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Cost Efficiency and Convergence in the European Nonlife Insurance Industry

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Abstract

The European authorities undertook a number of legislative initiatives in the last twenty five years in an effort to improve the integration of the financial sector in Europe. The Eurozone crisis that started at the end of 2009 brought a number of countries before bankruptcy and forced the European countries to implement various financial programs. This paper is an effort to see how the crisis affected the level of efficiency and the process of insurance integration in the European Union. It uses Stochastic Frontier Analysis to estimate cost efficiency for a sample of 947 nonlife insurance firms operating in 24 European countries for the period 2006-2014. In a second stage a two-step system Generalized Method of Moments (GMM) is used to examine cost efficiency convergence by looking at β-convergence and σ-convergence criteria. The results indicate that cost efficiency has declined over the period suggesting that the financial crisis negatively affected efficiency. The average cost efficiency over the whole period is found to be 86.7% with Denmark to be the most efficient nonlife European insurance market and Greece the worst. Evidence of beta convergence is found but not of sigma convergence.

JEL classification numbers: G10, G22, G22.
Keywords: Cost efficiency, Integration, β-convergence, σ-convergence, European Union, Nonlife insurance, Stochastic frontier analysis.

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1. Introduction

The process of financial integration across the European Union (EU) countries has attracted considerable attention from researchers and policy makers for more than twenty years now. Knowing the benefits of an integrated market, the policy makers through initiatives and reforms tried to improve the integration of the European financial sector.

When firms operate in a unified market, they are forced to produce in the most efficient way in order to cope with the higher competition. In a competitive environment only efficient firms can survive in the long run. More efficient insurance firms imply lower cost, better allocation of financial resources, and a more stable financial system. Insurance firms being able to operate on the same terms across the EU can achieve better regional diversification (Beckmann et al., 2003). It is only logical to expect that the unified financial environment will reduce the differences in cost efficiency of the European insurers operating in different countries.[3]

Our study is undertaken for the years 2006-2014 and therefore includes the period during which the Eurozone sovereign debt crisis occurred. This paper tries to answer two questions: How is the efficiency level among the nonlife insurance firms operating in the EU? How did the financial crisis affect cost efficiency and integration process? On a theoretical basis one could argue that at hard times firms should become more cost efficient in order to face easier the bad economic situation. Empirical studies on European financial integration covering the after deregulation period are rather inconclusive as they display mixed results (e.g., Casu and Girardone, 2010; Weill, 2009).

This paper, one of the first to include a very large sample of countries and firms, contributes to the existing literature in two important aspects. First, it is the only study that provides cost efficiency estimates for a sample of European nonlife insurers operating both in major and in new European countries that entered the EU after the so-called Fifth Enlargement Part II. Second, it considers the level of convergence of the European insurance industry by estimating β-convergence and σ-convergence. To our knowledge, no other study has examined the efficiency convergence of the European nonlife insurance industry.

The next section presents a brief review of the literature. Section 3 outlines our methodology, describes the data and reports the estimated model. Section 4 contains the empirical results. The final section includes a summary of our findings and some concluding observations.

[3] On the other hand, some authors (e.g., Casu and Girardone, 2010) argue that higher integration might come with a higher degree of consolidation and negative effects on competition.

2. Literature Review

During the last three decades, frontier efficiency methodologies have been extensively used in the literature in order to estimate insurers' efficiency. These methodologies are "benchmarking" methodologies that estimate efficiency according to a "best practice" frontier that is formed by the most efficient firms in the sample. The initial studies of the early 1990s examined the efficiency of insurance firms in a national level. Only after the early 2000s a few papers that estimate insurance efficiency in a multinational level are observed. Especially in Europe, the deregulation that took place by the enactment of the single European market and the Third Generation Directives, attracted the interest of the researchers and practitioners. Eling and Luhnen (2010a), as well as Wise (2017), display an analytical review of the existing literature that concentrates on the efficiency estimations of the insurance sector both nationally and worldwide.

Indicatively, some of the studies that estimate efficiency in a national European level are the following. Fecher et al. (1991) estimated cost efficiency for a sample of French life and nonlife insurers during the 1984-1989 period finding evidence of increasing returns to scale. Cummins and Turchetti (1996) measured technical efficiency for the life and nonlife insurers operating in Italy over the period 1985-1993. They found that efficiency remained relatively stable over this period while productivity decreased about 25%. Mahlberg and Url (2000) estimated technical efficiency for the German life and nonlife insurers over the period 1992-1996 and found that the average German insurer can reduce its total costs at about 20% while the variation in average efficiency scores remained relatively stable. Cummins et al. (2004) calculated technical, cost, and revenue efficiency using a sample of life and nonlife insurers operating in Spain over the period 1989-1997. They found that stock insurers are more efficient than mutual ones concerning the production of the stock output while small mutuals are more efficient in producing the mutual output, with their results confirming the "efficient structure" hypothesis. Barros et al. (2005) estimated the technical efficiency and productivity for the Portuguese life and nonlife insurers over the period 1995-2001 finding that efficiency level was improved over this period. Biener et al. (2016) studied technical, cost, and revenue efficiency for a sample of Swiss life and nonlife insurers over the period 1997-2013 and showed that the nonlife sector experienced efficiency and productivity improvements over the sample period while life insurers experienced a decline.

Despite the plethora of European efficiency studies in a national level, there are only a few papers measuring the efficiency and its determinants in the European insurance market at a cross-country level. Diacon et al. (2002) estimated technical efficiency using a sample of insurers located in 15 European countries over the period 1996-1999. Technical efficiency was reduced over their sample period while important efficiency differences among the countries were observed. Fenn et al. (2008) adopted different cost frontiers for a sample of European life, nonlife, and composite insurers operating in 14 European countries over the period 1995-2001. According to their results, composite insurers are the most cost efficient ones while life insurers are the least cost efficient. Klumpes (2008) examined the relationship among mergers and acquisitions, efficiency, and scale economies using a sample of European insurers located in seven countries over the period 1996-2002. Evidence for technical efficiency improvements is reported but scale efficiency deteriorated after the consolidations taking place.

Kasman and Turgutlu (2011) computed the cost efficiency of the European nonlife insurers based in 22 European countries during the 1995-2005 period and found an average cost inefficiency of 11.8%. Eling and Schaper (2017) estimated both technical and cost efficiency scores using a sample of European life insurers located in 14 European countries over the period 2002-2013. Their results indicate an efficiency increase in this period and that the economic conditions (e.g., inflation/interest rates) greatly affect the efficiency. Bahloul and Bouri (2016) estimated cost efficiency for a panel of European nonlife insurers based on seven European countries during the 2002-2008 period and found that the firms were approximately 69% cost efficient.

Empirical research concerning the impact of integration on the efficiency's convergence for the insurance industry is rather scarce. To our knowledge, only two papers examine integration and efficiency convergence for insurance firms. Mahlberg and Url (2010) are the first to use the long-run economic growth literature (β- and σ-convergence) in order to analyze efficiency's convergence for the German insures. They found σ-convergence for cost efficiency among German insurance companies and σ-convergence for revenue efficiency only for the year 2003. Cummins and Rubio-Misas (2016) examined the effect of integration on the convergence of cost and revenue efficiency of the European life insurers located in 10 countries over the period 1998-2007. They found low levels of revenue efficiency and evidence for beta and sigma convergence.

It is clear from the literature review that only one paper has examined the impact of integration on efficiency convergence but it covers only the pre-crisis period without including the global financial crisis of 2007 and the European debt crisis of 2010. Our paper contributes to this matter by covering the crisis period as no other study has done it.

3. Data and Methodology

3.1 Definition of inputs, outputs and input prices

Before proceeding with the description of the methodology used for the estimations, it is indispensable to determine the inputs used and the outputs produced by the insurers. Looking at the insurance literature (e.g., Eling and Luhnen, 2010a), it becomes obvious that researchers largely agree on the determination of the inputs utilized in the production process. Based on this literature, this paper adopts labor, debt capital, and equity capital to be the inputs used by the insurers. As in other international efficiency studies (e.g., Eling and Luhnen, 2010b), the labor input includes also the expenses for business services and materials due to data restrictions in the international databases. Furthermore, Ennsfellner et al. (2004)

advocated for this simplification since it reduces the number of the estimated parameter in the frontier and increases the degrees of freedom. Thus, the item "total operating expenses" in the database is used in order to proxy this combined input.

According to the existing literature, the operating expenses of life and nonlife insurers are mostly labor related with employee salaries and commissions being the largest expenses of them (e.g., Cummins and Weiss, 2012). In the literature some papers proxy the input price for labor by using annual wages data for each country's insurance sector (e.g., Fenn et al., 2008) while other papers take the ratio of net operating expenses to total assets (e.g., Kasman and Turgutlu, 2011). In this paper the second approach is preferred because it takes into account more accurately the possible differences in salaries across large and small insurance companies. Debt capital includes the funds borrowed from policyholders and is proxied by the "total liabilities" reported in the database used. Ten-year bonds' annual interest rates for the home country of each insurer are used as a proxy for the price of debt and are obtained from the European Central Bank data warehouse. Equity capital includes the capital belonging to shareholders after the obligations have fulfilled and is proxied by the "capital and surplus" item reported in the Orbis database. The 10-year rolling average annual return of the MSCI stock index for each country is used to proxy the price of equity input (e.g., Eling & Luhnen, 2010b). The data for these calculations are retrieved from Bloomberg database.

Despite the widespread agreement in insurance efficiency literature concerning the determination of the inputs utilized, there is an open debate concerning output selection. Some insurance efficiency studies (e.g., Yuengert, 1993) use the claims paid by the insurer in each year plus the additions to reserves for this year in order to determine the insurers' output and criticize the use of premiums as an output stating that premiums are affected by the pricing policies followed by the insurers and do not depict accurately their production efforts. On the other side of the literature, many authors (e.g., Greene and Segal, 2004) state that the use of the incurred claims/losses plus additions to reserves is not accurate since the reserves change when policies age and any variation in reserves from year to year is in practice a variation on the insurer's liabilities but not on its production abilities. Yao et al. (2007) state that even if incurred claims/benefits are used as an output, it is in practice an undesirable output and thus it is more accurate to consider it as an input. Thus, we use net premiums written as an output that proxies the risk pooling/risk bearing function of the insurers. Investments are used as a second output by nonlife insurance firms and proxy their intermediation process.

Table 1 below presents the descriptive statistics for all the variables used. All the monetary values for each year were deflated by the Harmonized European Consumer Price Index (CPI) using year 2014 as the base year while data for this index were obtained from the Eurostat database.

Table 1: Descriptive Statistics for the European Nonlife Insurance Sector

Variable	Mean	St. Deviation	Minimum	Maximum
Inputs				
Labor and Business Services Expenses (in thousands €)	263,517	975,870	10	17,268,090
Debt Capital (in thousands €)	7,775,926	46,196,389	12	1,060,431,000
Equity Capital (in thousands €)	708,226	2,967,754	99	60,747,000
Prices of the Inputs Utilized by the Insurers				
Labor Price (%)	14.66	0.37	0.00	56.78
Debt Capital Price (%)	3.79	0.02	1.22	22.53
Equity Capital Price (%)	9.90	0.07	0.34	55.70
Outputs				
Investments (in thousands €)	7,451,233	42,091,898	829	709,567,631
Premiums Written (in thousands €)	509,697	1,879,168	16	34,598,434
Environmental Variables				
Total Assets (in thousands €)	8,484,152	48,727,351	2,227	1,110,081,000
Market Share (%)	2.71	0.07	0.00	36.71
Equity to Total Assets (%)	27.11	0.19	0.00	99.69
Inflation (%)	2.09	0.01	-1.70	15.30
Gross Domestic Product Change (%)	1.48	0.04	-15.80	7.55

We collect data from the Orbis database that includes data for over 200 million companies worldwide with all information standardized for easy cross-border comparisons. Companies are included in the sample if they have positive values for all the inputs and outputs and are not required to have values for all the years of this study. Thus, we ended up with an unbalanced panel data sample containing 947 companies with 7,926 firm-year data operating in 24 European countries.

3.2 Methodology

3.2.1. Efficiency Estimations

Frontier efficiency methodologies for measuring inefficiency are divided into two main categories: the parametric and the nonparametric. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the main representatives for each category respectively. In the literature there is a controversy concerning the advantages and disadvantages of each approach, although some researchers advocate over the parametric one (e.g., Berger, 1993; Greene, 2008). The main advantage of the SFA approach is that it allows the existence of a composite error term and can distinguish between inefficiency effects and random noise effects while the nonparametric approach considers any variation from the frontier totally as inefficiency. However, the parametric approach requires the determination of a functional form that depicts the frontier and the selection of a wrong functional form raises estimation problems. In this paper we prefer SFA over DEA because we have a multi-national sample and the SFA allow us to take into account the environmental differences among the countries. These differences were taken into account in the banking efficiency literature (e.g., Fiordelisi and Molyneux, 2010), but not by the majority of the international insurance efficiency studies. Only Eling and Luhnen (2010b), Kasman and Turgutlu (2011), as well as Gaganis et al. (2013) used the Battese and Coelli (1995) method that estimates the inefficiency while at the same time takes into account the effects of the exogenous conditions on inefficiency.

For efficiency estimations we adopt the Battese and Coelli (1995) model as it has the advantage of estimating in one step both the inefficiency/efficiency scores and the impact of the environmental country-related variables on these scores. This model is a variation that belongs to the SFA methods and so the first step needed is to determine the functional form of the cost frontier. In the insurance efficiency literature, the translog functional form is the most commonly adopted functional form while the flexible Fourier comes second. According to Berger and Mester (1997), these functional forms give similar ranking with respect to average efficiency scores. The translog functional form is preferred in this paper as it has fewer parameters needed to be estimated and thus it increases the degrees of freedom. The cost function takes the following form:

$$\ln\left(\frac{TC_{it}}{p_{Kit}}\right) = \alpha_0 + \sum_{m=1}^{M}\alpha_{mi}\ln(q_{mit}) + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N}\alpha_{mn}\ln(q_{mit})\ln(q_{nit}) + \sum_{k=1}^{K-1}\beta_k\ln(p^*_{kit}) +$$
$$+\ \frac{1}{2}\sum_{\kappa=1}^{\mathrm{K}-1}\sum_{l=1}^{L-1}\beta_{kl}\ln(p^*_{kit})\ln(p^*_{lit}) + \sum_{k=1}^{K-1}\sum_{m=1}^{M}\phi_{km}\ln(p^*_{kit})\ln(q_{mit}) + \sum_{w=1}^{8}\rho_w T_w +$$
$$+ v_{it} + u_{it} \qquad (1)$$

where:
i=1,2,..., 947 are the insurers included in our sample, t=2006,2007,..,2014 are the years of our study, TC_{it} is the total operating cost for each insurer for each year including marketing, underwriting, and administrative costs. The q_{it} are for the outputs produced by each insurer in the sample for each year, p_{it} are for the input prices of the inputs utilized by the insurers and the T_w's are eight time dummy variables (w=1,2,..,8) for the year 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014 respectively and zero elsewhere (year 2006 is excluded as a reference category). In the summations above M=N=2 represent the number of outputs produced while K=L=3 represent the number of inputs used by the insurers. For ensuring linear homogeneity of degree one in input prices, we randomly chose one of the input prices (p_{Ki} , the price of equity capital) and divide the dependent variable as well as the other input prices variable in equation (1) by the selected input price variable. Thus, $p^*_{kit} = p_{kit} / p_{Kit}$. This is why all summations in (3) involving p^*_{kit} are over K-1 and not K. The v_{it} symbolizes the random noise in the equation (1) and is assumed to be independent and identically distributed as $N(0,\sigma_v)$, independent from the inefficiency term u_{it}. The u_{it} depicts the inefficiency of each insurer and is created by truncating at zero point the normal distribution $\mathrm{N}(\mu_{it},\sigma^2)$, where μ_{it} is the mean of the inefficiency term u_{it} and is affected by a set of firm-specific, industry-specific, and macroeconomic factors as:

$$\mu_{it} = \delta_0 + \delta_1 STOCK_{it} + \delta_2 LNL_{it} + \delta_3 SIZE_{it} + \delta_4 ETA_{it} + \delta_5 MKTSHR_{it} + \delta_6 INFL_{it} + + \delta_7 GDPCH_{it} \quad (2)$$

where:
STOCK is a dummy variable that equals one if the insurer adopts the stock organizational form and zero if it follows the mutual one. LNL is a dummy variable equal to one if the insurer provides both life and nonlife services and zero if it provides only nonlife services. SIZE depicts the size of each firm and is equal to the natural logarithm of its total assets; ETA is the ratio of equity capital to total assets and expresses the solvency level of each firm. MKTSHR is for the market share of each insurer in its home-country market for each year and is measured by dividing its net premium written by the total net premiums written in its home-country the respective year. INFL is the annual rate of inflation for each firm's home country and GDPCH is the real Gross Domestic Product (GDP) growth for each firm's home country. The parameters $\alpha_0, \alpha_{mi}, \alpha_{mn}, \beta_k, \beta_{kl}, \phi_{km,} \rho_w$ and the $\delta_0, \delta_{1,} ...., \delta_7$ of the system of equations (1) and (2) are estimated contemporaneously by the maximum likelihood method.

3.2.2. Convergence Estimations

Young et al. (2008) give the definition of beta and sigma convergence stating that "when the dispersion of real per capita income across a group of economies falls overtime, there is σ-convergence. When the partial correlation between growth in income over time and its initial level is negative, there is β-convergence" (pp. 1083). In this paper, we advance the work of Casu and Girardone (2010) in order to examine whether or not efficiency convergence has been achieved among the European insurance markets. Based on panel data techniques, our econometric model for examining the existence of beta convergence is given by equation (3):

$$\Delta y_{j,t} = \alpha + \beta \ln(y_{j,t-1}) + \omega \Delta y_{j,t-1} + \varepsilon_{j,t} \tag{3}$$

where:

j=1,2,..,24 depicts the number of the countries in the sample, t=2007,…,2014 are the years, $y_{j,t}$ and $y_{j,t-1}$ are the annual average cost efficiencies for each of the 24 insurance markets for the years t and t-1 respectively, and $\Delta y_{j,t} = \ln(y_{j,t}) - \ln(y_{j,t-1})$. α, β, and ω are coefficients to be estimated. The $\varepsilon_{j,t} = \zeta_j + \psi_{j,t}$ symbolizes the random error with ζ_j being independent and identically distributed as N(0, σ_ζ^2) and $\psi_{j,t}$ being independent and identically distributed as N(0, σ_ψ^2) , independent of each other and among themselves. According to the existing literature (e.g., Casu and Girardone, 2010), if the estimated coefficient β in (3) is negative and statistically significant then there is strong evidence for beta convergence.

The econometric model for estimating sigma convergence has the following mathematical form:

$$\Delta E_{j,t} = \gamma + \sigma E_{j,t-1} + \mu \Delta \mathrm{E}_{j,t-1} + \varepsilon_{j,t} \tag{4}$$

where:

$E_{j,t} = \ln(y_{j,t}) - \ln(\overline{y_t})$ and $E_{j,t-1} = \ln(y_{j,t-1}) - \ln(\overline{y_{t-1}})$. The $\overline{y_t}$ and $\overline{y_{t-1}}$ are the annual average cost efficiencies for all the 24 European insurance markets for the years t and t-1 respectively.

$\Delta E_{j,t} = E_{j,t} - E_{j,t-1}$ and γ, σ, and μ are coefficients to be estimated. The error term $\varepsilon_{j,t}$ has the same statistical properties as in equation (3). In order to claim that sigma convergence has been achieved, the σ coefficient in equation (4) must be negative and statistically significant.

Equations (3) and (4) are estimated by using the two-step system Generalized Method of Moments (GMM), a method that allows for dynamic behavior in our model (Arellano and Bond, 1991; Blundell and Bond, 1998, 2000). This approach is adopted against the conventional random and fixed effects panel data approaches since the GMM technique corrects potential endogeneity, heteroscedasticity, and autocorrelation in the model estimated, it utilizes the lag of the dependent variable and the exogenous regressors as instruments in order to account for simultaneity, and it captures possible correlations among the independent variables. As a robustness check, equations (3) and (4) are estimated by the pooled Overall Least Squares (OLS) method with and without the lagged dependent variables $\Delta y_{j,t-1}$ and $\Delta E_{j,t-1}$ respectively.

4. Empirical Results

4.1 Efficiency Results

Several conclusions emerge from Table 2 where the yearly average cost efficiency results are presented. First, the average cost efficiency for the 24 EU nonlife insurance markets has declined over the examined period from 88.3% in 2006 to 82.6% in 2014, something that might be attributable to the financial crisis that started to exert an impact on Europe in 2009. Second, for the period 2006-2008, just before the financial crisis, cost efficiency remains stable with a minor improvement. Third, cost efficiency in general starts declining after the year 2009 and is more dramatic for certain countries, like Greece where the efficiency dropped from 0.896 in 2009 to 0.654 in 2011, confirming the fact that the crisis in Greece was primarily the result of the debt crisis and not that of the banking sector. Fourth, the average cost efficiency score for the 24 European nonlife insurance markets over the period 2006-2014 is 86,7%, showing that on the average cost efficiency could be improved by 13.3%. Our average cost efficiency result is somewhat lower than the ones reported in Fenn et al. (2008) and in Kasman and Turgutlu (2011), with the first study finding cost efficiency 93% and the latter 88.2%. This difference in average cost efficiency might be attributed to the different time period of each study and the fact that our study covers a period during which financial and debt crises took place. Bahloul and Bouri (2016) found that the average cost efficiency of their sample was equal to 69.2% for the period 2002-2008.

Fifth, there are no large differences among the countries in the sample with the variation in cost efficiency between the most and the least efficient country being equal only to 0.114. As far as country ranking, Denmark (0.906), Ireland (0.903), and Luxembourg (0.899) are the three most cost efficient nonlife European insurance markets. These results are consistent with previous research since Fenn et al. (2008) also find that Denmark and Ireland have the most cost efficiency nonlife insurance markets in Europe. The lowest cost efficiency values are found for Greece (0.792), Czech Republic (0.794), and Slovakia (0.818).

Table 2: Cost Efficiency Scores by Year and Country, 2006-2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0.867	0.884	0.877	0.861	0.846	0.844	0.817	0.816	0.808	0.847
Belgium	0.895	0.893	0.894	0.891	0.883	0.885	0.881	0.869	0.890	0.887
Croatia	0.873	0.887	0.906	0.924	0.881	0.852	0.892	0.831	0.699	0.861
Czech Republic	0.877	0.856	0.872	0.856	0.838	0.829	0.739	0.666	0.613	0.794
Denmark	0.910	0.908	0.904	0.903	0.899	0.881	0.915	0.919	0.916	0.906
Finland	0.909	0.894	0.883	0.871	0.869	0.859	0.877	0.892	0.900	0.884
France	0.876	0.883	0.882	0.876	0.867	0.873	0.856	0.850	0.851	0.868
Germany	0.889	0.895	0.894	0.876	0.871	0.868	0.848	0.847	0.858	0.872
Greece	0.897	0.899	0.887	0.896	0.709	0.654	0.726	0.732	0.730	0.792
Hungary	0.903	0.901	0.914	0.926	0.889	0.889	0.878	0.851	0.752	0.878
Ireland	0.891	0.894	0.905	0.912	0.916	0.929	0.908	0.893	0.882	0.903
Italy	0.860	0.869	0.859	0.865	0.860	0.883	0.877	0.869	0.850	0.866
Latvia	0.880	0.897	0.910	0.930	0.920	0.870	0.839	0.777	n.a.	0.878
Luxembourg	0.905	0.827	0.928	0.894	0.913	0.915	0.904	0.893	0.913	0.899
Malta	0.873	0.891	0.902	0.900	0.902	0.891	0.891	0.889	0.887	0.892
Netherlands	0.901	0.904	0.902	0.896	0.893	0.891	0.878	0.878	0.882	0.892
Poland	0.880	0.891	0.880	0.880	0.862	0.864	0.813	0.794	0.769	0.848
Portugal	0.854	0.868	0.865	0.855	0.863	0.910	0.913	0.869	0.824	0.869
Romania	0.912	0.896	0.872	0.915	0.865	0.843	0.879	0.806	n.a.	0.874
Slovakia	0.823	0.842	0.854	0.826	0.826	0.846	0.826	0.795	0.726	0.818
Slovenia	0.878	0.894	0.878	0.883	0.858	0.871	0.879	0.879	0.831	0.872
Spain	0.871	0.877	0.879	0.875	0.873	0.883	0.883	0.856	0.851	0.872
Sweden	0.856	0.872	0.874	0.861	0.838	0.840	0.838	0.870	0.861	0.857
United Kingdom	0.920	0.917	0.903	0.883	0.890	0.871	0.871	0.871	0.881	0.890
EU-24	0.883	0.885	0.888	0.886	0.868	0.864	0.860	0.842	0.826	0.867

4.2 Convergence Results

Table 3 reports the estimated parameters of equation (3) applying to our sample of the European nonlife insurers for the period 2006-2014. The beta coefficient obtained by the two-step GMM method is negative (-0.4412) and statistically significant and we can conclude that beta convergence for cost efficiency among the 24 European nonlife insurance markets has taken place. This result is verified by estimating equation (3) with the OLS method with and without excluding the lagged dependent variable.

Table 3: Beta Convergence for Cost Efficiency for the European Nonlife Insurers

Coefficients	**Equation (3) without the Lag of the Dependent Variable**	**Equation (3)**	**Equation (3)**
	Pooled OLS Method	Pooled OLS Method	Two-Step GMM Method
β	-0.3176*** (0.0745)	-0.2402*** (0.0859)	-0.4412*** (0.1719)
ω	-	-0.1526* (0.0876)	-0.1382 (0.0981)
α	-0.1189*** (0.0271)	-0.1031*** (0.0334)	-0.1557*** (0.0689)
Goodness of fit			
R^2	0.2389	0.3081	-
Bhargava/Sargan Spec. Test	-	-	0.00034

Notes: Asymptotic standard errors are in parentheses. Bhargava/Sargan specification test examines the validity of the restrictions implicit in the dynamic model. Two-step estimates are Windmeijer (2005) corrected. ***, **, * imply statistic significance at 1%, 5%, and 10% respectively.

The results for σ-convergence concerning cost efficiency are reported in Table 4. A negative σ coefficient in equation (4) implies convergence of each country's average efficiency towards the EU-24 average. In other words, the σ coefficient indicates how quickly each country's average cost efficiency converges to the European average cost efficiency. The greater the absolute value of the σ coefficient in equation (4), the faster the convergence to the European average cost efficiency. In the case that the σ coefficient is positive and statistically important we have evidence of σ-divergence. The σ estimate is negative but is not statistically significant (-0.2734), so we cannot allege that sigma convergence has been achieved in the European nonlife insurance sector. This result contradicts that of Cummins and Rubio-Misas (2016) who find that sigma convergence has been achieved. Probably the GFC and the Eurozone sovereign debt crisis negatively affected the σ-convergence of the European nonlife insurance markets.

Table 4: Sigma Convergence for Cost Efficiency for the European Nonlife Insurers

Coefficients	**Equation (4) without the Lag of the Dependent Variable**	**Equation (4)**	**Equation (4)**
	Pooled OLS Method	Pooled OLS Method	Two-Step GMM Method
σ	-0. 1011 (0.2356)	-0.1517 (0.1979)	-0.2734 (0.5952)
μ	-	-0.2503 (0.1726)	-0.97871*** (0.11515)
γ	-0. 1412*** (0. 0982)	-0.1690*** (0.0346)	-0.1551*** (0.0136)
Goodness of fit			
R^2	0.1189	0.1274	-
Bhargava/Sargan Spec. Test	-	-	0.00331

Notes: Asymptotic standard errors are in parentheses. Bhargava/Sargan specification test examines the validity of the restrictions implicit in the dynamic model. Two-step estimates are Windmeijer (2005) corrected. ***, **, * imply statistic significance at 1%, 5%, and 10% respectively.

5. Conclusions

This paper is a response to the need for more empirical studies in finding out at which level the financial integration tried in EU has eliminated differences concerning cost efficiency in the European financial markets and especially in insurance markets. Cost efficiencies are estimated by means of SFA. Our results show that cost efficiency for the European nonlife insurers declined over the period 2006-2014. The financial crisis seems to have negatively affected efficiency. There are no large differences among the countries in the sample with the variation in cost efficiency between the most and the least efficient country being equal only to 11.4%.

Dynamic panel data methods are employed to test beta and sigma convergence in order to examine the speed of the nonlife insurance markets' integration after the removal of cross-country restrictions mentioned above. Evidence is provided only for β-convergence but not for σ-convergence concerning cost efficiency. The lack of σ-convergence is possibly attributed to the impact of the Eurozone debt crisis on nonlife insurers' performance. European authorities, while the crisis had already broken out, only in May 2010 established facilities to resolve the problem. Until that moment the response to crisis was heterogeneous among countries and so under these conditions it is possible to have performance differences. Thus, our findings suggest that both efficiency and integration have been negatively affected by the European debt crisis. Policymakers in the EU should be able to respond in a faster and more decisive ways in the future in order to protect the stability of the financial system.

This is the first study, to the best of our knowledge, that examines the effects of the financial integration in EU on the cost efficiency convergence for the EU nonlife insurance markets. The study can be further extended by conducting an analysis of revenue and profit efficiency or of productivity convergence over time. Last but not least, it would also be important to measure average efficiency scores by using different methods such as the non-parametric DEA methodology.

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