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UNDER PRESSURE: HOW THE BUSINESS ENVIRONMENT AFFECTS PRODUCTIVITY AND EFFICIENCY OF EUROPEAN LIFE INSURANCE COMPANIES

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Abstract: Deregulation and widespread economic changes have fundamentally affected the business environment of European life insurance companies over the last decades. We apply multi-stage data envelopment analysis to identify the impact of the changing environment on productivity and efficiency of European life insurance companies. Considering a sample of 960 life insurance companies from 14 European countries, we show that general economic, capital market, and insurance market conditions are important drivers of efficiency. Furthermore, we demonstrate that the impact of some firm-specific characteristics on efficiency is influenced by the business conditions. Our results reveal no technical change in the life insurance sector, but an efficiency increase in the 2002–2013 period that leads to an increase in the total factor productivity; these trends can be explained by more challenging business conditions in the 2000s.

1 Introduction

The 1994 deregulation of the financial services industry and widespread economic changes such as internationalization and low interest rates signify significant competitive pressure for European life insurers. More competitive markets bring pressure on productivity and efficiency, forcing those firms unable to adapt to state-of-the-art technology to be displaced.[1] Bad underwriting practices are further penalized because they can no longer be compensated by high capital market returns. Moreover, the increased divergence of business conditions across European countries since the financial crisis has put additional pressure on the sector.[2]

We analyze the impact of these major environmental challenges on productivity and efficiency of European life insurance companies with a new innovative measurement approach. The innovative element is that we incorporate uncontrollable variables in a multi-stage data envelopment analysis (DEA), an approach that enables us to identify which parts of productivity and efficiency changes are due to the environment and which aspects are due to managerial ability.

To the best of our knowledge, only one paper has so far considered the impact of uncontrollable variables on efficiency in an insurance context. Huang and Eling (2013) analyze the efficiency of non-life insurance companies in the BRIC (Brazil, Russia, India, China) countries and document that the environment strongly affects the efficiency of non-life insurers operating in these countries. We build upon and expand their analysis using an analysis of the life insurance sector and considering the European marketplace.[3] Moreover, we are the first to analyze the impact of economic maturity, unemployment, and stock market performance on life insurer efficiency.[4]

The main contribution of our empirical analysis is to show how the business environment affects life insurers' productivity and efficiency; to this end, we consider general economic, capital market, and insurance market conditions. As a by-product, we also analyze the interaction between the business environment and firm-specific characteristics – namely, how size, ownership, and solvency impact efficiency before and after controlling for the business environment. Finally, we also illustrate how the productivity and efficiency of the European life insurance sector develops over time. Given the

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1 Productivity is evaluated by comparing aggregated output levels to aggregated input levels. Efficiency is a relative measure of productivity, where the productivity of firms is analyzed relative to the firms with the highest productivity in an industry (see, e.g., Cummins and Weiss, 2013).

2 Although in the early 2000s most European economies were experiencing economic growth, conditions have diverged since 2008. Central European economies (e.g., Germany) have been relatively robust, while Southern European countries have shown especially negative growth rates (e.g., Spain; see OECD, 2014; European Commission, 2015). European markets have also experienced diverged interest rate developments with relatively low overall interest rate levels, but significant increases have occurred in some countries, such as Italy, Ireland, and Spain (see, e.g., Barrios et al., 2009).

3 The application of this methodology on European life insurance is especially meaningful given the widespread economic changes that have fundamentally affected their business environment over the last decades. We thus contribute to the growing number of innovative DEA applications, such as the inclusion of uncontrollable variables (Yang and Pollitt, 2009; Huang and Eling, 2013), two-stage bootstrapping procedures (Barros et al., 2010), relational two-stage DEA modeling (Kao and Hwang, 2008, 2014), and cross-frontier analysis (Biener and Eling, 2012).

4 One recent study by Cummins et al. (2015) also shows that integration and performance in the European life insurance sector are affected by financial market development, competition, as well as legal and governmental systems and, as such, underlines the relevance of this research.

increasingly difficult and more heterogeneous business environments, we expect productivity to decline and efficiency to increase over our sample period.[5]

We analyze 960 life insurance companies (6,657 firm years) from 14 European countries for the 2002–2013 period, which makes this paper one of the largest empirical analyses ever conducted on life insurance.[6] Our findings can be summarized as follows: We show that general economic, capital market, and insurance market conditions are important drivers of efficiency.[7] We also demonstrate that the impact of some firm-specific characteristics on efficiency is influenced by these business conditions – that is, inferences about the impact of ownership and solvency on efficiency depend on whether we control for the business environment.[8] Finally, we show that challenging business conditions might cause productivity losses and efficiency increases over the sample period.[9]

Our findings are useful for insurance managers, regulators, and policymakers to enhance the understanding of the driving forces behind productivity and efficiency of the European life insurance sector. The results are useful for defining productivity and efficiency effects due to changes in the business environment and due to managerial improvements. The findings are also relevant for other jurisdictions outside Europe and other fields, such as banking, which are also exposed to the same business challenges as European life insurers.

The remainder of the paper is organized as follows. In Section 2, we discuss the theoretical background and our hypotheses. Section 3 presents the methodology and data. Section 4 presents the empirical results and, finally, we conclude in Section 5.

2 Background and Hypotheses

Traditionally, efficiency studies implicitly assume that inefficiency is caused by bad management and occurs under identical environmental conditions (Yang and Pollitt, 2009). However, in a cross-country setting this assumption should be questioned as management only controls factors internal to production; the environment is not under its control. If the impact of uncontrollable variables is not

[5] Biener et al. (2015) find significant productivity losses in the Swiss life insurance market and argue that this reflects more challenging business conditions. This gives reason to expect a similar development of productivity for the entire European market.

[6] In the context of efficiency, to our knowledge, only the worldwide studies of Eling and Luhnen (2010) and Biener and Eling (2012) have considered a larger sample.

[7] More specifically, the results reveal that stock market performance and competition are positive drivers of efficiency whereas economic maturity, unemployment, inflation, interest rate level, and regulation are negatively associated with efficiency. Using these results, we can show that Switzerland (due to comparatively low interest rates, good stock market performance, and low inflation) has the least inefficiency due to the business environment and Ireland has the highest inefficiency due to the business environment. These results also reflect the economic development of these markets over the last years.

[8] This is an important finding in reference to other papers that consider ownership and solvency effects on efficiency, but do not control for the development of the operating environment (e.g., Eling and Luhnen, 2010; Biener and Eling, 2012). It emphasizes the importance of controlling for the business environment in cross-country studies.

[9] An insignificant technical change over our sample period is overcompensated for by a significant efficiency growth, leading to an overall productivity increase. However, we find evidence for a negative technical change, especially after the financial crisis. Our result mirrors country-specific findings for Spain (see Cummins and Rubio-Misas, 2006) and Switzerland (see Biener et al., 2015) where the business conditions prevented technical progress and technical losses, respectively.

considered, the efficiency of firms in an adverse external environment could be underestimated. We incorporate this aspect by using multi-stage data envelopment analysis (DEA). The consideration of uncontrollable variables in estimation is widespread in banking (see, e.g., Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Fries and Taci, 2005; Liu and Tone, 2008), while in insurance its application is limited to one paper from the non-life sector (Huang and Eling, 2013). Thus, our study is the first to apply this methodology in a life insurance context.

Theory offers limited guidelines regarding which determinants are important for explaining the business environment of the life insurance industry in different countries. For this reason, the derivation of hypotheses and selection of variables rely on previous empirical studies (see Lozano-Vivas et al., 2002, for a comparable discussion in the banking sector). We consider three central dimensions constituting the business environment of life insurers: general economic, capital market, and insurance market conditions (see Huang and Eling, 2013; Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002). Within these three dimensions, we analyze seven components in detail; four of these have already been analyzed in insurance literature, while three have not yet – to our knowledge – been analyzed. In the following we discuss the theoretical relationship between each environmental dimension and efficiency, present extant empirical evidence (if it exists), and consequently formulate our hypotheses (see Table 1 for an overview). In most cases our hypotheses follow the same line of reasoning: Adverse business conditions force managers to conduct more productivity-enhancing activities (e.g., cost-savings programs). Moreover, adverse conditions and productivity improvements force inefficient firms to leave the market, resulting in a smaller variation of productivity and on average higher efficiency levels.

Table 1 Hypotheses and Extant Literature

Hypothesis	Specification	Extant Insurance Literature
H1: *General economic conditions*		
H1a: *Economic maturity*	Positive relationship between GDP per capita and efficiency.	Not yet analyzed in existing literature
H1b: *Unemployment*	Positive relationship between unemployment rate and efficiency.	Not yet analyzed in existing literature
H1c: *Inflation*	Negative relationship between inflation and efficiency.	Huang and Eling (2013)
H2: *Capital market conditions*		
H2a: *Interest rate level*	Negative relationship between interest rate level and efficiency.	Huang and Eling (2013)
H2b: *Stock market performance*	Positive relationship between stock market performance and efficiency.	Not yet analyzed in existing literature
H3: *Insurance market conditions*		
H3a: *Competition*	Positive relationship between competition and efficiency.	Fenn et al. (2008); Bikker and van Leuvensteijn (2008); Choi and Weiss (2005); Berry-Stoelzle et al. (2011)
H3b: *Regulation*	Positive relationship between solvency (i.e., capital adequacy) and efficiency.	Rees and Kessner (1999); Eling and Luhnen (2010); Huang and Eling (2013)

H1a: Economic maturity

Various authors (Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Kasman and Yildirim, 2006) have emphasized the importance of macro-economic factors as environmental constituents for banking efficiency. Countries with high income per capita are assumed to have a more mature banking sector, resulting in competitive profit margins (see, e.g., Dietsch and Lozano-Vivas, 2000). Although companies in growing markets and under expansive demand conditions feel less pressured to control their costs, there is greater pressure to engage in productivity-enhancing activities if the market is mature and demand conditions are strict (see, e.g., Maudos et al., 2002).[10] Strict demand conditions might also force inefficient firms to leave the market. Thus, we expect a positive link between GDP per capita and efficiency.

[10] Macro-economic conditions influence a variety of factors related to the demand and supply side (see, e.g., Semih Yildirim and Philippatos, 2007). A variety of studies (see, e.g., Fortune, 1973; Headen and Lee, 1974; Enz, 2000; Zietz, 2003) have examined the relationship between macro-economic factors and life insurance demand. Note that the link between macro-economic development and demand should be positive, but it might be linear or non-linear (see, e.g., the s-curve in Enz, 2000). Jahromi and Goudarzi (2014) show that in the long run there is a causal relationship between GDP per capita and insurance penetration ratio (one measure for insurance market maturity).

H1b: Unemployment

Unemployment is an adverse driver of life insurance demand, especially in the context of lapse: the higher the unemployment rate, the higher the lapse rate (see, e.g., Eling and Kochanski, 2013). Two potential consequences are the incurred loss due to high upfront investments (Pinquet et al., 2011) and the additional loss of future profits (Eling and Kiesenbauer, 2014). In addition, economies of scale could be used as an argument here. If the number of contracts decreases due to lapse, then fixed costs have to be allocated across a smaller number of contracts, which *ceteris paribus* increases the cost ratio. In a scenario with high lapse, more liquidity is needed, which reduces the investment return potential. Lapsing thus challenges both liquidity and profitability (see, e.g., Kuo et al., 2003); therefore, it is especially important for life insurers to control costs and productivity in an environment with relatively high lapse rates. Poorly managed firms with high lapse rates will be the first to disappear in a high lapse scenario. High lapse should thus force increases in productivity and efficiency. Therefore, we expect a positive relationship between unemployment and efficiency.

H1c: Inflation

In the non-life insurance industry, inflation increases the costs of claims (see, e.g., Qaiser, 2006). In the life insurance industry, this is not expected as most products have fixed future payouts. However, given that life insurance benefits are not adjusted for inflation, higher inflation might have an eroding effect on demand (see Neumann, 1969). Clark (1982) discusses inflation-induced efficiency losses, highlighting how the inflation process affects relative prices and their perception by consumers. The higher the level of inflation, the higher the perceived inflation risk is as well. Hence, higher levels of inflation should be challenging for life insurers, consequently putting pressure on their operations. Initial empirical evidence for the insurance industry confirms this relationship (see Huang and Eling, 2013). Therefore, we expect a negative relationship between inflation and efficiency.

H2a: Interest rate level

Interest income constitutes one of the main profit sources of life insurance companies, given that the majority of their funds are invested in interest-bearing instruments. For decades a common strategy of life insurers was to buy safe bonds with long-term maturity and relatively high interest rates.[11] A high interest rate environment offers a relatively high degree of freedom as bad underwriting and higher costs can be compensated for with interest income. However, in a low interest rate environment, insurance companies have to be very strict in their underwriting and cost management as bad underwriting and inefficient cost structures can no longer be compensated for with high capital market

[11] This previously common strategy is becoming problematic given the low interest rate environment because long-term investments that come to term have to be replaced by bonds carrying much lower interest rates. Against this background, the minimum interest rate guarantee and further product options, which are especially prevalent in life insurance contracts, are difficult to maintain. Carson et al. (2008) and Swiss Re (2012) document the interest rate sensitivity of life insurers.

returns. Lower interest rates put special pressure on life insurance products with guaranteed interest payments (see, e.g., Swiss Re, 2010). Moreover, lower interest rates, *ceteris paribus*, increase liabilities (present value of future payments) (Ahlgrim and D'Arcy, 2012), which puts pressure on the balance sheet. For non-life insurance, Huang and Eling (2013) identified a negative connection between the interest rate level and efficiency. Given the theoretical arguments and the empirical results, we expect a negative link between the interest rate level and efficiency.

H2b: Stock market performance

Because stock returns are also one profit component of life insurers, the economic rationale for the derivation of H2b could be the same as for the interest rate level (i.e., the higher the return, the lower the need for cost savings). However, stock investments make up only a small portion of life insurers' portfolios; therefore, stock returns are less relevant (i.e., compared to interest income). Other aspects related to stock market performance, besides the income component, might be more relevant. Lorson and Wagner (2012) find that, under good stock market conditions, the decision of which life insurer to choose is influenced by the total return offered to policyholders (i.e., shares of the capital income, underwriting, and cost result). Life insurers that offer higher total returns can therefore attract more policyholders. Improving cost structures and underwriting results to increase total returns when stock markets are doing well should also be mirrored in increased productivity. Therefore, we expect a positive link between stock market performance and efficiency.

H3a: Competition

Leibenstein (1966) and Demsetz (1973) provide theoretical foundations for the relationship between competition and efficiency. Leibenstein (1966) argues that X-inefficiencies (i.e., firms do not exploit their full efficiency potential) might exist due to less motivational force. Sparse competitive pressure can evoke such a lack of motivation; in other words, more competitive pressure could enhance efficiency. However, a reverse relationship between competition and efficiency can be inferred from Demsetz (1973), who defines the efficient-structure hypothesis. This hypothesis argues that firms' efficiency determines the structure of the market on which they operate. Because more cost-efficient firms can charge lower prices, they can gain more market shares. This hypothesis, in contrast to Leibenstein's theory, implies a negative relationship between competition and efficiency (see, e.g., Fenn et al., 2008).

Divergent empirical evidence supporting both theories can be found for the insurance industry. Bikker and van Leuvensteijn (2008) examine the Dutch life insurance sector and document high levels of X-inefficiencies, determining that this is a consequence of insufficient competition. Furthermore, Fenn et al. (2008) find evidence for increases in X-inefficiencies in the European life insurance sector. In line with documented increases in seller concentration levels of Western and Central European markets (e.g.,

Eling and Kochanski (2013) discuss the importance of interest rates for the profitability of life insurers.

France, Germany, the Netherlands, the United Kingdom) a decline in competitive pressure can be associated with this trend. On the contrary, Choi and Weiss (2005) find evidence in favor of the efficient-structure hypothesis for the U.S. property/liability insurance market. Berry-Stoelzle et al. (2011) further support the efficient-structure hypothesis in the European property-liability insurance market. Based on the competing theoretical foundations and these divergent results, the relationship between competition and insurer efficiency is ambiguous. However, following the empirical results for the European life insurance sector, we expect a positive relationship between competition and efficiency.

H3b: Regulation (capital adequacy)

Regulation in the insurance sector is mainly concerned with avoiding insolvencies; as done in other studies, we consider the industry average of equity to assets as an indicator of capital adequacy (see, e.g., Huang and Eling, 2013, for insurance; Dietsch and Lozano-Vivas, 2000, for banking). Increased security levels associated with higher equity-to-asset ratios come at the expense of costly equity capital.[12] Because equity capital is one of the inputs in efficiency measurement, an increase in equity, reflected in an increase of solvency ratios, *ceteris paribus*, leads to a reduction in productivity; however, if the increase in equity applies to the entire industry, the impact on efficiency is not trivial.[13]

Bankruptcy is a competitive mechanism that forces inefficient firms to leave the market (Rees and Kessner, 1999). Hence, in the absence of solvency regulation, the risk of bankruptcy should incentivize firms to operate efficiently. However, without solvency regulation there is a potential for market failure, because insurers might adopt riskier behaviors than is optimal from policyholders' perspective (Rees and Kessner, 1999). Because riskier activities increase insolvency risk and require more costly risk management activities, efficiency losses might be the consequence. Another argument that could be made is that, in the long run, increased security levels might result in an increased premium volume, because policyholders should value low levels of insolvency risk (see, e.g., Epermanis and Harrington, 2006).[14]

These arguments imply a positive relationship between capital adequacy and efficiency; this direction of relationship is also generally found in the banking literature (see, e.g., Barth et al., 2013; Chortareas et al., 2012; Pasiouras, 2008). The existing empirical evidence for insurance reveals two different pictures. Eling and Luhnen (2010) confirm a positive relationship between capital adequacy and technical efficiency (negative for cost efficiency) for the global life and non-life insurance market;

12 The interaction with other risk management instruments needs to be mentioned here. Higher required capital can also be accounted for by changes in reinsurance, asset allocation, or underwriting strategy. In our analysis we control for such differences as these different strategies impact both inputs and outputs. For example, with more reinsurance, incurred losses are lower, and less equity capital is needed.

13 If, for example, a proportional loading is added on the existing equity capital (e.g., every insurer has to hold 10% more equity), then efficiency remains unchanged. If a fixed loading is added (e.g., every insurer has to hold 1 million more equity), then efficiency could either increase or decrease.

14 Wakker et al. (1997) illustrate that an increase in insolvency risk drastically reduces the willingness to pay for insurance

Huang and Eling (2013) find capital adequacy to be an adverse driver of efficiency for non-life insurance.[15] We follow the theoretical predictions and the empirical evidence for life insurance and expect a positive relationship between regulation (i.e., capital adequacy) and efficiency.

3 Methodology and Data

3.1 Methodology

We adapt the multi-stage DEA approach introduced by Fried et al. (1999)[16] and control for environmental conditions on a per-country as well as per-anno basis in order to obtain cross-country efficiency scores that fully reflect managerial efficiency. This approach also allows us to identify those countries with the relatively least favorable and most favorable business environments during the sample period (i.e., 2002 to 2013). In addition, the procedure allows inferences whether the business environment in the European life insurance sector overall had a beneficial (i.e., efficiency enhancing) or adverse impact.

DEA measures firm productivity against the productivity of best-practice firms, which determine the so-called efficient frontier (Farrell, 1957). We estimate input-oriented frontiers with constant returns to scale (CRS) to measure technical efficiency (TE) and variables returns to scale (VRS) to measure pure technical efficiency (PTE); in addition, we measure scale efficiency (SE), allocative efficiency (AE), and cost efficiency (CE).[17] The estimation of the efficiency of *N* decision-making units (DMUs, i.e., firms) using *M* inputs to produce *K* outputs is illustrated by the following linear programming problem (Charnes et al., 1978):

$$TE_j = \min \theta_j \text{, s.t. } \lambda_j X \le \theta_j x_j \text{, } \lambda_j Y \ge y_j \text{, } \lambda_j \ge 0 \ (j = 1, 2, 3......N) \text{,}$$

where TE represents Farrell's measure of technical efficiency for DMU j ($j = 1, 2, ...N$), X is a $M \times N$ matrix of all inputs used by *N* DMUs, Y is a $K \times N$ matrix of all outputs produced by *N* DMUs, x_j is a $M \times 1$ input vector for DMU j, y_j is a $K \times 1$ output vector and λ_j is an $N \times 1$ intensity vector of DMU j. We estimate cross-country frontiers – namely, efficiency is measured relative to a European benchmark.[18]

There are two sources of inefficiency in the standard DEA approach: differences in the business

and, thus, premium volume. Alternatively, a decrease in insolvency risk might lead to an increase in premium volume.

15 Cummins and Nini (2002), who analyze the capitalization of the U.S. property/liability insurance industry from 1993 to 1998, find that most insurers significantly overutilize equity capital. An overutilization of equity capital leads to significant costs of capital, resulting in efficiency losses.

16 The benefit of the multi-stage approach is that various uncontrollable variables can be incorporated without a priori assumptions or understandings of their relationship to the efficiency scores (see, e.g., Yang and Pollitt, 2009).

17 We rely on the Simar and Wilson (2000) bootstrapping approach to estimate bias-corrected efficiency scores and, therefore, account for sample variations. Due to data limitations, we cannot estimate revenue and profit efficiency, especially because it is not possible to estimate firm-specific prices. For example, estimating the price of the second output would require information about the asset structure of each life insurer, which is not available in our data.

18 We thus assume that European insurance companies use the same set of technologies to produce their outputs. An approach for testing this assumption is cross-frontier analysis; see Biener and Eling (2012).

environments and differences in firm management. To control for differences in the business environments and comparing only pure managerial efficiency, we conduct the following four stages. The first stage is the previously described standard DEA with commonly used inputs and outputs (we call this Model 1). In the second stage, total input slacks regressed[19] against a set of uncontrollable variables representing the business environment.[20] In the third stage, the initial input values from the first stage are adjusted with respect to the impact of the environmental variables on efficiency resulting from the second stage (i.e., companies that operate in an favorable environment are penalized with higher input values, which *ceteris paribus* reduces efficiency). Finally, in the fourth stage, we rerun the DEA model based on the adjusted input values from the third stage (we call this Model 2).

We also analyze the impact of the environmental conditions on technical and cost efficiency by regressing uncontrollable variables on efficiency scores. This procedure allows for the testing of the impact (significant or insignificant) and direction (positive or negative) of the business environment on European life insurer efficiency. We choose a truncated regression procedure, rather than a Tobit analysis, as both Simar and Wilson (2007)[21] and McDonald (2009) demonstrate that Tobit regressions provide undesirable results in Monte Carlo experiments.

The development of efficiency and productivity over time is analyzed by estimating input-oriented Malmquist indices of total factor productivity (TFP) (see, e.g., Cummins and Weiss, 2013). We follow Simar and Wilson (1999) and use bootstrapping for this purpose in order to obtain robust results. TFP changes are further decomposed into its two central sources: technical and technical efficiency change. Furthermore, technical efficiency change is divided into two components: pure technical efficiency and scale efficiency change.

3.2 Data

We consider all life insurers included in the AM Best Insurance Reports database and operating in Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom during the sample period (i.e., 2002–2013). Extreme data, such as zero or negative total asset values, were eliminated from the sample. For comparative purposes, all numbers were deflated to 2002 and converted into U.S. dollars; consumer price indices and exchange rates were obtained from AXCO Insurance Information Services. The sample consists of 960 life insurers (6,657 firm years). Panel A of Table 2 presents an overview of the

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19 Following Fried et al. (2002), we use a stochastic frontier analysis (SFA) slack regression. Alternatively, a truncated slack regression approach could be used in the second stage, although Huang and Eling (2013) emphasize that an SFA slack regression approach is preferred. To show that the SFA slack regression results (Table A1 in the Appendix) are robust, we also present truncated slack regression results in Table A2 in the Appendix.

20 Through this procedure, so-called allowable input slacks due to the business environment can be obtained. The allowable input slacks mean that a certain amount of input waste is acceptable because it is caused by an adverse external environment, not by managerial inefficiency. The remaining input slacks represent management's excessive use of inputs.

21 OLS is applied as a robustness check; the OLS results support the conclusions drawn from the truncated regression model, with only two exceptions. The OLS results are available upon request.

inputs, input prices, outputs, environmental variables, and firm characteristics used in this analysis. Panel B of Table 2 shows summary statistics.

Inputs and input prices

We follow the literature and use the number of employees (x_1), debt capital (x_2), and equity capital (x_3) as inputs (see, e.g., Huang and Eling, 2013). As the number of employees is not available in the data, we divide total operating expenses from the AM Best database by country-specific prices of labor (as done in many other studies; see, e.g., Cummins et al., 2004; Fenn et al., 2008). The price of labor (p_1) was obtained from the International Labor Organization (ILO; see http://laborsta.ilo.org/), which collects data on the average annual wages for either financial and insurance activities or financial intermediation activities. The few missing values in the ILO data were estimated by linear interpolation. Long-term interest rates obtained from the OECD are used as a proxy for the price of debt (p_2). For the price of equity (p_3), we consider 15-year rolling returns on MSCI country-specific stock market indices.[22]

Outputs

For the selection of outputs, we follow Cummins and Weiss (2013) and use the value added-approach. The three services that insurers provide are risk-pooling/bearing services, intermediation, and financial services. We use losses plus additions to reserves as the first output variable (y_1) and total invested assets as the second output variable (y_2).[23]

Uncontrollable (environmental) variables

The selection process for the environmental variables is oriented according to the banking literature (e.g., Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2002; Fries and Taci, 2005; Liu and Tone, 2008) and the non-life insurance study of Huang and Eling (2013). Whenever appropriate, we make reasonable adaptions to the life insurance context. All variables are measured on a per-annum and per-country basis—that is, all life insurers operating in the same country show the same corresponding uncontrollable variable value in each year.

For the general economic conditions, we follow Dietsch and Lozano-Vivas (2000) and proxy the economic maturity by GDP per capita (GDP). We use yearly mean unemployment rates as a measure of unemployment (UNE). Similar to Huang and Eling (2013), we include inflation (INFL) and measure it by consumer price indices (basis: 2002 = 100). Regarding the capital market conditions, we use OECD long-term interest rates as an indicator of the interest rate level (IR) and 15-year rolling returns of country-specific MSCI indices to measure stock market performance (MSCI). Regarding the insurance

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22 The definition of prices also follows other papers, such as Cummins and Weiss (2013) as well as Bikker and Groter (2001). MSCI does not provide an index for Luxembourg; therefore, we use the MSCI Europe stock market index for this country.

23 Both losses and total invested assets are highly correlated with the third service of insurers (financial services) and is thus generally not modeled as a separate output (see, e.g., Eling and Luhnen, 2010b).

market conditions, we use the concentration ratio at the four-firm level (CR4; see, e.g., Huang and Eling, 2013) to measure competition (COMP). This measure is the sum of the market shares held by the four largest (in terms of gross written premiums) insurers in each country (see, e.g., Cummins et al., 2004; Fenn et al, 2008); the higher CR4, the more concentrated and less competitive the market is. The premium data for the competition measure were obtained from Insurance Europe. In addition, we use the country average of equity to total assets to represent differences in capital adequacy (SOLV) among countries (see, e.g., Lozano-Vivas et al., 2002; Hussels and Ward, 2007).

Firm characteristics

In order to examine how firm characteristics influence the efficiency of European life insurers, we also investigate selected firm factors in second-stage regressions. We measure ownership (OWN) by binary variables where the value of 1 is allocated to stock and 0 to mutual companies. Size (SIZE) is measured in terms of total assets. Solvency ($SOLV_j$) is integrated by the firm-specific ratio of equity to total assets.

Table 2 Sample of European Life Insurers

Panel A: Definition of Controllable and Uncontrollable Variables

Controllable variables	Inputs	Labor	x1	1,000s	A.M. Best operating expenses/ILO average annual wage
		Debt	x2	Mil.. USD	A.M. Best total liabilities
		Equity capital	x3	Mil. USD	A. M. Best capital and surplus
	Outputs	Benefits + additions to reserves	y1	Mil. USD	A. M. Best net benefits + additions to reserves
		Investments	y2	Mil. USD	A. M. Best total invested assets
	Input prices	Price of labor	p1	USD	ILO average annual wage insurance and financial activities
		Price of debt capital	p2	%	OECD long-term interest rates
		Price of equity capital	p3	%	15y rolling returns on MSCI country-specific stock market indices
Uncontrollable (environmental) variables	General economic conditions	Economic maturity	GDP	USD	Gross domestic product per capita
		Unemployment	UNE	%	AXCO unemployment rates
		Inflation	INF	%	World Bank consumer price indices (year 2002 = 100)
	Capital market conditions	Interest rate level	IR	%	OECD long-term interest rates
		Stock market performance	MSCI	%	15y rolling returns on MSCI country-specific stock market indices
	Insurance market conditions	Competition	COMP	%	Concentration ratio for each country at the four-firm level
		Regulation	SOLV	%	Equity to total assets (country average)
Firm characteristics		Ownership	OWN	Dummy	(1= stock, 0=mutual)
		Size	SIZE	Mil. USD	Total assets
		Solvency	$SOLV_j$	%	Equity to total assets (firm specific)

Panel B: Summary Statistics (mean values and standard deviations [in parentheses])

Variable	Austria	Belgium	Denmark	Finland	France	Germany	Ireland	Italy	Luxembourg	Netherlands	Norway	Sweden	Switzerland	United Kingdom
x1	1.51	0.22	0.10	0.96	1.57	1.62	1.94	5.51	0.68	4.07	2.06	2.35	1.73	7.18
	(0.96)	(0.29)	(0.19)	(1.79)	(2.87)	(3.64)	(2.55)	(8.95)	(1.14)	(10.89)	(2.29)	(4.55)	(3.26)	(19.4)
x2	2716136.94	804483.86	3998714.65	7488835.25	8563159.99	5732507.16	4266031.96	5827840.87	2666172.66	9712398.71	14713374.94	10963645.35	15186448.88	21488922.25
	(1884845.57)	(2356517.38)	(5361055.29)	(9159446.54)	(13211194.63)	(14405904.40)	(10477956.68)	(9024940.78)	(3048378.28)	(19011803.43)	(15296029.25)	(12853068.18)	(29399567.21)	(44533988.63)
x3	61798.02	36574.87	434199.68	591436.01	369054.39	104043.69	218851.03	241819.36	50571.88	851811.87	1004411.13	4658861.78	631028.24	974427.29
	(46654.93)	(96944.73)	(507582.74)	(902063.72)	(525978.64)	(193922.67)	(412868.07)	(426689.21)	(34108.97)	(1762560.89)	(968584.7)	(7377580.07)	(1479914.87)	(1771368.8)
p1	54490.14	51304.51	104983.19	48633.47	61023.33	72225.43	48363.42	29164.62	81433.99	54108.41	83301.68	67320.91	109263.09	54732.28
	(17492.43)	(9969.83)	(20512.49)	(11235.38)	(12676.27)	(12513.08)	(12204.16)	(2242.42)	(21292.37)	(8629.73)	(28830.52)	(15053.33)	(22456.83)	(9189.84)
p2	0.04	0.04	0.03	0.04	0.04	0.03	0.05	0.04	0.04	0.04	0.04	0.04	0.02	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
p3	0.08	0.10	0.11	0.16	0.11	0.09	0.05	0.08	0.07	0.12	0.08	0.14	0.12	0.10
	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
y1	609832.14	295912.37	815231.35	2035097.52	1944006.63	1148108.21	1119934.87	1972864.40	924731.84	1622531.12	3358280.80	2096487.34	2724593.64	4884075.62
	(487436.80)	(1223913.26)	(1167980.28)	(2861541.94)	(3664051.13)	(3034089.16)	(2107758.87)	(3955206.83)	(1197319.09)	(3307136.88)	(4372987.29)	(3268551.86)	(5191431.72)	(11135911.93)
y2	2573078.89	788308.92	4326531.46	7474697.29	8294342.48	5412775.31	3239426.98	5496520.88	2404161.90	9731776.85	15254473.81	15076651.02	14929178.58	19459192.66
	(1756863.56)	(2379066.53)	(5552625.11)	(8943250.89)	(12802030.20)	(13317547.93)	(6410814.65)	(8213489.01)	(2870498.05)	(19136854.21)	(15819557.79)	(18246562.37)	(28972965.36)	(42242032.75)
GDP	40544.97	38312.34	51117.41	39912.40	36919.14	37516.16	47772.08	31383.50	90159.39	29067.48	80521.34	45563.42	60649.15	36510.55
	(7603.65)	(7443.50)	(8888.60)	(7282.60)	(6389.68)	(5919.30)	(7725.4)	(4751.79)	(21001.58)	(5450.52)	(19019.2)	(8599.06)	(14354.18)	(5014.72)
UNE	0.07	0.08	0.05	0.08	0.09	0.09	0.08	0.08	0.04	0.13	0.03	0.07	0.03	0.06
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
INF	1.10	1.10	1.11	1.07	1.09	1.09	1.13	1.11	1.12	1.10	1.12	1.07	1.04	1.10
	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)	(0.09)	(0.07)	(0.05)	(0.03)	(0.1)
IR	0.04	0.04	0.03	0.04	0.04	0.03	0.05	0.04	0.04	0.04	0.04	0.04	0.02	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MSCI	0.08	0.10	0.11	0.16	0.11	0.09	0.05	0.08	0.07	0.12	0.08	0.14	0.12	0.10
	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
COMP	0.61	0.65	0.51	0.82	0.48	0.42	0.71	0.53	0.72	0.62	0.84	0.53	0.72	0.39
	(0.12)	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.08)	(0.04)	(0.12)	(0.05)	(0.03)	(0.07)	(0.02)	(0.05)
SOLV	0.04	0.08	0.14	0.08	0.09	0.09	0.14	0.07	0.03	0.11	0.09	0.30	0.09	0.11
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.00)	(0.01)	(0.02)	(0.06)	(0.04)	(0.02)
OWN	0.67	0.87	0.36	0.58	0.79	0.57	0.90	0.83	0.93	0.80	0.86	0.65	0.82	0.89
	(0.47)	(0.34)	(0.48)	(0.49)	(0.41)	(0.50)	(0.3)	(0.37)	(0.25)	(0.40)	(0.34)	(0.48)	(0.38)	(0.31)
SIZE	3161157.94	909288.90	5092709.96	8782310.98	9914780.94	6429995.31	5083421.67	6749387.47	3103845.73	11893102.92	17815914.47	16850731.06	16698130.05	25860820.20
	(2270977.07)	(2558060.62)	(6716106.85)	(10803166.22)	(15310337.19)	(16166308.85)	(12284348.2)	(10334673.73)	(3667650.66)	(23743964.27)	(18844210.23)	(20690503.78)	(32722355.81)	(55814457.02)
$SOLV_j$	0.03	0.08	0.14	0.08	0.08	0.08	0.13	0.06	0.03	0.11	0.08	0.30	0.07	0.10
	(0.02)	(0.07)	(0.10)	(0.06)	(0.11)	(0.16)	(0.19)	(0.09)	(0.04)	(0.10)	(0.06)	(0.23)	(0.1)	(0.12)

4 Empirical Results

4.1 Efficiency Measurement

Table 3 shows average bias-corrected technical efficiency (TE) and cost-efficiency (CE) scores for Model 1 and Model 2 per country as well as for the total sample. The efficiency scores of Model 1 are based on unadjusted input values (stage 1). Meanwhile, the efficiency scores of Model 2 reflect efficiency after controlling for the business environment (i.e., using adjusting input values for the DEA in stage 4). Pure technical efficiency (PTE), allocative efficiency (AE), and scale efficiency (SE) scores are given in Table A3 in the Appendix.

Table 3 DEA efficiency scores

	Model 1		**Model 2**		**Delta (Model 2 - Model 1)**	
Country	TE	CE	TE	CE	TE	CE
Austria	0.94	0.53	0.90	0.51	-0.04	-0.02
Belgium	0.90	0.59	0.86	0.57	-0.04	-0.02
Denmark	0.97	0.72	0.94	0.70	-0.03	-0.02
Finland	0.94	0.69	0.87	0.64	-0.07	-0.05
France	0.90	0.66	0.86	0.63	-0.04	-0.03
Germany	0.93	0.59	0.90	0.56	-0.03	-0.03
Ireland	0.83	0.49	0.84	0.50	0.01	0.01
Italy	0.91	0.56	0.89	0.57	-0.02	0.01
Luxembourg	0.92	0.66	0.87	0.61	-0.05	-0.05
Netherlands	0.91	0.55	0.87	0.54	-0.04	-0.01
Norway	0.96	0.71	0.91	0.67	-0.05	-0.04
Sweden	0.95	0.50	0.92	0.47	-0.03	-0.03
Switzerland	0.92	0.55	0.84	0.48	-0.08	-0.07
United Kingdom	0.83	0.61	0.82	0.60	-0.01	-0.01
Total Sample	0.91	0.60	0.88	0.58	-0.03	-0.02

Model 1 implicitly assumes that all companies operate under the same environmental conditions. In this situation, TE is relatively high. The mean of TE, for example, across all countries and years is 0.91 showing that European life insurers on average could improve TE by 9 percentage points. For CE, there is much more room for improvement. The average CE score is 0.60, meaning that there is on average 40 percentage points of improvement potential. One explanation for the relatively low CE levels (in contrast to TE) is the high variance of input prices across the sample countries, which causes large variations when comparing actual costs against minimal costs in the DEA optimization process. For example, the average labor input price for Italy (29,165 USD) is almost four times less than the highest average labor price (109,263 USD, Switzerland). Regarding the variation across countries, Denmark has the highest efficiency value,[24] followed by the other three Northern European countries—namely, Norway, Sweden, and Finland. At the bottom range in terms of TE are Ireland and the United Kingdom. Controlling for the business environment rearranges the order of countries (see Model 2).[25] The largest decrease in TE (-0.08) and CE (-0.07) can be observed for Switzerland, illustrating that this country obtained the highest input adjustments. In addition, Luxembourg, Finland, and Norway have high adjustments, revealing that the environmental conditions in these countries caused comparatively low inefficiency. Meanwhile, Irish life insurers have the least favorable conditions (i.e., inefficiency might be due to the business environment). This result might be explained by the fact that the economy of Ireland was more severely affected by the financial crisis. Hence, the efficiency of life insurers operating in this country should be underestimated in Model 1, while Model 2 gives a more realistic picture of the actual managerial performance. The mean TE and CE scores for the total sample are marginally lower in Model 2 than in Model 1. This illustrates that controlling for the business environment decreased the average efficiency of life insurers. Overall, Denmark is still the most efficient country in terms of TE and CE.

4.2 Regression Analysis

In Table 4, we investigate the relationship between the efficiency scores of Model 1 and Model 2 as dependent variables and the environmental variables and firm characteristics.[26]

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[24] For example, Denmark is 14 percentage points more technically efficient than Ireland, the least efficient country. The finding that Denmark has the highest average efficiency levels across European countries is in line with Eling and Luhnen (2010), who analyze insurer efficiency in 36 countries, including all countries in our sample.

[25] Table A4 in the Appendix summarizes the input adjustments (stage 3) with respect to the slack regression results. The slack regression results (stage 2) are presented in Table A1 in the Appendix.

[26] Our regression analysis approach is as follows. First, we regress environmental factors on the efficiency scores of Model 1 (Panel A). Second, we regress firm characteristics on these efficiency scores (column Model 1 of Panel B). We do not use a joint regression model for either variable types (environmental and firm-specific), because we sought to analyze the impact of firm characteristics before and after controlling for the business environment. Incorporating both types in one model would have yielded coefficients for the firm characteristics after controlling for the impact of the environmental characteristics (for the sake of completeness, we present the regression results of the joint regression model in Table A5 in the Appendix). Third, we regress firm characteristics on the efficiency scores of Model 2 (two columns for Model 2 in Panel B).

Table 4 Regression Results

	Variable	Definition	Model 1 (unadjusted) TE	Model 1 (unadjusted) CE	Model 2 (adjusted) TE	Model 2 (adjusted) CE
Panel A: Regression of environmental conditions						
General economic conditions						
Economic maturity	GDP	GDP per capita	1.12 *** (0.287)	60.96** (26.843)		
Unemployment	UNE	Unemployment rate	0.56*** (0.203)	100.18*** (35.667)		
Inflation	INF	Consumer price indices (2002=100)	10.55*** (0.656)	-7.29 (12.541)		
Capital market conditions						
Interest rate level	IR	Long-term interest rates	3.36*** (0.237)	-45.42** (17.824)		
Stock market performance	MSCI	Rolling returns on MSCI indices	-1.78*** (0.255)	-156.56*** (47.91)		
Insurance market conditions						
Competition	COMP	Concentration ratio 4-firm-level	-2.02*** (0.201)	-41.72*** (10.506)		
Regulation	SOLV	Equity to total assets (country-average)	0.35* (0.217)	88.69*** (26.222)		
Year fixed effects/constant term			Yes	Yes		
Observations			6‘657	6‘657		
Panel B: Regression of firm characteristics						
Organizational form	OWN	Dummy (1= stock, 0=mutual)	34.24*** (3.588)	107.01*** (25.634)	0.30 (1.462)	52.48*** (17.688)
Size	SIZE	ln(Total assets)	-1.66*** (0.313)	-30.52*** (8.054)	-1.97*** (0.607)	-24.94*** (7.952)
Solvency	$SOLV_j$	Equity to total assets (firm-specific)	10.26*** (2.685)	44.64*** (9.678)	-56.03*** (14.317)	-297.39*** (87.377)
Year fixed effects/constant term			Yes	Yes	Yes	Yes
Observations			6‘657	6‘657	6‘657	6‘657

Note: *** (**, *) represents significance at the 1% (5%, 10%) level based on a two-sided test with a *t*-distribution; the numbers in parentheses are standard errors. TE = technical efficiency, CE = cost efficiency. We use the inverse of Farrell efficiency scores as dependent variables. Therefore, the interpretation of the coefficients has to be reversed (see, e.g., Luhnen, 2009; Biener et al., 2015). In this regard, a positive (negative) coefficient infers a negative (positive) relationship to efficiency. The dependent variables are truncated at the 1st and 99th percentiles. In Panel A, the independent variables are mean centered and scaled by their standard deviations.

Economic maturity: We proxy economic maturity by GDP per capita (GDP) and expect a positive relationship to efficiency (H1a). However, Table 4 does not confirm this expectation; the coefficients for TE and CE are positive and significant. We thus do not find support for H1a. This result could be discussed in light of a non-linear link between GDP and efficiency, especially regarding the s-curve of Enz (2000). Huang and Eling (2013) find a negative link between GDP growth and efficiency, showing that – under expansive demand conditions – efficiency is not a major concern of life insurers. However, a turning point might emerge where markets start to mature and a positive impact on efficiency is observable.

Unemployment: Unemployment (UNE) is considered one central driver of lapse. Because lapsed policies negatively affect life insurers' liquidity and profitably, we expect a positive relationship with efficiency. Yet Table 4 reveals a negative relationship for both TE and CE. One explanation for this finding is that employers (e.g., life insurers) have to pay higher wages during periods of low unemployment, which increases the costs of production and could decrease productivity. Thus, we cannot confirm H1b.

Inflation: Inflation (INF) is measured by consumer price indices (CPI, 2002=100). Based on a theoretical derivation, we expect a negative relationship between inflation and efficiency. Table 4 confirms this expectation for TE; for CE, the coefficient is negative but insignificant. Hence, we find evidence for inflation-induced efficiency losses; unlike with non-life insurance, these might be due to falling demand (see, e.g., Clark, 1982), which puts pressure on life insurers and not die to increased costs of claims.

Interest rate level: The expected negative relationship (H2a) is revealed for TE, as shown in Table 4, indicating that European life insurers operate more efficiently in lower interest rate environments, probably to compensate for lower interest income and adapt to the difficult business environment. Meanwhile, the coefficient for CE is positive and significant, which might be explained by the fact that interest rates determine the price of debt[27]; with declining interest rates, the cost of production decreases and thus productivity increases, while the impact on efficiency is negative in general.[28] Therefore, an interest rate increase has a negative impact on TE, but encourages firms to choose more cost-optimal input combinations because the costs of production increase. Therefore, we find support for H2a, but only for TE.

Stock market performance: For the stock market performance measure MSCI, Table 4 reveals a positive relationship for both TE and CE, thereby supporting H2b. When stock markets are performing well, insurers seem to be encouraged to operate more efficiently (e.g., by optimizing cost structures). Increasing total returns offered to policyholders in this way as a response to competition from other life insurers and alternative product providers is one potential explanation.

Competition: In line with the empirical findings for the life insurance industry, we expect a positive relationship between competition (COMP) and efficiency. This expectation implies a positive coefficient for COMP as increases in COMP go along with the assumption of competition losses. Table

27 The technical explanation for this finding stems from the fact that the interest rate level is one determinant of the isocost line slope, which yields the cost-efficient input combination. If the interest rate level increases, the tradeoff between equity (in general, the more expensive input) and debt becomes less relevant in determining the cost-efficient input combination. As a result, insurers with high equity levels also tend to become more efficient; the overall effect in our sample is positive (for an illustration, see Table A6 in the Appendix).

28 If, for example, interest rates decline by 100 basis points, the costs of production decrease by a fixed amount and, thus, productivity increases. If the output is unaffected, the efficiency (relative productivity between the companies) might either increase or decrease. See note 13 for the same discussion in a different context.

4 reveals a negative coefficient for both TE and CE. Hence, increases in COMP have a positive impact on efficiency. Considering both the summary statistics (Table 2) and the efficiency results (Table 3) shows that especially countries with high levels of COMP, such as Norway, Finland, and Switzerland, also have high efficiency levels. The results do not confirm our hypothesis H3a, but rather support the efficient market structure hypothesis (see, e.g., Demsetz, 1973).

Regulation (capital adequacy): We use the country average of equity to total assets (SOLV) to analyze differences in capital adequacy. Based on a theoretical discussion and in line with empirical evidence for the life insurance sector, we expect a positive relationship between capital adequacy and efficiency. However, for TE and CE, Table 4 shows a negative relationship, which can be explained by the fact that higher capital adequacy forces life insurers to hold more costly equity capital, which constrains companies trying to find (cost-)optimal input combinations.[29] Therefore, capital adequacy seems to be a constraint for life insurers in choosing optimal input combinations from a cost perspective as well. Overall, we do not find empirical evidence supporting our hypothesis H3b.

Considering the firm characteristics, Table 4 documents that mutual insurers are both more technical and more cost-efficient than stock insurers.[30] However, this result only holds for CE when controlling for the business environment (Model 2). Thus, environmental conditions should be considered when analyzing ownership effects in cross-country settings. Furthermore, Table 4 shows that increases in size have a positive impact on TE and CE for Model 1; the positive size expansion effect also holds after controlling for the business environment (Model 2). Therefore, we conclude that size expansions tend to increase TE and CE. For the firm-specific solvency measure ($SOLV_j$), we find a negative relationship with TE and CE in Model 1. However, after controlling for the business environment (Model 2), the coefficient of $SOLV_j$ changes signs. According to Diacon (2001), the impact of solvency on efficiency depends on environmental factors; policyholders possibly value solvency-induced security differently across countries, resulting in efficiency gains due to increased premium levels in some countries and non-significant or negative impacts in other countries.[31]

4.3 Development of Productivity and Efficiency over Time

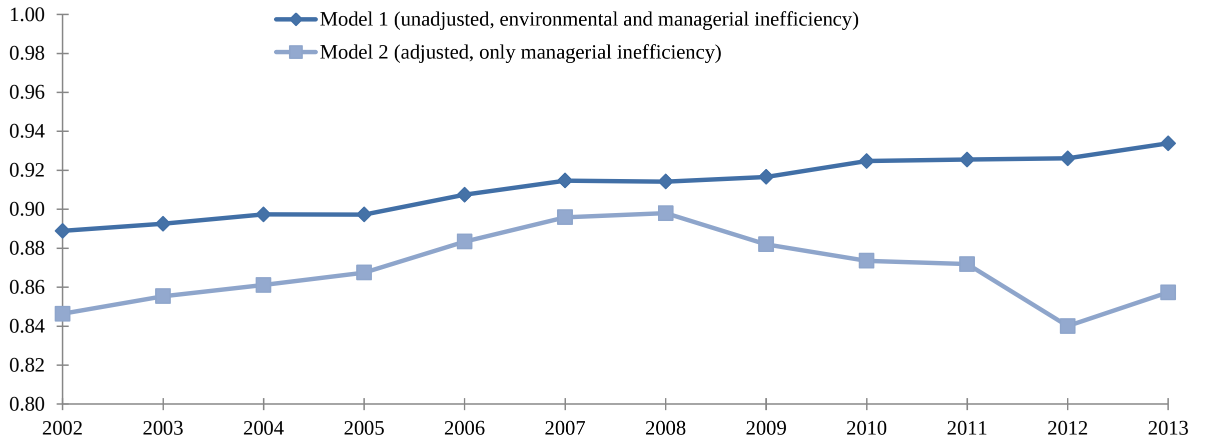
In this section, we show how productivity and efficiency develop under heterogeneous environmental conditions (Model 1) and under homogenous conditions (Model 2). Figure 1 presents yearly average bias-corrected TE scores for the total sample and depicts the development of efficiency in the European

29 This finding mirrors our explanation of the negative coefficient of IR for CE. Equity is generally the more expensive input of life insurers, implying that life insurers in countries with higher capital adequacy might induce efficiency losses due to cost of capital penalties (compare, e.g., Cummins and Nini, 2002, with an analysis of equity overutilization in the U.S. non-life insurance industry).

30 More empirical analyses are needed to derive firm conclusions on this topic, but our general finding that mutuals are better than stocks is in line with Biener et al.'s (2015) finding for the Swiss life insurance market, Luhnen's (2009) finding for the German non-life market, and Biener and Eling's (2012) finding for the European and U.S. life and non-life markets. Our results do not confirm the expense preference hypothesis, but might provide some indication for the managerial discretion hypothesis. For a detailed discussion of these hypotheses, we refer to Biener and Eling (2012).

life insurance sector over the sample period.

Figure 1 Development of Efficiency Over Time



Note: Figure 1 is based on TE scores estimated according to Simar and Wilson's (2000) bootstrapping approach in order to account for sample variations.

Figure 1 illustrates that average efficiency in the European life insurance sector increases over the sample period (Model 1). Different[32] business environments increasingly placing more pressure on life insurers could explain the efficiency progress.[33] Furthermore, Model 2 shows that, during the pre-crisis period (i.e., 2002–2008), business environments converged in the sample (Model 2 TE levels approach Model 1 efficiency levels). However, after 2008, the differences between Model 1 and Model 2 become larger. Figure A1 (Appendix) shows the average input adjustments per annum during the sample period. This reveals that post-financial crisis countries were affected differently by the business environment, causing higher input adjustments.[34] Overall, we can confirm our expectations of increased efficiency and increased divergence in efficiency following the financial crisis.

To further investigate the development of efficiency and productivity over time, we analyze TFP changes and its sources (i.e., technical and technical efficiency changes). Table 5 presents mean (arithmetic and geometric) annual changes and changes for the complete sample period

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31 For example, the impact is positive for the Netherlands and the UK but negative for France.

32 This is an important point as we assert that not only the "difficulty" of the business conditions is relevant, but also the differences across countries due to the nature of efficiency as a relative measure. Because life insurers are exposed to country-specific conditions but can theoretically offer products (due to the internal European market) abroad as well, pressure not only arises from "internal" but also from "external" business conditions (i.e., if one company operates under relatively more favorable conditions, it can have a competitive advantage when offering services in other European countries).

33 Huang and Eling (2013) note a decrease in efficiency decrease from 2000 to 2008 for the BRIC countries and trace it back to overall favorable market developments, which did not require focusing on efficiency-enhancing activities. This emphasizes our point that difficult business conditions put pressure on efficiency, which we document for European life insurers.

34 If only one country experiences comparatively bad environmental conditions (with all other countries operating under equal conditions), all other countries would be penalized with the same proportional input adjustment. The net effect on efficiency for the total sample should be marginal in this case. If the environmental conditions across all countries vary, input adjustments are not proportional and countries are penalized differently. In our sample, this causes a significant

(average changes per country are given in Table A7 in the Appendix).[35] The results are presented separately for Model 1 and Model 2.

Table 5 Malmquist Index of Total Factor Productivity

Period		Average No. Of firms	Technical change	Technical efficiency change	Pure technical efficiency change	Scale efficiency change	TFP Change
Model 1: Unadjusted							
Annual change (arithmetic mean)		479	1.00	1.00	1.00	1.00	1.00
Annual change (geometric mean)		479	1.00	1.00	1.00	1.00	1.01
Sample period:	2002 - 2013	219	1.00	1.02***	1.02*	1.00	1.02**
Pre-crisis period:	2002 - 2007	430	1.01**	1.02***	1.02***	1.00	1.03***
Post-crisis period:	2008 - 2013	191	0.99	1.01	1.00	1.01***	1.00
Model 2: Adjusted for the environment							
Annual change (arithmetic mean)		479	1.00	1.00	1.00	1.00	1.00
Annual change (geometric mean)		479	1.00	1.00	1.00	1.00	1.00
Sample period:	2002 - 2013	219	0.99***	0.98**	1.00	0.99***	0.97***
Pre-crisis period:	2002 - 2007	430	1.02***	1.04***	1.03***	1.01***	1.07***
Post-crisis period:	2008 - 2013	191	0.98***	0.95***	0.96***	0.99***	0.93***

Note: Test of significance is based on two-tailed *t*-test using the bootstrapped Malmquist indices. *** (**, *) represents significant differences from unity at the 1% (5%, 10%) level. For illustrative purposes, the reciprocal of the indices is shown in Table 5 (see, e.g., Färe et al., 1992). Hence, a value > 1 represents progress and a value < 1 represents regress.

For Model 1 we do not find significant annual TFP changes when we consider only samples of firms present in every adjacent two-year period between 2002 and 2013. However, when we consider the total sample period, we identify a significant TFP growth of approximately 2%. This growth stems solely from technical efficiency improvements, while the technology in the market did not change.[36] Therefore, European life insurers on average enhanced efficiency and consequently increased total factor productivity.[37] This finding mirrors the conclusions drawn from Figure 1: Different and harsher business conditions put pressure on European life insurers to increase efficiency. The findings are robust in the

reduction in the efficiency level.

35 The annual average values were calculated based on samples of firms present in every adjacent two-year period. The average values for the complete sample period were calculated based on a sample of firms that operated in every year.

36 Cummins and Rubio-Misas (2006) argue that the costs of adjusting to new environmental conditions (e.g., new regulatory conditions) might lead to a slippage in the production frontier, thereby preventing favorable shifts or even causing negative shifts in the production frontier. This could also explain why we cannot observe technical progress in our sample, which should be carefully considered. If the sector is exposed to constantly changing conditions (e.g., regulation) in conjunction with other obstacles, such as low interest rates, these developments could prevent technical progress or even cause technical decline. This is mirrored in country-specific evidence for the Swiss life insurance market. Biener et al. (2015) relate significant technical regress to an increasingly challenging business environment of low interest rates and increased competition from other financial service providers, such as banks. Although the level of inputs remains largely unchanged, in many cases the output levels decline due to, for instance, the loss of business to competitors in other industries or lower investments. Table 5 shows that the pre-crisis technical progress disappears in the post-crisis period (the period with increased difficult conditions) for Model 1 as well as for the European sample. For Model 2, we even observe technical regress.

37 We cannot find evidence to support our expectation that productivity declined (negative TFP change). If technical efficiency change is positive (as in Table 5), TFP change could only become negative if the positive technical efficiency change is overcompensated for by negative technical change. Biener et al.'s (2015) findings for Switzerland gave reason to expect this. However, our findings reveal no significant technical changes; therefore, in total, the TFP change is positive.

sense that if we control for the business environment (Model 2), efficiency and productivity decline throughout the sample period (Table 5). In other words, the differences between Model 1 and Model 2 must be due to environmental impacts. Without pressure from the environment, management does not seem to be encouraged to enhance efficiency. This again illustrates that European life insurers are under pressure due to the challenging changes in their business environment and that this is the main channel for productivity improvements. These results thus again emphasize the importance of decomposing productivity and efficiency changes into environmental and managerial effects.

5. Conclusions

We analyze the impact of environmental conditions on the productivity and efficiency of European life insurance companies using multi-stage DEA. This approach enables us to distinguish environmental changes and changes in management practices. We also identify environmental conditions and firm-specific drivers of efficiency in a truncated regression analysis. Our results confirm the significant impact of the business environment (i.e., general economic, capital market, and insurance market conditions) on life insurer efficiency. Furthermore, our study emphasizes the need to control for the business environment in cross-country efficiency studies; otherwise, the conclusion about the impacts of firm characteristics could be biased. We also show that the difficult business environment affects technical change and might thus endanger productivity growth in the future; we further document that efficiency increases throughout the sample period—results that also illustrate the consolidation process in the European life insurance market, where inefficient firms have to leave the market. These findings have implications for insurance managers, regulators, and policymakers: They show that the life insurance industry is facing increasing pressure and that bad internal performance (underwriting practices, cost management) can no longer be compensated for via a good environmental situation (such as high capital market returns). The findings thus help to validate and better understand the determinants of productivity and efficiency in the insurance sector. The results also indicate that some life insurers are overutilizing equity capital, a finding which might be important for the appropriate definition of risk-based capital standards by regulators.

The analysis presented here also opens room for future research in various directions. For example, on the methodological side, other types of efficiency (e.g., revenue efficiency, profit efficiency), other types of adjustments (e.g., conditional mean approach used in stochastic frontier analysis), and other types of relationships (e.g., non-linear link between GDP and efficiency as indicated by the s-curve; see Enz, 2000) could be analyzed. Cross-frontier analyses (Biener and Eling, 2012) could be used to further validate how different the business environments are 20 years after the liberalization of the European marketplace. Regarding the industry and geographical coverage, the European non-life sector has not yet been considered in the context of multi-stage DEA. In addition, as the economic and regulatory developments discussed in this paper are a global phenomenon, it would be interesting to analyze how

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Still the development of technical change, as mentioned above, should be carefully considered.

the life insurance industry outside Europe (North American and Asian markets) handles the increasingly difficult business environment.

Appendix

Table A1 Slack regression results (SFA model)

	Variable	Definition	**Slack1** Labor	**Slack 2** Debt	**Slack 3** Equity
General economic conditions					
Economic Maturity	GDP	ln(GDP per capita)	-0.300*** (0.0247)	-0.048*** (0.0092)	-0.049*** (0.0093)
Unemployment	UNE	ln(unemployment rate)	0.048*** (0.0156)	-0.016*** (0.0056)	-0.020*** (0.0057)
Inflation	INF	ln(consumer price indices (2002=100))	0.709*** (0.1022)	0.013 (0.0366)	0.017 (0.0369)
Capital market conditions					
Interest rate level	IR	ln(long-term interest rates)	0.030* (0.0164)	0.048*** (0.0059)	0.050*** (0.0059)
Stock market performance	MSCI	ln(rolling returns on MSCI indices)	-0.265*** (0.0184)	-0.060*** (0.0066)	-0.063*** (0.0066)
Insurance market conditions					
Competition	COMP	ln(concentration ratio 4-firm-level)	0.079*** (0.0196)	-0.004 (0.0070)	-0.003 (0.0071)
Regulation	SOLV	ln(equity to total assets)	-0.078*** (0.0116)	0.018*** (0.0042)	0.019*** (0.0042)
Log likelihood function			-2602.72	4253.74	4217.92
Sigma_v			0.128	0.016	0.016
γ^m			0.00068	0.00001	0.00002
Number of observations			6‘657	6‘657	6‘657

Note: *** (**, *) represents significance at the 1% (5%, 10%) level based on a two-sided test with a *t*-distribution; the numbers in parentheses are standard errors. Table A1 presents slack regression results based on a SFA slack regression model. The SFA regression equation is specified as follows:

$$S_{mj} = f^m(Z_j; \beta^m) + v_{mj} + u_{mj}\text{; m=1, 2, ……, M; j=1,2,….., N,}$$

where S_{mj} is the percentage of total input slacks in the usage of input m for DMU j. Z_j is a vector of uncontrollable variables for DMU j. β^m is a vector of coefficients. It is further assumed that v_{mj} (normally distributed with zero mean and variance σ^2_{vm}) reflects statistical noise, and u_{mj} (half-normal distributed with variance σ^2_{um}) reflects managerial inefficiency. Regarding the functional form of f^m, we follow Cooper et al. (2007) and set the environmental variables into logarithms. Note that we need SFA only for the second-stage regression and not for the determination of efficiency scores.

Table A2 Slack regression results (truncated model)

	Variable	Definition	**Slack1** Labor	**Slack 2** Debt	**Slack 3** Equity
General economic conditions					
Economic maturity	GDP	GDP per capita	-0.530*** (0.0509)	-0.043*** (0.0089)	-0.043*** (0.0089)
Unemployment	UNE	Unemployment rate	0.107*** (0.0305)	-0.015*** (0.0055)	-0.018*** (0.0055)
Inflation	INF	Consumer price indices (2002=100)	1.242*** (0.2047)	-0.002 (0.0354)	0.003 (0.0357)
Capital market conditions					
Interest rate level	IR	Long-term interest rates	0.059* (0.0304)	0.049*** (0.0057)	0.051*** (0.0058)
Stock market performance	MSCI	Rolling returns on MSCI indices	-0.629*** (0.0304)	-0.062*** (0.0064)	-0.065*** (0.0064)
Insurance market conditions					
Competition	COMP	Concentration ratio 4-firm-level	0.235*** (0.0379)	-0.004 (0.0068)	-0.003 (0.0069)
Regulation	SOLV	Equity to total assets	-0.106*** (0.0216)	0.013*** (0.0040)	0.014*** (0.0041)
Log likelihood function			-1680.90	4471.30	4415.30
Sigma_v			0.491	0.124	0.125
Number of observations			6‘657	6‘657	6‘657

Note: *** (**, *) represents significance at the 1% (5%, 10%) level based on a two-sided test with a *t*-distribution; the numbers in parentheses are standard errors. Table A2 presents slack regression results based on a truncated slack regression model. The regression equation is specified as follows.

$$S_{mj} = f^{m}(Z_j; \beta^m; \varepsilon^m) \text{; m=1, 2, ……, M; j=1,2,….., N,}$$

where $S_{mj} = (rs_{mj} + nrs_{mj}) / x_{mj}$ are the percentages of total input slacks obtained from stage 1 in the usage of input *m* for DMU j. Z_j is a vector of uncontrollable variables for DMU j. β^m is a vector of coefficients; ε^m is the statistical noise. The independent variables are scaled. The only difference between multi-stage DEA models based on a truncated slack regression or an SFA slack regression is the employed regression equation in stage 2. Because the results of the truncated regression are consistent with the SFA (see Table A1) regression results, which is nevertheless also the preferred regression approach for the multi-stage DEA (see Huang and Eling, 2013, Fried et al., 2002), we only present stage 2 (slack regression results) as a robustness check here.

Table A3 PTE, AE, and SE efficiency scores

	Model 1			**Model 2**			**Delta (Model 2 - Model 1)**		
Country	PTE	AE	SE	PTE	AE	SE	PTE	AE	SE
Austria	0.94	0.56	1.00	0.90	0.57	1.00	-0.04	0.01	0.00
Belgium	0.90	0.66	1.00	0.87	0.66	0.99	-0.03	0.00	0.00
Denmark	0.98	0.75	1.00	0.96	0.74	0.99	-0.02	0.00	-0.01
Finland	0.95	0.73	0.99	0.89	0.74	0.98	-0.06	0.01	-0.02
France	0.91	0.73	0.99	0.88	0.73	0.97	-0.03	0.00	-0.01
Germany	0.94	0.63	0.99	0.91	0.63	0.99	-0.03	0.00	-0.01
Ireland	0.84	0.59	0.99	0.85	0.60	0.98	0.01	0.01	0.00
Italy	0.92	0.62	1.00	0.90	0.64	0.99	-0.01	0.02	-0.01
Luxembourg	0.92	0.72	1.00	0.87	0.70	1.00	-0.05	-0.01	0.00
Netherlands	0.92	0.61	0.98	0.90	0.62	0.97	-0.03	0.01	-0.01
Norway	0.97	0.74	0.99	0.94	0.73	0.97	-0.03	0.00	-0.02
Sweden	0.96	0.52	0.99	0.95	0.51	0.97	-0.02	-0.01	-0.02
Switzerland	0.93	0.60	0.99	0.88	0.58	0.97	-0.06	-0.02	-0.02
United Kingdom	0.85	0.73	0.99	0.84	0.73	0.97	0.00	0.00	-0.02
Total Sample	0.92	0.65	0.99	0.90	0.66	0.98	-0.02	0.00	-0.01

Model 1 PTE levels are on average (0.92) relatively equal to the average TE level (0.91) for the total sample. This is mirrored in an average SE score of 0.99. Thus, European life insurers could only improve their size of operations by 1% to become fully scale efficient. In Model 2, the average PTE level is 0.2 higher than the average TE (0.88) value. Average AE scores are almost equal in Model 1 and Model 2. As it is the case for CE as well as AE, there is much room for further improvement.

Table A4 Summary statistics of adjusted input data

	Input 1 Labor					Input 2 Debt					Input 3 Equity capital				
Country	Mean	STD	Min	Max	Adjust-ment	Mean	STD	Min	Max	Adjust-ment	Mean	STD	Min	Max	Adjust-ment
Austria	1.7370	1.1121	0.0748	3.8617	15 %	2930679	2081342	224046	5753747	8 %	67131	52530	10460	198148	9 %
Belgium	0.2659	0.3598	0.0044	1.5857	23 %	863135	2526946	5053	19200000	7 %	39315	104242	588	696384	7 %
Denmark	0.1573	0.2801	0.0015	2.3385	52 %	4418214	6019551	1623	34400000	10 %	477076	563476	1480	2970132	10 %
Finland	1.3616	2.3496	0.0154	23.7166	42 %	8374750	10300000	21363	41300000	12 %	659220	995710	596	5036277	11 %
France	2.0804	3.8161	0.0031	22.8304	32 %	9289605	14400000	1458	93900000	8 %	401792	575431	1735	3972288	9 %
Germany	2.0886	4.7504	0.0000	77.3875	29 %	6197613	15600000	131	219000000	8 %	113141	211885	296	2361902	9 %
Ireland	2.1786	2.8901	0.0032	20.4180	12 %	4314892	10600000	3477	97100000	1 %	221162	416883	1524	3297199	1 %
Italy	5.9728	9.5795	0.0046	60.3156	08 %	6087366	9431208	6812	67500000	4 %	253362	447582	5118	3485363	5 %
Luxembourg	0.9152	1.5196	0.0879	9.7524	35 %	2964363	3515622	363726	25200000	11 %	56127	39172	7993	190751	11 %
Netherlands	4.8967	12.8578	0.0035	101.6752	20 %	10400000	20400000	2394	92700000	7 %	917442	1906777	336	11600000	8 %
Norway	3.0458	3.3363	0.0004	14.9117	48 %	16100000	17000000	7713	62000000	10 %	1099352	1073010	4719	3626772	9 %
Sweden	3.5968	6.7948	0.0002	48.1742	53 %	11900000	14100000	71	70200000	8 %	5082182	8080594	730	29700000	9 %
Switzerland	2.7588	5.0288	0.0044	41.3438	60 %	17400000	34300000	1242	202000000	14 %	731099	1749427	4135	12700000	16 %
United Kingdom	9.5389	26.3618	0.0003	318.4361	33 %	22700000	47400000	2146	422000000	6 %	1030661	1882445	893	14500000	6 %
Total sample	3.2384	10.7156	0.0000	318.4361	28 %	8996787	22200000	71	422000000	8 %	562540	1986452	296	29700000	8 %

Table A5 Alternative model specification

			Model 1	
	Variable	Definition	TE	CE
General economic conditions				
Economic maturity	GDP	GDP per capita	0.02 (0.288)	-1.57 (1.203)
Unemployment	UNE	Unemployment rates	0.33* (0.176)	2.93*** (0.616)
Inflation	INF	Consumer price indices (2002=100)	7.77*** (0.479)	-0.82 (1.145)
Capital market conditions				
Interest rate level	IR	Long-term interest rates	2.48*** (0.173)	-2.95*** (0.680)
Stock market performance	MSCI	Rolling returns on MSCI indices	-2.07*** (0.238)	-8.81*** (0.754)
Insurance market conditions				
Competition	COMP	Concentration ratio 4-firm-level	-2.09*** (0.189)	-4.06*** (0.588)
Regulation	SOLV	Equity to total assets (country-average)	0.45** (0.193)	2.80*** (0.437)
Organizational form	OWN	Dummy (1= stock, 0=mutual)	2.40*** (0.180)	9.30*** (0.592)
Size	SIZE	Total assets	-0.33*** (0.120)	-11.16*** (0.984)
Solvency	$SOLV_j$	Equity to total assets (firm-specific)	0.49*** (0.072)	5.98*** (0.289)
Year fixed effects/constant term			Yes	Yes
Observations			6‘657	6‘657

Note: *** (**, *) represents significance at the 1% (5%, 10%) level based on a two-sided test with a *t*-distribution; the numbers in parentheses are standard errors. TE = technical efficiency, CE = cost efficiency. We use the inverse of Farrell efficiency scores as dependent variables. Therefore, the interpretation of the coefficients has to be reversed (see, e.g., Luhnen, 2009; Biener et al., 2015). In this regard, a positive (negative) coefficient infers a negative (positive) relationship to efficiency. The dependent variables are truncated at the 1st and 99th percentiles. The independent variables are mean centered and scaled by their standard deviations.

Table A6 Change in CE with increases in interest rate level

$SOLV_j$ Deciles	**CE_1 (observed prices)**	**CE_2 (IR + 1 %)**	**Delta (CE2 - CE1)**
Q1	0.7259	0.7505	3.40%
Q2	0.6900	0.7186	4.15%
Q3	0.6017	0.6343	5.41%
Q4	0.6251	0.6565	5.03%
Q5	0.5979	0.6304	5.43%
Q6	0.6077	0.6396	5.24%
Q7	0.5808	0.6140	5.72%
Q8	0.5799	0.6195	6.84%
Q9	0.3942	0.4289	8.82%
Q10	0.3728	0.4184	12.23%
Mean (Arithmetic)	0.5773	0.6108	5.80%

For this example, we estimate CE in our sample for the year 2002 based on observed input prices (CE_1). Next, we artificially increase the interest rate (IR) level, which is the price of the input debt (x3), by 1% (keeping all other input prices unchanged) across all countries and re-estimated CE (CE_2). We report the CE scores as mean values separately for $SOLV_j$ (firm-specific equity to total assets) deciles and for the total sample. Table A6 reveals that insurers with lower $SOLV_j$ ratios (accordingly classified in lower deciles) are on average more cost efficient. Furthermore, if the interest rate level increases, CE on average increases. Moreover, the efficiency gains seem to be higher for higher $SOLV_j$ levels. Because equity is generally more expensive than debt, more solvent firms appear to be less cost efficient at first glance. However, if the interest rate level increases, the difference between equity price and debt price becomes less relevant.

Figure A1 Average Input Adjustments p.a.

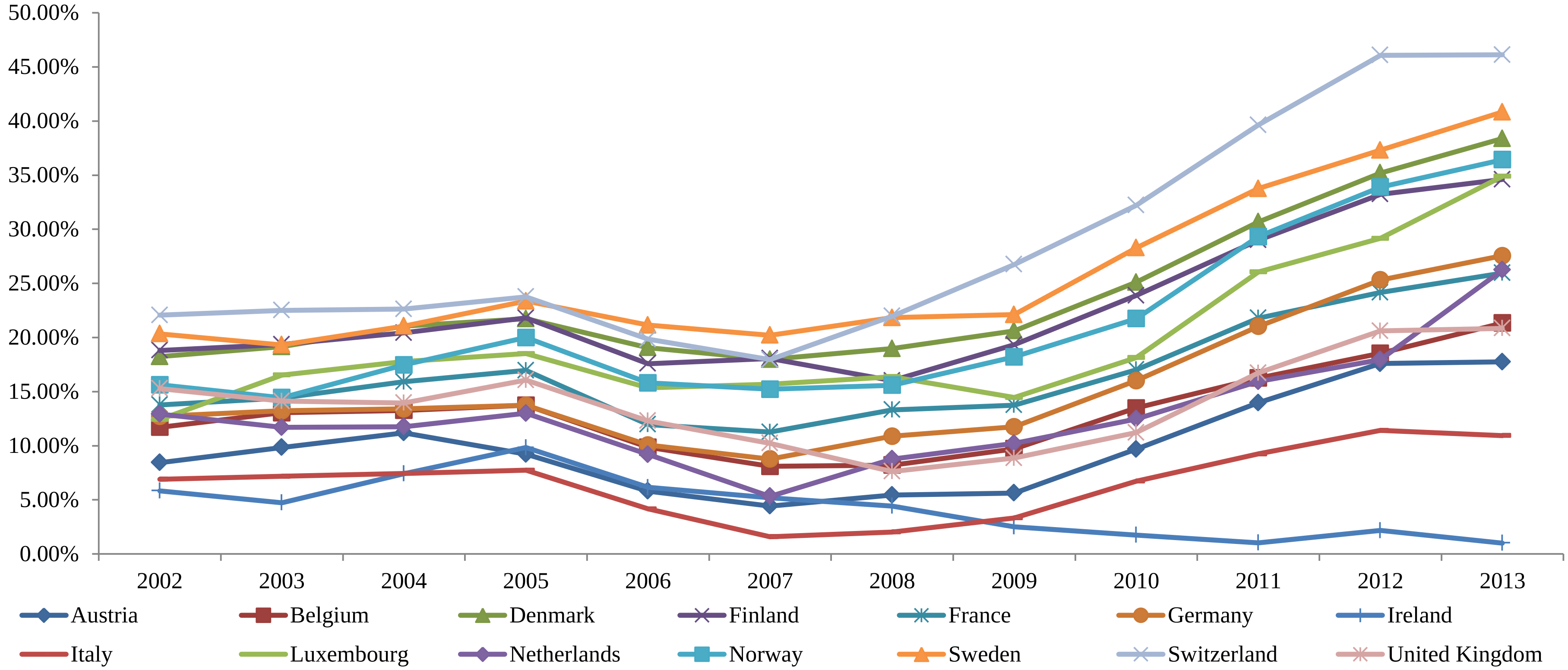

Table A7 Productivity over time

Year	2002/2003			2003/2004			2004/2005			2005/2006			2006/2007			2007/2008			2008/2009			2009/2010			2010/2011			2011/2012			2012/2013			2002/2013		
Model 1	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP
Austria	1.03	1.00	1.03	0.98	1.00	0.98	1.01	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.08	1.00	1.08
Belgium	1.00	1.03	1.03	1.00	1.00	1.00	1.02	1.00	1.02	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.03	0.97	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.05	1.00	1.05
Denmark	0.98	1.02	1.00	1.01	1.00	1.01	1.01	0.99	1.00	1.00	1.00	1.00	1.01	1.00	1.01	0.99	0.99	0.98	1.00	1.01	1.01	1.01	1.00	1.02	1.00	0.97	0.97	1.00	1.01	1.02	1.01	0.97	0.98	1.02	1.00	1.02
Finland	1.00	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.98	1.02	1.00	1.02	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.02	0.97	0.99
France	1.00	1.00	1.01	1.01	1.00	1.01	1.02	1.00	1.02	1.02	1.00	1.02	1.00	1.00	1.00	1.01	0.98	1.00	1.01	1.01	1.02	1.01	1.00	1.01	1.00	1.00	1.00	0.97	1.02	1.01	1.01	1.00	1.00	1.02	1.00	1.02
Germany	0.99	1.01	1.01	1.01	1.00	1.00	1.02	0.99	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	0.97	0.97	1.00	1.01	1.01	1.00	0.96	0.97	1.00	1.00	1.01	1.00	1.00	1.00	1.01	0.99	1.00	1.04	1.00	1.04
Ireland	0.98	1.06	1.04	0.99	1.01	0.99	0.99	1.00	0.99	0.93	1.00	0.93	0.98	1.00	0.98	0.93	0.93	0.88	0.93	1.03	0.98	1.02	0.97	0.99	0.99	1.02	1.01	1.01	0.98	0.99	1.01	1.00	1.00	0.92	1.00	0.92
Italy	1.01	1.01	1.02	1.01	1.00	1.01	1.01	1.00	1.01	0.99	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.02	1.00	1.02	1.00	0.99	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.03	0.94	0.97
Luxembourg	1.01	1.01	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	0.98	1.00	0.98	0.78	1.03	0.79	0.94	0.95	0.90	1.06	0.95	1.01	1.05	1.03	1.08	1.00	0.94	0.94	1.03	1.03	1.06
Netherlands	1.00	1.01	1.01	1.01	1.00	1.01	1.03	1.00	1.03	1.02	1.00	1.02	1.00	1.00	1.00	0.98	1.00	0.98	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.04	1.00	1.04
Norway	1.01	1.00	1.01	1.02	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.10	0.99	1.09	1.03	1.00	1.03	1.00	1.00	1.00	0.99	0.97	0.96	1.00	1.00	1.00	1.00	0.99	0.99	1.02	1.00	1.02
Sweden	1.01	1.00	1.01	0.99	1.00	0.99	1.02	1.01	1.03	1.01	1.00	1.01	1.00	1.01	1.01	1.02	0.88	0.91	1.00	0.99	0.99	0.97	0.99	0.97	0.98	1.00	0.98	0.99	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.01
Switzerland	1.00	1.01	1.01	0.99	1.01	1.00	0.81	1.03	0.89	1.05	1.01	1.06	0.90	1.00	0.89	1.00	1.00	1.00	1.00	1.00	1.00	1.01	0.98	0.99	1.00	1.02	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.03	1.00	1.03
United Kingdom	1.00	1.05	1.05	1.01	0.99	1.00	1.01	1.00	1.00	0.99	1.00	1.00	1.01	0.99	1.00	1.10	0.96	1.05	1.01	1.00	1.01	1.00	1.00	1.00	0.98	1.00	0.98	0.99	1.04	1.03	1.00	0.97	0.97	0.97	1.03	0.99
Total Sample	1.00	1.02	1.02	1.00	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.97	1.00	1.01	1.01	1.01	0.98	0.99	1.00	1.00	1.00	1.00	1.01	1.01	1.00	0.99	0.99	1.02	1.00	1.02
Model 2	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP	TEC	TC	ΔTFP
Austria	1.03	1.00	1.03	0.98	1.01	0.99	1.02	1.00	1.02	1.01	1.00	1.01	1.02	1.00	1.02	1.01	0.98	0.99	0.98	1.02	1.01	0.98	0.99	0.96	0.99	0.98	0.97	0.99	1.01	1.00	1.00	0.99	1.00	1.04	1.00	1.04
Belgium	1.01	1.04	1.05	0.99	1.01	0.99	1.02	1.00	1.02	1.01	1.00	1.01	1.01	1.00	1.01	1.00	0.99	0.99	0.98	1.01	0.99	1.01	0.96	0.97	1.01	0.96	0.97	0.96	1.04	1.00	1.03	0.99	1.02	1.04	0.99	1.04
Denmark	0.98	1.02	1.01	1.01	1.02	1.03	1.01	0.99	1.00	1.01	1.01	1.01	1.01	1.01	1.02	0.99	0.97	0.96	0.99	1.01	1.00	1.00	0.98	0.98	1.00	0.93	0.93	0.96	1.03	1.00	1.01	0.99	1.00	0.98	1.00	0.98
Finland	1.01	1.02	1.03	1.01	1.01	1.02	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.98	0.97	1.00	1.02	1.02	0.99	1.00	0.98	1.02	0.95	0.97	0.94	1.05	0.99	1.03	0.98	1.02	0.97	0.98	0.95
France	1.00	1.01	1.02	1.01	1.01	1.02	1.02	1.00	1.02	1.02	1.01	1.03	1.01	1.00	1.01	1.02	0.97	0.99	0.97	1.03	1.00	0.99	0.99	0.98	1.01	0.96	0.97	0.94	1.05	1.01	1.02	0.98	1.01	0.97	1.01	0.98
Germany	0.99	1.02	1.01	1.01	1.00	1.01	1.02	0.99	1.01	1.02	1.00	1.02	1.01	1.01	1.02	1.00	0.96	0.95	0.98	1.02	1.00	0.99	0.95	0.94	1.00	0.97	0.97	0.96	1.02	0.99	1.03	0.98	1.02	0.99	0.99	0.98
Ireland	0.98	1.08	1.05	0.98	1.02	1.00	0.99	0.99	0.98	0.93	1.00	0.93	0.98	1.00	0.98	0.93	0.92	0.88	0.93	1.03	0.98	1.02	0.95	0.98	0.99	1.02	1.01	1.01	0.98	0.98	1.01	0.98	0.99	0.93	0.99	0.93
Italy	1.01	1.02	1.04	1.01	1.01	1.02	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.01	1.01	0.98	0.99	0.97	0.97	0.99	0.97	1.01	1.00	1.02	1.01	0.99	1.00	1.03	0.93	0.96
Luxembourg	0.99	1.02	1.02	0.99	1.01	1.00	1.00	1.00	1.00	1.01	1.00	1.02	1.01	1.00	1.01	0.99	0.98	0.97	0.77	1.05	0.80	0.93	0.93	0.87	1.03	0.93	0.95	1.00	1.05	1.06	1.04	0.88	0.92	1.02	1.01	1.03
Netherlands	1.00	1.02	1.02	1.01	1.01	1.02	1.03	1.00	1.03	1.03	1.00	1.03	1.01	1.00	1.01	0.98	0.99	0.97	0.99	1.01	1.01	1.00	0.99	0.99	0.99	0.98	0.97	0.99	1.01	1.00	1.01	0.99	0.99	1.02	1.00	1.02
Norway	1.00	1.01	1.01	1.01	1.01	1.02	1.01	1.00	1.01	1.01	1.00	1.02	1.00	1.00	1.00	1.08	0.99	1.06	1.00	1.02	1.02	0.98	0.99	0.96	0.98	0.93	0.93	0.96	1.03	0.99	1.02	0.99	1.01	0.96	1.01	0.97
Sweden	1.01	1.00	1.01	1.00	1.01	1.00	1.02	1.01	1.03	1.02	1.01	1.02	1.01	1.01	1.02	1.02	0.89	0.91	0.99	1.00	0.99	0.96	0.97	0.93	0.96	0.98	0.94	0.96	1.02	0.98	1.05	0.98	1.03	1.01	0.98	0.99
Switzerland	0.99	1.02	1.01	1.00	1.01	1.01	0.82	1.03	0.89	1.06	1.02	1.08	0.91	1.00	0.90	1.01	0.99	1.00	0.96	1.02	0.98	0.98	0.97	0.95	0.99	0.98	0.98	0.95	1.03	0.98	1.04	0.98	1.03	0.97	1.00	0.97
United Kingdom	1.01	1.06	1.06	1.01	1.00	1.01	1.02	1.00	1.01	1.00	1.01	1.01	1.01	0.99	1.00	1.10	0.95	1.04	0.99	1.01	1.00	0.98	0.99	0.97	0.98	0.97	0.95	0.97	1.05	1.01	1.04	0.96	1.00	0.97	1.01	0.98
Total Sample	1.00	1.03	1.03	1.01	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.00	1.00	1.01	1.00	0.96	0.96	0.98	1.02	0.99	0.99	0.97	0.96	1.00	0.97	0.97	0.97	1.03	0.99	1.03	0.98	1.01	0.98	0.99	0.98

Note: TEC = technical efficiency change, TC = technical change, TFP = total factor productivity.

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Under Pressure: How the Business Environment Affects Productivity and Efficiency of European Life Insurance Companies

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