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Performance of the Life Insurance Industry Under Pressure: Efficiency, Competition, and Consolidation

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Abstract

This article investigates efficiency and competition in the Dutch life insurance market by estimating unused scale economies and measuring efficiency-market share dynamics during 1995–2010. Large unused scale economies exist for small- and medium-sized life insurers, indicating that further consolidation would reduce costs. Over time average scale economies decrease but substantial differences between small and large insurers remain. A direct measure of competition confirms that competitive pressure is lower than in other markets. We do not observe any impact of increased competition from banks, the so-called investment policy crisis or the credit crisis, apart from lower returns in 2008.

Introduction

Using a unique, not publicly available, insurer-specific supervisory data set, this article investigates efficiency and competitive behavior on the Dutch life insurance market.[1] In the Netherlands, the life insurance sector is important with a business volume of €22 billion in terms of annual premiums paid, invested assets of €337 billion, and insured capital of €990 billion at end-2010.[2] This market provides important financial products, such as endowment insurance, annuities, term insurance, and burial funds, of frequently sizable value to consumers. Financial planning of many households depends on the proper functioning of this market. The complexity of the products and dependency on future investment returns make many life insurance products rather opaque. Therefore, competition and efficiency in this sector are important for consumers (Bikker and Spierdijk, 2010). Most life insurance policies have long life spans, which makes

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[1] Different from most other countries, in the Netherlands, health, disability, and accident insurance is not included in the life sector, but in "nonlife."

[2] Insured capital is the sum over all policies of (1) the benefit in case of a death or expiration (€639 billion) and (2) 10 times the future annual benefit in case of survival (€351 billion), a standard measure used by life insurance companies.

consumers sensitive to the continuity of the respective firms. Life insurance firms need to remain in a financially sound condition over decades in order to be able to pay out the promised benefits.

In recent years, the life insurance sector has been confronted with several major challenges. First, the ongoing, long-lasting decline in interest rates, world-wide but particularly in the euro area, has reduced insurers' income that is—among other things—needed to cover future benefits to policyholders. Second, the credit and government debt crises have lowered the value of stocks and PIIGS countries bonds, which have impaired insurance firms' buffers. In the Netherlands, two additional problems for life insurers have emerged. In order to increase competition between banks and insurers, tax privileges for insurance products, such as old-age savings and redemption plans for mortgage loans, have since 2008 also been available for comparable banking products. The impact of this tax reform has been huge: more than half of the new production on the respective life insurance markets has been generated by banks. We expect that this change has contributed further to the need for insurance companies to increase efficiency in order to improve their competitive position. Finally, insurers are faced with the aftermath of the scandal about mis-selling and hidden costs of insurance policies in the Netherlands. Around 2006, public awareness increased that various types of unit-linked saving policies (such as annuities and mortgage redemption saving plans), which were based on capital market investment at the risk of policyholders, carried high operational costs and relatively high premiums on included life risk policies, eating 50–60 percent of the premiums paid. Under public pressure, insurers agreed to pay compensation to policy holders for incurred and future costs on the respective policies, estimated at €2.5 to 4.5 billion,[3] while potential claims may come to a multiple of that amount. One of the consequences of this crisis is that consumer trust in insurance firms and the volume of new production have decreased.

Competition and efficiency in financial markets is difficult to measure, particularly due to the unavailability of data with respect to costs and prices of individual financial products (Bikker, 2010). The solution in the literature has been to assume a single insurance (or banking) product and to use balance sheet and profit and loss data of entire financial institutions. As a measure of inefficiency, this article estimates unused scale economies, which at the same time is an indirect measure of competition: where competition is high, insurers are forced to reduce their cost level wherever possible. Further, we apply a rather new measure of competition that has to date been rarely used in the literature, namely, a performance-conduct-structure (PCS) model, also known as the *Boone indicator*, developed by Hay and Liu (1997) and Boone (2000, 2008). For an overview, see Bikker and Van Leuvensteijn (2014). Where the well-known structure-conduct-performance (SCP) paradigm of Mason (1939) and Bain (1951) explains performance via conduct from market structure, this alternative model explains market structure via conduct or competition from performance, as in the so-called efficiency hypotheses (Smirlock, 1985; Goldberg and Rai, 1996). This approach is based on the notion that competition rewards efficiency and punishes inefficiency. In competitive markets, efficient firms are expected to perform better—in terms of market share and hence profit—than inefficient firms. The PCS indicator measures the extent to which efficiency differences between firms

[3] http://www.verzekeraars.nl/sitewide/general/nieuws.aspx?action=view&nieuwsid=880.

are translated into performance differences. The more competitive the market is, the stronger is the relationship between efficiency and performance. The PCS indicator is usually measured over time, giving a picture of the development of competition.

Other measures of competition, such as the Lerner index and the Panzar and Rosse model, are less suitable because the required data (output prices, cost price, profit margin) are lacking, while the Concentration index and the SCP model have serious shortcomings (see Bikker and Bos, 2008). Another advantage of the PCS indicator is that it requires only a small number of data series. We combine the two measures of efficiency and competition, unused scale economies and PCS indicator, to find out whether they match or differ.

Earlier research on the life insurance market has revealed that the efficiency of life insurers tends to be poor (Cummins and Weiss, 2012) and that competition between insurers is not strong (Bikker and Van Leuvensteijn, 2008). Unused scale economies point to weak competition: stronger pressure on cost efficiency would lead to further consolidation. The four above-mentioned problems facing the Dutch life insurance sector (declining interest rates, falling share prices, crumbling tax privileges, and the mis-selling and hidden cost policy scandal) all have in common that cost efficiency would help to (1) maintain market shares in the competition struggle against banks and (2) either restore profitability and impaired buffers, or reduce the hidden costs in unit-linked products (or both).

Life insurance firms sell several different products through various distribution channels, thereby creating several submarkets. The degree of efficiency and competition varies across these submarkets. For instance, the submarket where parties negotiate collective contracts (mainly employer-provided pension schemes) is expected to be more competitive than the submarkets for individual policy holders. Our data sets allow the subdivision of insurance policies into collective and individual contracts and, for each submarket, a split into unit-linked policies (where investment results are for the risk of policyholders) and policies guaranteeing benefit payouts in euro. Collective unit-linked policies consist mainly of annuities where individual policies with benefits expressed in euro (or fixed-benefit policies) usually take the form of endowment policies. Therefore, the two approaches measuring scale economies and competition will be estimates for the four submarkets too. Data on submarkets enable us also to further investigate the structure of the life market: do insurers, over time, go for specialization or do they, on the other hand, tend to sell all types of life insurance products in order to take full advantage of scope economies?[4] Furthermore, we pay attention to developments in efficiency and competition over time, in order to assess how insurers have responded to the challenges mentioned earlier. We relate this to the structure of the market and to entry and exit of insurers.

This article is structured as follows. "The Production of Life Insurances" section presents a short review of the production of life insurances, followed by a survey on the literature on efficiency and competition in the insurance industry. The next section highlights stylized facts of the Dutch insurance markets and its developments over time, while "The

[4] Scope economies reflect the lowering of the average cost for a firm by combining the production of two or more products.

Measurement of Efficiency and Competition" section provides a theoretical background to the measures of efficiency and competition used. The "Estimation Results on Scale Efficiencies" and "Estimates of the PCS Indicator of Competition" sections present the empirical findings for, respectively, scale economies and the PCS indicator of competition, and compare them with the results of the other studies in the field. The last section summarizes and concludes.

The Production of Life Insurances

Life insurance covers deviations in the timing and size of contractual cash flows due to (non) accidental death or disability. While some life insurance products pay out only in the incident of death (level term insurance and burial funds), others do so either in the incident of death or at the end of a specified term or number of terms in the absence of death (endowment insurance). A typical annuity policy pays an annual amount starting from a given date (if a specific person is still alive) and continues to do so until that person passes away. The nominal amount of the benefits can be guaranteed up front so that the insurance firm bears the risk that invested premiums may not cover the promised payments. Such guaranteed benefits may be accompanied by some kind of profit sharing, for example, depending on indices of bonds or shares. Alternatively, the insurance benefits may be linked to capital market investments, for example, a basket of shares, so that the insurance firm bears no investment risk at all. Such policies are usually referred to as unit-linked funds or variable products. We also observe mixed products, for example, unit linked funds with guaranteed minimum investment returns.

A major feature of life insurance is its long-term character, often continuing for decades. In the Netherlands, the average modified duration of insurers in 2010 was 12 years, which, in a going-concern insurance firm, points to long-term policies.[5] This makes policyholders vulnerable to the viability, continuity, and efficiency of the insurer, and insurers sensitive to their reputation. Life insurers need large provisions to cover their calculated insurance liabilities. These provisions are financed by—annual or single—insurance premiums and invested mainly in the capital market. A major risk of life insurers concerns interest rate mismatches between liabilities and assets. Idiosyncratic life risk is negligible as it can be adequately diversified. Systematic life risk, however, such as increasing life expectancy, can also pose a threat to life insurers, depending on their policy portfolio. Note that the risk of annuities increases with longevity, whereas the risk of term insurance and endowment policies decreases with longevity. Hence, the dominant risk will generally be investment risk. The main services that life insurance firms provide to their customers are life (and disability) risk pooling and financial intermediation. Significant expenditures include sales expenses, whether in the form of direct sales costs or agency, administrative costs, asset management, and product development

Literature on Performance in the Life Insurance Industry

In the literature, direct measurements of competition on the life insurance market are virtually absent. Bikker and Van Leuvensteijn (2008) use the PCS indicator (earlier

[5] Modified duration is the percentual portfolio value change due to a parallel shift in the interest rate term structure and is an estimate of the weighted average timing of future cash flows. The number of 12 years follows from own calculation using DNB data.

referred to as the Boone index) to measure competition in the Dutch life insurance sector. They conclude that life insurance competition is weaker than competition in the industrial markets. It has long been common practice to measure efficiency in the life insurance industry on the basis of unused scale economies. Using a flexible Fourier (FF) function, Fenn et al. (2008) examine 14 major European countries over 1995–2001 and find large-scale economies ranging from 40 percent for the smallest life insurers to 10 percent for larger firms. Employing data envelopment analysis (DEA), Cummins and Rubio-Misas (2006) focus on Spain and find scale inefficiencies ranging from 20 percent for small firms via 5 percent for larger firms to 12 percent for the largest firms. The latter increase is due to diseconomies of scale for the largest 60 percent of firms. Strong consolidation, on average, brings decreased scale inefficiencies over time. Using a translog cost function (TCF), Kasman and Turgutlu (2009) observe scale economies in Turkey over 2000–2004 of, on average, 30 percent. All three studies present lower scale efficiency for small insurers, higher scale efficiency for medium-sized and larger firms, while the largest companies show again lower scale efficiency, pointing to a certain optimal scale. This optimal scale has not been found by Bikker and Van Leuvensteijn (2008) for the Netherlands, but their range of scale economies from small insurers (30 percent) to large firms (10 percent) is similar. Grace and Timme (1992) and Yuengert (1993) also find increasing returns to scale for most U.S. life insurers, but the latter observes constant returns to scale for the largest ones. Finally, Fecher et al. (1991) report that French insurers have scale economies of 15 percent.

The literature on cost efficiency of life insurers is large, as becomes clear from, for example, the thorough overview of Cummins and Weiss (2012, table 6). Remarkable is the huge spread in cost (and profit) inefficiencies, due to the variation across countries and sample periods, but also to the different parametric and nonparametric measurement approaches of inefficiency and varying definitions (e.g., allocative vs. technical inefficiency). A general problem is that inefficiency cannot always be accurately distinguished from model and measurement errors, particularly if a production function has an unknown form or data on input prices and output quantities are incomplete or defective. Typically, half of the studies into cost efficiency in the life sector find that up to 50 percent of costs could be avoided by applying best practices,[6] while the other half state even higher percentages.[7]

Other studies focus on the impact of organizational form on cost performance. Since utility-maximizing managers have a preference to spend more on salaries, staff, office furniture, and other perquisites, mechanisms are needed to control managerial opportunism. Agency theory hypothesizes that stock ownership can prove more effective to control owner–manager conflicts than mutuals, the so-called expense preference hypothesis (EPH) (see Mester, 1991). Erhemjamts and Leverty (2010) find evidence for the

[6] See Pottier (2011) and Jeng et al. (2007), both applying data envelope analysis (DEA) for the United States; Kasman and Turgutlu (2009; Turkey); Fenn et al. (2008, EU); Bikker and Van Leuvensteijn (2008, the Netherlands); Klumpes (2004, United Kingdom), all applying stochastic cost frontier analysis (SCFA).

[7] See Mahlberg and Url (2010, Germany), Cummins et al. (2010, United States); Cummins and Rubio-Misas (2006, Spain); Cummins et al. (2004, Spain); and Erhemjamst and Leverty (2010, United States), all applying DEA; and Elling and Luhnen (2010), applying SCFA.

EPH in the U.S. life insurance sector. Efficiency, taxes, and access to capital explain the increasing share of stock insurers. Cummins et al. (2004) and Chen et al. (2013) do not find support for the EPH. Stock insurers and mutuals have different production functions, so that comparative cost advantages determine the dominance of each type on the various submarkets, in line with the efficient structure hypothesis. Many studies do not find evidence for the EHP, for example, Bikker and Gorter (2011) for the Netherlands, Gardner and Grace (1997) and Cummins and Zi (1998) for the United States, and Fukuyama (1997) for Japan, while for France, Fecher et al. (1993) find higher efficiency for stock life insurers than for mutuals.

THE STRUCTURE OF THE DUTCH LIFE INSURANCE INDUSTRY

We explain the structure of the Dutch life insurance industry using the key data presented in Table 1. Total assets entrusted to life insurers, expressed in prices of 2010, continuously increase over time, but at a gradually lower pace. The volume of premiums did increase around the turn of the century, but fell slightly during the crisis years. The latter indicates a decline in the sale of new life policies. When total assets are shown as a percentage of GDP, we observe that since 2002, life insurance funds no longer grow in line with GDP. Other developments, such as heavily increased competition from banks and declining trust caused by the mis-selling and hidden cost scandal, also contributed to the fall in new production. Net investment income is an important source of additions to provisions. Investments can be split into the part related to unit-linked policies, where policyholders bear the risk, and the part related to policies with benefits expressed in euro, where insurers bear the risk.[8] Net investment income depends, of course, on market conditions. During the dot-com bubble crash (2002), these returns were—on an aggregated level—almost zero, and during the credit crisis (2008), they were even firmly negative. The steady decline in nominal interest rates over time is also important here. Benefit payments increase strongly over time, reflecting increasing numbers of maturing policies. "Addition to the insurance provisions" makes clear that new production and extension of the coverage of existing policies still exceeds benefit payments albeit by declining amounts. This is in line with the slowdown in growth of the insurance provisions presented in the top of Table 1. As a result, insurance output, the sum of incurred benefits and additions to the provisions, is fairly constant over time.

Profits are remarkably stable when presented as 4-year averages, but fluctuate strongly within these periods with a close to zero profit in 2002 and a strong loss in 2008. Note that the profit on a life policy becomes available gradually, year after year over the life span of the contract, so that actual profit reflects the result over all the existing policies rather than the expected profit on the new production. In the (hypothetical) case of declining excess profit on new production due to increasing competition, this would show up only gradually in the financial reporting figures, over a long time span. The equity allocation declined due, in part, to stock market losses, reflecting that insurers nowadays no longer have the large buffers of earlier years. Operating costs as a percentage of premiums are stable over time at 13 percent. Remarkably, increased competition with banks and the criticism on the high hidden costs have so far not led to a reduction in costs.

[8] Investments and investment returns in Table 1 are based on the sum of both types of investments.

TABLE 1
Key Data of the Dutch Life Insurance Market Over Time (Averages)

	1995–1998	1999–2002	2003–2006	2007–2010
In billions of euro, at 2010 prices				
Total assets (abbreviated to ta)	232.7	289.3	304.4	325.3
Insurance provisions (ip)	177.0	223.3	244.6	264.5
Of which: for own account	126.8	144.6	151.7	158.2
Insured capital[a]	845.0	992.7	997.3	993.0
Gross premiums (gp)	22.1	28.4	27.4	25.3
Percentages				
Total assets/GDP	52.1	56.4	55.8	55.2
Net premiums/gp[b]	94.0	96.4	97.3	96.0
Net investment income/gp	68.7	40.6	61.5	42.6
Net investment income/ta	6.5	4.0	5.5	3.3
Benefit payments/gp	44.0	60.7	71.1	89.9
Addition to ip/gp	72.7	41.0	49.0	27.4
Insurance output/gp[c]	116.7	101.7	120.1	117.2
Profits before taxes/gp	13.1	12.7	13.3	13.0
Equity/ta	11.4	9.7	8.8	7.1
Operating costs/gp[d]	13.1	12.7	13.3	13.0
Marginal costs/gp	12.3	12.0	12.9	12.9
Acquisition costs/gp	6.9	6.0	6.5	6.4
Management costs/gp	6.5	6.8	7.0	7.3
Reinsurance costs/gp	6.0	3.6	2.7	4.0
Collective premiums/gp	31.0	31.7	31.8	34.9
Lump-sum premiums/gp	40.1	45.4	46.5	44.1
Unit-linked premiums/gp	30.2	44.5	43.3	40.7
Insurance provisions endowments/ip	63.6	64.0	64.0	64.7
Stock firms/all firms	88.7	90.5	90.0	91.7
Natural units				
Concentration index (HHI)	7.9	8.0	10.0	14.9
Number of firms	101.5	94.3	77.8	60.0
Number of policies, in millions	34.7	39.2	39.8	38.5

[a]Insured capital is the sum over all policies of (1) the benefit in case of a death or expiration and (2) 10 times the future annual benefit in case of survival.
[b]The ratio "net premiums/gp" is calculated as the sum of net premiums of all firms divided by the gross premiums of all firms. This is equal to the weighted average of individual observations of this ratio, weighted by the firm size in terms of gross premiums. This holds also, *mutatis mutandis*, for the other ratios.
[c]Insurance output is the sum of benefit payments and addition to insurance provisions.
[d]Operating costs is the sum of marginal and acquisition costs minus "provisions and profit sharing from reinsurers." For our calculations, we ignored the latter item, which is zero or negligible for most insurers but substantial for some.

Management costs tend to rise over time. Note that the profit and cost margins together take away at least one-fourth of the new savings under life policies. On top of this, there are the investment costs, varying from one-third to twice the operating costs. During 2008, the investment costs peaked at €8 billion against investment losses of €5 billion (in percentages of gross premiums: 30.4 percent against, for instance, 3.3 percent in 2005); the full sample average is 8 percent. We have doubts as to whether investment costs and losses are always separated correctly. We do not analyze investment costs in the same way as operating costs: where operating costs are a pure overhead, investment costs may lead to higher expected returns.[9]

An important feature of the market structure is the number of firms. According to the literature, the larger the number of firms (and the lower the entry/exit barriers in the market), the more competitive the life insurance market will be. The number of insurers increased from 95 in 1995 to 105 in 1998, but afterward declined strongly to 48 in 2010. The decline to 48 insurers is the net effect of 32 new entries and 80 exits, indicating fairly strong dynamics in this market, particularly in the earlier years. The concentration index HHI, based on premiums, rises from 7 in 1998 to 21 in 2010. The increased skewness in market shares has had a larger impact on the HHI than the fall in the number of life insurers. On the HHI scale running from 0 to 10,000, the index values remain low (and the number of insurers is still high), particularly compared to the banking market, explaining that consolidation on this market is still very low. Competition may come under threat when concentration increases, because—as the theory explains—tacit collusion can then be achieved more easily. But the decrease may also be due to mergers and acquisitions under competitive pressure. Given the existence of substantial unused scale economies (Bikker and Van Leuvensteijn, 2008), it is remarkable that operating costs do not decline over time as a consequence of up scaling. The number of mutual firms declines more rapidly than the number of stock firms. In the bottom part of Table 1, we split the life policy market into subdivisions (collective vs. individual policies, lump-sum vs. periodical payments, unit-linked policies vs. fixed benefits in euro policies, and endowment policies vs. annuities), based on their shares in premiums and insurance provisions; we do not observe substantial changes over time. An exception is the unit-linked market, which increases during the earlier years but falls back more recently.

The Life Submarkets

Table 2 presents key data on two submarkets, fixed-benefit policies and unit-linked policies, each split further into individual and collective policies, for two subperiods: 1995–2002 and 2003–2010. Expressed in either premiums or insurance output, we observe that fixed-benefit policies take up 60 percent of the life market, while unit-linked products have a share of 40 percent. Similarly, the figures show that the market share of individual policies, at 60 percent, is larger than that of collective contracts. The investment income on unit-linked policies of individuals is rather low, particularly in the initial period. Benefit payouts are relatively large for individual fixed-benefit policies

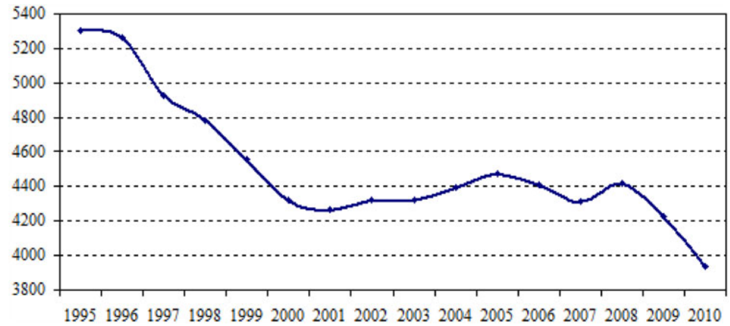
[9] Complex assets classes generally require higher research and risk management costs but have higher expected returns. Although scale economies may be expected in investment activities, large insurers may typically move earlier to complex assets classes. This behavior has been observed for pension funds (see De Dreu and Bikker, 2012).

TABLE 2
Key Data of the Dutch Life Insurance Submarkets Over Time (Averages)

	Fixed-Benefit Policies		Unit-Linked Policies	
	Individually	Collective	Individually	Collective
	1995–2002			
Shares of submarkets in percentages				
Premiums, gross (gp)	43.9	16.9	24.2	15.1
Net investment income	44.2	32.9	2.4	20.5
Benefit payouts	47.3	23.4	6.8	22.5
Addition to insurance provisions	39.9	20.6	23.6	15.9
Insurance output[a]	42.9	21.8	16.6	18.6
Profit	49.4	44.8	1.1	4.7
Operating costs	51.3	13.0	30.7	5.0
Insured future endowment benefits	62.7	10.1	23.9	3.3
Insured future annuity benefits	12.5	50.4	1.1	36.0
Shares of lump sums in percentages				
Premiums, gross	50	47	31	52
Annual average				
Operating costs as % of gp	15	10	16	4
Number of firms	88	43	65	20
HHI	10.2	35.5	7.8	104.3
	2003–2010			
Shares of submarkets in percentages				
Premiums, gross (gp)	41.7	15.7	24.5	18.1
Net investment income	39.5	26.4	14.6	19.6
Benefit payouts	51.0	18.9	14.1	16.1
Addition to insurance provisions	23.0	20.1	30.9	26.0
Insurance output[a]	40.1	19.4	20.6	19.9
Profit	66.0	25.5	5.3	3.2
Operating costs	42.0	14.7	33.2	10.0
Insured future endowment benefits	55.3	8.6	30.5	5.7
Insured future annuity benefits	13.1	48.2	1.4	37.2
Shares of lump sums in percentages				
Premiums, gross	59	55	17	48
Annual average				
Operating costs as % of gp	13	12	18	7
Number of firms	60	27	46	18
HHI	15.6	68.2	17.1	108.0

[a]Insurance output is the sum of benefit payouts and addition to insurance provisions.

FIGURE 1
Development in Life Insurance Specialization Over Time (HHI^{w})



and relatively small for individual unit-linked policies, reflecting, on average, more mature individual fixed-benefit policies. While the profit margin on unit-linked policies is very minor, the profit margin on fixed-benefit policies is relatively high, during the first period especially on collective policies, and during the second subperiod particularly on individual policies. Operating cost margins are much lower for collective policies than for individual ones, reflecting another element of scale economies. This also holds for costs expressed as a percentage of premiums (lower in the subperiod panels of Table 2), but much more strongly for unit-linked business than for fixed-benefit policies.

Information about the structure of the market is given by the number of insurers. It is clear that not all insurers are active on all submarkets. Individuals hold mainly endowment policies, often linked to mortgage loans, while collective contracts relate often to pension schemes provided by employers. This holds for fixed-benefit policies, but even more strongly for unit-linked policies.[10] Concentration is much stronger on collective contract markets and strongest in the unit-linked part of that market. Large contracts often concern pension benefits for employees of a company and are negotiated between experts at both ends of the table, in sharp contrast to individual contracts with uninformed private persons. Furthermore, they are typically renegotiated every 5 years. Relatively few insurers are active on this more demanding submarket of collective contracts and much more competition is expected here.

Figure 1 presents a weighed HHI of individual insurers' market shares on submarkets that describes the focus of insurers on specialization over time (as in Bikker and Gorter, 2011).

$$\mathrm{HHI}_{\mathrm{t}}^{\mathrm{w}} = \sum_{s=1}^{S} w_{st} \sum_{j=1}^{J} ms_{stj}^{2}, \tag{1}$$

[10] Table 2 presents shares of submarkets. Note that the volumes of the annuity markets (in terms of "insured future benefits") are calculated using the following rule of thumb: multiplying annual rents by 10 as a proxy for the average length of periodical benefits.

with ms_{stj} the premiums of submarket j as a share of all gross premiums of insurer s (where ms refers to market share), while the weight w_{st} is the total premium of insurer s as share of all premiums in the life market, all in year t. The graph shows a decline in specialization over time, particularly in the earlier years and most recently. Apparently, life insurers tend to operate increasingly on all submarkets, which suggests that scope economies are more important than specialization benefits. This outcome contrasts with the greater focus and specialization Bikker and Gorter (2011) observe on the Dutch nonlife market.

THE MEASUREMENT OF EFFICIENCY AND COMPETITION

While we will estimate scale economies to obtain a measure of efficiency, we interpret the existence of unused scale economies also as lack of competitive pressure to push down costs. Furthermore, we will measure competition directly using the PCS indicator.

Scale Economies

The intuition behind using unused scale economies to measure inefficiency is that a highly competitive market is expected to force life insurance companies to improve their efficiency in order to be able to survive and gain sustainable profit. As a competitive market forces firms to be efficient, unused scale economies may be used as an indicator of competition intensity. The existence of unused scale economies across size classes also indicates what level of consolidation would be optimal from an efficiency point of view (see Bikker and Van Leuvensteijn, 2008). The translog cost function (TCF), introduced by Christensen, Jorgenson and Lau (1973), has long been used extensively to measure scale economies and is regarded as one of the most effective models. The TCF is based on a U-shaped unit cost function that reflects all the underlying assumptions of the general cost minimization model.[11] It places no prior restrictions on the substitution possibilities among production factors and thus permits scale economies to vary with output and input proportions. The TCF is flexible and less complex than alternatives such as the Fourier function. In light of this, the TCF will be used in order to develop an accurate estimate of scale economies in the Dutch insurance industry. The same TCF will also be used to estimate the marginal costs that will be incorporated as a proxy of efficiency in the PCS model of competition.

A classical expression of a cost function is $C = f(Y, P, t)$, where Y is the output vector, C is total cost, P is a vector of input prices, and t is time.[12] In our empirical application

[11] The assumptions are: input demand is downward sloping, cross-price effects are symmetric, the shift in marginal cost with respect to an input price is equal to the shift in the input's demand with respect to output, the sum of own and cross-price elasticities is equal to zero, and a proportional increase in all input prices must shift cost by the same amount, holding output constant.

[12] Here, we follow a so-called dual approach which involves deriving output supply and input demand directly from an estimated cost function, without—as in the primal approach—the need to estimate a production function (Coelli et al., 1998, chap, 3).

we do not have insurer-specific input prices available,[13] so that the TCF simplifies into:

$$\ln OC_{st} = \beta_0 + \sum_{i=1}^{N} \beta_{Yi}(\ln Y_{ist} - \ln Y_{i\bullet\bullet}) + \frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N} \beta_{Yik}(\ln Y_{ist} - \ln Y_{i\bullet\bullet})(\ln Y_{kst} - \ln Y_{k\bullet\bullet})$$
$$+ \sum_{j=1}^{L} \gamma_s X_{jst} + \varepsilon_{st}. \tag{2}$$

OC_{st} is operational cost of firm s in year t,[14] Y_{ist} is output of type i ($i = 1, \ldots, N$; k also refers to output type), and X_{jst} represents either insurance firm-specific control variables or market-wide variables that only change over time ($j = 1, \ldots, L$). Operational costs and outputs are expressed in logarithms. ε_{st} is the random error term. The model contains squares and cross-terms of output components. All output terms (in logarithms) are expressed as deviations from their averages (in logarithms),[15] calculated over all insurer-year combinations (cf. the Taylor series expansion).[16] The average for output type i is denoted as $\ln Y_{i\bullet\bullet}$, which dots for the subindices over time and across insurance firms.[17] The variables expressed as deviations from their averages help to split linear and quadratic effects of output on costs and simplify the interpretation of the coefficients, as explained below Equation (3).

Usually, scale economies are defined as the relative increase in output level resulting from a proportional increase in factor inputs. However, Hanoch (1975) has argued that looking at scale economies as an association between output level and total costs—where costs are minimized for every output level and input prices are constant—is the most appropriate method. Hence, scale economies can be derived from a proportional increase in total costs resulting from a proportional increase in the output level, that is, the elasticity of total costs with respect to output level. In light of this, the ray scale economies (SE) for firm s in year t can be defined as a unit minus this cost elasticity:

$$SE_{st} = 1 - \sum_{i=1}^{N} \frac{\partial \ln OC_{st}}{\partial \ln Y_{ist}} = 1 - \sum_{i=1}^{N} \left(\beta_{Yi} + \frac{1}{2} \sum_{k=1}^{N} \beta_{Yik}(\ln Y_{kst} - \ln Y_{k\bullet\bullet}) \right). \tag{3}$$

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[13] But we do have a wage index of the financial industry to explain developments over time.

[14] Operating costs are the sum of management costs and acquisition costs. We do not include investment costs, which may in our data set be unreliable, see "The Structure of the Dutch Life Insurance Industry" section.

[15] Note that $\ln Y_{k\bullet\bullet}$ is the logarithm of the geometric, not the arithmetic, average of the insurers output measure k.

[16] White (1980) and Shaffer (1998, p. 95) explain that this specification also helps to avoid multi-collinearity.

[17] In the Taylor series expansion, the output observations are in deviation from their expectations. Here, the expectations are estimated by their full-sample averages. The deviations in the linear output terms are equivalent to a change in the estimates of the constant of Equation (2), that is, β_0, and deviations in the cross-terms are equivalent to changes in the estimates of the coefficients of the linear terms (β_{Yi}).

A positive *SE* value refers to scale economies whereas a negative *SE* indicates diseconomies of scale. *SE* equal to 1 reflects constant returns to scale (CRS). As *SE* depends on variables that are expressed in natural logarithm form, its interpretation will be in percentage terms. The *SE* for the (geometric) average of all life insurers is $1-\Sigma_i\ \beta_{Yi}$, hence based on the linear output elasticities only. This is an example of easier interpretation where output is expressed in deviation from its (geometric) sample average. Similarly, the *SE* can be calculated for, for instance, the (geometric) mean of the 10 percent smallest insurance firms, or the 10 percent largest ones.

The PCS indicator as a measure of competition will be based on the relationship between profits or market shares on the one hand, and marginal costs on the other. Since marginal costs are unobserved, they need to be estimated. We base them on the translog cost function of Equation (2). The marginal costs (MC) of producing output i for firm s in year t follow from the first derivative of operational cost (OC) to output (Y). Given Equation (2) the MC is expressed as:

$$MC_{sit} = \left(\frac{\partial \ln OC_{st}}{\partial \ln Y_{ist}}\right)(OC_{\mathrm{st}}/\,Y_{ist}) = \left(\beta_{Yi} + \sum_{k=1}^{N} \beta_{Yik}(\ln Y_{kst} - \ln Y_{k\bullet\bullet})\right)(OC_{\mathrm{st}}/\,Y_{ist}). \quad (4)$$

The average *MC* over the entire sample is obtained by summation of Equation (4) over all insurers s, all output types i, and all years t. Similarly, average MC numbers can be obtained for separate size classes. Note that marginal costs do not included unused scale (in)economies, as the constant costs are ignored. To confirm that, we have reestimated Equation (2) with MC instead of total costs, and indeed do not observe any relationship with output. Hence, reversed causality, that is, potential impact of market share (size) on efficiency, is not a problem in our analyses.

Definition of Output. In the life insurance sector, output is intangible. Many efficiency studies choose premiums as an output proxy (Cummins and Weiss, 2012, table 4). Yuengert (1993) criticizes this as premiums represent price times output quantity, not output itself. Systematic price differences across large and small firms may lead to misleading inferences about average costs if premiums are used as output proxy. Furthermore, premiums ignore investment performance. Following Yuengert (1993) and Berger et al. (2000), we use "incurred benefits plus additions to provisions" as a measure of insurance output. Insurance provisions of firm s in year t develop as follows (ignoring nonrecurrent items):[18]

$$\begin{aligned}\text{Provisions}_{s,t+1} = {} & \text{Provisions}_{st} + \text{Net premiums}_{st} - \text{Cost}_{st} - \text{Profit BT}_{st} + \text{Net inv. inc}_{st} \\ & -\text{Benefits}_{st}. \qquad (5)\end{aligned}$$

[18] This is based on Thiele's differential equation (Jørgensen, 1913). This formula holds as long as the discount rate to calculate future liabilities is constant, as until recently has been the case in the Netherlands. When an insurer changes the discount rate, or another basis principle of provisioning, Equation (5) is extended with a "nonrecurrent item."

Costs are operating costs and Profit BT are profits before taxes. Additions to provisions ($\text{Provisions}_{s,t+1}$ – Provisions_{st}) plus "incurred benefits" are equal to:

$$\text{Net premiums}_{st} - \text{Costs}_{st} - \text{Profit BT}_{st} + \text{Net inv. inc}_{st}. \tag{6}$$

This term can be split into (1) the prime price of the insurance policy, that is, new production (Net premiums – Costs – Profit BT), which represents services to (new) clients, and (2) investment services, that is, the annual return on the invested funds (Net investment income), which describes services to existing clients. Note that the key function of life insurance, risk bearing or risk pooling, does not (or hardly) count toward costs, which is why it does not show up in Equations (5) and (6): losses and gains on life policies cancel each other out for the insurance firm, unless the mortality pattern of their clients deviates from the mortality tables used. For instance, during the past decades longevity risk has been underestimated repeatedly, and insurers have incurred losses in order to repair this.

Equation (6) shows that premiums have been corrected for the profit and cost margins, so that potentially distorting systematic differences in costs and profits across large and small firms are excluded. On the other hand, costs may reflect deadweight (e.g., scale inefficiency), but they are also related to administrative and communicational services (providing policies and advice, etc.). Similarly, profits may consist of excess profits, but also of a risk premium for stockholders bearing unexpected risk. We will use premiums as an alternative output measure, with and without "net investment income," as a robustness test and for comparison with the literature. Cummins and Weiss (2012) recommend splitting insurance output into individual and group policies and, next, into annuities and life insurances,[19] as each of these four categories has its own properties. We have followed this alternative in one of the robustness tests. Alternatively, we have also applied the TCF model of Equation (2) to each of these four categories separately.

Insurance output, and its components benefits and investment income, are expressed in (euro) amounts and ignore the granularity of the output: each policy is a contract that provides a service to a client. Note that when an insurer, with a given output, has more or, on average, smaller policies, this implies providing more client services, which go hand in hand with higher operating costs. We include this granularity dimension of output by adding the number of policies as a separate, second output measure.

The Translog Cost Model. Besides output terms, the translog cost model (2) contains control variables, which have an impact on operational costs and help to refine scale economies measurement. The model we will estimate reads as follows:

$$\begin{aligned}\ln OC_{st} = {} & \beta_0 + \sum_{i=1}^{N} \beta_{Yi}\tilde{y}_{ist} + \frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N}\beta_{Yik}\tilde{y}_{ist}\tilde{y}_{kst} + \gamma_1\text{Stock}_{st} + \gamma_2 Acq/GP_{st} + \gamma_3 CPP_{st} \\ & + \gamma_4 LSP/GP_{st} + \gamma_5 ULP/GP_{st} + \gamma_6 HHI_t + \gamma_7\text{Wage}_t + \gamma_8\text{Time}_t + \varepsilon_{st},\end{aligned} \tag{7}$$

[19] In our data set this second split is replaced by a split into unit-linked policies and policies in euro.

where $\tilde{y}$ denotes the logarithm of an output component in deviation of its average. An important issue, discussed extensively in the literature, is the effect of the organizational form on performance (cf. Cummins et al., 1999). A prominent hypothesis in this context is the "expense preference hypothesis of organizational form," which is derived from agency theory. This hypothesis predicts that mutual insurers will have higher costs than stock-based insurers, because the stock market imposes a more effective mechanism for corporate control and reduces excessive consumption of perquisites by managers and possible deviation from profit maximization principles (Mester, 1989). We examine the effect of organizational form on scale efficiency by simply adding a dummy variable (*Stock*, which is 1 for stock firms) to allow for different cost levels between stock and mutual companies.

Operating costs consist of managerial costs and acquisition costs. Insurers have different distribution strategies, which cause huge variation in the acquisition costs margin across insurance firms. We express the acquisition costs as share of gross premiums (Acq_{st}/GP_{st}). Similarly, we expect that insurers with relatively more collective policy premiums (CPP_{st}/GP_{st}) and those with lump-sum premiums (LSP_{st}/GP_{st}) have, on average, lower costs. The share of unit-linked premiums (ULP_{st}/GP_{st}) may also affect the cost level. The final three control variables describe the entire life insurance market, which show variation over time only. The Herfindahl-Hirschman Index[20] (HHI), based on premiums, measures concentration of insurance firms, and increases over time. Concentration may be the consequence of strong competition (negative coefficient) or may enable tacit collusion so that less pressure exists to cut cost (positive effect). The real wage level is an input price (*Wage*). As the firm-specific "wage rate" is not observed, the general wage index of the financial industry, deflated by the cost-of-living price index, may at least pick up cost changes over time. Finally, "time" presents technical progress (*Time*) and is expected to have a negative effect on costs.

The PCS Model of Competition

The PCS model assumes that more efficient firms (i.e., firms with lower marginal costs) will gain higher market shares or profits, and that this effect will be stronger with competition. In order to support this intuitive market characteristic, Boone develops a broad set of theoretical models (see Boone, 2000, 2001, 2004, 2008; Boone et al., 2004; CPB, 2000). We use one of Boone's theoretical models to explain the PCS model. Following Boone et al. (2004), and replacing "firms" by "insurers," we consider an insurance industry where each insurer s produces one product q_s (or portfolio of insurance products), which faces a demand curve of the form:

$$p\left(q_s, q_{r\neq s}\right) = a - bq_s - d\sum_{r\neq s} q_r \tag{8}$$

[20] Concentration indices have the following general form: $\sum_{s=1}^{n} w_s ms_s$, where ms_s represents the market share of firm s and w_s stands for weight (Bikker and Haaf, 2002). The HHI, defined as $\sum_{s=1}^{n} ms_s^2$, uses market shares as weights. An alternative would be the CRx-index (with x an integer), where the weights of the largest x firms are 1, and the weights of the other firms are 0.

and has constant marginal costs mc_s. This insurer maximizes profits $\pi_s = (p_s - mc_s)\, q_s$ by choosing the optimal output level q_s. We assume that $a > mc_s$ and $0 < d \leq b$. The first-order condition for a Cournot-Nash equilibrium can then be written as:

$$a - 2bq_s - d\sum_{r \neq s} q_r - mc_s = 0, \tag{9}$$

where N insurers produce positive output levels; we can solve the N first-order conditions (9), yielding:

$$q_s\,(c_s) = \left[(2b/d - 1)\,a - (2b/d + N - 1)\,mc_{is} + \sum_r mc_r\right] / \left[(2b + d\,(N-1))\,(2b/d - 1)\right]. \tag{10}$$

We define profits π_s as variable profits excluding entry costs ε. Hence, in equilibrium, an insurer enters the insurance industry if and only if $\pi_s \geq \varepsilon$. Note that Equation (10) provides a relationship between output and marginal costs. It follows from $\pi_s = (p_s - mc_s)\, q_s$ that profits depend on marginal costs in a quadratic way. Competition in this market increases as the (portfolios of) services produced by the various insurers become closer substitutes, that is, as d increases (with d kept below b). Furthermore, competition increases when entry costs ε decline. Boone et al. (2004) prove that market shares of more efficient insurers (with lower marginal costs mc) increase both under regimes of stronger substitution and amid lower entry costs.

The Empirical PCS Model. Equation (10) supports the following regression model for market share, defined as $ms_s = q_s \,/\, \Sigma_r\, q_r$:

$$ms_{st} = \alpha + \beta_t mc_{st} + \sum\nolimits_{t=1,\ldots,} (T-1)\gamma_t d_t + u_{st}, \tag{11}$$

where α, β_t, and γ_t are parameters; ms_{st} denotes the market share of insurer s in year t; mc_{st} stands for the marginal costs of the respective insurer; d_t is a time dummy; and u_{st} an error term. The parameter of interest, β_t, is expected to have a negative sign, because relatively efficient insurers will gain higher market shares. Equation (11) may also be specified in log-linear terms in order to deal with heteroskedasticity, which is mainly an empirical issue that can be investigated with the Box-Cox test (Liu and Hay, 1997, p. 608). Moreover, this specification implies that β_t is an elasticity, which facilitates its interpretation, particularly across industries or countries.[21] We will refer to β_t as the PCS indicator in year t. Boone shows that where differences in performance in terms of market shares are increasingly determined by marginal cost differences, this indicates increased competition. The PCS indicator requires data on fairly homogeneous products.

Marginal costs are not observed but can be derived, using the translog cost function, from Equation (4), as we will do. An alternative, namely, average costs, would ignore

[21] The few existing empirical studies based on the PCS model have all used a log linear relationship. See, for example, Bikker and Van Leuvensteijn (2008).

the distinction between fixed and variable costs, but appears to be a quite useful approximation in practice (Bikker and Van Leuvensteijn, 2008). The competition coefficient β is negative in the case of effective competition and ranges from 0 (no competition) to - ∞ (extreme competition). Increases or decreases, in absolute terms, in β, for instance, over time, can be interpreted. With due reservation, the life insurance β can be compared across industrial sectors or across countries. Note that an efficient insurer can use its cost advantage to gain a higher market share through setting the output price below the market price (fitting well with Equation (11)), to gain a higher profit margin through maintaining its market price, or to pass through a portion of its efficiency gains to its customers. In all these cases market shares in Equation (11) can be replaced by profit, which is the product of profit margin and market share. Finally, efficiency gains can also translate into innovation attractiveness, improved design, or quality.

ESTIMATION RESULTS ON SCALE EFFICIENCIES

We estimate Equation (7) using data over 1995–2010 to obtain a measure of the scale economies (SE) present in the Dutch life insurance industry. The first row of Table 3 presents results for insurance output (I.O.) as output size measure. The coefficient of insurance output, the cost elasticity, is 0.817, so that the average SE effect is 18.3 percent, implying that a (small) increase in size would save almost one-fifth of the costs on the additional production. The positive coefficient of the squared insurance output term indicates that the SE effect is concave, meaning that the effect is largest for the smallest insurance firms and decreases for larger firms, where at some point scale economies swift over to diseconomies in scale, that is, where the cost elasticity becomes larger than 1. We plot this in Figure 2, where the cost elasticity has been calculated for 10 size classes (based on premiums), each with a number of around 120 annual observations of insurance firms.[22] Note that the graph would look fully concave if the insurance firms were not allocated to size classes, but were expressed in (the logarithm) of output size itself. Under constant returns to scale (CRS) the cost elasticity would be 1 and the coefficient of the squared term would be 0. A Wald test on this null hypothesis makes clear that the SE effect is significantly different from zero, as in the CRS case (see last row in Table 3).

The coefficients of the other variables of Equation (7) imply the following. Stock firms have significantly higher cost than mutual firms. This is in contrast to the "expense preference hypothesis of organizational form," which predicts that mutuals will have higher costs than stocks, because the stock market imposes a more effective mechanism for corporate control and reduces excessive consumption of perquisites by managers and possible deviation from profit maximization principles. Our outcome is in line with most of the literature (see the "Literature on Performance in the Life Insurance Industry" section).

The acquisition cost share has a strong and significant impact on operational costs as well. Acquisition cost varies strongly across insurers, depending on their distribution model, while managerial costs are more stable. This explains the sensitivity of operational costs for the acquisition cost share. Various types of life insurance business go with lower

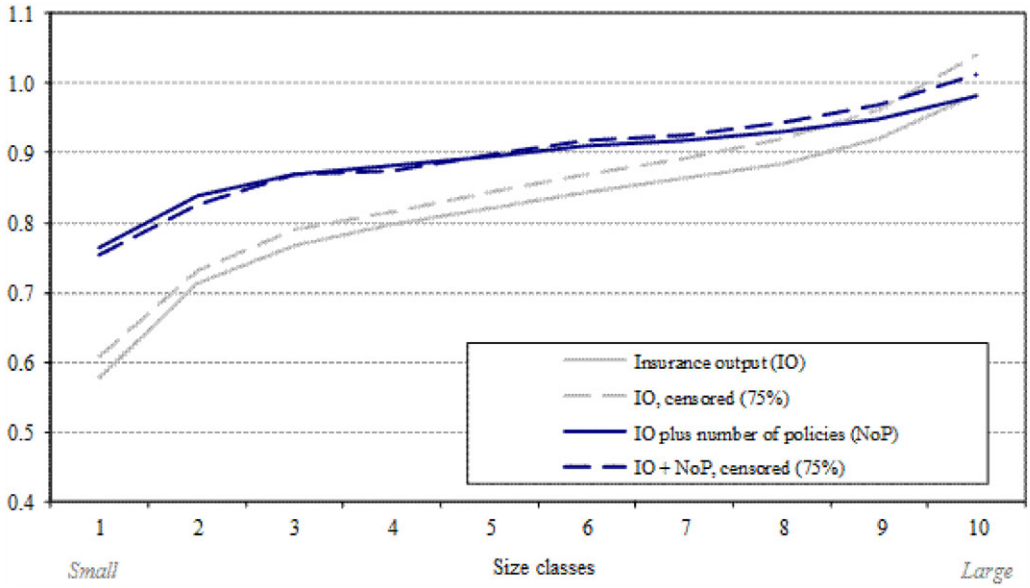
[22] Insurers in class 1 have premiums below €1.5 million. Maximum premiums in the other classes are, in million euro: 8, 19, 36, 59, 87, 135, 241, 581, and 4,378.

TABLE 3
Estimates of the Translog Cost Function for Dutch Life Insurers (1995–2010)

	Uncensored Data Set				Cost/Premium Rate Censored at 75%			
	Insurance Output		I.O. & Policies		Insurance Output		I.O. & Policies	
Output Measures	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value
Insurance output (I.O.), in logs[a]	0.817	67.4	0.474	26.5	0.848	78.7	0.580	33.5
Id. in squares[a]	0.023	8.6	0.003	0.5	0.028	9.6	0.008	1.2
Number of policies, in logs[b]			0.419	23.7			0.318	18.8
Id. in squares[b]			−0.014	−2.0			−0.021	−3.2
Cross term[a, b]			0.022	1.9			0.028	2.3
Stock firms	0.718	7.4	0.721	9.0	0.521	6.1	0.562	7.5
% of collective policy premiums	−0.620	−6.5	−0.222	−2.8	−0.326	−4.1	−0.114	−1.6
% of lump-sum premiums	−0.444	−5.3	0.520	6.5	−0.512	−7.3	0.246	3.4
% of unit-linked premiums	−0.390	−5.4	0.200	3.1	−0.202	−3.3	0.173	3.0
% of acquisition costs	2.604	19.0	1.937	16.8	6.381	32.5	4.737	25.0
Concentration (HHI)	−0.022	−1.7	0.001	0.1	−0.028	−2.6	−0.007	−0.7
Wage rate, in logs	1.961	1.8	0.443	0.5	1.384	1.5	0.400	0.5
Time trend	−0.012	−0.7	−0.016	−1.0	−0.005	−0.3	−0.011	−0.8
Intercept	1.951	0.6	6.419	2.2	3.872	1.3	6.785	2.7
Number of observations	1,216		1,196		1,156		1,137	
R^2, adjusted	85.5		90.4		88.9		91.7	
SE spread[c]	41.0		21.7		43.9		25.8	
F-test on constant returns to scale	235.1		54.6		200.1		60.4	

[a]Expressed as the deviation from the average of (logs of) insurance output across all insurer-year combinations (see Equation (7)), allowing for easier interpretation of the coefficients.
[b]Similarly for policies instead of insurance output.
[c]SE spread: difference in scale economies between smallest and largest size class where 10 size classes are considered.

FIGURE 2
Cost Elasticities Across 10 Insurer-Size Classes



Note: Based on the estimates of the four models in Table 3.

cost than others: collective contracts are more cost efficient than individual ones, and lump sum policies have lower costs than periodical payment policies, both as expected. Unit-linked policies, with investment risk at the cost of policyholders, are more cost effective than fixed-benefit policies, with investment risk at the cost of the insurer. So far, all coefficients are highly significant. Concentration, measured with the HHI, has a negative effect on costs at the 10 percent level of significance. As we already control for scale economies, the HHI may reflect improved (X-) efficiency, or else its downward trend may pick up the effect of technical progress over time. Wage rate has a positive effect on cost, as expected, albeit at the 10 percent level of significance only. This coefficient reflects the impact of wage changes over time, as we do not have firm-specific wage information. The time trend coefficient, representing cost-saving technical progress over time is negative but, again, not statistically significant.

The second column of Table 3 shows the estimates of an alternative model with two output variables. Apart from insurance output, which reflects the firm size in money terms, we also have the number of policies, which reflects the insurer's size in terms of administrative (and acquisition) activities, so that they complement each other. The estimates make clear that the average scale economies level—one minus the sum of the two linear output coefficients (see Equation (3))—is at 0.107 somewhat smaller than in the case of the single-output measure, but still significantly different from CRS (see the test in the last row of Table 3). Figure 2 confirms that we have again concavity: larger SE for smaller insurers and vice versa. The coefficients of number of stock firms and the share of acquisition costs are fairly unchanged, but the impact of type of life insurance policies differs from before, now we not only control for the monetary value of the output but also for the number of policies. Where the annual premium amount per policy is relatively high—as holds for collective contracts, lump-sum policies, and, likely, unit-linked contracts—the respective coefficients shift downward when controlled for the number of policies: the relatively lower costs are now also attributed to a relatively lower number of policies. The goodness of fit for models including number of policies is significantly higher, suggesting that operating costs are better explained by this model specification.

The data were selected by deleting negative or zero values for the key variables: operating costs, premiums, benefits, insurance provisions, and number of policies.[23] We notice also that the cost/premium ratio has a nonrepresentative high value for some insurer-year observations. This could point to insurance firms in their start-up or winding-down stages. In a sensitivity analysis, we delete all observations where this ratio is above 75 percent, a condition that holds for 5 percent of the sample. The advantage of such censoring is that we exclude "nonrepresentative" firm-year combinations, at although the risk of omitting observations with (large) positive error terms (reflecting high cost inefficiency, all else being equal). This risk would increase the lower we set the cost-premium threshold. Table 3, right-hand panel, and Figure 2 indicate that scale economies are somewhat lower after the data censoring, as might be expected after deletion of large positive errors. As the results lead to the same conclusions, however, including concavity and rejection of CRS, our approach appears to be robust against censoring.

Table 4 builds on Equation (7) but investigates alternative output measures, where the first two rows correspond to Table 3. The third row refers to a TCF model with—as output measure—the two components of insurance output taken separately instead of added up. This more general specification allows for different output effects on operating costs for benefits and additions, both in terms of SE and concavity of scale economies. In the literature, premiums are often used as volume measures, although critics argue that this measure includes the profit margin. Premium income is also combined with another output indicators, such as number of policies, total assets, and net investment income, where the latter two reflect services provided through the entrusted funds. Furthermore, each of these three output indicators also represents the output volume separately. Finally, we apply the model to stock-based insurers only, with the same results. The cost elasticities, and hence the scale economies, do not depend heavily on the chosen output measure and remain quite stable.

Starting with the uncensored results, we find that all model specifications have a scale economy that is significantly different from CRS. Ten out of 12 output measures give concave scale economies; 2 yield a linear relationship, indicating constant scale economies across size classes. It is clear that the approach is robust against the choice of output measure. A general outcome is that models based on a combination of two indicators have a consistently higher cost elasticity (after summing) than single-indicator models. The more volatile variable "net investment income" has a lower cost elasticity, probably due to the errors-in-variable bias, which may indicate lower suitability. Continuing with the censoring cases, we observe as before that the cost elasticities generally are larger. Still,

[23] This concerns small numbers; for example, 6 observations of gross premiums out of the total sample of 1,334 observations have been excluded.

TABLE 4
Cost Elasticity Estimates for Various Life Insurance Output Measures

	Uncensored					Censored at Cost/ Premium Ratio of 75%				
Output measure	CE	FF	# of Obs.	R^2	Test	CE	FF	# of Obs.	R^2	Test
Insurance output	0.817	Ca	1,216	85.5	234.8	0.848	Ca	1,156	88.8	200.0
Idem & # of policies	0.893	Ca	1,196	90.5	54.6	0.898	Ca	1,137	91.8	60.4
Benefits & additions to provisions separately	0.803	Ca	1,091	86.5	162.6	0.824	Ca	1,054	90.6	215.6
Net premiums	0.847	Ca	1,273	90.6	536.8	0.927	Ca	1,168	93.7	79.9
Gross premiums	0.887	Ca	1,293	90.0	290.8	0.940	Li	1,220	93.3	24.1
Idem & # of policies	0.927	Ca	1,268	91.4	46.8	0.957	Li	1,199	93.9	11.3
Idem & total assets	0.919	Ca	1,293	91.1	47.7	0.940	Li	1,220	93.6	21.1
Idem & net inv. income	0.904	Ca	1,167	92.8	97.9	0.937	Li	1,098	93.6	22.8
Total assets	0.870	Li	1,293	85.5	61.2	0.885	Li	1,220	89.7	64.3
Net investment income	0.772	Ca	1,167	84.2	233.6	0.771	Ca	1,098	84.2	228.4
Number of policies	0.845	Li	1,268	83.0	69.4	0.840	Cv	1,199	82.2	60.0
Insurance output, stocks	0.818	Ca	1,108	81.2	216.5	0.856	Ca	1,068	87.0	208.4

Note: CE is short for cost elasticity; FF stands for functional form; Ca stands for concave; Li stands for linear; R^2 refers to the goodness of fit, adjusted for the used number of degrees of freedom; and Test refers to the Wald test on the CRS hypothesis.

scale economies are again significantly different from CRS in all model specifications. Note that the concavity reduces under censoring, because—apart from nonrepresentative firm-year combinations—the smaller and relatively more scale inefficient insurers are typically excluded. This may affect the reliability of the censoring results. Cummins and Weiss (2012) recommend splitting insurance output into individual and group policies and, next, into annuities and life insurances,[24] as each of these four categories has its own properties. We have followed this suggestion. The outcome is closely in line with the variant without splitting (the first line in Table 4), but the number of observations is much smaller as not all firms operate on all four product markets.

[24] In our data set this second split is replaced by a split into unit-linked policies and policies in euro.

TABLE 5
Estimates of the Translog Cost Function for Life Insurers Split into Four Subperiods

	Entire Sample		1995–1998		1999–2002		2003–2006		2007–2010	
	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value
Insurance output, in logs[a]	0.818	67.4	0.830	41.8	0.802	37.1	0.868	41.1	0.872	38.8
Id. in squares[a]	0.023	8.6	0.032	7.3	0.017	3.8	0.034	7.6	0.019	3.2
Stock firms	0.717	7.4	0.802	5.8	0.798	4.7	0.784	4.3	−0.055	−0.3
% of collective policy prem.	−0.620	−6.5	−0.641	−4.3	−0.551	−3.2	−0.419	−2.5	−0.370	−2.2
% of lump-sum premiums	−0.444	−5.3	−0.773	−5.1	−1.015	−7.0	−0.550	−3.8	−0.192	−1.3
% of unit-fund premiums	−0.387	−5.4	−0.358	−2.9	0.202	1.6	−0.519	−4.2	−0.442	−3.2
Concentration (HHI)	−0.021	−1.7	0.254	0.9	0.063	0.4	0.454	1.8	−0.241	−3.1
Wage rate	1.930	1.8	7.481	0.8	−1.909	−0.5	2.309	0.8	21.986	3.0
Time trend	−0.012	−0.7	0.124	0.7	0.242	1.9	−0.253	−2.1	0.504	2.4
% of acquisition costs	2.604	19.0	3.434	11.8	1.232	7.5	6.435	18.4	5.865	16.1
Intercept	2.044	0.6	−18.878	−0.6	12.585	1.0	−1.880	−0.2	−70.191	−2.7
Number of observations	1,216		372		344		289		211	
R^2, adjusted	85.5		87.7		87.6		90.8		91.4	
SE spread[a]	41.0		55.1		31.2		61.8		33.8	
F-test on CRS	234.8		123.3		73.7		78.7		26.4	

[a]See footnotes below Table 3.

Estimation Results Over Time

Table 5 presents cost elasticity effects over time. For comparison, the first two columns give the full-period estimates of Table 3. We find that the cost elasticity in the earlier years is lower and even decline to 0.80 in 1999–2002 from 0.83 during 1995–1998. Over the years, cost elasticity increases to 0.87, for both subperiods. This implies that the average scale economies moved over time from 0.17 via 0.20 to 0.13. In a test we find that the hypothesis of "constant scale economies over time" is rejected at a confidence level of 95 percent. In "The Structure of the Dutch Life Insurance Industry" section we observed that concentration in the life insurance sector did increase over time. It is plausible to expect that after a wave of concentration, scale economies decrease. On the other hand, other developments may have shifted the optimal scale to a higher level, by increasing fixed costs, thereby causing new unused scale economies. Examples of such developments may be tougher regulatory requirements, the expansion of risk management possibilities and needs, and the steady growth of profitable ICT investments. Apparently, the first effect, concentration, dominated possible optimal scale shifting developments, so that scale economies fell over time. Concavity in the scale economies and rejection of CRS are observed in each of the four subperiods.[25]

Going into the detail of the control variable coefficients, we see for some variables a certain variation in the coefficient, for example, for stock firms in the last subperiod. We attribute the latter to the very small and declining number of mutual firms (to 5, on average, against 12 in the first subperiod) in this period, which may distort the comparison with the stock firms that, by the way also declined in number. As a robustness analysis we repeat the estimates of Table 5 for the 75 percent censoring case and the alternative model that also includes the number of policies as measure of output.[26] In the censoring case, scale economies decline by one-third over time, similar to the uncensored case, while in the model with "number of policies" included, the SE remain unchanged. CRS is rejected significantly in all cases.

Estimation Results Per Product Type

We estimate Equation (7) also for the four product types: the subdivision of all polices *either* into unit-linked policies versus policies with benefits expressed in euro (left-hand panel of Table 6), *or* into individual versus collective policies (right-hand side). Remarkably, at 0.78–0.79 the average linear cost elasticity in the first split is somewhat higher than that in the second subdivision (0.85–0.86); we attribute this to stochastic variation. In line with expectations, the scale economies are by far the smallest for collective policies (11 percent) where concentration is higher than elsewhere and the policies themselves are, of course, already on a larger scale. Other characteristics are similar as before, whether or not we apply censoring. When we split the policies further (first into unit-linked policies and policies with benefits expressed in euro and each group further into individual and collective policies), we find the smallest SE of 10 percent for euro-collective against 20 percent for the other three combinations.[27]

ESTIMATES OF THE PCS INDICATOR OF COMPETITION

The PCS indicator measures competition. The more strongly market shares or profits of life insurance firms are determined by their marginal costs, the stronger competition on that market is. In the literature, market shares or profits are used as the dependent variable in the PCS model. Equation (11) in "The Empirical PCS Model" section regards market shares (ms_{st}), which in our application are based on gross premiums. We also apply an alternative model based on profits. Market shares tend to change rather gradually over time. One reason is that not all premiums come from new production.[28] We have

[25] The critical value of the CRS test statistic for the last column in Table 5, $F(2, 211)$, at the 1 percent significance level, is 4.71.

[26] Not shown here, available on request from the author.

[27] Not shown here, available on request from the author.

[28] New production consists of lump-sum premiums, and the first year of periodical premiums, together around 55 percent of total premiums. The remaining 45 percent consists of annual premiums for existing (long-term) policies.

TABLE 6
Estimates of the Translog Cost Function for Life Insurers Split Into Four Product Types

	Unit-Linked		Euro		Individual		Collective	
	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value	Coeff.	*t*-Value
Insurance output, in logs[a]	0.78	36.0	0.79	57.7	0.82	58.9	0.89	45.1
Id. in squares[a]	0.03	4.4	0.02	5.6	0.02	7.3	0.02	4.9
Stock	0.94	3.0	0.62	6.2	0.64	6.1	0.46	2.3
Share lump-sum policies	−0.26	−1.6	−1.21	−11.7	−0.69	−6.9	−1.35	−6.5
HHI	−0.09	−4.7	0.00	0.0	−0.02	−1.5	−0.03	−1.8
Wages, in logs	−0.13	−0.1	1.26	1.0	−0.13	−0.1	−0.98	−0.5
Time	0.09	2.3	0.02	0.9	0.02	0.9	0.13	3.5
Constant	8.22	1.2	3.85	0.9	8.78	2.1	10.41	1.5
Number of observations	740		1130		1180		517	
R^2, adjusted	69.2		81.4		81.4		84.3	
SE spread[a]	0.39		0.32		0.40		0.35	
F-test on CRS	79.0		188.7		178.6		34.0	

[a]See footnotes below Table 3.

two instruments to deal with such gradual adjustment of market shares to marginal costs. First, we use the partial adjustment model of Nerlove (1958) by including the lagged endogenous variable, the so-called Koyk lag. Second, following Hay and Liu (1997), Boone (2004), and Creusen et al. (2006), we also introduce so-called fixed effects (or dummy variables d_s) for insurance firms, so that firm specific characteristics such as scale are wiped out.[29] Thus adapted, Equation (11) appears as:

$$ln\,(ms_{st}) = \alpha ln\,(ms_{s,t-1}) + \beta_t ln\,(mc_{st}) + \sum\nolimits_k \gamma_k X_{stk} + \sum\nolimits_s \delta_s d_s + u_{st}. \tag{12}$$

The coefficient $(1-\alpha)$ determines the speed of adjustment. The parameter β_t is the elasticity that reflects competition over time: the more negative beta, the stronger the underlying competition. Following Bikker and Van Leuvensteijn (2008), we include control variables (X_{stk}). These are dummy variables that indicate for each of the four considered product market whether the respective insurer is active on that market or not. Considered product markets are collective, unit-linked, lump-sum, and endowment policies. Evidently, an insurer's (overall) market share increases with the number of submarkets where the firm is active. Note that we express *ms* and *mc* in logarithms. Actually, we apply the Box-Cox test for each model specification to find whether linear or log-linear is most appropriate. In all cases, the linear functional form is rejected in favor of the log-linear one.

[29] We also include time or annual effects; they appear to be negligible.

TABLE 7
PCS Model for the Dutch Life Industry

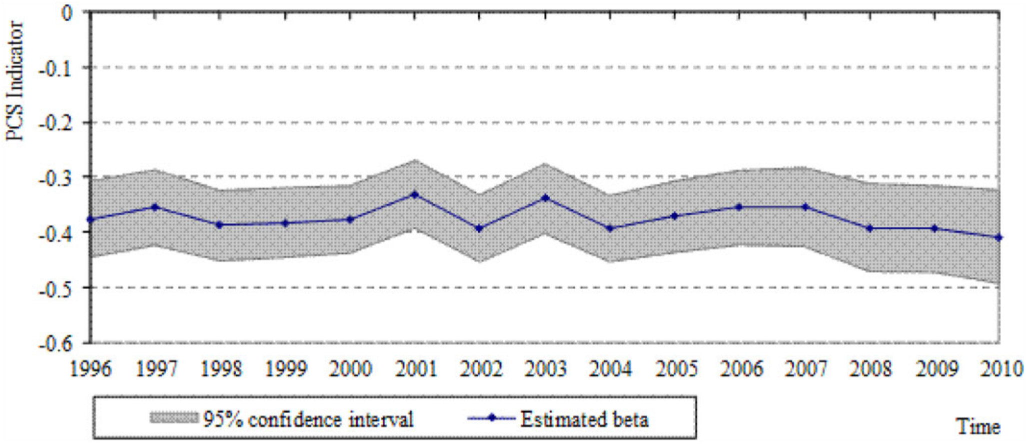
		With Lagged Dependent		Without Lagged Dependent	
Market Shares		FE	OLS	FE	OLS
Marginal costs	S.-T.	−0.374***	−0.071***		
	L.-T.	(−0.92***)	(−1.51***)	−0.749***	−1.335***
Lagged MS		0.594***	0.953***		
Average costs	S.-T.	−0.292***	−0.093***		
	L.-T.	(−0.75***)	(−1.60***)	−0.652***	−1.346***
Lagged MS		0.613***	0.948***		
Profits					
Marginal costs	S.-T.	−0.066	−0.057		
	L.-T.	(−0.10)	(−0.51)	−0.034	−0.509***
Lagged profits		0.334***	0.889***		
Average costs	S.-T.	−0.076	−0.074**		
	L.-T.	(−0.11)	(−0.65**)	−0.009	−0.614***
Lagged profits		0.322***	0.887***		

Note: MC stands for marginal costs; AV stands for average costs; MS stands for market shares; S.-T. stands for short term; L.-T. stands for long term. Calculated values are in parentheses. *** indicates 1% significance level. Coefficients of control variables (dummies for presence on product markets) have not been shown.

Table 7 presents the estimates of the PCS indicator β for market shares and profits for both marginal costs and average costs. Marginal costs are based on Equation (7) and the estimates in the first column of Table 3. Average costs have the disadvantage of including fixed costs but do not suffer from possible model specification or estimation errors. Here, we assume that $\beta_t = \beta$ for all t, which provides an indication of competitive pressure over the entire sample period (1995–2010) and allows a quick comparison across model specifications. For the development of competitive pressure over time, we refer to Figure 3, which shows the estimated annual β_t, based on the most appropriate specification. We focus first on market shares using marginal costs in a model with a lagged endogenous variable, the first panel on the left in Table 7. Estimating with OLS, we observe that the market shares are determined dominantly by previous market shares—the lagged endogenous coefficient is roughly 0.95—and only slightly by contemporary marginal costs (with coefficient −0.07, significantly different from zero), which points to (some) competitive pressure. Inclusion of fixed effects (FE; our preferred approach) for 124 insurance firms has a heavy impact on the estimates, indicating that market shares depend strongly on (unknown) firm-specific characteristics, and underlining the limited direct role of efficiency.[30] With fixed effects included, the lagged endogenous

[30] The Wu-Hausman test rejects the random effect model.

FIGURE 3
Effect of Marginal Costs on Market Shares of Dutch Life Insurers Over Time



Note: This graph presents estimates of β_t over time using the FE market share model, based on marginal costs (see the first rows of the left-hand FE column in Table 7).

coefficient α falls roughly from 0.95 to 0.60, so that the speed of adjustment increases from 5 percent to 40 percent, indicating that gradual adjustment remains important. At the same time, the (short-term) PCS indicator of competition is, in absolute terms, much larger at −0.37. Its long-term (L.-T.) effect, calculated as $\beta/(1-\alpha)$, is more substantial still, at −0.92. Although all the results are highly significant, they should be considered with great caution, as the market shares in terms of premiums are not determined by new production only but also by existing policies, so that changes may be underestimated (see footnote 28).

Replacing marginal cost by average costs yields similar results as regards sign, level, and significance, but may be inferior as proxies are used for marginal costs instead of the true—albeit estimated—values. This outcome makes clear that the PCS model may be applied without the marginal cost calculations based on the cumbersome estimation of the TCF model. The upper-right-hand panel of Table 7 presents the direct long-term effects of marginal costs, from Equation (7) without the lagged dependent variable. The estimation results of the PCS indicator are fairly similar, although in absolute terms, the coefficients are slightly larger. An important conclusion is that the indicator invariably carries a negative sign, corresponding with competition, and is always statistically significant. We checked that these results do not depend on the control variables: exclusion would not change the outcomes.

Finally, we consider the profit model instead of the market share model. Again, the PCS indicator carries a negative sign in all specifications, pointing to competitive pressure, although in the FE model it is not statistically significant and, in absolute terms, attains lower levels. Profits, too, adjust only slowly to marginal costs, if at a slightly less sluggish pace than market shares. Firms with high profits tend to be able to maintain that favorable position. This is, of course, partly due to accounting principles, where profits per policy become available gradually over time. Note also that the within goodness of fit of the FE profit model is low compared to the in-between R^2 (not shown), confirming that profitability differs substantially across insurers, but changes little over time, indicating absence of strong cost–profit dynamics.

Figure 3 shows the development of the PCS indicator over time, using the FE market share model, but estimating beta for each year separately, that is, dropping the $\beta_t = \beta$ restriction. We see that the short-term effect of marginal costs, β_t, hovers around its average value of −0.35, which corresponds to a long-term effect of around −1. An important conclusion is that β is negative in each year and significantly different from zero at the 1 percent level, pointing to permanent competitive pressure. The confidence interval increases over time, probably due to the 50 percent reduction in the number of life insurance firms. If anything, the beta is slightly more negative during 2008–2010, indicating slightly more competition.

A remarkable result is that competitive pressure did not change more. Particularly, we do not see a substantial increase in competition in more recent years where the public focus on (hidden) costs has increased dramatically. Apparently, the clients of insurance firms have not responded to the mis-selling and hidden cost policy scandal with greater awareness of costs. A caveat is, again, the fact that premiums do not reflect only new policies (around 55 percent), but also existing ones, so that market share changes are underestimated.

In order to assess whether our estimates for the PCS indicator are high or low, we compare them with estimates for other industries. Creusen et al. (2006) estimates the PCS model based on profits for the Dutch manufacturing and service industries and found elasticities between average variable costs and profits of around, respectively, −5.7 and −2.5. Our long-term "profit" PCS indicator of the life insurance industry ranges from −0.1 to −0.6, indicating far weaker competitive pressure. Van Leuvensteijn et al. (2011, 2013) estimate the "market share" indicator for the banking sectors in the United States, Japan, and the larger EU countries. The average long-run value for the Netherlands is −2.5, in absolute terms substantially above that of the life insurance sector, which ranges from −0.8 to −1.6. Bikker and Popescu (2014) find PCS indicator estimates for the Dutch nonlife insurers ranging from −3.1 to −3.8, which also points to more competitive pressure than on the life insurance market. As noted above, differences in accounting practices for profits and losses may impair the cross-sector comparison.

Table 8 presents competition estimates for submarkets of the Dutch life industry. We take market shares as the dependent variable, marginal costs as explanatory variables, and include the lagged endogenous variable. Of course, the product market control variables disappear. Note that the life insurance market is split *either* into unit-linked policies and fixed-benefit policies, *or* into individual and collective policies. On the unit-linked policy market, we do not find any evidence of competitive pressure (see upper-left-hand panel). These policies are complex and private persons are likely to depend on advice from intermediaries. If intermediaries are sensitive to the relatively high commissions paid by insurance companies for selling this type of product, competition will be impaired (CPB, 2005, pp. 55–82; Gorter, 2012). The PCS model does not indicate any competitive pressure on this market. The collective policy markets is more competitive, given the (highly) significant coefficients of marginal costs for both estimation approaches

TABLE 8
PCS Model for Submarkets of the Dutch Life Insurance Industry (1995–2010)

		Unit-Linked Policies		Fixed-Benefit Policies	
		FE	OLS	FE	OLS
Marginal costs	S.-T.	0.006	−0.036	−0.121***	−0.011
	L.-T.	(0.02)	(−0.55)	(−0.54***)	(−0.54)
Lagged MS		0.622***	0.934***	0.774***	0.980***
		Individual Policies		**Collective Policies**	
		FE	OLS	FE	OLS
Marginal costs	S.-T.	−0.047**	−0.006	−0.172***	−0.050**
	L.-T.	(−0.18**)	(−0.35)	(−0.44***)	(−2.08*)
Lagged MS		0.737***	0.983***	0.613***	0.976***

Note: MS stands for market shares; S.-T. stands for short-term; L.-T. stands for long-term. ** and *** indicate 5% and 10% significance levels, respectively.

(see lower-right-hand panel). This is in line with expectations, as collective contracts are negotiated with experts at both ends of the table. Competition takes an intermediate position in the remaining two submarkets, fixed-benefit policies and individual policies, where the marginal cost coefficient is significantly negative, but for FE only, and—in absolute terms—less than in the collective policies market.

CONCLUSIONS

Efficiency and competition on the life insurance sector are important for companies and households to keep prices low and innovation and quality high. This article investigates efficiency and competition on this market with—given the large unfavorable changes in economic, financial, and institutional conditions for life insurers—special attention to developments over time. We use unused scale economies as an indirect measure of competition and find that for 1995–2010 life insurers have, on average, significant scale economies of 10 to 20 percent. These economies decrease significantly with the size of the insurer: they are twice as large for the 10 percent smallest firms and are close to zero for the 10 percent largest ones. Such unused scale economies cannot exist under strong competition and suggest that further consolidation for the smaller life insurers would be cost efficient.

When we split the sample into two subperiods, we observe less scale economies in more recent years (13 percent vs. 18 percent). This is in line with the consolidation of the last 15 years: the number of life insurers fell from 100 to 50. In this light it is remarkable that the operating costs as a percentage of gross premiums remained the same: cost efficiency did not improve. Another structural change over time is the tendency for life insurers to operate increasingly on all product submarkets, indicating that scope economies are more important than specialization benefits.

The PCS indicator observes competitive pressure directly. We find a statistically significant effect of marginal costs on market shares, indicating that competitive pressure exists: efficient insurers are rewarded with increasing market shares. But this competitive pressure is weak, compared to the indicator values in other industrial sectors including banks and nonlife insurers. Changes in the indicator over time are limited, but if anything, they point to further weakening. Competition is relatively stronger on the collective policies market and, according to the indicator, weaker or absent on the individual policies market. These results should be considered with great caution as the market shares in premiums are not only determined by premiums of the new production but also by premiums over existing policies, so that changes in market shares (and hence, competition) may be underestimated.

Combining the empirical results for scale efficiency (TCF model) and competition (PCS indicator), we see improvement of scale efficiency over time, but do not see stronger competition in later years, meaning that the evidence is mixed. However, a consistent result is found if we break down the insurance market: markets for group policies are most efficient and the most competitive, while the opposite holds true for the individual policies markets.

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