Market Structure and the Efficiency of European Insurance Companies: a Stochastic Frontier Analysis[1]

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Abstract
This paper is motivated by the progressive liberalisation of the European insurance market in recent years. It uses stochastic frontier analysis to estimate Flexible Fourier cost and profit functions for European insurance companies. Separate frontiers are estimated for life, nonlife and composites companies. We adopt a maximum likelihood approach to estimation in which the variance of both one-sided and two-sided error terms is modelled jointly with the frontiers. This approach allows us to simultaneously control for the impact of heteroskedasticity on the estimation of scale economies as well as estimating the effect of firm size and market structure on X-inefficiency. The study draws on Standard & Poor's Eurothesys data set of financial reports for the period 1995 to 2001. This provides technical and non-technical accounts at year-end for life, non-life and composite insurance businesses in 14 major European countries. Our estimates suggest that most European insurers are operating under conditions of decreasing costs, and that company size and market share are significant factors determining X-inefficiency with respect to both costs and profits. Larger firms, and those with high market shares, tend to have more cost inefficiency but less profit inefficiency.

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1 Introduction

There is a growing interest and concern about the international competitiveness and efficiency of European financial institutions in general and insurance companies in particular. Over the past 15 years the European Union has gradually deregulated the financial services sector through a series of banking and insurance directives with a view to creating a single European market in financial services. For the first time, true price and product competition in both life and non-life insurance were introduced in European retail insurance markets[2]. The directives implemented the concept of the "single passport", whereby, from 1994, an insurer can do business in all EU countries provided that it is licensed in one EU country. The consequence of deregulation has been an unprecedented wave of mergers and acquisitions (M&As) of European financial institutions. From 1990-2002 there were 2,595 M&As involving European insurers of which 1,669 resulted in a change in control[3]. The presumption behind the creation of a single market is that increased competition across national boundaries will drive down costs through reduced X-inefficiency, and consolidation through M&As will further reduce costs as a consequence of scale economies. However, a corollary of the latter is that the increasing size of companies within their national markets will permit a degree of local market power and higher prices and profits[4].

In spite of these dramatic changes in European financial markets, there has been little research to date on the economic impact of these developments[5]. This is particularly true for the insurance market, where some of the more dynamic changes in market structure have been taking place. Rees and Kessner (2000) assess the direct effects of deregulation on the efficiency of German and British life insurance companies and find some (relatively modest) evidence which suggests that lighter regulation, competition and the risk of bankruptcy caused a significantly higher proportion of firms to achieve efficiency levels closer to those of the most efficient firms. Using DEA analysis, Cummins and Rubio-Misas (2001) find that consolidation in the Spanish insurance industry over the period 1989-1998 led to significant improvements in efficiency and to price reductions in both life and non-life insurance. Cummins and Weiss (2004) use an event study approach to identify the impact of European insurance mergers and acquisitions during the period 1990-2002 on shareholder value, and find clear gains from cross-border M&A transactions, but ambiguous results in relation to within-border transactions.

The objective of this paper is to model and measure cost and profit efficiency in the European insurance sector using stochastic frontier analysis (SFA), and to explore variations in efficiency in relation to firm size and market structure. A principal advantage of SFA in the estimation of cost and profit frontiers lies in its potential to discriminate between measurement error ("two-sided" error) and systematic inefficiencies ("one-sided" error) in the estimation process. However, the means by which this is achieved is inevitably sensitive to distributional assumptions, both in relation to the frontier itself and the stochastic nature of the error terms. We address these issues in two ways. The functional form assumed in our estimation is the Flexible Fourier, which has been shown to be particularly suitable where the size distribution of firms is highly skewed with large numbers of small units. Second, we recognise the potential for estimation bias due to heteroskedasticity in both the one- and two-sided errors by modelling these explicitly as functions of firm size and market share (see Kumbhakar and Lovell, 2001). This

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[2] See Cummins and Weiss (2004); 217

[3] Cummins and Weiss (2004); 232

[4] There are a number of reasons why firms retain advantages in their home markets in spite of deregulation. Differences in taxation and contract law, cultural heterogeneity, and informational advantages have all been cited as reasons for weak cross-border competition (see Cummins and Rubio-Misas, 2001, fn 6; Muller-Reichart , 2005).

[5] Some recent contributions relating to the banking sector include Kraft et al (2002), Schure and Wagenvoort (1999).

simultaneously addresses the frontier estimation bias due to heteroskedasticity[6] and measures systematic variations in efficiency due to size and dominance. This approach has considerable advantages over the more usual approach to estimating the impact of exogenous influences on (in)efficiency, in which the efficiency scores are used as dependent variables in a second stage regression. We apply this methodology using a panel from Standard's & Poor's Eurothesys data set for the period 1995 to 2001, consisting of year end technical, non-technical and balance sheet accounts from insurance businesses in 14 major European countries. Separate frontiers are estimated for life, non-life and composite firms. Efficiency scores are obtained and scale economies estimated.

This paper is structured as follows. Section 2 reviews hypotheses relating to the impact of competition and market structure on efficiency. Section 3 discusses the methodology behind estimation. Section 4 describes the data and section 5 discusses the results. A concluding section follows.

2 Competition and efficiency

2.1 Hypotheses

The rationale behind the explicit link between market structure and efficiency was first proposed by Hicks (1935), who argued that monopoly power gives managers a quiet life free from competition. This allows them to appropriate their share of monopoly rents through discretionary expenses or a reduction in their efforts (X-inefficiency). However, it was not clear why the existence of monopoly rents would encourage owners of monopolistic firms to turn a blind eye on slack managerial effort as opposed to a competitive market. This has given rise to complementary theories suggested by Liebenstein (1966) and Demsetz (1973). Liebenstein (1966) in particular provides an explanation as to why X-inefficiencies exist inside firms and why they are reduced by product market competition, which induces a challenge-response mechanism that reduces the managerial slack. The intuition is that the existence of imperfections in the internal organization of firms impact on the level of information asymmetries between owners and managers. Incomplete labour contracts make the effort of managers at least partially discretionary, since the production function is not wholly known and owners cannot therefore check the level of effort exerted by managers. Competition potentially reduces such X-inefficiencies in two ways. First, to avoid the personal cost of bankruptcy of the organisation, managers now have incentives to increase their work efforts. Secondly, the entry of other firms in the market enables owners to judge the performance of their organisation vis-à-vis the rivals and therefore have a better judgement of the level of effort exercised by managers and have the power to proceed to changes in management if necessary. Managers being aware of this have an additional incentive to increase their effort and reduce inefficiency. A few studies have formalized Leibenstein's works (e.g. Hart, 1983, Selten, 1986 and Scharfstein, 1988).

Demsetz (1973) proposes an alternative assumption, namely the efficient-structure hypothesis which predicts a reverse causality between competition and cost efficiency. The central argument here is that more efficient firms have lower costs which directly increase their profits. These firms are also able to capture larger market shares that may result in high levels of concentration. The greater efficiency may be in the form of X-efficiency, in which some firms have superior management or production processes that allow them to operate at lower costs and subsequently reap higher profits. The resulting higher market shares may also lead to higher market concentration. Alternatively, the greater efficiency may be in the form of scale efficiency, in which some firms simply produce at output levels closer to the minimum average cost point (the scale efficiency hypothesis). Firms operating at optimal economies of scale will

[6] This bias can be significant (see Khumbhakar and Lovell, 2000, Ch 7). Previous studies have attempted to reduce the problem by means of normalising all scale-related variables with respect to a given input or output variable (e.g. Berger and Mester, 1997). We believe it is preferable to model the nature of the heteroskedasticity explicitly.

have the lowest costs and the resulting higher profits will lead to higher market concentrations. In the efficient-structure hypothesis, the positive relationship between efficiency and market structure is spurious because efficiency is the principal determinant of market structure. There is therefore reverse causality running from efficiency to competition as compared to the "Structure-Conduct-Performance" paradigm. Given that higher market concentration means lower competition, there should be an inverse relationship between competition and efficiency. The efficient-structure hypothesis received some theoretical support with the influence of scale economies on the efficiency of firms (Martin, 1993 and Bertoletti et Poletti, 1996). Indeed, the existence of scale economies on a market means that an increase in the number of competitors results in higher average costs for each incumbent firm. Consequently, competition would decrease cost efficiency.

In a recent contribution, Choi and Weiss (2005) have outlined a framework for testing hypotheses on the relationship between market structure and efficiency in insurance markets. Of particular relevance to this paper is their formalization of the efficient structure hypothesis, distinguishing between the impact of scale efficiency and X-efficiency on performance. In their paper, they estimate equations for prices and profits in which cost and revenue efficiency scores as well as scale economies are used as independent variables. In our paper, we use a one-stage estimation approach to explore directly the relationship between market structure and cost or profit efficiency and at the same time use the estimated frontiers to calculate scale economies (see section 4 below).

2.2 Evidence

The empirical evidence relating competition and efficiency in the financial services industry is rather scarce. Of the very few studies available, most have been undertaken for the banking sector. Most of these studies have attempted to test the SCP paradigm or Demsetz's (1973) efficient-structure hypothesis. These studies measure cost efficiency using a stochastic frontier approach, while market structure is measured using market share or concentration indices. Because of the causality running from efficiency to market structure, empirical tests of the efficient-structure hypothesis usually tend to follow a two-stage approach, whereby measures of efficiency (X-efficiency or scale efficiency) are obtained in a first stage and then used in equations that regress market shares on efficiency measures. Berger (1995) finds weak evidence of a positive relationship between cost efficiency and market power while Berger and Hannan (1997) on the other hand, find that efficiency has a negative impact on market structure for U.S. banks. These same authors find evidence that market structure significantly influences X-efficiency (Berger and Hannan, 1995, 1997) while Goldberg and Rai (1996) fail to find evidence of this for European banks.

Hardwick (1997) examines the effects of increasing competition on the structure of the UK life insurance industry over 1989-1993 by employing a stochastic frontier approach. He reports high levels of economic inefficiency (costs are on average about 30% above the estimated cost frontier) and significant positive economies of scale. He argues that the principal beneficiaries from the European single market are likely to be large companies with lower levels of economic inefficiency.

Noulas (2001) analyses the performance efficiency of Greek non-life insurance firms over the pre-deregulation/consolidation period of 1991-1996 employing DEA approach. Average efficiency is found to be 64.69%. Moreover significant differences in efficiency among the firms were reported. Cummins and Rubio-Misas (2001) study the effects of deregulation and consolidation on Spanish insurance industry efficiency over 1989-1998 using DEA and Malmquist indices. They report low average cost efficiency (22.7% in 1998) which is mainly due to low allocative efficiency (41.2% in 1998). In addition, firms in the largest size quartile are found to be more cost efficient due to higher pure technical efficiency. Over the period, the proportion of firms operating with IRS reduced while that of firms with DRS increased due to consolidation. They report average TFP growth mainly due to technical efficiency growth with the productivity growth being driven by stock insurers rather than mutuals. The authors conclude that overall, there is substantial evidence that deregulation and consolidation have had beneficial effects on efficiency in the Spanish insurance industry. Fuentes et al. (2001), in contrast, report very low rates of productivity growth and technical change despite the deregulation process and expansion of activity for Spanish insurance firms for a relatively earlier period of 1987-1994 by employing Malmquist productivity indexes within the deterministic and parametric-stochastic frontier approaches.

Ennsfellner et al (2004) analyse whether changes in market structure and regulatory environment had an influence on the production performance of Austrian insurance companies over 1994-1999 by employing a Bayesian stochastic frontier. They show that the process of deregulation had positive effects on the production efficiency of the Austrian insurance companies. Mahlberg and Url (2000) assess the consequences of the Single Market Project of the EU on the German insurance industry (life, health and P-L) over 1992-1996 by employing DEA and Malmquist analysis. They report average VRS efficiency of 49%, CRS efficiency of 39% and scale efficiency of 78% with more firms experiencing DRS. Total factor productivity is found to be increased by 12.8%. However the results show that the increased competition did not cause efficiency scores to converge. There exist cost saving potentials and an increasing divergence between fully efficient firms and others. Moreover, the measured scale economies imply an L-shaped average cost curve for the industry and thus low cost savings potential from further merger activities.

Diacon et al (2002), provide the only cross-country analysis of the performance of European insurers. Using DEA, they analyse the efficiency of European specialist and composite insurers transacting log term insurance business in 15 European countries over 1996-1999. They report that average pure technical efficiency has declined since 1996 while the average scale and mix efficiencies increased between 1996 and 1998 only to decline sharply in 1999.

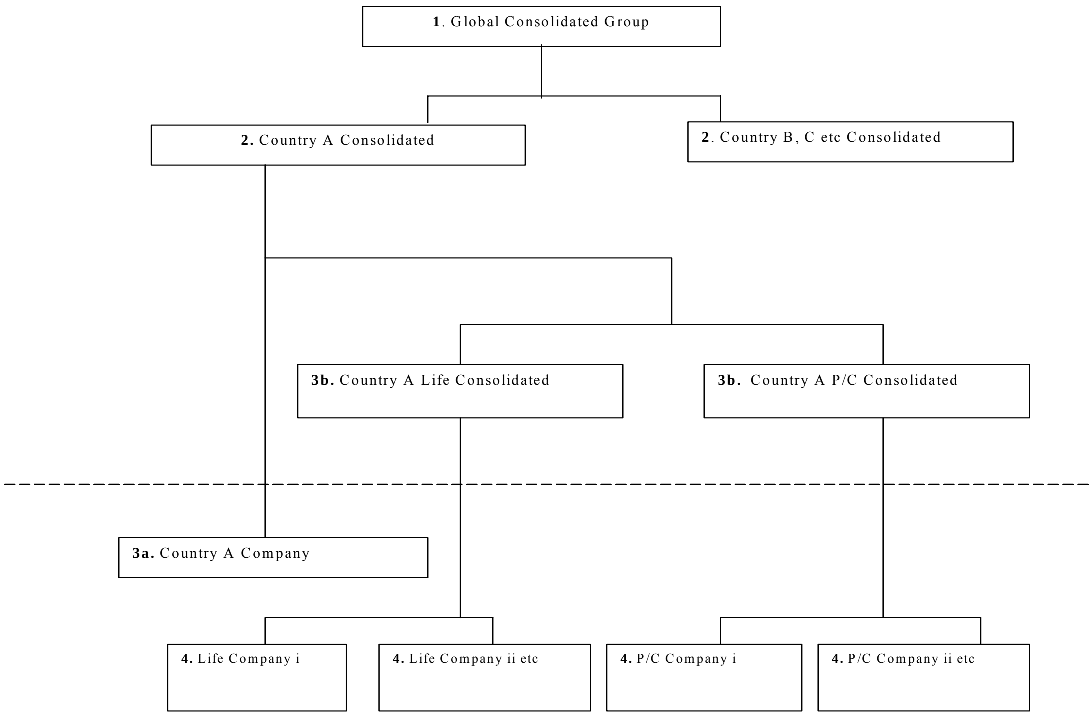
3 Data

3.1 Unit of analysis

The main source of data used in this paper is Standard and Poor's Eurothesys dataset of insurance company accounts for 14 major European countries, comprising Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the U.K. from 1995-2001.[7] The European insurance market is characterised by the co-existence of several distinctive organisational forms. There are many large, multinational composite companies selling both life and non-life products through a range of subsidiaries which may themselves specialise in one particular product line. These subsidiaries may have their operations summarised in consolidated accounts for regulatory and market value purposes. However, these subsidiary companies will typically have some (varying) degree of independence with which they conduct their business, and they do of course co-exist with a large number of fully independent companies who may choose to specialise in life or non-life business, or indeed, to engage in both. Figure 1 summarises a typical insurance holding-company structure. The dashed line indicates the partition of insurers analysed in this paper; our unit of analysis is the individual company operating in the insurance sector – those companies below the dashed line. The sector is classified into life business, non-life business and composite business.

Figure 1

[7] Our original data set spans the period 1994 to 2002. The year 1994 was dropped due to the use of lagged values (see below). We also applied a filtering criterion that sweeps out badly behaved companies in the dataset based on adjacent year's data and this meant that we were unable to use 2002 observations for the analysis.



3.2 Revenue, costs and profits

For each company and each year, we are able to construct consistent measures of revenue, profits and operating costs from the accounting data in Eurothesys. Revenue is defined as net earned premiums plus investment income, where net earned premiums are gross written premiums less outwards reinsurance premiums less the increase in unearned premium reserve (as reported in long-term (life) technical and property/casualty (non-life) technical accounts at the year-end). Costs are defined as total administrative costs and expenses before deductions for deferred acquisition costs and including investment management expenses and claims management costs (as reported in the technical and non-technical accounts at the year-end). Profits are the difference between revenue and costs so defined[8].

3.3 Output measures

There has been an extensive and unresolved debate in the literature about the appropriate measure of insurance firms' outputs (see Cummins and Weiss, 2000; pp791-793). Our view is that the product provided by insurers to their policyholders can best be viewed as the expected present value of the future claims that might be paid on those policies[9]. This is a latent unobservable variable and consequently must be measured using proxy variables. One such proxy is the premium income paid by policyholders, but this would normally exceed the expected value of future claims due to a combination of producers' and consumers' surplus. An alternative proxy is the insurer's estimation of incurred claims – that is, claims paid together with the reserves set against future payments. This may differ from the expected value of future claims for two reasons: the value of claims paid is subject to random fluctuation, and the reserving

[8] Thus profits are defined without deducting net incurred claims costs, as in Berger, Cummins and Weiss (1997) and Berger, Cummins, Weiss and Zi (2000). This avoids a confusion between profits and our measure of output (see below) and has the added advantage that profits are almost always positive. To allow for the few cases where profits are negative in a logarithmic model, we add to the profit variable a constant equal to $[1+|\min(\Pi)|]$.

[9] Obviously, some policyholders extract more value (consumers' surplus) from this product than others depending on their "risk premium".

estimates are subject to prediction error[10]. While in principle either proxy is valid (Cummins and Weiss (2000), fn 20), for the purpose of this paper the use of incurred claims is preferable, as we are concerned to explore the pricing behaviour of insurers and premium income would clearly not be an exogenous measure of output in that context (see Yuengert, 1993).

To approximate the output of insurers, we therefore use net incurred claims on life and nonlife policies respectively. These are defined for each type of business as gross claims paid less claims received from reinsurers plus increase in loss reserves plus bonuses and rebates, but before the addition of claims management costs. They can be calculated for each insurer from the life and nonlife technical accounts at the year-end.

3.4 Inputs

From Eurothesys we have measures of total capital and reserves, technical provisions, and other debt capital. *Total capital and reserves* are defined to include shareholders' capital, capital and reserves, participating rights capital, special untaxed reserves, minority interests, subordinated liabilities, subordinated debt, and the long-term fund for future appropriations as reported in the balance sheets at start of year. *Total technical provisions* include unearned premium reserves and loss reserves, and mathematical reserves for linked and unlinked long-term business as reported in the balance sheets at start of year[11]. *Debt capital* is defined as total borrowings from creditors (such as banks or reinsurers); as reported in the balance sheets at start of year. We assume that debt capital together with labour are variable inputs – capable of being changed in the short run. We follow Berger, Cummins and Weiss (1997) and Berger, Cummins, Weiss and Zi (2000) by assuming that total capital and reserves, and technical provisions, are fixed inputs - stocks which have been built up over a long time and are difficult to adjust quickly.

3.5 Input prices

For input prices we have an insurance-specific wage variable and a rate of interest variable to reflect the cost of debt capital. The wage variable was extracted from the nominal wages data classified under 'Insurance and pension funding sector, except compulsory social security' provided in *Eurostat* and the *October Labour Inquiry.* The rate of interest variable is obtained from long-term government bond rates (from *Eurostat* and individual countries' central banks).

3.6 Summary statistics

Table 1 presents summary statistics for the variables used in the analysis as described above. The dispersion in all financial variables is evident.

[10] The estimation problems raised by measurement error are considered in section 4.2 below.

[11] This is sometimes referred to as "policyholder-supplied debt capital" – see Berger, Cummins and Weiss (1997).

Table 1- Summary Statistics on Key Variables

Variable	Mean	Std. Dev.	Min	Max
Assets	2935.11	11266.01	2	507480
Revenue	695.51	2221.65	1	81523
Costs	95.94	409.80	1	21479
Profits	612.17	1926.93	1	60049
Capital	339.63	1499.22	1	46397
Technical provision	2317.19	8288.50	1	323947
Debt capital	617.93	3412.48	1	183533
Claims (life)	422.17	1696.93	0	55873
Claims (nonlife)	126.26	388.87	0	11881
Claims (total)	548.44	1740.63	1	55873
Interest rate (%)	5.97	1.45	4.49	12.205
Yearly wages (Euros)	53419.05	7887.44	29236	65957

Note: All variables measured in million euros apart from wages which are in euro units.

Table 2 shows developments in the structure of the European insurance sector since 1995. The table is based on data from the Center for European Assurance (CEA), which provides yearly reports on the insurance sector of most of the European countries. Included in these reports is a 5-firm, 10-firm and 15-firm concentration ratio for each of the countries covered and for both the life and the non-life insurance market. The picture that emerges from table 2 is that competition in the insurance sector has not intensified much in many of these countries between 1995 and 2001. In the non-life insurance market, very few domestic markets seem to have opened up further to competition. In the life insurance market, however, the leading markets such as the UK, Germany, France and the Netherlands do seem to have become less concentrated over the period.

Table 2: Five-firm concentration ratios in life and non-life business[12]

	Life Specialists			Non-life specialists		
	1995	1998	2001	1995	1998	2001
Austria	57.40	56.20	54.90	45.40	48.40	48.90
Belgium	61.10	57.80	57.50	74.40	73.50	73.10
Germany	.	46.00	27.70	31.80	31.20	31.60
Denmark	68.70	70.80	70.20	58.30	56.20	56.20
Spain	27.80	27.80	36.80	26.00	32.90	41.10
Finland	90.50	89.30	91.70	99.70	99.70	94.75
France	61.90	56.80	54.30	63.90	58.20	52.50
Ireland	39.60	58.80	73.30	33.90	56.70	70.50
Italy	36.60	35.70	59.10	34.70	30.20	40.05
Luxembourg	.	.	45.30	.	34.00	64.90
Netherlands	80.90	56.60	51.80	78.20	66.50	59.75
Portugal	79.00	61.30	72.20	94.10	82.40	77.80
Sweden	.	98.30	89.00	50.80	64.90	74.20
U.K.	66.20	47.90	36.80	15.90	35.70	47.50

Source: Centre for European Assurance (and authors' extrapolations and computations).

4 Estimation

4.1 Cost and profit functions

Given the difficulties surrounding the definition and measurement of outputs in the insurance sector, the direct (primal) estimation of production functions in order to explore supply equations can be problematic. It is therefore more common to use the dual approach and estimate the supply conditions directly from cost and profit functions. This approach is based on the assumption of an objective function (either cost minimisation or profit maximisation). A cost function is thus defined as the minimum cost (C) of producing a particular output vector (**x**) with given input prices (**w**):

$$C = C(\mathbf{x}, \mathbf{w}) \tag{1}$$

whereas a profit function is normally defined as the maximum profit (Π) associated with particular input prices (**w**) and output prices (**p**):

$$\Pi = \Pi(\mathbf{p}, \mathbf{w}) \tag{2}$$

These functions must satisfy a number of properties to ensure that they are consistent with the assumed objective behaviour. In particular, they should be continuous, twice differentiable, and symmetric, as well as being homogeneous of degree one in all prices.

In addition it is also assumed in the above that the price and output vectors are exogenous. In the case of the cost function, this implies that insurers choose input levels in order to mimimise the costs involved in producing a given output. In the case of the standard profit function, this implies that insurers are price takers in all markets and that they seek to maximise profit by selecting output and input levels. We prefer to modify these assumptions in this paper. First, as discussed above in section 3.4, we believe that some of the inputs described there are unlikely to be significantly under the control of management in typical planning periods; we therefore hold these inputs fixed in both cost and profit functions. The cost function to be estimated here is therefore written as:

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[12] The extrapolation exercise for this measure resulted in negative and over 100 percent ratios; so these are excluded from the analysis, and thus explains missing data for some countries and years in this table.

$$C = C(\mathbf{x}, \mathbf{w}, \mathbf{z}) \tag{3}$$

where the vector **z** represents the fixed inputs.

Second, given our objective in this paper of exploring the extent to which market power has evolved in the European insurance market post-liberalization, it seems inappropriate to assume that the insurers are price takers in all markets. To address this problem, we follow Humphrey and Pulley (1997) and others in defining an "alternative" profit function in which insurers are assumed to set prices in order to maximise profits associated with a given output level and fixed inputs:

$$\Pi = \Pi(\mathbf{x}, \mathbf{w}, \mathbf{z}) \tag{4}$$

The functions as presented above at (3) and (4) are deterministic – they ignore the possibility of measurement error and they assume perfect cost minimisation or profit maximisation at the specified level of activity. Because both measurement error and X-inefficiency are invariably present, the estimation process required to fit the cost and profit frontiers has to find a way to separate these out, and, if necessary, estimate their structure. Stochastic frontier analysis (henceforth SFA) represents one approach to this problem, and the following section describes the techniques adopted in this paper.

4.2 Functional form and distributional assumptions

The analysis of efficiency in the services industry using SFA has led researchers to estimate a wide range of functional forms for cost and profit frontiers[13]. Generally, the more parameters in the estimated function, the more flexible it is, such that it is possible to estimate a frontier which is as close as possible to the "true" (non-parametric) frontier. While the translog function is generally considered a flexible functional form, the superiority of the Fourier functional form has appealed to many researchers in terms of its capacity to globally approximate the underlying function over the entire range of data.[14] This functional form has been shown to provide a better fit of the data than translog (e.g. McAllister and Mcmanus,1993; Mitchell and Onvural, 1996; Berger and Mester, 1997). In this study, for both functions, we therefore use the Flexible Fourier (FF) specification, given as[15]:

$$\begin{aligned}
\ln Y = {} & \alpha + \sum_{i=1}^{n} \beta_i \ln x_i + \sum_{k=1}^{m} \gamma_k \ln p_i + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i . \ln x_j \\
& + 0.5 \sum_{k=1}^{m} \sum_{l=1}^{m} \gamma_{kl} \ln p_k . \ln p_l + 0.5 \sum_{i=1}^{n} \sum_{k=1}^{m} \delta_{ik} \ln x_i . \ln p_k \\
& + \sum_{j=1}^{m+n} [\phi_j \sin(z_j) + \varphi_s \cos(z_j)] + \sum_{j=1}^{m+n} \sum_{k=1}^{m+n} [\phi_{jk} \sin(z_j + z_k) + \varphi_{jk} \cos(z_j + z_k)] \\
& + \sum_{j=1}^{m+n} \sum_{k=1}^{m+n} \sum_{l=1}^{m+n} [\phi_{jkl} \sin(z_j + z_k + z_l) + \varphi_{jkl} \cos(z_j + z_k + z_l)] \\
& + \sum_{j=1}^{m+n} \sum_{k=1}^{m+n} \sum_{l=1}^{m+n} \sum_{m=1}^{m+n} [\phi_{jkl} \sin(z_j + z_k + z_l + z_m) + \varphi_{jkl} \cos(z_j + z_k + z_l + z_m)] + v_i \pm u_i
\end{aligned} \tag{5}$$

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[13] These include Cobb-Douglas, Box-Cox, quadratic, the composite function, translog and the flexible Fourier form.

[14] This is due to the addition of trigonometric transformations of the variables to the translog function (the translog function is thus nested within the Fourier function). It is therefore particularly appropriate where the data cover a wide range of company sizes, as is the case here.

[15] The specification here assumes trigonometric terms up to the fourth level; the number of levels included is normally chosen by reference to a view about the total number of terms which are optimal (typically $N^{2/3}$). We choose to exclude interactions of the trigonometric terms to avoid problems of multicollinearity.

where Y represents either costs or profits. The x variables are outputs and fixed inputs; the p variables are the prices of the variable inputs. The z variables inside the trigonometric terms are rescaled values of the original (logged) variables, such that each rescaled value is in the interval $\left[0, 2\pi\right]$. As in Berger & Mester (2003), to reduce approximation problems, we cut 10 % off each of the end of the $\left[0, 2\pi\right]$ interval, such that the rescaled value spans the interval $\left[0.1\times 2\pi, 0.9\times 2\pi\right]$.[16] The measurement error (v_i) and X-inefficiency term (u_i) are now included in this specification. Because the inefficiency term is expected to increase costs and decrease profits, the sign on u_i is positive or negative accordingly. Consistent maximum likelihood estimation of the above functions for each sector of the industry will reveal both the structure of the cost and profit functions (and therefore permit analysis of scale economies in each sector), and the firm-specific X-inefficiency effects. The error term distributional assumptions used in estimation are discussed below in section 4.3.

For each company (i) and each year (t) from 1995-2001, we have from Eurothesys consistent measures of costs (C_{it}) and profits (Π_{it}). We measure outputs in terms of net incurred life and non-life claims. We recognise that there are measurement problems with this choice of output measure. As discussed above incurred claims measured at the year end (X^l_{it} and X^n_{it}) could be used as proxies for the latent expected present value of future claims on current policies. However, stochastic variation in paid claims and prediction error on future claims leads to the potential for estimation bias due to measurement error. One solution to this problem is to use the lagged measurements of claims - incurred claims at the previous year end (X^l_{it-1} and X^n_{it-1}) – as instrumental variables for the contemporaneous measurements (see Cummins and Weiss, 2000; fn 20).

Eurothesys also provides measures of year end share capital and reserves (K_{it}) and technical provisions (T_{it}), each of which we assume to be fixed inputs (see section 3.4 above). Because of the potential for a similar measurement error problem as with outputs, we again use the measurements from the previous year end K_{it-1} and T_{it-1}.

Finally, corresponding to the assumed variable inputs (labour and debt), we have an insurance-specific wage variable (w_{it}) and a rate of interest variable (r_{it}) reflecting the cost of debt. Given these variables, we can specify cost and (alternative) profit functions as follows:

$$\text{Cost:} \quad \frac{C_{it}}{w_{it}} = \psi_C\left(\boldsymbol{X}_{it-1}, K_{it-1}, T_{it-1}, \frac{r_{it}}{w_{it}}, t, u_{it}, v_{it} \right) \tag{6}$$

$$\text{Profit:} \quad \frac{\Pi_{it}}{w_{it}} = \psi_\Pi\left(\boldsymbol{X}_{it-1}, K_{it-1}, T_{it-1}, \frac{r_{it}}{w_{it}}, t, u_{it}, v_{it} \right) \tag{7}$$

where $\psi_C(.)$ and $\psi_\Pi(.)$ represent the flexible Fourier functional forms as specified above in (5). $\boldsymbol{X}_{it-1}$ represents the appropriate vector of net incurred claims from the previous year end for the relevant category of insurer (life, nonlife, composite). The inclusion of a time variable (t) ensures that changes over time in technology and the underwriting cycle can be captured. By dividing through the dependent variables and the rate of interest by the wage rate, these specifications guarantee that the input prices are included in a way that ensures linear homogeneity[17]. Symmetry can also be imposed in estimation.

[16] The formula for the i'th rescaled variable is $z_i = 0.2\pi - (\mu_k \times a_k) + (\mu_k \times y_i)$, where y_i is the original variable, and $\mu_k \equiv [(0.9\times 2\pi) - (0.1\times 2\pi)]/(b_k - a_k)$. $\left[a_k, b_k\right]$ is the range of y_i over the sample.

[17] In principle, the linear homogeneity property is not required for the alternative profit function, but we apply the constraint here in order to obtain consistency between cost and profit functions.

4.3 Estimation methodology

SFA methodology was originally proposed independently by Aigner, Lovell and Schmidt (1977) and Meeusen and Van Den Broeck (1977), and has since generated an extensive literature, both methodological and empirical (e.g. Forsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990), Battese (1992) and Greene (1993)). Explicit assumptions about the distribution of the measurement errors and the X-inefficiency terms allow the frontiers to be estimated and scale economies or diseconomies revealed. As they are assumed to capture the effect of measurement error, the v_{it} terms are typically assumed to be random errors independently distributed as $N(0,\sigma_v^2)$. These are therefore often referred to as the "two-sided" error terms as they are symmetrically distributed around the "true" frontier. By contrast the inefficiency terms u_{it} are assumed to have an independent distribution which is truncated below by the frontier itself: For this reason these inefficiency terms are often referred to as the "one-sided" error terms. For example, it is sometimes assumed that $u_{it} \sim N^{+}(\theta,\sigma_u^2)$, where if $\theta=0$ the assumed distribution is half-normal, and if $\theta\neq0$ the assumed distribution is truncated normal [18].

A less frequently explored issue is the impact of exogenous variables which have a significant influence on the X-inefficiency of the insurer. Early empirical papers (e.g. Pitt and Lee, 1981 and Kalijaran, 1981) raised the issue of systematic determinants of the X-inefficiency of firms and adopted a two-stage approach to the problem. In the first stage, the firm-specific inefficiency effects u_i, assumed to be identically distributed, are retrieved from the estimated stochastic frontier. In the second stage, the predicted inefficiency effects are used as a dependent variable in a regression model in which explanatory exogenous variables seek to explain differences in these effects (e.g. Mester, 1993). A recurring criticism of this two-stage approach is that the second stage analysis of systematic determinants of the inefficiency effects contradicts the assumption of an identical distribution of these effects that is made in the first stage, when the stochastic frontier is estimated. This and other criticisms have given rise to a substantial empirical literature on the modelling of the inefficiency effects, leading to the emergence of a one-stage approach, whereby these inefficiency effects are modelled jointly with the frontier[19].

One approach to estimating the effect of systematic influences on X-inefficiency is to assume that the truncation point of the one-sided distribution (θ) shifts depending on the exogenous factors assumed to determine efficiency. This is known as the conditional mean approach (Huang and Liu (1994); Battese and Coelli (1995)), where the one-sided error is modelled as $N^{+}(\gamma' s_i,\sigma_u^2)$ where and s_i is a vector of systematic influences on efficiency (e.g. firm size and market share). In these models the two-sided error is typically assumed to be $N(0,\sigma_v^2)$.

However, while this approach will identify systematic factors correlated with shifts in the mean of the one-sided error, it retains the assumption that the variances of both types of error are constant. This assumption may be implausible and can lead to inconsistent estimates. First, homoskedasticity in the two-sided error term may not be an appropriate assumption, especially when using incurred claims as measures of outputs as in our case.[20] The size of an insurer is likely to affect the variability of costs and

[18] Alternative distributions have been suggested; Yuengert (1993), for example, uses a gamma distribution to characterise the X-inefficiency effects.

[19] Contributions to the development of the one-stage approach include Khumbhakar, Ghosh and McGuckin (1991); Reichsneider and Stevenson (1991); Yuengert (1993); Simar, Lovell and Vanden Eeckaut (1994); Huang and Liu (1994); Caudill, Ford and Gropper (1995) and Battese and Coelli (1995), Wang and Schmidt (2002) and Wang (2003) amongst others. For a discussion and review of this literature, see Kumbhakar and Lovell (2000), Ch 7.

[20] If σ^2_{vi} varies directly with company size, then ignoring heteroscedasticity results in efficiency scores that are biased upward for relatively small producers and biased downward for relatively large producers, since heteroscedasticity is

profits.[21] Similarly, any systematic influence on X-inefficiency will potentially lead to heteroskedasticity in the one-sided error term, and Caudill et al (1993) have shown that if this is ignored there can be significant estimation biases which affect both the shape of the estimated frontier and the efficiency effects[22][23].

In the light of the above, we adopt the procedure suggested by Khumbhakar and Lovell (2000) and explicitly model the variances of both types of error when fitting the cost and profit functions. The error variances are modelled simultaneously with the frontier as $u_{it} \sim N^{+}(0,\sigma_{ui}^{2})$ and $v_{it} \sim N(0,\sigma_{vi}^{2})$ where

$$\sigma_{ui}^{2} = g_{u}(s_{i},\phi_{ui}) \tag{8}$$

$$\sigma_{vi}^{2} = g_{v}(s_{i};\phi_{vi}) \tag{9}$$

s_i as before denotes a vector of systematic influences[24]; ϕ_{ui} and ϕ_{vi} are coefficient estimates from the one-sided and two-sided heteroskedasticity models respectively. Khumbhakar and Lovell (2000) point out that this approach offers the possibility of solving two problems at once – correcting for heteroskedasticity and incorporating exogenous influences on X-inefficiency. In our estimates below, we test for the impact on the error structure of firm size (measured by the log of the firm's total assets), domestic market share (measured by the ratio of the firm's net written premium to the industry aggregate net written premium income for the relevant year, sector and country), and organisational structure (whether the firm had a mutual or stock ownership structure).

Maximum likelihood estimation techniques are required to simultaneously estimate the parameters of the stochastic frontier and of the heteroskedasticity models. The cost and profit efficiency scores are estimated using the formula:

$$E_i = \exp(\pm u_i) \tag{10}$$

where the sign depends on whether u_i is estimated from the cost or profit function.

Once the maximum likelihood parameter estimates are available for the cost frontier, it is possible to estimate ray scale economies using the formula for the elasticity of scale and evaluating it at the mean output and fixed input levels for the relevant sample:

$$S = \sum_{i} \frac{\delta \ln C}{\delta \ln x_i} \tag{11}$$

S is the sum of the partial derivatives of the cost function with respect to each of the (logged) output and fixed input variables. That is, it measures the proportionate increase in total costs at the frontier as the mean vector of outputs and fixed inputs is increased by a given proportion. If S<1, we have decreasing costs (economies of scale); if S>1 we have increasing costs (diseconomies of scale). We evaluate this

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improperly attributed to technical efficiency. Given the joint estimation of both frontier and efficiency effects, this could have the consequence of underestimating the extent of economies of scale.

[21] The two-sided error term *v*, which measures the effect of measurement error and random shocks, might be expected to have more variability amongst larger companies as a simple consequence of scale.

[22] For a review of the biases associated with ignored heteroskedasticity in both error terms, see Khumbhakar and Lovell (2000), p115-122.

[23] Yuengert (1993) incorporated heteroskedasticity into a frontier model of life insurance firms using a gamma distribution for the one-sided error, whereas we assume the half-normal distribution. Yuengert's model of heteroskedasticity was restricted to an assumption that the variance of the error terms varied across seven firm size classes.

[24] We assume a loglinear model for these relationships: i.e. g_v(.)=exp(.) and g_u(.)=exp(.)

below for varying firm size groups, constructed by dividing each sample of business types (life, nonlife, composites) into asset deciles, and obtaining the mean vector of outputs and fixed inputs for each decile[25].

5.0 Results and Discussion

5.1 Heteroskedasticity, cost and profit efficiency

The parameter estimates from the six Flexible Fourier functions (cost and profit functions for three business types) are presented in the Appendix. These are estimates corrected for heteroscedasticity in both error terms. Each regression fits the data well when judged by the likelihood ratio tests of overall model fit. The chi-squared tests of the restrictions implied by translog functional form fail to reject the null that the FF terms are jointly greater than zero. The FF parameter estimates by themselves have little informational value; they are simply means to the end of producing a frontier with which to estimate company-specific cost and profit efficiency scores. Of more interest are the coefficient estimates from the heteroskedasticity models, which we report below for the six frontiers (Tables 3 and 4). The upper part of each table shows the coefficient estimates and standard errors for the model of the two-sided error term σ_{vi}^2; the lower part of each table shows the coefficient estimates and standard errors for the model of the one-sided error term σ_{ui}^2.

Table 3 shows that, where significant, the coefficients estimated on firm size and market share for the one-sided error term tend to be positive, particularly for specialist companies, indicating that size tends to increase X-inefficiency in the European market. By contrast, the variance of the two-sided error term tends to be negatively related to size and market share, implying that costs fluctuate more for a given level of activity in small firms.

Table 3: Impact of firm size and market share on cost efficiency

	Life		Nonlife		Composite	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
σ_{vi}^2 :						
Ln(assets)	-0.040**	0.018	0.016	0.018	-0.015	0.051
Mkt share (life)	-0.002	0.006			-0.085***	0.025
Mkt share (nonlife)			-0.033***	0.008	-0.026*	0.016
σ_{ui}^2 :						
Ln(assets)	0.975***	0.045	1.024***	0.054	0.440	0.298
Mkt share (life)	-0.101	0.115			0.028	0.097
Mkt share (nonlife)			-0.067	0.106	0.078**	0.030

Table 4 shows the equivalent results for the alternative profit function. In relation to the one-sided error, there is a consistent increase in profit efficiency with firm size and with the share of the domestic market, confirming perhaps the ability of larger firms to use both domestic and Europe-level market power to

[25] As S is a linear combination of the FF coefficient estimates, we calculate appropriate standard errors around these estimates from the estimated variance-covariance matrix.

charge higher premiums[26]. It appears that firm size increases the two-sided error, implying a strong size-related increase in the volatility of profit efficiency.

Table 4: Impact of firm size, market share and mutuality on profit efficiency

	Life		Nonlife		Composite	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
σ_{vi}^2 :						
Ln(assets)	0.316***	0.035	0.418***	0.027	0.382***	0.060
Mkt share (life)	0.038***	0.009			0.021	0.025
Mkt share (nonlife)			-0.049***	0.007	-0.044**	0.018
Mutual	1.292***	0.099	-0.521***	0.134		
σ_{ui}^2 :						
Ln(assets)	-0.259***	0.035	-0.279***	0.039	-0.489**	0.113
Mkt share (life)	-0.190***	0.040			0.057	0.055
Mkt share (nonlife)			-0.852***	0.122	-1.658***	0.563
Mutual	0.732***	0.102	-0.033	0.116		

5.2 Cost and profit efficiency scores

We now report the cost and profit efficiency scores retrieved from each of the cost and profit functions estimated. Table 5 shows the results broken down by firm size. The table shows the mean scores for firms which fall into nine distinct size groupings within each business sector. The size groupings were determined by dividing the distribution of total company assets within each sector into deciles. Cost efficiency is relatively high for smaller companies in all sectors, but then declines with increasing size, most severely in the life insurance sector, and least severely for composite firms. Profit efficiency by contrast increases with size for firms in all insurance sectors, and this is particularly marked for composite firms. Overall, the most significant profit efficiency losses are experienced in the bottom two or three deciles of the size distribution; for firms larger than this, the gradient is relatively shallow, perhaps indicating that the benefits of size in terms of higher premiums are partially offset by the cost inefficiency effects which increase with size.

Table 5: Mean efficiency scores by firmsize

	Cost			Profit		
Asset deciles	Life	Nonlife	Composite	Life	Nonlife	Composite
10	0.980	0.986	0.984	0.764	0.741	0.777
20	0.962	0.978	0.981	0.798	0.763	0.832
30	0.947	0.972	0.976	0.829	0.782	0.924
40	0.934	0.965	0.973	0.841	0.800	0.897
50	0.921	0.956	0.970	0.849	0.813	0.917
60	0.905	0.946	0.964	0.859	0.843	0.947
70	0.881	0.934	0.962	0.858	0.862	0.946

[26] Interestingly, Choi and Weiss (2005) also find a positive (but insignificant) effect of market share on profits for US non-life insurers when using company data and correcting for heteroskedasticity (Table 5, p657). Their results for group data are not strictly comparable with ours.

80	0.851	0.915	0.931	0.869	0.892	0.964
90	0.807	0.892	0.932	0.880	0.909	0.963

Table 6 summarizes the mean cost and profit efficiency scores across countries. Clearly, given the results in Table 5, the variations across countries may well be chiefly determined by variations in average firm size across countries. Nevertheless, certain patterns emerge. First, the cost efficiency of composites appears not to vary very much across countries, whereas the cost efficiency of nonlife specialists companies is lower in the major markets of Germany, France, the UK and the Netherlands. As far as profit efficiency is concerned, the results vary across sectors. The lowest mean profit efficiency scores for life insurers are found in Austria, Italy and the UK. Germany, Denmark and Sweden also do relatively poorly in this sector. For the nonlife sector, the major markets of Germany, the UK, France and Italy do relatively poorly, along with Austria, Sweden and Denmark. The profit efficiency of composites is, on the whole good, as described above, but the countries with relatively low profit efficiencies in this sector are Austria, Sweden and the UK.

Table 6: Mean efficiency scores by country

	Cost			Profit		
Country	Life	Nonlife	Composite	Life	Nonlife	Composite
Austria	0.941	0.952	0.964	0.724	0.842	0.871
Belgium	0.934	0.954	0.965	0.913	0.887	0.918
Germany	0.871	0.914	0.942	0.854	0.846	0.943
Denmark	0.926	0.956		0.829	0.849	
Spain	0.936	0.953	0.966	0.893	0.870	0.926
Finland	0.936	0.963		0.880	0.903	
France	0.883	0.913	0.956	0.869	0.848	0.935
Ireland	0.946	0.953	0.960	0.894	0.910	0.998
Italy	0.920	0.940	0.957	0.813	0.812	0.958
Luxembourg	0.958	0.970		0.900	0.966	
Netherlands	0.878	0.942	0.961	0.896	0.885	0.967
Portugal	0.964	0.968	0.952	0.903	0.902	0.974
Sweden	0.914	0.945	0.865	0.842	0.815	0.877
U.K.	0.867	0.943	0.954	0.811	0.770	0.900

Finally, table 7 below summarises the mean efficiency scores depending on whether the company is known to have a mutual or a stock organisational form. There is reltively insignificant differences in terms of cost efficiency, but mutuals tend to have lower profit efficiencies in the life and composite sectors.

Table 7: Mean efficiency scores by business type

	Cost			Profit		
Business type	Life	Nonlife	Composite	Life	Nonlife	Composite
Stock	0.895	0.934	0.956	0.853	0.833	0.924
Mutual	0.876	0.944	0.972	0.813	0.838	0.870

5.3 Scale economies

While the X-efficiency scores discussed in the previous section give an indication of the systematic factors associated with managerial performance at given output levels, they do not tell us whether European insurers have chosen to adopt an appropriate scale of operation at the company level. Table 8 summarizes the estimated ray scale economies (*S*) as derived from the parameter estimates of the FF cost frontiers. The results are broken down by firm size; as before the size groupings were determined by dividing the distribution of total company assets within each sector into deciles. The output/fixed input rays were then determined by the means for these variables within each size group for each sector. Standard errors were calculated using the variance-covariance matrix from the frontier estimates.

Insurance companies of all types appear to be mainly operating under conditions of decreasing costs (increasing returns to scale). This is particularly true of life specialists and composites, for which even the largest firms are experiencing decreasing costs. For nonlife specialists, a similar pattern of decreasing costs is found for small to medium size firms, but the largest 20% of nonlife specialists are operating under constant returns to scale. For no size groups or business types is there any evidence of decreasing returns to scale.

Table 8: Cost elasticities of scale (*S*) by firm size

Asset	Life		Nonlife		Composite	
deciles	*S*	s.e.	*S*	s.e.	*S*	s.e.
10	0.5188	0.0512	0.5210	0.0604	0.6460	0.2796
20	0.5647	0.0388	0.6026	0.0449	0.7037	0.0835
30	0.6720	0.0335	0.6405	0.0370	0.8677	0.0714
40	0.7934	0.0296	0.6385	0.0295	0.7321	0.0546
50	0.8853	0.0278	0.6870	0.0255	0.6988	0.0533
60	0.8985	0.0303	0.7646	0.0253	0.7279	0.0524
70	0.8724	0.0302	0.8618	0.0260	0.7875	0.0533
80	0.8022	0.0318	0.9571	0.0339	0.8302	0.0482
90	0.7196	0.0399	1.0239	0.0458	0.8034	0.0715

The lack of evidence of decreasing returns in insurance production is in line with findings of previous research based on parametric frontiers (e.g. for life insurance, see Grace and Timme, 1992; Yuengert, 1993; Hardwick, 1997). This is perhaps to be expected at this level of analysis, since international conglomerate groups which wish to operate beyond minimum efficient scale in any one national market can simply establish multiple sister subsidiaries (as described in figure 1 above) and generate benefits analogous to multiplant economies of scale.

6 Conclusion

This paper uses a stochastic frontier methodology to model the efficiency of European insurance companies during the deregulation period. We estimate flexible form frontiers for the three main business types observed in the EU: life and nonlife specialists, and composite companies which produce both type of insurance product. We adopt a one-stage approach to estimation that simultaneously controls for the effect of size and market share on X-efficiency, and also corrects for the potential estimation bias arising from heteroskedastic error terms. The estimated frontiers are then used to explore the scale economies under which European insurance companies are operating, and to compare these with the estimated cost and profit efficiency scores. We believe that this study is one of the first to explore these issues in the enlarged European Union - an insurance market with the potential for true price and product competition. The international perspective allows us to take advantage of national as well as temporal variation in interest rates and input and output prices - and to explore the impact of differences in local market concentration and competition.

We have used company level data in this paper, and it is important bear in mind that one feature of the emerging European insurance market has been the growth of consolidated groups across Europe which bind together companies which might be life or nonlife specialists, or even composites operating within a group structure. These groups exist alongside independent companies of all types which of course have access to both domestic and European markets. The importance of this distinction is to emphasise that consolidation in Europe may be in part a response to the scale and efficiency effects reported here. While we find that scale economies are prevalent, it is also the case that larger companies have significantly higher levels of cost inefficiency, presumably as a result of coordination difficulties in larger organisations. It is possible that consolidation through acquisition is a response to this situation. We also find that the domestic market share of insurers is positively associated with profit efficiency. The implication is that insurers can still exercise market power at the domestic level, even in an era with supposedly open borders. This may be another factor behind expansion by acquisition. Moreover, because we find that firm size improves profit efficiency even after controlling for market share, our results are consistent with extensive returns to scale permitting higher profitability for larger firms even where markets are competitive, and even where cost inefficiency rises with scale.

Finally, a natural question when addressing the relationship between domestic and European markets is whether to estimate a common frontier for Europe as a whole or whether to estimate country-specific frontiers. In this study, we have adopted a common European frontier and assumed that all the insurance companies in the 14 major countries operate on or below this common frontier. The presumption has been that the underlying technology of producing insurance is the same, and the accounting data consistent, across all European countries. The impact of country-specific influences on the performance of firms relative to this frontier has been partially addressed through estimates of the impact of domestic market shares on efficiency. The significance of these estimates indicates that the single European market is not as yet a complete reality, but the fact that the largest companies Europe-wide tend to be the most profit-efficient is perhaps evidence that market power at the European level can also be effective. The overall message for European regulators would seem to be that there remains a continuing case for the pragmatic balancing of the benefits of size against the detrimental effects of market concentration.

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Appendix: Frontier Parameter Estimates

Life Cost Function

Variable	Parameter	s.e	Variable	Parameter	s.e
lnX1	-4.356***	1.317	sin(Z1+Z2+Z3)	-0.375***	0.089
lnX2	3.085***	0.815	sin(Z1+Z2+Z4)	-0.287	0.179
lnX3	2.485**	1.128	sin(Z1+Z3+Z4)	-0.138	0.103
lnX4	12.659	9.870	sin(Z2+Z3+Z4)	0.245	0.173
$\ln X1^2$	-0.224**	0.107	Cos(Z1+Z2+Z3)	0.022	0.090
$\ln X2^2$	-0.149**	0.064	Cos(Z1+Z2+Z4)	-0.158	0.159
$\ln X3^2$	-0.010	0.093	Cos(Z1+Z3+Z4)	-0.309**	0.109
$\ln X4^2$	1.925	1.530	Cos(Z2+Z3+Z4)	0.138	0.154
lnX1lnX2	0.099***	0.020	Sin(Z1+Z2+Z3+Z4)	-0.015	0.077
lnX1lnX3	-0.013	0.025	Cos(Z1+Z2+Z3+Z4)	-0.056	0.079
lnX1lnX4	-0.757***	0.174	yr_1996	-0.116**	0.055
lnX2lnX3	-0.026	0.019	yr_1997	-0.281***	0.059
lnX2lnX4	0.405***	0.119	yr_1998	-0.429***	0.072
lnX3lnX4	0.321**	0.159	yr_1999	-0.472***	0.076
Sin Z1	-2.128***	0.342	yr_2000	-0.275***	0.070
Sin Z2	-0.290	0.209	yr_2001	-0.288***	0.076
Sin Z3	-0.132	0.347	Constant	38.823	31.73
Sin Z4	0.065	0.164			
Cos Z1	0.123	0.736			
Cos Z2	0.418	0.406			
Cos Z3	1.643**	0.775			
Cos Z4	-0.167	0.232			
Sin(Z1+Z2)	-0.103	0.173			
Sin(Z1+Z3)	-0.536***	0.151			
Sin(Z1+Z4)	0.489**	0.226			
Sin(Z2+Z3)	-0.248	0.185			
Sin(Z2+Z4)	-0.254	0.173			
Sin(Z3+Z4)	-0.269	0.244			
Cos(Z1+Z2)	-0.193	0.196			
Cos(Z1+Z3)	0.443**	0.198			
Cos(Z1+Z4)	-0.468**	0.202			
Cos(Z2+Z3)	0.178	0.194			
Cos(Z2+Z4)	0.100	0.124			
Cos(Z3+Z4)	0.061	0.210			

No. of observations: 3057

Chi-squared (for testing of Fourier terms): 145.414***

Life Profit Function

Variable	Parameter	s.e.	Variable	Parameter	s.e.
lnX1	1.079**	0.347	Sin(Z1+Z2+Z3)	0.045*	0.027
lnX2	0.070	0.250	Sin(Z1+Z2+Z4)	-0.108**	0.051
lnX3	-0.355	0.281	Sin(Z1+Z3+Z4)	0.043	0.030
lnX4	5.421**	2.435	Sin(Z2+Z3+Z4)	0.085*	0.048
$lnX1^2$	0.148***	0.033	Cos(Z1+Z2+Z3)	0.029	0.028
$lnX2^2$	0.009	0.022	Cos(Z1+Z2+Z4)	0.047	0.041
$lnX3^2$	0.057**	0.028	Cos(Z1+Z3+Z4)	-0.005	0.031
$lnX4^2$	0.798**	0.378	Cos(Z2+Z3+Z4)	-0.033	0.040
lnX1lnX2	-0.026***	0.006	Sin(Z1+Z2+Z3+Z4)	0.005	0.023
lnX1lnX3	-0.038***	0.007	Cos(Z1+Z2+Z3+Z4)	0.031	0.023
lnX1lnX4	0.120**	0.043	yr_1996	0.101***	0.014
lnX2lnX3	0.010*	0.005	yr_1997	0.229***	0.015
lnX2lnX4	0.000	0.035	yr_1998	0.385***	0.018
lnX3lnX4	-0.045	0.041	yr_1999	0.408***	0.019
Sin Z1	-0.119	0.107	yr_2000	0.257***	0.017
Sin Z2	-0.050	0.079	yr_2001	0.265***	0.019
Sin Z3	0.204*	0.108	Constant	16.199**	7.853
Sin Z4	0.007	0.044			
Cos Z1	-0.129	0.224			
Cos Z2	-0.016	0.129			
Cos Z3	-0.361	0.230			
Cos Z4	-0.081	0.062			
Sin(Z1+Z2)	-0.048	0.050			
Sin(Z1+Z3)	0.110**	0.045			
Sin(Z1+Z4)	-0.023	0.058			
Sin(Z2+Z3)	0.088	0.055			
Sin(Z2+Z4)	0.017	0.050			
Sin(Z3+Z4)	-0.001	0.063			
Cos(Z1+Z2)	0.078	0.055			
Cos(Z1+Z3)	-0.032	0.056			
Cos(Z1+Z4)	0.289***	0.053			
Cos(Z2+Z3)	-0.070	0.053			
Cos(Z2+Z4)	-0.047	0.034			
Cos(Z3+Z4)	-0.135**	0.061			

No. of observations: 3057

Non-Life Cost function

Variable	Parameter	s.e.	Variable	Parameter	s.e.
lnX1	1.600*	0.954	Sin(Z1+Z2+Z3)	0.010	0.066
lnX2	0.162	0.947	Sin(Z1+Z2+Z4)	-0.607***	0.121
lnX3	-4.673***	1.107	Sin(Z1+Z3+Z4)	0.234**	0.095
lnX4	-9.221	7.011	Sin(Z2+Z3+Z4)	0.235*	0.121
$lnX1^2$	0.060	0.098	Cos(Z1+Z2+Z3)	0.060	0.056
$lnX2^2$	0.110	0.080	Cos(Z1+Z2+Z4)	0.102	0.112
$lnX3^2$	0.397***	0.103	Cos(Z1+Z3+Z4)	0.225**	0.083
$lnX4^2$	-1.570	1.092	Cos(Z2+Z3+Z4)	-0.246**	0.110
lnX1lnX2	0.001	0.019	Sin(Z1+Z2+Z3+Z4)	-0.117**	0.053
lnX1lnX3	0.079***	0.021	Cos(Z1+Z2+Z3+Z4)	-0.014	0.049
lnX1lnX4	0.290**	0.133	yr_1996	0.142**	0.046
lnX2lnX3	0.024	0.020	yr_1997	0.193***	0.049
lnX2lnX4	0.090	0.133	yr_1998	0.400***	0.057
lnX3lnX4	-0.352**	0.152	yr_1999	0.415***	0.059
Sin Z1	-0.670**	0.299	yr_2000	0.359***	0.056
Sin Z2	0.338	0.213	yr_2001	0.423***	0.058
Sin Z3	0.378	0.352	Constant	-25.706	22.382
Sin Z4	-0.116	0.103			
Cos Z1	-0.733	0.513			
Cos Z2	-1.186**	0.422			
Cos Z3	-3.650***	0.636			
Cos Z4	0.286*	0.171			
Sin(Z1+Z2)	-0.206	0.132			
Sin(Z1+Z3)	0.020	0.118			
Sin(Z1+Z4)	-0.327*	0.173			
Sin(Z2+Z3)	0.335**	0.137			
Sin(Z2+Z4)	-0.143	0.154			
Sin(Z3+Z4)	0.447**	0.199			
Cos(Z1+Z2)	0.543***	0.131			
Cos(Z1+Z3)	-0.437***	0.130			
Cos(Z1+Z4)	0.436**	0.133			
Cos(Z2+Z3)	-0.832***	0.136			
Cos(Z2+Z4)	-0.186*	0.102			
Cos(Z3+Z4)	-0.193	0.137			

Non-Life Profit Function

Variable	Parameter	s.e.	Variable	Parameter	s.e.
lnX1	0.653**	0.315	Sin(Z1+Z2+Z3)	0.123***	0.026
lnX2	0.030	0.374	Sin(Z1+Z2+Z4)	-0.100**	0.045
lnX3	-0.647*	0.390	Sin(Z1+Z3+Z4)	0.063	0.040
lnX4	4.297*	2.437	Sin(Z2+Z3+Z4)	0.015	0.047
$lnX1^2$	0.290***	0.039	Cos(Z1+Z2+Z3)	0.097***	0.022
$lnX2^2$	0.109**	0.034	Cos(Z1+Z2+Z4)	0.020	0.042
$lnX3^2$	0.161***	0.041	Cos(Z1+Z3+Z4)	-0.046	0.034
$lnX4^2$	0.590	0.379	Cos(Z2+Z3+Z4)	-0.027	0.041
lnX1lnX2	-0.082***	0.007	Sin(Z1+Z2+Z3+Z4)	-0.029	0.020
lnX1lnX3	-0.065***	0.008	Cos(Z1+Z2+Z3+Z4)	-0.030	0.021
lnX1lnX4	0.086**	0.044	yr_1996	0.165***	0.017
lnX2lnX3	-0.012	0.008	yr_1997	0.258***	0.018
lnX2lnX4	-0.024	0.052	yr_1998	0.419***	0.020
lnX3lnX4	-0.063	0.053	yr_1999	0.375***	0.021
Sin Z1	0.252**	0.120	yr_2000	0.289***	0.020
Sin Z2	0.584***	0.097	yr_2001	0.259***	0.020
Sin Z3	0.524***	0.151	Constant	12.388	7.799
Sin Z4	-0.020	0.039			
Cos Z1	-0.597**	0.205			
Cos Z2	0.002	0.172			
Cos Z3	-0.425*	0.238			
Cos Z4	-0.170**	0.065			
Sin(Z1+Z2)	0.216***	0.052			
Sin(Z1+Z3)	0.188***	0.049			
Sin(Z1+Z4)	-0.040	0.061			
Sin(Z2+Z3)	0.141**	0.052			
Sin(Z2+Z4)	0.047	0.063			
Sin(Z3+Z4)	0.000	0.072			
Cos(Z1+Z2)	0.105**	0.051			
Cos(Z1+Z3)	-0.165**	0.052			
Cos(Z1+Z4)	0.035	0.051			
Cos(Z2+Z3)	0.084	0.052			
Cos(Z2+Z4)	0.051	0.042			
Cos(Z3+Z4)	-0.118**	0.053			

Composites Cost Function

Variable	Parameter	s.e.	Variable	Parameter	s.e.
lnX1	-0.173	0.846	Sin(Z1+Z2+Z3)	-0.022	0.228
lnX2	-0.561	0.495	Sin(Z1+Z2+Z4)	0.212	0.153
lnX3	0.514	1.265	Sin(Z1+Z2+Z5)	0.297	0.234
lnX4	10.645***	2.659	Sin(Z1+Z3+Z4)	-0.538**	0.169
lnX5	14.613*	7.861	Sin(Z1+Z3+Z4)	0.239	0.304
$\ln X1^2$	-0.291*	0.176	Sin(Z1+Z4+Z5)	-0.161	0.152
$\ln X2^2$	0.366***	0.077	Sin(Z2+Z3+Z4)	0.041	0.203
$\ln X3^2$	-0.401**	0.199	Sin(Z2+Z3+Z5)	-0.020	0.154
$\ln X4^2$	-1.198***	0.334	Sin(Z2+Z4+Z5)	-0.455*	0.243
$\ln X4^2$	2.504**	1.277	Sin(Z3+Z4+Z5)	0.587**	0.241
lnX1lnX2	-0.072**	0.027	Cos(Z1+Z2+Z3)	-0.449	0.280
lnX1lnX3	0.063	0.041	Cos(Z1+Z2+Z4)	0.035	0.177
lnX1lnX4	0.036	0.046	Cos(Z1+Z2+Z5)	0.568**	0.218
lnX1lnX5	-0.218*	0.119	Cos(Z1+Z3+Z4)	0.722***	0.192
lnX2lnX3	0.007	0.020	Cos(Z1+Z3+Z4)	-1.131***	0.250
lnX2lnX4	-0.026	0.029	Cos(Z1+Z4+Z5)	0.556**	0.173
lnX2lnX5	-0.018	0.058	Cos(Z2+Z3+Z4)	0.047	0.261
lnX3lnX4	0.103*	0.056	Cos(Z2+Z3+Z5)	0.466**	0.160
lnX3lnX5	-0.088	0.153	Cos(Z2+Z4+Z5)	-0.792**	0.244
lnX4lnX5	0.550**	0.210	Cos(Z3+Z4+Z5)	1.107***	0.258
Sin Z1	0.002	0.975	Sin(Z1+Z2+Z3+Z4)	-0.124	0.102
Sin Z2	0.395*	0.222	Sin(Z1+Z2+Z3+Z5)	-0.210	0.261
Sin Z3	-0.295	0.667	Sin(Z1+Z2+Z4+Z5)	0.030	0.155
Sin Z4	-0.805	1.053	Sin(Z1+Z3+Z4+Z5)	-0.118	0.111
Sin Z5	-0.097	0.109	Sin(Z2+Z3+Z4+Z5)	0.749***	0.198
Cos Z1	2.512**	1.071	Cos(Z1+Z2+Z3+Z4)	0.119	0.110
Cos Z2	-1.039**	0.434	Cos(Z1+Z2+Z3+Z5)	-0.547**	0.245
Cos Z3	1.149	1.221	Cos(Z1+Z2+Z4+Z5)	-0.046	0.154
Cos Z4	12.256***	2.906	Cos(Z1+Z3+Z4+Z5)	-0.086	0.112
Cos Z5	0.041	0.227	Cos(Z2+Z3+Z4+Z5)	0.509**	0.230
Sin(Z1+Z2)	0.675**	0.235	Sin(Z1+Z2+Z3+Z4+Z5)	-0.014	0.106
Sin(Z1+Z3)	-0.458	0.324	Cos(Z1+Z2+Z3+Z4+Z5)	-0.132	0.094
Sin(Z1+Z4)	0.120	0.402	yr_1996	0.016	0.050
Sin(Z1+Z5)	-0.075	0.256	yr_1997	0.112**	0.055
Sin(Z2+Z3)	0.570**	0.185	yr_1998	0.347***	0.064
Sin(Z2+Z4)	-0.199	0.257	yr_1999	0.325***	0.065
Sin(Z2+Z5)	0.138	0.120	yr_2000	0.243***	0.059
Sin(Z3+Z4)	-0.520	0.352	yr_2001	0.314***	0.061
Sin(Z3+Z5)	-0.079	0.200	Constant	25.465	24.603
Sin(Z4+Z5)	-0.096	0.293			
Cos(Z1+Z2)	-0.964**	0.323			
Cos(Z1+Z3)	0.080	0.309			
Cos(Z1+Z4)	1.845***	0.393			
Cos(Z1+Z5)	0.578**	0.242			
Cos(Z2+Z3)	-0.530**	0.257			
Cos(Z2+Z4)	1.715***	0.314			
Cos(Z2+Z5)	-0.128	0.111			
Cos(Z3+Z4)	0.339	0.521			
Cos(Z3+Z5)	0.189	0.240			
Cos(Z4+Z5)	0.192	0.375			

N=886.

Composites Profit Function

Variable	Parameter	s.e.	Variable	Parameter	s.e.
lnX1	0.731**	0.347	Sin(Z1+Z2+Z3)	0.003	0.094
lnX2	0.715**	0.249	Sin(Z1+Z2+Z4)	0.142**	0.071
lnX3	1.181**	0.599	Sin(Z1+Z2+Z5)	-0.150	0.101
lnX4	1.695	1.309	Sin(Z1+Z3+Z4)	0.238**	0.077
lnX5	6.024*	3.185	Sin(Z1+Z3+Z4)	-0.187	0.124
$\ln X1^2$	0.010	0.082	Sin(Z1+Z4+Z5)	0.060	0.075
$\ln X2^2$	0.039	0.035	Sin(Z2+Z3+Z4)	0.196**	0.087
$\ln X3^2$	-0.064	0.095	Sin(Z2+Z3+Z5)	-0.184**	0.065
$\ln X4^2$	-0.343**	0.172	Sin(Z2+Z4+Z5)	0.052	0.098
$\ln X5^2$	0.738	0.517	Sin(Z3+Z4+Z5)	0.060	0.105
lnX1lnX2	-0.068***	0.017	Cos(Z1+Z2+Z3)	0.092	0.122
lnX1lnX3	-0.026	0.017	Cos(Z1+Z2+Z4)	0.056	0.088
lnX1lnX4	-0.007	0.022	Cos(Z1+Z2+Z5)	-0.278**	0.088
lnX1lnX5	-0.028	0.049	Cos(Z1+Z3+Z4)	0.198**	0.095
lnX2lnX3	0.004	0.010	Cos(Z1+Z3+Z4)	0.003	0.091
lnX2lnX4	-0.007	0.017	Cos(Z1+Z4+Z5)	-0.076	0.070
lnX2lnX5	0.025	0.030	Cos(Z2+Z3+Z4)	0.275**	0.116
lnX3lnX4	0.002	0.030	Cos(Z2+Z3+Z5)	0.131*	0.073
lnX3lnX5	0.104	0.072	Cos(Z2+Z4+Z5)	0.126	0.092
lnX4lnX5	-0.135	0.095	Cos(Z3+Z4+Z5)	-0.131	0.106
Sin Z1	-0.029	0.501	Sin(Z1+Z2+Z3+Z4)	0.120**	0.048
Sin Z2	0.485***	0.112	Sin(Z1+Z2+Z3+Z5)	-0.057	0.103
Sin Z3	-0.217	0.329	Sin(Z1+Z2+Z4+Z5)	-0.098	0.069
Sin Z4	1.320**	0.528	Sin(Z1+Z3+Z4+Z5)	-0.039	0.056
Sin Z5	-0.076	0.048	Sin(Z2+Z3+Z4+Z5)	-0.121	0.082
Cos Z1	1.567**	0.476	Cos(Z1+Z2+Z3+Z4)	0.086	0.056
Cos Z2	0.660**	0.205	Cos(Z1+Z2+Z3+Z5)	-0.123	0.101
Cos Z3	1.215**	0.584	Cos(Z1+Z2+Z4+Z5)	-0.066	0.064
Cos Z4	3.636**	1.476	Cos(Z1+Z3+Z4+Z5)	-0.025	0.056
Cos Z5	-0.394***	0.093	Cos(Z2+Z3+Z4+Z5)	0.168*	0.092
Sin(Z1+Z2)	-0.182*	0.106	Sin(Z1+Z2+Z3+Z4+Z5)	-0.109**	0.046
Sin(Z1+Z3)	0.300**	0.136	Cos(Z1+Z2+Z3+Z4+Z5)	-0.050	0.042
Sin(Z1+Z4)	0.346*	0.191	yr_1996	0.127***	0.018
Sin(Z1+Z5)	0.042	0.093	yr_1997	0.287***	0.022
Sin(Z2+Z3)	0.112	0.087	yr_1998	0.570***	0.025
Sin(Z2+Z4)	0.390***	0.116	yr_1999	0.520***	0.026
Sin(Z2+Z5)	-0.068	0.056	yr_2000	0.332***	0.024
Sin(Z3+Z4)	0.007	0.167	yr_2001	0.420***	0.025
Sin(Z3+Z5)	-0.205**	0.092	Constant	14.507	10.023
Sin(Z4+Z5)	-0.030	0.119			
Cos(Z1+Z2)	0.325*	0.185			
Cos(Z1+Z3)	0.283**	0.139			
Cos(Z1+Z4)	0.555**	0.177			
Cos(Z1+Z5)	-0.198**	0.093			
Cos(Z2+Z3)	0.468***	0.114			
Cos(Z2+Z4)	-0.136	0.165			
Cos(Z2+Z5)	0.093*	0.055			
Cos(Z3+Z4)	0.524**	0.237			
Cos(Z3+Z5)	0.075	0.103			
Cos(Z4+Z5)	-0.236	0.149			

N=886