurers, which include balance sheet and income statement, collected from Orbis, Fame and ISIS (or Insurance Focus) provided by Bureau van Dijk. Our sample covers at least 90% of the insurance market capacity from 1996 to 2017. To this end, we can estimate efficiency scores and productivity growth for all major insurers of the U.K. market, which is a global competitor. In terms of the estimator of this study, we examine various methods, and we opt for the estimator of Kumbhakar et al. (2014) which has the advantage to control for persistency in efficiency while treats efficiency as time varying, which is of importance for the current study that it tests also for convergence in efficiency.

The application of SFA efficiency measurement for the insurance industry is a cumbersome task due to measurement issues with the outputs mainly. In previous studies, there are many unresolved debates around the definition of outputs in the insurance industry (e.g. Cummins & Weiss, 2011; Eling & Luhnen, 2010b; Yaisawarng et al., 2014) also stated that different measures of output lead to different conclusion on efficiency. Zanghieri (2009) mentioned that one of the most important challenges is how to proxy outputs for analysing efficiency in the financial services industry. According to Cummins and Weiss (2011), Eling and Luhnen (2008), Zanghieri (2009), the output produced by the insurer is the provision of three principal services, and the pragmatic approach is therefore to identify these services and to find measurable proxies that are highly correlated with these services (Diacon, Starkey & O'Brien, 2002). To be more specific, the three principal services are risk pooling and risk taking, financial intermediation, and 'real' financial services relating to insured losses.[2]

This paper is organized as follows. Section 2 provides the methodology and discusses the data. Next, in Section 3 reports efficiency scores from different models, as well as productivity and its components. Finally, the main conclusion is summarized in the last section.

2 | MEASURING U.K. INSURANCE EFFICIENCY

2.1 | The stochastic frontier analysis

There are several methods associated with efficiency measurement. These methods opt for an underlying functional form like a production, cost, profit or a revenue function with a specific shape, while certain assumptions about the distribution of error and inefficiency term are made (Cummins & Weiss, 2011; Eling & Luhnen, 2010a). There are three main methods for estimating efficiency: the SFA,[3] the distribution-free approach (DFA)[4] and the thick frontier approach (TFA).[5] In this study, we follow the specification of Battese and Coelli (1988) that suggests a cost functional from as follows:

$$\mathrm{TC}_{it} = f(Y_{it}, P_{it}, T) + \varepsilon_{it} \tag{1}$$

in which the TC_{it} stands for the total cost of insurer i in year t, the Y_{it} stands for a vector of outputs, P_{it} stands for vector of input price, and ε_{it} stands for the composited error term, which is specified as, $\varepsilon_{it} = v_{it} + u_{it}$. Apart from this, the inclusion of a time trend variable (T) ensures that changes over time in technology and underwriting cycle can be captured. The term v_{it} stands for the error term, u_{it} denotes insurer's inefficiency, and the inefficiency term u_{it} is usually assumed to follow a half normal or truncated normal distribution, and the truncated normal distribution is adopted in this paper, as half normal distribution is special case of truncated normal distribution.

Moreover, we select a flexible translog cost function:

$$\ln \mathrm{TC}_{it} = \alpha_0 + \sum_{g}^{2} \alpha_g \ln Y_{igt} + \sum_{j}^{3} \beta_j \ln P_{ijt} + \frac{1}{2}\left[\sum_{g}^{2}\sum_{k}^{2} \alpha_{gk} \ln Y_{igt} \ln Y_{ikt} + \sum_{j}^{3}\sum_{h}^{3} \beta_{jh} \ln P_{ijt} \ln P_{iht}\right] + \sum_{g}^{2}\sum_{j}^{3} \delta_{gj} \ln Y_{igt} \ln P_{ijt} + \mu_1 T + \frac{1}{2}\mu_2 T^2 + \sum_{g}^{2} \rho_g T \ln Y_{igt} + \sum_{j}^{3} \xi_j T \ln P_{ijt} + \varepsilon_{it} \quad (2)$$

where TC is total cost (or Π = Operating Profit); Y_1 is output 1 incurred losses; Y_2 is output 2 total investment; P_1 is input price 1 of labour and business; P_2 is input price 2 of financial capital; P_3 is input price 3 of technical reserves; T is time trend. The symmetry property requires that $\alpha_{ik} = \alpha_{ki}$, $\beta_{jh} = \beta_{hj}$ and $\delta_{ij} = \delta_{ji}$.

The cost function is homogeneous of degree 1 in input price, and so the following restrictions apply: $\sum \beta_j = 1$, $\sum\sum \beta_{jh} = 0$, $\sum\sum \delta_{gj} = 0$, $\sum\sum \xi_j = 0$. These constraints can be substituted into the model; therefore, the homogeneity conditions are satisfied. This procedure amounts to using one of the input prices (e.g. P_1) to normalized total cost and another input price. Using P_1 as the normalizing price, the tranlsog cost function can be simplified as follows:

$$\ln\left(\frac{\mathrm{TC}}{P_1}\right) = \alpha_0 + \alpha_1 \ln Y_1 + \alpha_2 \ln Y_2 + \beta_2 \ln\left(\frac{P_2}{P_1}\right) + \beta_3 \ln\left(\frac{P_3}{P_1}\right) + \frac{1}{2}\left[\alpha_{11} \ln Y_1 \ln Y_1 + \alpha_{22} \ln Y_2 \ln Y_2 + \beta_{22} \ln\left(\frac{P_2}{P_1}\right)^2 + \beta_{33} \ln\left(\frac{P_3}{P_1}\right)^2\right] + \alpha_{12} \ln Y_1 \ln Y_2 + \beta_{23} \ln\left(\frac{P_2}{P_1}\right) \ln\left(\frac{P_3}{P_1}\right) + \delta_{12} \ln Y_1 \ln\left(\frac{P_2}{P_1}\right) + \delta_{13} \ln Y_1 \ln\left(\frac{P_3}{P_1}\right) + \delta_{22} \ln Y_2 \ln\left(\frac{P_2}{P_1}\right) + \delta_{23} \ln Y_2 \ln\left(\frac{P_3}{P_1}\right) + \mu_1 T + \frac{1}{2}\mu_2 T^2 + \rho_1 T \ln Y_1 + \rho_2 T \ln Y_2 + \xi_2 T \ln\left(\frac{P_2}{P_1}\right) + \xi_3 T \ln\left(\frac{P_3}{P_1}\right) + \varepsilon_{it} \quad (3)$$

There is a plethora of estimating methods for cost efficiency. In this paper, we opt for the firm effects and time-varying efficiency method of Kumbhakar et al. (2014).

Once the parameters are available for the cost frontier, it is possible to estimate cost scale efficiency by using the formula for the elasticity of scale:

$$\text{Cost scale efficiency} = \sum_i \frac{\partial \ln TC}{\partial \ln Y_i} = \sum_i \left[\alpha_i + \frac{1}{2}\sum_k \alpha_{ik} \ln Y_k + \sum_j \delta_{ij} \ln P_j\right] \quad (4)$$

This formula represents the sum of the partial derivatives of the cost function, with respect to each of the output variables. If this value <1, economies of scale (decreasing cost) is existed; if the value >1, it indicates diseconomies of scale (increasing costs). Economies of scale are present if average costs per unit of output decline as the volume of output increases. The source of scale economies is the spreading of the insurer's fixed costs over a larger volume of output, for example, operating at larger scale may reduce the firm's cost of capital.

2.2 | TFP growth decomposition

In terms of measuring productivity, there are two main approaches: the frontier approach and non-frontier approach.[6] The financial industry literature has extensively followed the frontier approaches (parametric and non-parametric), which base on identifying the best-practice firms in the market (see e.g. Cummins & Weiss, 2011; Eling & Schaper, 2017).[7]

Herein, we employ Kumbhakar et al. (2015),[8] TFP growth where there are multiple inputs (j inputs) and multiple outputs (m outputs):

$$\dot{\mathrm{TFP}} = \sum_m R_m \dot{y}_m - \sum_j S_j \dot{x}_j \quad (5)$$

where $R_m = p_m y_m / R$ and $S_j = w_j x_j / C$, in which p is the output price, y is output vector and $R = \text{total revenue} = \sum_m p_m y_m$; and w is the input price, x is the input vector and $C = \text{total cost} = \sum_j w_j x_j$. Note that the dot above TFP implies growth rate.

Thus, following Kumbhakar et al. (2015), the TFP growth and its components can be defined as:

$$\dot{\mathrm{TFP}} = \mathrm{TCC} + \mathrm{EC} + \left[\left(1 - \mathrm{RTS}^{-1}\right)\dot{y}_c\right] + \left[\dot{y}_p - \dot{y}_c\right] \quad (6)$$

TABLE 1 Descriptive statistics

Variable	Obs.	Mean	*SD*	Min.	Max.
Total Cost	5716	10,380.93	42,863.84	0.07	979,190
Total Profit	6252	969.42	4901.93	0	178,617.8
Output 1	5794	4058.68	15,927.84	0	431,176.4
Output 2	6972	55,529.61	444,324.39	0	26,883,116
Input Price 1	5418	0.12	0.57	0	26.71
Input Price 2	5395	0.38	0.93	0	1509
Input Price 3	6412	0.54	0.35	0	5.27
Variable	**Obs.**	**Median**	**p25**	**p75**	**CV**
Total Cost	5716	1130.671	174.283	4886.974	4.129
Total Profit	6252	102.061	19.847	499.013	5.057
Output 1	5794	425.873	59.072	1881.550	3.924
Output 2	6972	1919.802	348.924	11,153.850	8.002
Input Price 1	5418	0.071	0.018	0.145	4.542
Input Price 2	5395	0.041	0.019	0.082	2.447
Input Price 3	6412	0.576	0.246	0.827	0.649

Note: Total cost equals to operating expenses − claim paid. Total profit is the profit before tax shown in the income statement. Output 1 is Net Claims Paid, and Output 2 is total investment. Input Price 1 equals to the ratio of Administration Expenses to Total Asset. Input Price 2 is the ratio of Ordinary Profits to the sum of Equity and Reserve. Input Price 3 equals to Net Technical Provisions/Total Asset. p25 and p75 report the 25th and 75th percentile respectively while CV is the coefficient of variation.

where TCC is the technical change component; EC is the efficiency change component; $(1-\text{RTS}^{-1})\dot{y}_c$ is scale component and $\text{RTS}^{-1}=\sum_m \partial \ln C/\partial \ln y_m; \dot{y}_p-\dot{y}_c$ is the markup component, in which $\dot{y}_p=\text{RTS}\{\sum_m(\partial \ln C/\partial \ln y_m)\dot{y}_m\}$ and $\dot{y}_p=\sum_m R_m\dot{y}_m$; $\dot{y}_m=\partial \ln y_m/\partial t$ and $\dot{x}_m=\partial \ln x_j/\partial t$.

The above TFP growth represent percentage changes and is estimated in a single stage together with the estimation of the SFA cost and profit efficiency scores of Equations (3) and (4). Note that the underlying components of TFP growth, such as efficiency (whether cost or profit) and the scale component, are estimated from Equations (3) and (4), respectively.

2.3 | Testing for convergence in insurance efficiency scores

Lastly, we test for convergence in insurance efficiency. The tendency for insurers to achieve an identical level of efficiency over time is defined as efficiency convergence. The β-convergence and σ-convergence are the most widely used concepts in the classical literature; β-convergence refers to the ability of inefficient firms to become efficient or improve their efficiency for those efficient one, and σ-convergence refers to the reduction in the dispersion of efficiency over time. According to Sala-i-Martin (1996), both β- and σ-convergence are related, and evidence of β-convergence is a necessary condition for σ-convergence. Therefore, β-convergence need to be confirmed first, and estimated by employing Alhassan and Biekpe's (2015) dynamic regression model:

$$\Delta y_{i,t}=\alpha+\delta\Delta y_{i,t-1}+\beta \ln y_{i,t-1}+\varepsilon_{i,t} \quad (7)$$

where $y_{i,t}$ is the efficiency score for insurer i at time t; $y_{i,t-1}$ is the efficiency score for insurer i at time $t-1$; $\Delta y_{i,t}=\ln y_{i,t}-\ln y_{i,t-1}$; α is the constant term and $\varepsilon_{i,t}$ is the time-varying error term; δ is the coefficient of the lagged depend variable; β is the coefficient of interest that represents the rate of efficiency convergence. The β-convergence is occurred if the value of β is negative, it indicates the catch-up excised; and the higher absolute value of β means a faster speed of convergence.

After confirming β-convergence, the model for σ-convergence is as followed:

$$\Delta E_{i,t}=\alpha+\varphi\Delta E_{i,t-1}+\sigma \ln E_{i,t-1}+\varepsilon_{i,t} \quad (8)$$

where $\Delta E_{i,t}=E_{i,t}-E_{i,t-1}$, in which $E_{i,t}=\ln y_{i,t}-\ln \bar{y}_t$ and $E_{i,t-1}=\ln y_{i,t-1}-\ln \bar{y}_{t-1}$. Similarly, $\Delta E_{i,t-1}=E_{i,t-1}-E_{i,t-2}$. $y_{i,t-1}$ is the efficiency score for insurer i at time $t-1$; $\bar{y}_t$ and $\bar{y}_{t-1}$ are the average efficiency scores for the market at time t and $t-1$, respectively. α and $\varepsilon_{i,t}$ remains as defined before; and the coefficient of dynamic variables $\Delta E_{i,t-1}$ is φ. σ is the parameter that the rate of convergence from $y_{i,t}$ to $\bar{y}_t$.

Both Equations (7) and (8) are estimated using the system generalized method of moments of Arellano and Bover (1995); Blundell and Bond (1998) with forward orthogonal and Windmeijer finite-sample correction (Windmeijer, 2005) so as to control for endogeneity.

3 | THE U.K. INSURANCE DATA

The database used in this paper is built on information from financial statements of individual insurers, which included balance sheet and income statement, collected from Orbis, Fame and ISIS (or Insurance Focus) provided by Bureau van Dijk. The sample covers at least 90% of the market capacity from 1996 to 2017. In line with Eling and Luhnen (2008), Fenn et al. (2008), Yaisawarng et al. (2014), insurance firms are included in our sample, if for all outputs, inputs and input price variables have positive values. Note the estimation of the SFA efficiency requires that the input prices are strictly positive. As there are missing values in the sample, it is unbalanced. To ensure all monetary values are directly comparable, we deflate each year's value by the consumer price index to the base year 2015.

Two types of efficiencies, cost, and profit efficiency are estimated. To estimate efficiency scores, definition of outputs, inputs and their prices that shown in Equation (1) must be specified. The output vectors and input price need to be exogenous, it implies that insurers choose input levels, to minimize cost (or maximized profit), involved in producing a given level of outputs (Fenn et al., 2008). First, the insurer's operating expenses that associated with both underwriting and administrative costs is used to determined total cost. Additional, this total cost is further adjusted by input factors as Hao and Chou (2005) suggested the observed cost should vary with input prices.[9] Following Fenn et al. (2008), the claim paid is excluded in order to avoid confusion with the output factor. Additional, total profit (TP) is the simple operating profit, profit before tax, presented in financial statement.

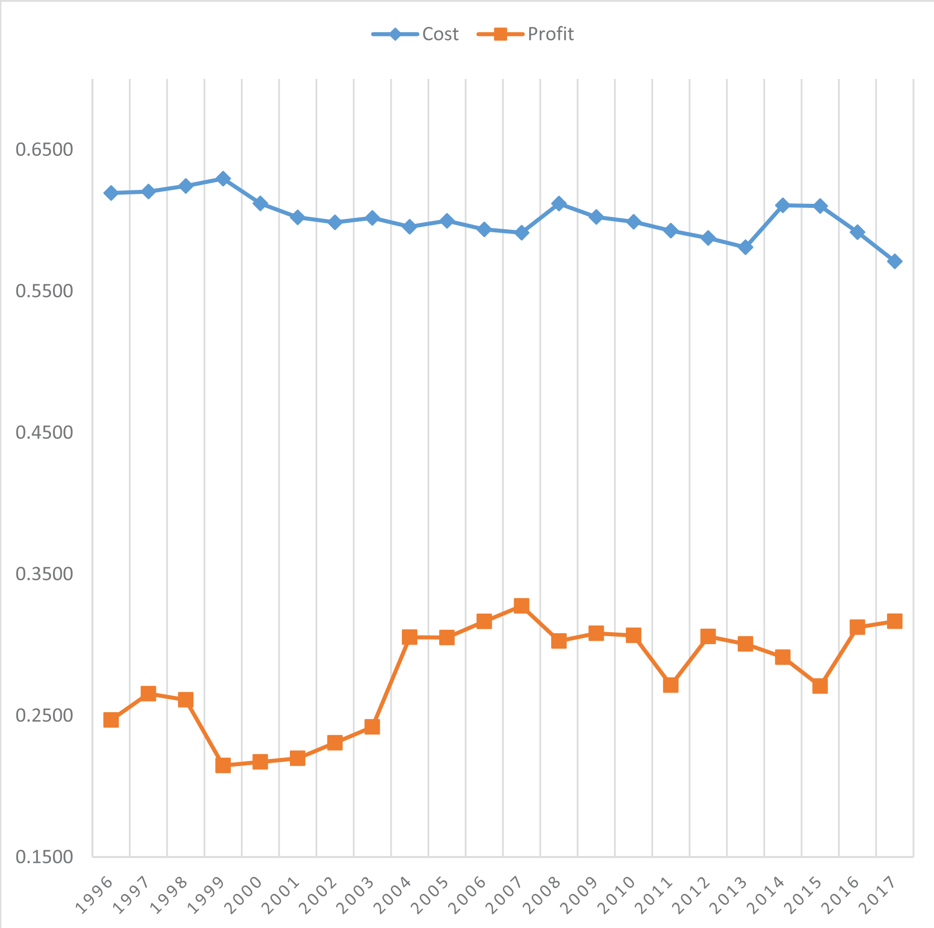
Donni and Fecher (1997) suggested two alternatives could be chosen as output proxy: premiums or incurred losses (claims or benefits paid to policyholders), and the number of policies contracted. Individuals tended to purchase insurance because they are risk averse. The price that individual willing to pay is an indicator of their degree of risk aversion and is their willingness to transfer risk, as such net premiums are a reflection of the value-added for each individual policyholder of the insurance firm (Ward, 2002). This could be one of the reasons of why premium could be included within the measure of output, particularly from a value-added perspective. Cummins and Weiss (2000) stated that no proxy was valid in principle for risk pooling/bearing activity. Thus, this study follows Fenn et al. (2008) and we opt for net claims paid (claims incurred net of reinsurance) to represent risk pooling/bearing activity and real financial services. And the second reason of applying this approach is that we need to make restricted homogeneous product assumption, if using premium as the proxy.

To represent financial intermediation service (net) investment income is used as a proxy of output by Boonyasai et al. (2002) and Diacon, Starkey and O'Brien (2002). In addition, Grace and Timme (1992), Klumpes (2004), Hao and Chou (2005), Eling and Luhnen (2010b), Yaisawarng et al. (2014) suggested to use a total investment as the second output proxy. Yaisawarng et al. (2014) argue that total investment should be selected

TABLE 2 Cost and profit efficiencies for all insurers

Year	Cost efficiency	Profit efficiency
1996	0.6193	0.2469
1997	0.6204	0.2654
1998	0.6243	0.2611
1999	0.6295	0.2147
2000	0.6120	0.2172
2001	0.6022	0.2198
2002	0.5986	0.2308
2003	0.6018	0.2419
2004	0.5955	0.3054
2005	0.5997	0.3051
2006	0.5937	0.3165
2007	0.5913	0.3274
2008	0.6119	0.3027
2009	0.6024	0.3081
2010	0.5990	0.3066
2011	0.5927	0.2715
2012	0.5876	0.3059
2013	0.5810	0.3006
2014	0.6107	0.2913
2015	0.6102	0.2708
2016	0.5917	0.3124
2017	0.5711	0.3166
Average	0.6001	0.2908

Note: Authors' estimations.



Note: Authors' estimations.

FIGURE 1 Cost and profit efficiencies for all insurers (Authors' estimations) [Colour figure can be viewed at wileyonlinelibrary.com]

because insurers are not only using their expertise in underwriting 'profitable' policies, but they are also making wise investments to meet obligations for both policyholders and stakeholders. Therefore, by following most of the studies, insurer's total investment is chosen as the second output proxy to represent financial intermediation service in here.

To find out the TFP growth and its components, the price of outputs also need to be involved. In line with Cummins and Xie (2008),[10] the price of output, associated to risk pooling/bearing activity and real financial activities, is defined as the insurer's underwriting income divided by net claim amount. In addition, the ratio of investment income to total investment can represent the price of output for financial intermediation services.

After considering the choice of outputs, the process of selecting appropriate input variables is much simpler and less controversial. By following the recent insurance efficiency studies, three input factors were selected as: labour cost, business cost and financial capital. It is necessary to simplify this selection by combining labour cost and business cost as administration expenses. Simplicity and data availability is the main reason of using this simplification, and this practice had used in many efficiency studies (e.g., Diacon et al., 2002; Fenn et al., 2008; Bahloul et al. 2013). This also helps to reduce the number of parameters (Ennsfellner, Lewis & Anderson, 2004). By focusing on Hasan and Marton (2003), Kasman and Turgutlu (2011), Kasman and Yildirim (2006), the proxy for the first input price, related to labour and business cost, is the ratio of administration expenses to total asset.

Financial capital can be regarded as the main input used to provide insurance services (see Diboky & Ubl, 2007; Jeng et al., 2007; Klumpes, 2007; Erhemjamts and Leverty, 2010). Cummins and Weiss (2000) pointed out the inclusion of financial capital is consistent with the modern theory of the firm, and the theory indicated that the contractual relationship (between capital supplier and the firms) was the part of firm's technology. Therefore, two types of capital are considered in recent efficiency studies: equity and debt capital. Equity capital is an input because it provides a source of funds that enable insurers to cover unexpected losses if the amount is larger than expected (Tone & Sahoo, 2005; Hardwick et al., 2011). However, equity was treated as the

TABLE 3 Cost efficiency from different sub-groups

Year	All	Non-life	Life	Lloyds	Stock	Mutual
1996	0.6193	0.5985	0.5753		0.5753	0.6855
1997	0.6204	0.5942	0.5782		0.5748	0.6875
1998	0.6243	0.6011	0.5718		0.5807	0.6851
1999	0.6295	0.5867	0.5677		0.5771	0.6962
2000	0.6120	0.5706	0.5786		0.5630	0.6728
2001	0.6022	0.5744	0.5429		0.5408	0.6793
2002	0.5986	0.5720	0.5594		0.5438	0.6700
2003	0.6018	0.5755	0.5563		0.5578	0.6533
2004	0.5955	0.5742	0.5205	0.8446	0.5442	0.6583
2005	0.5997	0.5721	0.5316	0.8417	0.5517	0.6495
2006	0.5937	0.5614	0.5258	0.8529	0.5364	0.6493
2007	0.5913	0.5640	0.5178	0.8532	0.5395	0.6526
2008	0.6119	0.5981	0.5294	0.8663	0.5641	0.6725
2009	0.6024	0.5896	0.5356	0.8464	0.5576	0.6740
2010	0.5990	0.5851	0.5264	0.8473	0.5567	0.6489
2011	0.5927	0.5743	0.5284	0.8468	0.5481	0.6566
2012	0.5876	0.5740	0.5321	0.8361	0.5431	0.6532
2013	0.5810	0.5690	0.5339	0.8131	0.5413	0.6423
2014	0.6107	0.5980	0.5138	0.8857	0.5636	0.6598
2015	0.6102	0.5919	0.5305	0.8613	0.5678	0.6627
2016	0.5917	0.5865	0.4663	0.8519	0.5402	0.6723
2017	0.5711	0.5435	0.4960	0.8326	0.5188	0.6596
Average	0.6001	0.5802	0.5356	0.8498	0.5526	0.6662

Note: Authors' estimations.

fixed input in some of previous studies (Berger, Cummins and Weiss, 1997; Fenn et al., 2008), as these authors assumed it had been built up over a long time and were difficult to adjust quickly. (Zanghieri, 2009) disagreed this point for two reasons: first, insurers were able to raise equity capital quite rapidly in EU capital market; and the price of equity partially explained the level of risk implied in investing in the firm, and the risk level was able to adjust over time. Therefore, equity capital would be treated as a variable input in this research. Debt capital, in insurance company, could be defined as the total borrowings from creditors (e.g. banks and policyholders), and it also represents the sources for the intermediation function of an insurance firm (Cummins & Weiss, 2011), which is a liability item. It can also be treated as a variable input.

Following Jeng and Lai (2005), Cummins and Weiss (2011), Yaisawarng et al. (2014), Alhassan and Biekpe (2016), the price of the equity capital is defined as the ratio of net income to equity capital. The price of debt capital is proxied as the ratio of investment income to total reserves. Due to data unavailability, it is hard to consider different proxies for capital prices separately. Therefore, the combination of two capital is preferred and the price of financial capital (the sum of equity and debt) is proxied as the ordinary profits[11] to the sum of equity capital and total reserve (Jeng & Lai, 2005).

In line with other studies on insurance firms (see Fenn et al., 2008), total net technical provisions (reserves)[12] is also considered as the third input. The input price is the ratio of total net technical provisions to total asset.

Table 1 shows the descriptive statistics of the discussed variables used to estimate the insurer's efficiency and productivity, and all variables are positive which is in compliance with the modelling restrictions of translog form. Overall the descriptive statistics are in line with prior studies (Alhassan & Biekpe 2016; Eling & Luhnen, 2010a; Hardwick et al., 2011). One of the issues in the underlying data generating process of our sample that we control for is the treatment of outlier. Rather than arbitraly excluding information content from our sample by omitting outliers, we opt to team them using winsorization. In this respect, the value of the outlier in the data set is set to the value of the nearest observation, which is not an outlier.[13]

TABLE 4 Profit efficiency from different sub-groups

Year	All	Non-life	Life	Lloyds	Stock	Mutual
1996	0.2469	0.4444	0.2135		0.2317	0.2829
1997	0.2654	0.4946	0.1813		0.2533	0.3026
1998	0.2611	0.5020	0.2056		0.2346	0.3171
1999	0.2147	0.4543	0.1653		0.1972	0.2722
2000	0.2172	0.4742	0.1604		0.2084	0.2378
2001	0.2198	0.4302	0.2350		0.2069	0.2746
2002	0.2308	0.4416	0.1724		0.2294	0.2249
2003	0.2419	0.4593	0.1757		0.2141	0.3062
2004	0.3054	0.4776	0.2233	0.5737	0.2671	0.3359
2005	0.3051	0.4981	0.2250	0.5747	0.2773	0.3367
2006	0.3165	0.4828	0.2690	0.5806	0.2775	0.3433
2007	0.3274	0.4985	0.2725	0.5993	0.2933	0.3372
2008	0.3027	0.4788	0.1776	0.5820	0.2892	0.2537
2009	0.3081	0.4798	0.2348	0.5905	0.2777	0.3274
2010	0.3066	0.4798	0.2207	0.5790	0.2771	0.3299
2011	0.2715	0.4473	0.2148	0.5414	0.2514	0.2887
2012	0.3059	0.4794	0.2268	0.6148	0.2710	0.3555
2013	0.3006	0.4609	0.2447	0.5833	0.2690	0.3297
2014	0.2913	0.4665	0.2083	0.5884	0.2641	0.2966
2015	0.2708	0.4281	0.2181	0.5425	0.2460	0.2460
2016	0.3124	0.4883	0.2262	0.6486	0.2830	0.3760
2017	0.3166	0.5363	0.2383	0.5683	0.2968	0.3444
Average	0.2908	0.4747	0.2148	0.5848	0.2638	0.3074

Note: Authors' estimations.

4 | RESULTS AND DISCUSSION

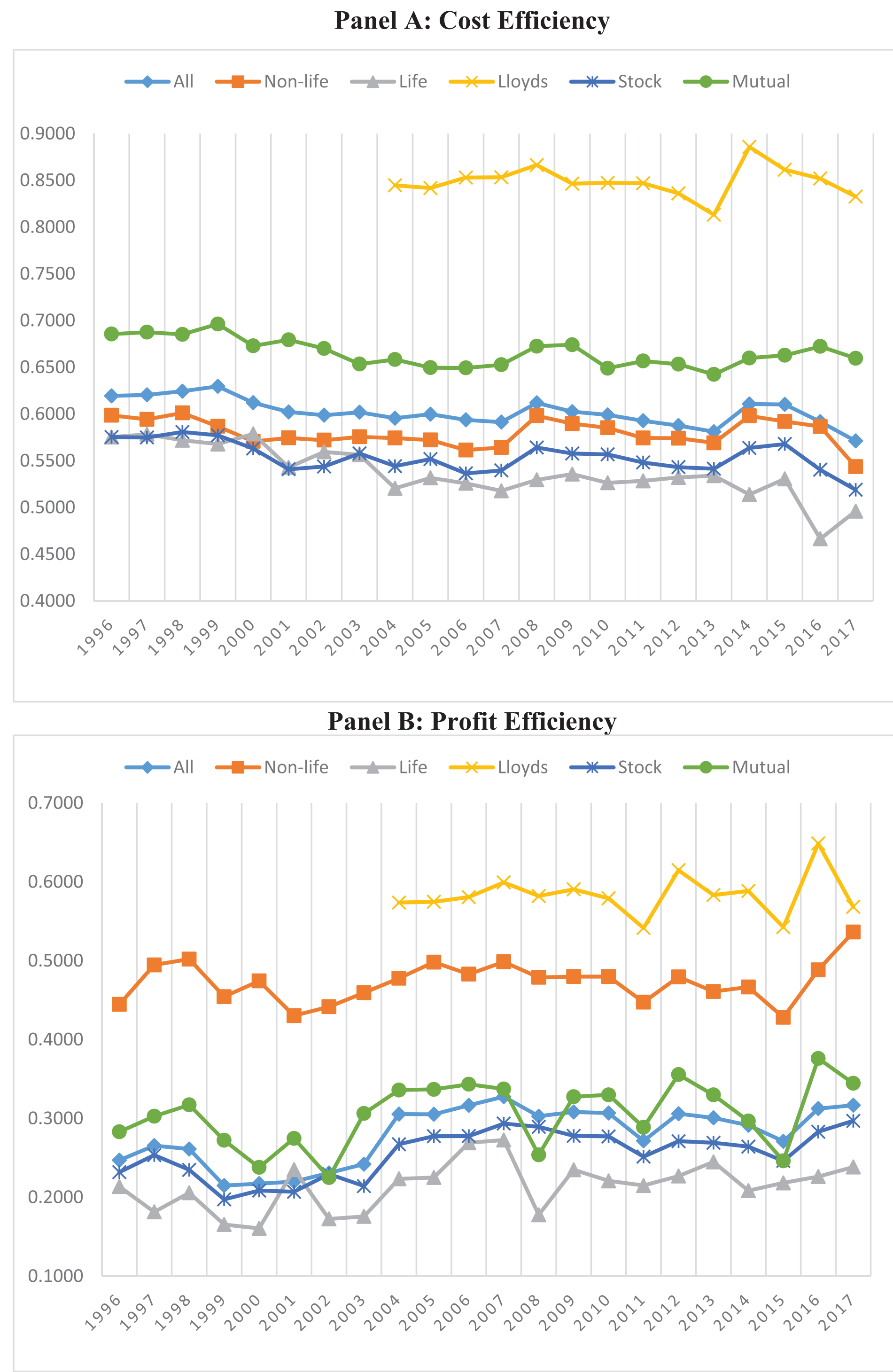
4.1 | SFA cost and profit efficiency

There is a plethora of different estimation approaches for the SFA efficiency scores. In Appendix A, we report various estimators of U.K. insurance efficiency scores and we select efficiency scores using the estimator of Kumbhakar et al. (2014) which is flexible while it controls for heterogeneity in the underlying data generating process with firm effects. In addition, this estimator has the advantage to also control for persistency in efficiency while treats efficiency as time varying, which is of importance for the current study that it tests also for convergence in efficiency.

Table 2 presents the annual means of the predicted score of cost and profit efficiencies. On average, the cost efficiency score is around 0.6, which is in line with Eling and Luhnen (2010a) result of 0.615, but it is lower than the average score of 0.90 observed by Fenn et al. (2008). Then, from the spending (or cost) perspective, it suggests that most of the U.K. insurers spend 40% more on the cost compared to the best-practice player in the market. On the other hand, the average score of profit efficiency is only about 0.30. Given the same level of input prices and outputs, most of the market players can only generate 30% of the profits attainable by the best-practice one. And, this score is much less than Hardwick et al.'s (2011) finding, which is 0.69 on average. These differences may be explained by the usage of different output and input vectors, estimation techniques and the study period.

This interesting finding of profit efficiency being around half of the cost efficiency for U.K. insurance is reported for the first time in the literature. The difference between the efficiency scores is not, though, unheard of in the financial industry. For example, in the banking industry Berger and Mester (1997) showed that cost efficiency is twice that of profit efficiency. The existence of differences between cost efficiency and profit efficiency is also confirmed by Alhassan and Biekpe (2016) and Mamatzakis and Bermpei (2014).

But, what might be the underlying cause of differences in cost vis a vis profit efficiency? Our estimation of



Note: Authors' estimations.

FIGURE 2 Cost (a) and profit efficiencies (b) for different sub-groups over time (Authors' estimations) [Colour figure can be viewed at wileyonlinelibrary.com]

higher cost efficiency score compared to profit efficiency reveal that there are higher inefficiencies on the income side of insurance industry as measured by the profit function. Figure 1 shows this higher insurer's cost efficiency compared to profit efficiency. This difference could indicate that the management of U.K. insurers is more sensitive towards cost management, that is reducing its cost, rather than generating premiums and thereby profits. Moreover, profit efficiency also exhibits more variability over time compared to cost efficiency.

Having derived the cost and profit efficiency scores, we estimate next the Spearman rank-order correlation coefficient that provides information about the strength and direction of association between the two efficiency scores. The Spearman rank order correlation coefficient show a negative correlation between cost and profit efficiency as

TABLE 5 Cost-scale efficiency for different sub-groups over-time

Year	(1) All	(2) Non-life	(3) Life	(4) Lloyds	(5) Stock	(6) Mutual
1996	0.9566	0.9734	0.8857		0.9406	0.9217
1997	0.9582	0.9744	0.8893		0.9434	0.9259
1998	0.9582	0.9750	0.9040		0.9452	0.9311
1999	0.9641	0.9823	0.9048		0.9521	0.9393
2000	0.9719	0.9838	0.8974		0.9606	0.9413
2001	0.9760	0.9802	0.8698		0.9648	0.9417
2002	0.9775	0.9863	0.8933		0.9679	0.9479
2003	0.9793	0.9874	0.8944		0.9707	0.9515
2004	0.9890	0.9989	0.8788	1.0972	0.9801	0.9594
2005	0.9875	0.9992	0.9017	1.0778	0.9805	0.9629
2006	0.9887	0.9979	0.8973	1.0635	0.9821	0.9626
2007	0.9938	1.0030	0.8948	1.0551	0.9885	0.9713
2008	0.9959	0.9978	0.9007	1.0370	0.9921	0.9703
2009	0.9975	1.0002	0.9107	1.0240	0.9954	0.9774
2010	1.0034	1.0044	0.9131	1.0128	1.0028	0.9849
2011	1.0037	1.0029	0.9194	0.9960	1.0041	0.9855
2012	1.0129	1.0118	0.9150	0.9868	1.0141	0.9940
2013	1.0150	1.0161	0.9167	0.9746	1.0169	0.9993
2014	1.0143	1.0176	0.9306	0.9627	1.0184	1.0083
2015	1.0163	1.0188	0.9343	0.9491	1.0216	1.0123
2016	1.0256	1.0282	0.9348	0.9404	1.0322	1.0234
2017	1.0270	1.0295	0.9489	0.9234	1.0353	1.0273
Average	0.9905	0.9979	0.9055	1.0628	0.9854	0.9686

Note: Authors' estimations.

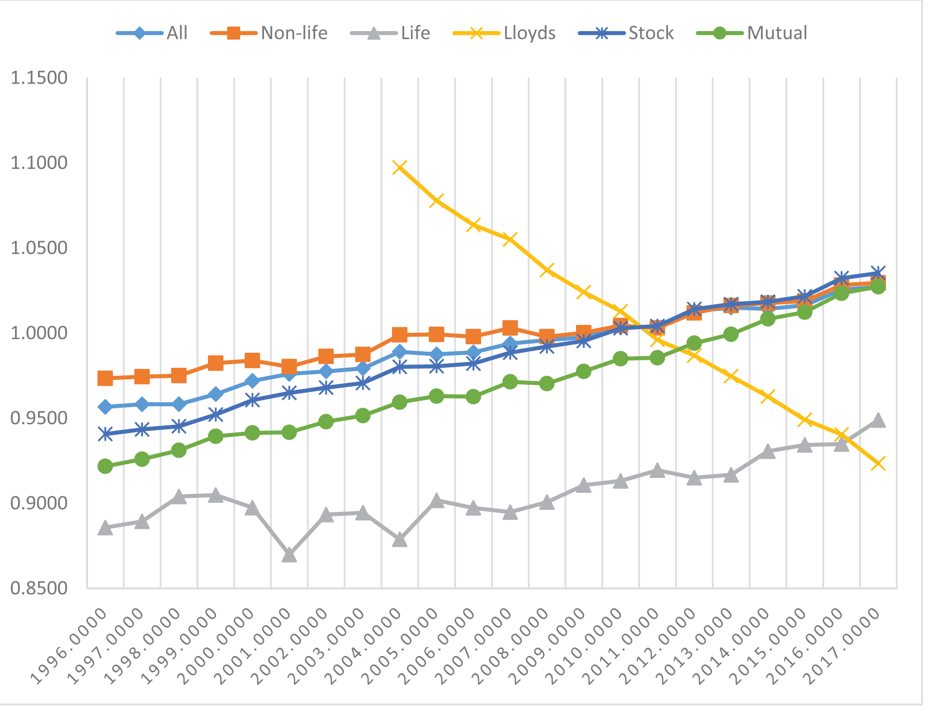
the rho is reported to be $r_s = -0.67$, while it is statistical significant at 7%. It is worth noting that the Spearman rank order correlation is a nonparametric test while the low significance implies that we should treat these results with some caution. Nevertheless, the negative correlation implies that U.K. insurance industry could benefit from a somewhat improvement in profit efficiency in periods when cost efficiency declines. This is evident in early 2000s. Similarly, in the aftermath of financial crisis in the period 2013–2015 cost efficiency improves while profit efficiency slightly declines. In addition, it might be the case that in periods, like the financial crisis period, when the U.K. insurance faces lower profits may compensate this apparent inefficiency by achieving lower costs, for example by enhancing its underlying cost efficiency or by driving for higher market power in premium setting. It could be also possible that the negative correlation could be due to insurance specialization, allowing higher premiums for insurers that provide specialized policies of high quality to compensate for higher costs for such policies.

4.2 | SFA cost and profit efficiency for sub-groups

Next, Table 3 presents cost efficiency scores over time for five sub-markets. Here, types of businesses and types of organizational forms are the two main sub-groups under concern. The former involves the non-life insurers, life insurers and the Lloyds, while the stock and mutual insurers are in the latter group. The life insurers are looking like the laggard, as they always have the lowest score for both cost efficiency over the period.

Table 4 presents profit efficiency scores over time for five sub-markets. Again, the life insurers are reporting the lowest score for profit efficiency over the period. In generating or maintaining a specified level of profit, life insurers face more uncertainties than non-life insurers. Between two organizational forms, mutual insurers are more likely to be the well-performed one. It suggests that the insurers may need to balance between generating profit and reducing costs from 2012 to 2017. To be

FIGURE 3 Cost-scale efficiency for different sub-groups over-time (Authors' estimations) [Colour figure can be viewed at wileyonlinelibrary.com]

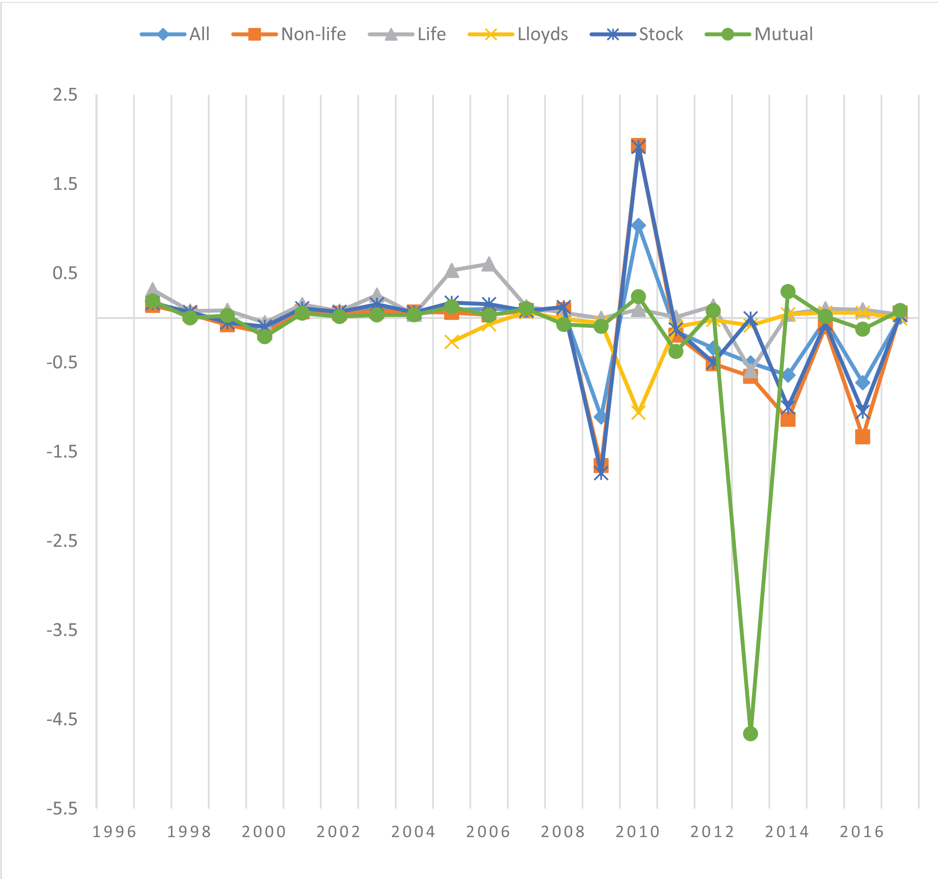


Note: Authors' estimations.

TABLE 6 Total factor productivity for different sub-groups

Year	(1) All	(2) Non-life	(3) Life	(4) Lloyds	(5) Stock	(6) Mutual
1996						
1997	0.1760	0.1378	0.3145		0.1637	0.1885
1998	0.0446	0.0400	0.0765		0.0652	−0.0012
1999	−0.0268	−0.0781	0.0837		−0.0539	0.0256
2000	−0.1383	−0.1682	−0.0537		−0.0979	−0.2123
2001	0.0858	0.0660	0.1489		0.1060	0.0503
2002	0.0471	0.0508	0.0749		0.0672	0.0138
2003	0.1091	0.0694	0.2546		0.1507	0.0316
2004	0.0424	0.0648	0.0393		0.0600	0.0324
2005	0.0885	0.0594	0.5317	−0.2694	0.1700	0.1227
2006	0.0996	0.0317	0.6036	−0.0721	0.1533	0.0276
2007	0.1001	0.0804	0.1248	0.0632	0.0795	0.1019
2008	0.0724	0.0915	0.0561	−0.0141	0.1204	−0.0753
2009	−1.1109	−1.6570	−0.0050	−0.0566	−1.7408	−0.0964
2010	1.0361	1.9299	0.0932	−1.0631	1.9151	0.2363
2011	−0.1533	−0.1943	0.0075	−0.1014	−0.1302	−0.3789
2012	−0.3405	−0.5145	0.1329	−0.0230	−0.5022	0.0801
2013	−0.5056	−0.6566	−0.5929	−0.0858	−0.0059	−4.6620
2014	−0.6439	−1.1392	0.0409	0.0376	−1.0042	0.2934
2015	−0.0249	−0.1003	0.1010	0.0575	−0.0633	0.0170
2016	−0.7279	−1.3337	0.0903	0.0562	−1.0537	−0.1283
2017	0.0061	0.0543	0.0363	−0.0078	0.0291	0.0818
Average	−0.1315	−0.2021	0.096	−0.1159	−0.1289	−0.1652

Note: Authors' estimations.



Note: Authors' estimations.

FIGURE 4 Total factor productivity for different sub-groups over time (Authors' estimations) [Colour figure can be viewed at wileyonlinelibrary.com]

specific, the U.K. insurers tend to pay more attention to cost management from 2012 to 2015, while thereafter their strategies focus on profit generation. Finally, it is worth to point out that there are no significant improvements in the U.K. market from both cost and profit perspectives over the study period.

In addition to the above tables, Figure 2 shows that the Lloyds insurers are in a leading position of reducing cost and generating profit. This should not be surprised, because Lloyds are specialized insurers who have expertise in particular area. In other words, they have better control of underwritings, while the special events which trigger the claim are hard to be influenced by the changing in external condition. It is also interesting to note that a concave curve is clearly found from 2012–2017 in profit efficiency graph, while there is a convex shape from 2013 to 2017 in the cost efficiency graph.

4.3 | Economies of scale estimations

Based on the results of the cost analysis, the parameters of the cost function can be used to measure cost-scale efficiency, as shown in Equation 4. Table 5 presents the average of insurers' scale efficiencies over time. It is measured for each insurer at its own output level. As mentioned, if the value is less than one, economies of scale are indicated. It means that the unit average cost decreases as the quality of output increases. Otherwise, if the unit cost is increased as the output quality increased, decreasing returns to scale (i.e. diseconomies of scale) exists. Column (1) in Table 5 shows that, on average, the U.K. insures could be scale efficient, as they operate close to constant returns to scale (i.e. scale $= 0.99 \approx 1$). When considering different sub-markets, Columns (2) and (3) confirms that the non-life insurers are more closed to scale efficient, if compared to the Life insurers. On the other hand, the Lloyds operates at diseconomies of scale, as the average score is beyond one.

The movements/changes of scale efficiency over time are shown in Figure 3. Except for the Lloyds sample, there is an upward trend in the cost scale-efficiency can be observed from all other sample groups. It potentially indicates that the insurers accept a higher unit cost as the output level increased. The period of 2009–2010 is an interesting one, because the changes occur here. For example, when considering all insurers together, the

TABLE 7 Decomposing total factor productivity growth for different sub-groups

Variable	Mean	*SD*	Min	Max
Panel A: All insurers				
Total factor productivity	−0.132	0.910	−1.151	6.071
Technical change	0.031	0.016	−0.017	0.093
Scale	0.003	0.165	−0.747	5.206
Markup	−0.183	0.817	−0.834	1.203
Efficiency change	−0.017	0.003	−0.022	−0.013
Panel B: Non-life insurers				
Total factor productivity	−0.202	1.071	−0.785	1.186
Technical change	0.042	0.019	−0.0131	0.103
Scale	0.002	0.423	−0.767	1.702
Markup	−0.180	2.117	−0.939	1.879
Efficiency change	−0.022	0.005	−0.0311	−0.015
Panel C: Life insurers				
Total factor productivity	0.096	1.217	−0.922	1.312
Technical change	0.049	0.041	−0.197	0.227
Scale	−0.005	0.689	−0.951	1.635
Markup	−0.191	1.822	−0.557	1.863
Efficiency change	−0.032	0.009	−0.046	−0.018
Panel D: Lloyds insurers				
Total factor productivity	−0.116	1.234	−1.428	8.240
Technical change	−0.022	0.064	−0.241	0.305
Scale	−0.008	0.621	−0.365	2.602
Markup	−0.166	0.827	−0.998	1.009
Efficiency change	0.032	0.014	0.013	0.062
Panel E: Stock insurers				
Total factor productivity	−0.129	0.955	−2.786	6.816
Technical change	0.038	0.020	−0.021	0.106
Scale	0.004	0.140	−0.454	5.054
Markup	−0.183	1.081	−0.182	1.827
Efficiency change	−0.024	0.005	−0.033	−0.016
Panel F: mutual insurers				
Total factor productivity	−0.165	1.452	−2.702	9.144
Technical change	0.043	0.024	−0.069	0.139
Scale	0.003	0.410	−0.802	1.948
Markup	−0.187	1.810	−0.951	2.868
Efficiency change	−0.020	0.004	−0.028	−0.014

insurers start to operate at diseconomies of scale from the year of 2010. Similar findings observed from sub-markets of non-life (Colum 2) and stock (Colum 5). In contrast, Lloyds start to operate at economies of scale since 2011 and keep running the business at even lower degree since then (i.e. a downward trend). Furthermore, the life insurer is the only sub-group that always enjoy the benefit of economies of scale, but with an upward trend. Compared between stock and mutual firm, the mutual insurers enter the stage of diseconomies of scale 4 years later than stock firms; and they have a slightly lower cost-scale efficiency than stock on average.

4.4 | TFP growth estimations

We report next productivity for different insurance groups, focusing on changes in productivity and decomposing it into different constituent parts. Table 6 presents TFP growth for the entire market and different sub-markets. The average over the period TFP growth is negative as well as in sub-groups, but for the life insurance. The negative growth of TFP implies additional inputs over time are required to produce constant quantity of outputs. This result raises some concerns for the industry as it reveals negative dynamism over time and thereby its potential growth is restricted by low levels of TFP growth. However, tracking the TFP growth over times shows that there are periods where the industry demonstrated positive TFP growth rates, see the period 2001–2008 (and early in the sample) for all U.K. insurance. The financial crisis period seems to impair the TFP growth of the industry, though towards the end of the sample in 2017 the industry appears to return to positive TFP growth rates.

As shown in Figure 4, there is variability in TFP growth since 2008, when the insurers enter a stage of decline due to the financial crisis. Prior to the financial crisis, the TFP is relatively stable over time. It is also worth to know that the Lloyds follow somewhat an interesting trajectory. For Lloyds results show positive TFP growth from 2014 to 2016, in contrast with the negative growth reported for the remaining insurance industry such as non-life group and stock group. This implies that Lloyds has been particularly resilient in the aftermath of the financial crisis. However, it is worth noting that the positive TFP growth performance in Lloyds from 2014 to 2016 has not proven sufficient to compensate for negative performances over the remaining years of the sample. Table 6, clearly, shows that in terms of TFP growth the life insurance has been a positive performer, though the TFP growth is small at 0.1% annual average over the examined period. Given that the life insurance is the dominant one in the industry, the average positive TFP growth is promising, though not substantial enough to compensate for the negative TFP growth in other insurance markets.

In Table 7, we report descriptive statistics of TFP growth and its underlying components. By studying various constituent parts, it helps us to understand how each component influences productivity. The results from

TABLE 8 Test for β-convergence and σ-convergence in cost and profit efficiency

Variables	(1) β-Convergence (Cost) Δy_{it}	(2) σ-Convergence (Cost) $\Delta E_{i,t}$	(3) β-Convergence (Profit) Δy_{it}	(4) σ-Convergence (Profit) $\Delta E_{i,t}$
$\delta\Delta y_{i,t-1}$	0.4546***		0.1432**	
	(3.179)		(2.261)	
$\beta \ln y_{i,t-1}$	−0.6174**		−0.2889**	
	(−2.369)		(−2.265)	
$\varphi\Delta E_{i,t-1}$		0.3534**		−0.4593***
		(2.218)		(−4.271)
$\sigma \ln E_{i,t-1}$		0.0314**		0.2858***
		(2.306)		(4.284)
Constant	−0.3421**	0.1172***	−0.3576**	0.5178***
	(−2.455)	(2.700)	(−2.044)	(4.780)
Observations	965	316	961	622
Number of firms	252	140	254	178
Number of instruments	66	45	119	82
Robust	Yes	Yes	Yes	Yes
F-test	5.187***	5.703***	2.804*	14.24***
AR(1)	−2.312**	−0.628	−2.948***	−2.471**
AR(2)	0.978	0.269	−1.042	0.161
Hansen (p-value)	63.14 (0.472)	48.95 (0.214)	135.4 (0.105)	82.29 (0.378)

Note: Authors' estimations. t-Statistics in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7 confirm that the life group (Panel C) is the only one with positive TFP growth, and further reveal that the main driver is technical changes that is related to technological innovations that are incorporated into the underlying production process of the insurance industry. The results from other panels demonstrate that the negative productivity growth has mainly driven by the decrease in the markup and decline in SFA efficiency, while there has been some improvement in terms of scale for all insurers, non-life insurers (except for the Lloyds). Note that the markup presents a measure of monopoly power in the insurance industry as it approximates the insurance premium over its marginal cost. Given that markup is negative for sub-groups including the life insurance, it implies that the insurance market is increasingly over time subject to competitive pressures.

4.5 | Testing for convergence in efficiency scores

Having derived cost and profit efficiency, we test next for β-convergence and σ-convergence, using the dynamic GMM estimation methods that also control for endogeneity. The results of the estimations are presented in Table 8. The first two columns show whether there is convergence in cost efficiency, while Columns 3 and 4 focus on profit efficiency. As discussed, the β-convergence is a necessary condition for σ-convergence. In some detail, Table 8 confirm the existence of β-convergence and σ-convergence in both cost and profit efficiency. By comparing Columns (1) and (3), the speed of convergence in cost efficiency is faster than the profit efficiency, as the absolute value of β-convergence parameter (see the parameter estimate of $\ln y_{i,t-1}$) is higher in magnitude and highly statistically significant in the case of cost efficiency compared to the case of profit efficiency. These findings indicate that when it comes to the insurance market the speed of convergence towards a higher efficient frontier is higher for cost efficiency vis a vis profit efficiency. In terms of σ-convergence, Columns (2) and (4) report that there is a higher σ-convergence for profit efficiency compared to cost efficiency. It is worth noting though that we observe that there is β- and σ-convergence both in terms of cost and profit efficiency,

From a policy point of view, the above reported evidence of convergence in efficiency scores shows that the insurance industry despite the observed variability in the underlying efficiency scores is moving towards the same direction of higher efficiency frontier, whether cost or profit. This might imply that the industry is competitive and drives forward innovative production processes.

5 | CONCLUSION

The purpose of this paper is to provide a comprehensive analysis of performance in the U.K. insurance market. First, a detailed literature review on two main performance measurements—efficiency and productivity—is provided in the first part of this chapter. It provides a basic understanding of the potential applications for using these indicators. Second, various mathematical approaches and the choices of model vectors are also discussed carefully in the methodology section. Finally, using a large unbalanced panel data from 1996 to 2017, cost and profit efficiency, scale-efficiency scores and productivity are calculated by the employing one of the latest developed SFA approaches, that is Kumbhakar et al.'s (2014) model.

The results suggest that there are chances for insurers to improve their performance: about 40% for cost efficiency and 70% for profit efficiency. On the other hand, the result also indicates that both cost and profit efficiency tend to remain at a relatively stable range over the study period, that is. no significant improvements in both cost and profit performance from the past 20 years. Besides, there is evidence to say that the U.K. insurers may tend to put more efforts on cost management, as the insurer's cost efficiency is higher than its profit efficiency. After splitting the entire market into five sub-groups, Lloyds insurers are in a leading position of reducing cost and generating profit, while the life insurers are the lagging position.

Regarding the insurer's cost-scale efficiency, except for life insurers, the year of 2010 is a vital one, as it acts as a 'break-even' point. To be specific, on average, the entire market (except the Lloyds and life insurers) starts to operate at diseconomies of scale, while Lloyds start to operate at economies of scale since 2010. And the life insurer always enjoys the benefit of economies of scale. Then, except for the life insurers, other insurers suffer productivity declines on average, that is more and more inputs are used to produce outputs. By decomposing it into various parts, the results find that the negative TFP growth has mainly driven by the enhanced competition that resulted to a drop in markup, while scale and cost efficiency has also driven TFP growth down. However, from a positive point of view, we report evidence of both β-convergence and σ-convergence in cost and profit efficiency.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Orbis, Fame and ISIS (or Insurance Focus) provided by Bureau van Dijk. Restrictions apply to the availability of these data, which were used under license for this study. The authors do not have the permission of Orbis, Fame and ISIS (or Insurance Focus) provided by Bureau van Dijk to share the data.

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ENDNOTES

[1] The concept is first developed and used by Barro and Sala-i-Martin (1990; 1991). This concept has been applied by many banking studies (see e.g. Weill, 2009; Casu and Girardone, 2010), and a few insurance studies, such as Alhassan and Biekpe (2015) and Mahlberg & Url (2010).

[2] The risk pooling and risk bearing implies that insurers collect premiums from the pool of policyholders and redistribute most of the funds to those policyholders who suffer losses. Zanghieri (2009) indicated that risk pooling and risk bearing function could be seen as the insurer provides a mechanism for policyholders, who exposed to insurable accidents/contingencies, to engage in risk reduction through pooling them together. Cummins and Weiss (2011) also stated that insurers create value added by supplying underwriting, actuarial and other operating expenses incurred in the risk pool, and by holding further equity capital to cushion unexpected loses. The financial intermediation argues that insurers invest the collected premiums in capital markets or traded securities that are not available to most of the individual policyholders, and return the capital plus interest payment at a pre-specified date or when the claims is due (Cummins & Weiss, 2011). And, last 'Real' financial services is relating to insured losses where according to Zanghieri (2009), insurers provide some services related to loss prevention, financial advice, pension and benefit schemes to policyholders. This service is closely related the first risk-pooling and risk bearing activities, which are also exploiting the insurer's expertise in risk management and finance.

[3] The composed error term (both error term and inefficiency term) in the production function is assumed to follow some kind of distributions within stochastic frontier approach (Aigner, Lovell and Schmidt, 1977; Meeusen and van Den Broeck, 1977; Stevenson, 1980).

[4] The distribution-free approach does not assume specific distribution assumptions on inefficiency term; therefore, it is assumed that the random noise averages out to zero and the efficiency of each firm is stable over time (Eling & Luhnen, 2010b).

[5] Thick frontier approach also did not make any distributional assumptions (Berger & Mester, 1997), yet, it could be built on the assumption that inefficiency appears difference between the lowest and highest quartile companies (Eling & Luhnen, 2010b).

[6] Vencappa et al. (2013) provides a short introduction on the difference between these two approaches.

[7] The main advantage of choosing parametric approach is that both estimating and decomposing TFP growth is allowed, which cannot be achieved by non-parametric approach (Kumbhakar & Lozano-Vivas, 2005).

[8] This method has certain advantages for using it in the case of insurance industry. First, the distance cost function can accommodate multi-output, which is consistent with setting regards to multi-output assumptions in efficiency estimation, which is quite common assumption in financial industry. Second, no restrictions on the implied return to scale. Third, the cost approach is more appropriate than production approach because insurers' output may be demand driven. Fourth restrictions on market competition is not necessary in cost function approach.

[9] Cummins and Weiss, (1993) also used the sum of input expenses to determine the observed total cost for insurers.

[10] Due to data availability, the exact measurements of output prices, from Cummins and Xie (2008), are not able to use in this study. However, the applied methods is selected based on the similar logic to Cummins and Xie (2008)'s suggestion. For example, the underwriting income is a reasonable variable to proxy the difference between premium earned and losses incurred for reporting period; meanwhile, expected return on invested asset is defined as return on total investment because of the lack of information on individual asset data.

[11] Ordinary profit is also called profit from operations, it could be calculated as the sum of underwriting profits, net investment income and other income minus other expenses related to investment; or the sum of total investment return (total investment multiplied by investment yield) and operating profit minus cost of investment.

[12] It includes unearned premium reserves, loss reserves, and mathematical reserves (Fenn et al., 2008).

[13] We apply winsorization of the bottom and the top 1.0% of the observations in our variables to the values corresponding to the 1st and the 99th percentile, respectively. This secures that we preserve information in our sample while we safeguard that we do not suffer from bias estimations in the efficiency scores due to extreme values in the sample.

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How to cite this article: Mamatzakis, E., Staikouras, C., Triantopoulos, C., & Wang, Z. C. (2023). Measuring the efficiency and productivity of U.K. insurance market. *International Journal of Finance & Economics*, 1–18. https://doi.org/10.1002/ijfe.2723

APPENDIX A: SFA ESTIMATIONS

SFA estimations of Model 1: Random-Effect Model (Kumbhakar, 1987); Model 2: Time-Varying Models (Kumbhakar, 1990); Model 3: Persistent Inefficiency model (Kumbhakar et al., 2014). To select the appropriate estimation, we follow Bauer et al. (1998) and apply differences-in-means tests to test the null hypothesis that the means of two or more efficiency scores are equal. Results reveal that the estimator of Kumbhakar et al. (2014) prevails over other estimators.

Year	KUM87	KUM90	KLH14
Cost efficiency			
1996	0.6206	0.6846	0.6193
1997	0.6240	0.6622	0.6204
1998	0.6127	0.6303	0.6243
1999	0.6231	0.6258	0.6295
2000	0.6047	0.5915	0.6120
2001	0.5623	0.5372	0.6022
2002	0.5669	0.5336	0.5986
2003	0.5695	0.5317	0.6018
2004	0.5716	0.5243	0.5955
2005	0.5667	0.5194	0.5997
2006	0.5544	0.5044	0.5937
2007	0.5435	0.4937	0.5913
2008	0.5828	0.5429	0.6119
2009	0.5640	0.5274	0.6024
2010	0.5522	0.5223	0.5990
2011	0.5602	0.5401	0.5927
2012	0.5541	0.5432	0.5876
2013	0.5482	0.5517	0.5810
2014	0.5632	0.5855	0.6107
2015	0.5623	0.6089	0.6102
2016	0.5484	0.6273	0.5917
2017	0.5353	0.6545	0.5711
Average	0.5669	0.5597	0.6001
Profit efficiency			
1996	0.4309		0.2469
1997	0.4210		0.2654
1998	0.4140		0.2611
1999	0.3739		0.2147
2000	0.3493		0.2172
2001	0.3638		0.2198
2002	0.3885		0.2308
2003	0.4020		0.2419
2004	0.4937		0.3054
2005	0.4705		0.3051
2006	0.4911		0.3165
2007	0.4980		0.3274
2008	0.4733		0.3027
2009	0.4726		0.3081
2010	0.4829		0.3066
2011	0.4563		0.2715
2012	0.4731		0.3059
2013	0.4769		0.3006
2014	0.4731		0.2913
2015	0.4817		0.2708
2016	0.4857		0.3124
2017	0.4768		0.3166
Average	0.4631		0.2908