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USING THE Z-SCORE TO ANALYZE THE FINANCIAL SOUNDNESS OF INSURANCE FIRMS

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KEYWORDS: Insurance sector; Z-score; economic crisis; European financial system.

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Abstract

This paper compares six different approaches to calculate Z-score using a final dataset of 183 insurers (1,382 observations) operating in the Spanish insurance sector during the period 2010-2017. This measure of risk has widely been used in the banking literature, and it has recently been applied to the insurance sector as an indicator of financial soundness. Using different methodologies (root mean squared error, ordinary least square and system-GMM regressions), we find that the best formula for calculating Z-score is the one that combines the current value of the return on assets and capitalization with the standard deviation of the returns calculated over the full period.

Key words: Insurance sector; Z-score; Economic crisis; European financial system.
JEL classification: G22, G28, G32, G33.

1. Introduction

The insurance industry plays a crucial role in the economy by allowing individuals and companies to transfer risk through insurance and reinsurance activities and thus enhancing financial stability (Das *et al.*, 2003). This industry, which significantly contributes to economic growth and notably impacts investors and stakeholders, has become an important pillar of the financial sector (Haiss and Sümegi, 2008). Although, traditionally, insurance companies have been considered less risky than banks because they are less exposed to liquidity risk (Caporale *et al.*, 2017), the increasing interactions among the insurance sector, financial markets and other financial intermediaries, as well as the financial innovation, globalization, and deregulation of the financial system, have made the operations of financial intermediaries over the last decades more complex and potentially riskier (Sharpe and Stadnik, 2007). While the contagion effects from the failures of insurers in the insurance sector may not be as consequential as those in the banking industry, they have relevant potential to disrupt the financial system and negatively impact the economy (Das *et al.*, 2003). Therefore, the soundness of insurance firms is of major importance not only for the welfare of the insurance sector and various stakeholders (Pasiouras and Gaganis, 2013) but also for the stability of the economy as a whole.

Consequently, policy makers are working to upgrade the regulatory and supervisory framework to reduce insolvency risk and promote confidence in the financial stability of the insurance sector. In the same vein, European insurers have recently implemented Solvency II, a risk-based economic approach aimed at adopting solvency requirements that better reflect the risk of companies (Cummins *et al.*, 2017). The new supervisory regime of the EU includes a risk-sensitive requirement that is based on a prospective calculation to ensure accurate and timely intervention by the supervisor (the Solvency Capital Requirement); for a minimum level of security below that, the amount of capital should not fall (the Minimum Capital Requirement).[1]

Despite the most sophisticated regulatory regime established in Solvency II, analysts should be able to consider other less complex indicators of soundness of insurers. The Z-score measure, which has traditionally been used as a proxy of individual risk for the banking sector (Boyd *et al.*, 2006; Laeven and Levine, 2009; Lepetit and Strobel, 2013; Baselga-Pascual *et al.*, 2015; Chiaramonte *et al.*, 2015; Khan *et al.*, 2017), may also be a useful tool to be applied in the insurance sector. The Z-score relates the bank's capital level to variability in its returns on assets (ROA), revealing how much variability in returns can be absorbed by capital without the bank becoming insolvent (Li *et al.*, 2017). The popularity of the Z-score is due to its relative simplicity and the capability to compute it using solely accounting information. In contrast to market-based risk measures, the Z-score is applicable when dealing with an extensive number of unlisted entities as well as listed entities (Chiaramonte *et al.*, 2016).

To the best of our knowledge, this study is the first to examine and compare different approaches to calculating Z-score in the insurance sector. This measure of risk has been widely used in the banking literature, and it has recently also been applied to the insurance sector as an indicator of financial soundness. The Z-score is a simple and easy-to-calculate measure that can be applied to firms with different risk strategies. The few available results on the predictive power of Z-score are mixed and focus on the banking sector (Lepetit and Strobel, 2013; Chiaramonte *et al.*, 2016). We focus on the Spanish insurance sector, which is one of the largest in Europe (IMF, 2017). Specifically, Spain is among the top ten European countries by gross premiums written and asset volume (EIOPA, 2017), and this country continues to lead growth among the major Eurozone economies (MAPFRE, 2018).

[1] "In order to promote good risk management and align regulatory capital requirements with industry practices, the Solvency Capital Requirement should be determined as the economic capital to be held by insurance and reinsurance undertakings in order to ensure that ruin occurs no more often than once in every 200 cases or, alternatively, that those undertakings will still be in a position, with a probability of at least 99,5 %, to meet their obligations to policy holders and beneficiaries over the following 12 months. That economic capital should be calculated on the basis of the true risk profile of those undertakings, taking account of the impact of possible risk-mitigation techniques, as well as diversification effects". [Directive 2009/138/EC of the European Parliament and of the Council of 25 November 2009 on the taking-up and pursuit of the business of insurance and reinsurance (Solvency II) (recast)].

The rest of the paper is organized as follows. Section 2 summarizes the previous literature on the analysis of financial soundness in the insurance industry. Section 3 describes the data and methodological aspects. Section 4 presents the main results. Finally, Section 5 concludes the paper.

2. Measuring the financial soundness of insurance companies: the Z-score

A broad strand of the literature on the financial soundness of insurance firms focuses on the analysis of diverse measures of capitalization (e.g., Cummins and Nini, 2002; De Haan and Kakes, 2010; Rubio-Misas and Fernández-Moreno, 2017; Moreno *et al.*, 2018; among others). These papers employ indicators such as the actual solvency margin, the required solvency margin, or the solvency ratio to make conclusions about the financial soundness of firms. However, limiting the analysis to insurers' capitalization could be too restrictive, and a wider approach is necessary to examine the different aspects that influence the financial soundness of an insurer (see, e.g., Hu and Yu, 2014; Mankaï and Belgacem, 2016; Altuntas and Rauch, 2017; Cummins *et al.*, 2017; Shim, 2017).

Fields *et al.* (2012), Eling and Marek (2013), Ho *et al.* (2013), Hu and Yu (2014) and Mankaï and Belgacem (2016), among others, examine the factors that influence the financial soundness of insurance companies by adopting different definitions of risk (e.g., investment risk, underwriting risk, product risk, financial risk, leverage risk, and risk-taking). Most of them highlight the significant impact of variables such as size, leverage, profitability, liquidity, capitalization, organizational form, specialization (life, nonlife), group affiliation, diversification or reinsurance on insurers' risk. In addition, macroeconomic variables such as the interest rate and GDP growth also appear to influence the risk of insurers (see Table 1). Similarly, Chen and Wong (2004), Sharpe and Stadnik (2007) and Caporale *et al.* (2017) focus on the particular event of insolvency or bankruptcy and propose models to identify or predict insurers experiencing financial distress. To do so, the probability of default, classification methods or external ratings are applied to the selected samples, which necessarily include firms that become insolvent during the analyzed periods. Therefore, the scarcity of this kind of analysis may be just due to the difficulty of finding data on the insolvency of insurance firms – the majority of these companies decide to transfer their business to other insurance firms or just stop underwriting new business instead of becoming "insolvent" (Caporale *et al.*, 2017).

[INSERT TABLE 1 ABOUT HERE]

Bearing in mind the increasing relevance of risk supervision under the European regulatory framework of Solvency II, this paper aims to explore insurers' financial soundness from a wider perspective, considering aspects beyond capitalization or the particular event of bankruptcy. For our study, the Z-score can be considered an appropriate alternative measure of risk and thus a good indicator of the financial soundness of insurers. Although the Z-score is traditionally used as an indicator of (individual) risk in the banking literature (Boyd *et al.*, 2006; Maechler *et al.*, 2007; Laeven and Levine, 2009; Čihák and Hesse, 2010; Lepetit and Strobel, 2013; Baselga-Pascual *et al.*, 2015; Chiaramonte *et al.*, 2015; Chiaramonte *et al.*, 2016; Khan *et al.*, 2017), some recent studies also use this measure to examine the financial soundness of insurance firms (see Table 2). This criterion may be a simple and effective predictor for insurer failure given the simplicity and transparency of its calculation (Plantin and Rochet, 2007).

As stated previously, the basic principle of the Z-score is to relate the capital ratio to the variability in the ROA, so that one can know how much variability in returns can be absorbed by capital without the firm becoming insolvent (Li *et al.*, 2017).

$$Z\text{–}score = \frac{ROA + Eq/TA}{\sigma ROA} \qquad [1]$$

where Eq/TA denotes the equity to total assets ratio and σROA represents the standard deviation of ROA.

Default is supposed to occur when losses consume capital (i.e., when ROA + Eq/TA ≤ 0; or, what is the same thing, when ROA ≤ – Eq/TA). Then, if we presume that ROA is a random variable, the Z-score represents the number of standard deviations between the expected value of the ROA, E(ROA), and that negative values of ROA, ROA = – Eq/TA, which would result in insolvency (Hannan and Hanweck, 1988). In other words, it indicates the number of standard deviations that the ROA would have to fall to deplete equity and force a failure. Hannan and Hanweck (1988) also show that the Chebyshev's inequality for any symmetric distribution allows us to presume the following upper bound of the probability of default (PD):

$$PD \leq \frac{1}{2}\left(\frac{\sigma ROA}{E(ROA) + Eq/TA}\right)^2 \leq \frac{1}{2}(Z\text{–}score)^{-2} \qquad [2]$$

Therefore, a higher Z-score is associated with a higher distance-to-default (a lower probability of insolvency). It does not require strong assumptions about the distribution of ROA (see, e.g., Strobel, 2011), which represents an especially attractive advantage from a practitioner's point of view.

As in the banking sector, equity serves as a buffer against unforeseen losses and is critical for an insurer's ability to meet its obligations (Cummins *et al.*, 2017). The Z-score can be applied to insurers with different risk strategies (Čihák and Hesse, 2010; Pasiouras and Gaganis, 2013): an institution with higher risk-adjusted returns may have the same or higher Z-score than other insurers with lower capitalization. Nevertheless, the Z-score has some disadvantages to be considered. First, as an accounting-based measure, its reliability depends on the quality of the underlying accounting and auditing framework, which is a serious concern in less-developed countries. Additionally, as firms may smooth accounting data over time, the Z-score may offer an excessively positive assessment of insolvency risk (Laeven and Majnoni, 2003). Second, as pointed out by Čihák (2007), the Z-score looks at each firm separately, potentially overlooking the risk that a distress in one financial institution may cause losses to other financial institutions in the system.

[INSERT TABLE 2 ABOUT HERE]

3. Data and methodological aspects

3.1 Sample

Our sample includes most of the insurance companies operating in Spain from 2008-2017. Data were obtained from the database maintained by the Spanish regulatory authority, the Directorate General of Insurance and Pension Funds (*Dirección General de Seguros y Fondos de Pensiones*) (DGSFP), an administrative body within the Ministry of Economy and Business.[2] However, as some of the components of the Z-score usually employ data up to two years prior to the calculation date (i.e., t-2, t-1), this reduces our time span to the period 2010-2017.[3] In addition, we do not consider social benefit institutions and reinsurance specialists because they have singular characteristics that may distort our analysis. We use unconsolidated financial statements, thereby reducing the possibility of introducing aggregation bias in the results. Merged insurers are considered to be separate firms before the merger and a single company afterward. Finally, we remove from the sample with abnormal ratios or extreme values, ensuring that the analysis is not affected by potential measurement errors and misreporting. After

[2] The database is available at http://www.dgsfp.mineco.es/sector/balancesycuentas.asp.

[3] This restriction does not apply if we estimate the Z-score combining the current period *t* values of ROA and capital with the standard deviation of ROA calculated over the full period (2008-2017). However, because we want to compare different Z-score measures, we will use the same observations in all of the analyses.

applying these filters, we obtain a final dataset consisting of an unbalanced panel with 183 insurers and 1,382 observations (see Table 3). We have a minimum of five consecutive observations for each company, having a 77.60% of the insurers observations for the entire period.

[INSERT TABLE 3 ABOUT HERE]

3.2. Different approaches for calculating the Z-score

Conscious of the potential value of the Z-score to inspect the soundness of financial institutions and considering the lack of research on this issue in the insurance sector, we examine different existing approaches to the construction of this measure in the previous literature. The most basic formulation defines the Z-score as the sum of the current period *t* values of the firm's ROA (ROA_t) and equity to total assets ratio (Eq/TA_t) divided by the standard deviation of ROA calculated with data from the current year (t) and the two previous years, i.e., t−1 and t−2 (σROA_3) (Pasiouras and Gaganis, 2013; Chiaramonte *et al.*, 2016; Cummins *et al.*, 2017)[4]:

$$Zs1_t = \frac{ROA_t + Eq/TA_t}{\sigma ROA_3\ (ROA_t, ROA_{t-1}, ROA_{t-2})} \quad [3]$$

Delis and Staikouras (2011) and Baselga-Pascual *et al.* (2015) derive a Z-score measure (Zs2) that uses data from the two previous years to calculate σROA at time *t* (σROA_2):

$$Zs2_t = \frac{ROA_t + Eq/TA_t}{\sigma ROA_2\ (ROA_{t-1}, ROA_{t-2})} \quad [4]$$

Maechler et al. (2007), Lepetit and Strobel (2013) and Chiaramonte et al. (2016) compute the Z-score using the three-year moving average of return of assets ($ROA_{\mu 3}$) plus the three-year moving average of the equity to total assets ratio ($Eq/TA_{\mu 3}$) over the three-year standard deviation of ROA (σROA_3):

$$Zs3_t = \frac{ROA_{\mu 3}(ROA_t, ROA_{t-1}, ROA_{t-2}) + Eq/TA_{\mu 3}(Eq/TA_t, Eq/TA_{t-1}, Eq/TA_{t-2})}{\sigma ROA_3\ (ROA_t, ROA_{t-1}, ROA_{t-2})} \quad [5]$$

[4] The three-year time rolling window in the standard deviation calculation avoids the problem that Z-scores are exclusively driven by changes in ROA and Eq/TA (Schaeck *et al.*, 2012). Although a longer period for the calculation of the standard deviation could result in more reliable Z-scores, we must consider the loss of observations created by imposing a stronger requirement (Pasiouras and Gaganis, 2013).

Yeyati and Micco (2007) compute the Z-scores for each firm and year combining the current values of Eq/TA with the sample mean and variance of ROA calculated over a three-year rolling period ($ROA_{\mu 3}$ and σROA_3):

$$Zs4_t = \frac{ROA_{\mu 3}(ROA_t, ROA_{t-1}, ROA_{t-2}) + Eq/TA_t}{\sigma ROA_3\ (ROA_t, ROA_{t-1}, ROA_{t-2})} \quad [6]$$

We also calculate the Z-score as the sum of the current values of ROA and the average of the three most recent equity to total assets ratios ($Eq/TA_{\mu 3}$) divided by the three-year standard deviation of ROA (σROA_3) (Boyd *et al.*, 2006; Chiaramonte *et al.*, 2016):

$$Zs5_t = \frac{ROA_t + Eq/TA_{\mu 3}(Eq/TA_t, Eq/TA_{t-1}, Eq/TA_{t-2})}{\sigma ROA_3\ (ROA_t, ROA_{t-1}, ROA_{t-2})} \quad [7]$$

Finally, we estimate a Z-score measure that combines the current year *t* values of ROA and Eq/TA (ROA_t and Eq/TA_3) with the standard deviation of ROA calculated over the full period (σROA_T) (Beck and Laeven, 2006; Hesse and Čihák, 2007):

$$Zs6_t = \frac{ROA_t + Eq/TA_t}{\sigma ROA_T\ (ROA_t, ROA_{t-1}, ROA_{t-2}, \dots)} \quad [8]$$

We take the natural logarithms of all the Z-score measures to control for the skewness exhibited by the original variable (Laeven and Levine, 2009; Liu *et al.*, 2013; Chiaramonte *et al.*, 2016).

3.3. Choosing the best Z-score approach

We aim to examine which of the different ways of computing the Z-score discussed in Section 3.2 is best when using actual data. To do this, we first examine which of the various mean and standard deviation estimates that are used to compute the time-varying Z-score measures Zs1 to Zs6 (i.e., ROA_t, $ROA_{\mu 3}$, Eq/TA_t, $Eq/TA_{\mu 3}$, σROA_2, σROA_3, σROA_T) best fit the data. Following a procedure similar to that employed by Lepetit and Strobel (2013) in the banking sector, we opt for a root mean squared error (RMSE) criterion to evaluate which of the "*x*" proposed estimates minimizes the (weighted) average RMSE of the *N* insurers *j*:

$$RMSE = \sum_{j=1}^{N} \frac{T_j}{\sum_{j=1}^{N} T_j} \sqrt{\frac{1}{T_j} \sum_{t=1}^{T_j} \left(x_{j,t} - \mu_{x,j,t-1}^{est} \right)^2} \quad [9]$$

Moreover, we estimate and compare the explanatory power of the following multivariate empirical model for the Spanish insurance sector:

$$Y_{i,t} = \alpha + \beta \cdot FS_{i,t} + \gamma \cdot M_t + \varepsilon_{i,t} \qquad [10]$$

where Y denotes the different approaches to estimate the Z-score of insurer i (i.e., Zs1 to Zs6) in year t (in logarithmic form). We consider some firm-specific accounting variables that the literature has recognized as good predictors of insurer risk. We also include a variable to account for the possible effect of industry concentration on insurer risk as well as some additional dummy variables to control for the insurer specialization (life versus nonlife) and the organizational form (mutual versus stock companies). Finally, we include a set of year dummy variables to account for macroeconomic conditions and time-specific effects. In the regression above, $\varepsilon_{i,t}$ is the disturbance term.

Table 4 summarizes the explanatory variables that are considered in the present study and their expected signs for the Z-score — remember that the Z-score (i.e., the distance-to-default) operates in the opposite direction to the insurer risk: the higher the Z-score, the lower the risk. We use the natural logarithm of total assets to account for the effect of size on risk and expect a positive relationship between size and the Z-score as financially distressed insurers are typically small in size (Sharpe and Stadnik, 2007). To examine the influence of profitability on insurer risk, we divide profits after tax by total assets (i.e., ROA). The empirical literature on insurance firms concludes that higher profitability indicates more efficient management and therefore contributes to lower failure risk (Sharpe and Stadnik, 2007; Pasiouras and Gaganis, 2013; Caporale *et al.*, 2017; among others). We include the equity to total assets ratio to control for the effect of capitalization on insurer risk. Altuntas and Rauch (2017) find that in the insurance sector, higher levels of capitalization are associated with higher levels of financial stability. To account for the effect of reinsurance on the Z-score models, we use the ratio of reinsurance premiums paid to total premiums earned. Reinsurance allows insurers to transfer part of their risk to third parties and results in more predictable future losses, thereby reducing the probability of default (Shiu, 2011; Caporale *et al.*, 2017). Consequently, we expect a positive relationship between the use of reinsurance by the insurer and the Z-score. We choose the share of equity securities in total assets to measure the effect of investment risk on insurer risk and expect a negative relationship between the portfolio risk and our distance-to-default measures. Similar to Ho *et al.* (2013) and Altuntas and Rauch (2017), we proxy underwriting risk with the standard deviation over the sample period of the loss ratio, defined as incurred losses divided by premiums earned net of reinsurance. As stated by Cummins and Sommer (1996), underwriting risk refers to the risk that loss payments will be greater than the expected losses allowed for in the premiums charged to policyholders. We thus anticipate a negative association between underwriting risk and the Z-score. To account for the effect on insurer risk of the time lag between the issuance and payment of claims, we use the ratio of technical provisions (i.e., loss reserves) over incurred losses. We presume that there is a negative effect of long-tailed business on insurer soundness (Sharpe and Stadnik, 2007). Finally, we account for the ownership structure of the firm and insurer specialization using two dummy variables.[5] Altuntas and Rauch (2017) report that mutual insurance firms have higher Z-score levels. We also expect a positive sign for the dummy that identifies life insurance companies, as nonlife insurers are considered riskier than life insurance companies because they operate as 'risk takers' (Chen and Wong, 2004). We measure industry concentration using the Herfindahl–Hirschman index. There is not a consensus regarding the expected relationship between industry concentration and insurer risk. The 'concentration-stability' view states that because large firms are likely to earn more profits due to market power, a concentrated industry is more stable. Therefore, this view favors greater values for the Z-score. However, the 'concentration-fragility' view affirms that the 'too-big-to-fail' protective mechanism may lead to excessive risk-taking by managers (Moreno *et al.*, 2018), resulting in lower values of the Z-score. In this vein, Shim (2017) shows that higher market concentration is associated with decreased financial stability in the U.S. property-liability insurance industry.

[INSERT TABLE 4 ABOUT HERE]

4. Results

4.1. Analysis of the different Z-score measures

Table 5 reports some descriptive statistics of the six different time-varying Z-score measures. The results for Zs1, Zs3, Zs4 and Zs5 are very similar, with means, as calculated per insurer, in the interval of 3.693 to 3.787. Zs2 presents a higher mean and standard deviation. Zs6, on the other hand, has results that are very different from the other measures, with average means and standard deviations in a lower range as well as a smaller average coefficient of variation of 0.32. We also observe that mutual insurance companies present higher mean values than stock companies for each of the six Z-score measures considered. Similarly, we find differences in these measures of life and nonlife specialized insurers, although in this case, they are not as large as in the

[5] We use the same criteria as the DGSFP (2018) to differentiate between life and non-life-specialized insurers.

former. Finally, the lowest average Z-score is reported in 2010, whereas the highest Z-score mean values are found in 2016 and 2017, which is in line with the improvement of the Spanish economy.

[INSERT TABLE 5 ABOUT HERE]

Table 6 presents the average correlation coefficients of our six different Z-score measures, confirming the existence of three clusters: Zs1, Zs3, Zs4 and Zs5 have correlation coefficients close to 1, whereas the coefficients of Zs2 and Zs6 are much lower.

[INSERT TABLE 6 ABOUT HERE]

Table 7 shows the results of the (weighted) average RMSE for each of the components of the Z-scores considered in the current study (i.e., Zs1-Zs6). Following a reasoning similar to that applied by Lepetit and Strobel (2013), our results indicate that Zs6 is the Z-score measure that best fits the data. Therefore, according to this criterion, the best way to calculate the Z-score is using the current period *t* values of ROA and Eq/TA together with the standard deviation of ROA calculated over the full sample, as proposed by Beck and Laeven (2006) and Hesse and Čihák (2007).

[INSERT TABLE 7 ABOUT HERE]

In Table 8, we estimate and compare the explanatory power of the six Z-score measures that are considered. First, however, we perform an analysis of multicollinearity for the previously selected independent variables (see Table 4). We confirm that collinearity is not a problem by calculating the variance inflation factor (VIF); this factor reaches a value that is less than 4 (and close to 1) for most of the variables.[6] The model that regress Zs6 presents the highest explanatory power, with values for the adjusted R^2 slightly higher than 30%. The rest of the models reach values close to 20%, except for Zs2, for which the adjusted R^2 falls to 12%. Therefore, we confirm that the Zs6 model is the best option to explain insurer risk, in accordance with the results reported by the RMSE criterion.[7]

[INSERT TABLE 8 ABOUT HERE]

[6] The only variable that has a VIF higher than 4 is the HHI used to account for industry concentration (which reaches a value close to 6). We regress our models with alternative variables (e.g., the concentration ratio CR5) and even without including that variable, leaving our conclusions practically unchanged.

[7] Although the explanatory value (as measured by the adjusted R^2) of the risk models considered is not very high, our results are very similar to those found by Shim (2011), Fields *et al.* (2012), Altuntas and Rauch (2017) and Cummins *et al.* (2017), among others.

4.2. Analysis of the determinants of insurer risk

Because some of the firm-specific factors that influence insurer risk may be endogenous (e.g., insurers could have incentives to increase their capital ratio if they become riskier) and others are difficult to measure or identify in an equation (e.g., managerial ability), in Table 9, we report the results of our baseline equation using the system-GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) for dynamic panel data models. The persistence of risk has been well documented in the banking literature (e.g., Baselga-Pascual *et al.*, 2015). We are able to use the system-GMM methodology because we have information for all of the variables analyzed over at least five consecutive years for each insurer.[8] As proposed by Windmeijer (2005), we employ the two-step estimation procedure with finite-sample corrected standard errors, which provides less biased coefficient estimates and more accurate standard errors. We treat insurer characteristics (except their organizational form and their specialization) as endogenous variables by using suitable instruments for both the equation in levels and the equation in differences.[9] Industry concentration and macroeconomic control variables (i.e., year dummies) are considered strictly exogenous. We verify the validity of the instruments by using Hansen's J-test of overidentifying restrictions.

[INSERT TABLE 9 ABOUT HERE]

The higher values of the lagged dependent variables (except for the Zs2 regression) confirm the dynamic character of the model specification, indicating strong persistence; i.e., the adjustment of the risk is very slow. As expected, the regression coefficients indicate a positive relationship between size and the Z-score; i.e., larger firms are less risky than smaller firms, supporting previous findings in the literature (Chen and Wong, 2004; Pasiouras and Gaganis, 2013; Shim, 2017). We demonstrate a strong positive relationship between ROA and the Z-score but only when Zs6 is used as the dependent variable. This result supports the hypothesis that highly profitable insurers are less likely to become insolvent because they manage expenses effectively and can set competitive premium rates (Caporale *et al.*, 2017). The relationship between capitalization, measured by the equity to total assets ratio, is positive and statistically significant in all of the analyzed models. This finding corroborates that more capitalized insurers have higher Z-scores, in line with Shim (2011) and Altuntas and Rauch (2017). We also report that greater use of reinsurance may increase the financial soundness of

[8] This is a required condition to test for the absence of second-order serial correlation.
[9] We also test regressions in which the organizational form and/or the specialization are considered as endogenous variables. The results hardly differ from those previously obtained.

firms; i.e., higher levels of reinsurance result in lower insurer risk by transferring part of this risk to third parties (as found by Alhassan and Biekpe, 2018). However, this result applies only to the Zs6 approach and has low statistical significance. The positive sign we find for the dummy that identifies mutual insurance companies is in accordance with the hypothesis that mutual companies are financially more stable than stocks companies because in mutual companies, policyholders are also owners of the firms. Therefore, managers' incentives to increase asset risk are lower in mutual companies than in stock firms (Shim, 2017). Similar to Pasiouras and Gaganis (2013), we also find a positive sign for the dummy that identifies life insurance companies, corroborating that life insurers are more financially stable than nonlife insurance companies, which may operate as 'risk takers'. The relationship between concentration and the Z-score is negative and significant only for the Zs6 approach. This result supports the concentration-fragility view, providing empirical evidence against the tendency towards the increasing concentration that is currently experiencing the Spanish insurance market. Finally, we do not find statistical significance for the variables that measure portfolio risk, underwriting risk and long-tailed business in any of the six models considered.

Once again, we observe that the Z-score measure that incorporates more statistically significant variables in the risk model is the one that combines current values of ROA and capitalization with the standard deviation of ROA calculated over the full period.

5. Conclusions

This paper compares six different approaches to calculating the Z-score. This measure of risk has widely been used in the banking literature, and it has recently also been applied to the insurance sector as an indicator of financial soundness. The Z-score relates the insurer's capital level to variability in its returns, revealing how much variability in returns can be absorbed by capital without the insurer becoming insolvent. Higher Z-scores are indicative of a higher distance-to-default ratio and thus greater stability. The results for the Z-scores are easily verifiable because this measure uses accounting data. Thus, information provided by this indicator, in addition to that given by more complex risk-based models, may be helpful for insurance regulators to obtain a better understanding of the insurance industry's risk factors.[10]

Our final dataset comprises 183 insurers (1,382 observations) operating in the Spanish insurance sector during the period 2010-2017. Using different methodologies

[10] Plantin and Rochet (2007) state that "prudential ratios should be defined simply and derived from public accounts, because these accounts are easily verifiable".

(RMSE, OLS and system-GMM regressions), we find that the best measure to calculate the Z-score is the one that combines current values of ROA and capitalization with the standard deviation of ROA calculated over the full period. This approach (i.e., the Zs6) has the advantage of allowing the construction of time-varying Z-scores that does not require initial observations to be dropped (Lepetit and Strobel, 2013).

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Table 1
Representative studies examining risk in the insurance sector

Authors	Sample	Method	Dependent variable	Independent variables
Chen and Wong (2004)	General and life insurance companies in Asia (1966-1999)	Classification method (HHM model) and logit regression	Financial stability	Firm-specific determinants of property-liability insurers' financial health: Firm size; Investment performance; Liquidity ratio; Premium growth; Surplus growth; Combined ratio[1]; and Operating margin. Firm-specific determinants of life insurers' financial health: Firm size; Change in assets; Investment performance; Operating margin; Change in product mix; and Leverage.
Sharpe and Stadnik (2007)	Australian general insurers (1999-2001)	Logit regression	Financial distress	ROA; Expense ratio; Cession ratio[2]; Size; Growth premiums; Equity ratio; Property ratio; Liquid assets Ratio; Debt ratio; Reinsurance assets ratio; Other assets ratio; and Premiums written by insurance lines.
Fields *et al.* (2012)	Publicly traded insurers (life, nonlife and composite) around the world (1992-2006)	OLS regression	Firm-level coefficient of variation of natural logarithmic of the solvency ratio and leverage	Investor protection: Antidirector; Anti-self-dealing; Disclosure index; Liability standards index; and Creditor rights. Government quality: Rule of law; Anticorruption; Common-law; and Regulation quality. Contract enforcement, competition and insider ownership: Judicial independence; Contract enforcement; Insider ownership disclosure; and Barriers to entry. Control variables: Growth; Ratio of net premiums written to gross premiums written; Liquidity ratio; Unquoted to total investment; Size; Ln (years of firm data); Interest rate mean; and Interest rate variance.
Eling and Marek (2013)	Insurers from the UK and Germany (1997-2000)	SEM (structural equation model)	Business risk (investing and underwriting); Product risk; Financial risk	Corporate governance variables: Executive compensation; Supervisory board compensation; Blockholders; Supervisory board independence; Board meetings. Control variables: Size; Country; Type (life/nonlife); Reinsurance; and Accounting standards.
Ho *et al.* (2013)	U.S. property casualty insurance companies (1996-2007)	Panel data regressions	Total risk; underwriting risk; investment risk; leverage risk	Organizational structure Board composition variables: Duality; Board size; and Insiders. Control variables: Audit quality; Firm size; Line of business; Geographical H-I; Percentage of net written premiums in the long-tail lines; and Reinsurance ratio.
Hu and Yu (2014)	Life insurance companies in Taiwan (2004-2009)	Two-stage least square (2SLS) and two-stage quantile (2SQR) regressions	Investment risk; underwriting risk	Firm Size; ROA; Global Financial Crisis; Foreign insurer; Publicly held company; Member of financial holding group; Family control-company; Capitalization.

(continued)

Table 1 (continued)

Authors	Sample	Method	Dependent variable	Independent variables
Mankaï and Belgacem (2016)	US property-liability insurers (1999-2008)	Three-stage least squares (3SLS)	Risk-taking: Volatility of the assets to liability ratio; ratio of risky assets and liabilities reinsurance	Business mix; Loss volatility; Geographic concentration; Size; Organizational form (mutual/stock); Group affiliation; Capital; and Reinsurance (in the risk equation).
Caporale et al. (2017)	General insurance firms in the UK (1986-2014)	Reduced-form models to estimate default probabilities	Insolvency risk (individual probabilities of default). Considers three dimensions: Credit quality of the investment portfolio; counterparty risk; and direct default risk	Traditional risk factors: Leverage; Profitability; Firm growth; Firm size; Liquidity. Insurance-specific risk factors: Reinsurance; Claims change; Capital; Growth in gross premiums written; Combined ratio; Line of business concentration, Organizational form (mutual/non-mutual), and Derivative dummy[3]. Macroeconomic variables: GDP growth; Change in the wholesale price index; Change in foreign direct investment; Net inflows; Real interest rate; Real effective exchange rate; and Change in the credit provided by financial institutions.

Notes: [1]Ratio of incurred losses to earned premiums + incurred expenses to written premiums. [2]Ratio of outward reinsurance expense to premium revenue. [3]Whether or not an insurance firm is involved in derivative trading.

Table 2
Representative studies using the Z-score (as the dependent variable) in the insurance sector

Authors	Sample	Method	Independent variables
Shim (2011)	U.S. property-liability insurance industry (1989-2004)	Pooled, cross-sectional and time-series data regressions	Merger & Acquisitions Indicator* and Product diversification*. Control variables: Size*; Size^2*; Capitalization*; Investment income*; Geographical diversity index; Distribution system*; Organizational form*; and Group/unaffiliated*.
Pasiouras and Gaganis (2013)	Life and nonlife insurance firms operating in 46 countries (2005-2007)	Random effect generalized least square (GLS)	Regulatory variables: Capital requirements index*; Official supervisory power index*; Technical provisions index*; Investments index*; and Corporate governance and internal control index. Control variables: Size*; Organizational form; Group structure; Business activity*; Economic growth*; Inflation*; Insurance market development; Economic freedom*; Overall institutional development*; and Economic development*.
Altuntas and Rauch (2017)	Property-liability insurers from 29 developed and developing countries (2004-2012)	OLS regression	Firm-specific variables: Reinsurance; Profitability*; Underwriting rigor*; Operating efficiencies; Leverage (capitalization)*; Investment income*; Size; Organizational form*; and Group affiliation*. Concentration variables: Market share of the five largest insurers in each country*; Market share of the three largest insurers in each country; and Market HHI*. Country-level factors: GDP per capita; Inflation; and Real interest rate.
Cummins et al. (2017)	Life insurance from 10 of the most important EU countries (1999-2011)	OLS regression	Competition (Boone indicator)**.** Firm-level characteristics: Size***,** Reinsurance, Efficiency of insurers' accounts receivable management***,** Leverage; and Ownership. Country-level variables: Inflation rate; Growth in real per capita GDP*; Market structure*; Level of insurance activity in the country*; Size of domestic insurance market*; Crisis*.
Shim (2017)	U.S. property-liability insurance industry (1992-2010)	OLS and 2SLS regressions with instrumental variables	Concentration*; Firm size*; Firm size^2*; Catastrophes*; Leverage*; Product diversification*; Geographic diversification*; Homeowners line share*; Investment in bonds*; Reinsurance ratio*; Asset growth; Mutual structure*; Group affiliation*; Interest rate change*; Premium growth; and GDP growth.
Alhassan and Biekpe (2018)	Nonlife insurance firms in South Africa (2007-2012).	Seemingly unrelated regression; Quantile regression; System-GMM	Competition (Lerner index)*; Firm size*; Capitalization*; Reinsurance*; Business line diversification*; and Foreign ownership*.

Notes: * indicates statistically significant variables.

Table 3
Number of observations in the final sample

Year	Mutual insurers	Stock insurers	Total
2010	29	146	175
2011	29	150	179
2012	30	152	182
2013	30	153	183
2014	30	153	183
2015	30	141	171
2016	29	131	160
2017	26	123	149
	233	1,149	1,382

Table 4
Explanatory variables and their expected signs in the Z-score regressions

Explanatory variable	Definition	Expected sign	Data source	References
Size	Natural log of total assets	+	Authors' calculation using DGSFP data	Chen and Wong (2004), Pasiouras and Gaganis (2013), Shim (2017)
Profitability	Profits after tax divided by total assets	+	Authors' calculation using DGSFP data	Sharpe and Stadnik (2007), Caporale et al. (2017)
Capitalization	Equity to total assets ratio	+	Authors' calculation using DGSFP data	Shim (2011), Altuntas and Rauch (2017)
Reinsurance	Reinsurance premiums paid divided by total premiums earned	+	Authors' calculation using DGSFP data	Ho et al. (2013), Mankaï and Belgacem (2016), Caporale et al. (2017)
Portfolio risk	Equity securities in the asset portfolio divided by total assets	-	Authors' calculation using DGSFP data	Cummins et al. (2017)
Underwriting risk	Standard deviation of loss ratio over sample period, defined as incurred losses divided by premiums earned net of reinsurance	-	Authors' calculation using DGSFP data	Altuntas and Rauch (2017)
Long-tailed business	Technical provisions (loss reserves) divided by incurred losses	-	Authors' calculation using DGSFP data	Sharpe and Stadnik (2007), Ho et al. (2013)
Mutual	Dummy variable that takes the value of 1 for mutual companies and 0 otherwise	+	Authors' calculation using DGSFP data	Pasiouras and Gaganis (2013), Shim (2017), Altuntas and Rauch (2017)
Life insurance	Dummy variable that takes value of 1 if life technical provisions are at least 80 percent of the whole technical provisions and 0 otherwise	+	Authors' calculation using DGSFP data	Chen and Wong (2004), Pasiouras and Gaganis (2013), Eling and Marek (2013)
Industry concentration	Herfindahl–Hirschman index calculated as the sum of the squares of all insurance companies' market shares in terms of premiums written (as a percentage)	+/-	MAPFRE (2018)	Ho et al. (2013), Caporale et al. (2013)
Year dummies	Dummy variables used to control for macroeconomic conditions and time-specific effects			

Table 5
Descriptive statistics of the different Z-score metrics

	Zs1	Zs2	Zs3	Zs4	Zs5	Zs6
Full sample						
Mean	3.787	4.232	3.772	3.780	3.693	3.085
St. Dev.	1.290	1.594	1.297	1.307	1.268	0.995
Min.	-2.642	-1.967	-2.759	-1.967	-0.389	-2.843
Max.	9.817	11.927	9.833	9.817	9.825	8.168
Mutual						
Mean	4.329	4.785	4.307	4.327	4.282	3.517
St. Dev.	1.255	1.488	1.252	1.258	1.240	0.927
Stock companies						
Mean	3.677	4.120	3.663	3.669	3.573	2.998
St. Dev.	1.269	1.593	1.280	1.290	1.241	0.985
Nonlife specialized insurers						
Mean	3.786	4.200	3.768	3.776	3.651	3.059
St. Dev.	1.277	1.548	1.295	1.303	1.334	1.143
Life specialized insurers						
Mean	3.790	4.319	3.781	3.789	3.708	3.095
St. Dev.	1.323	1.710	1.306	1.320	1.243	0.933
2010						
Mean	3.585	4.004	3.610	3.598	3.521	3.007
St. Dev.	1.342	1.662	1.246	1.274	1.233	1.070
2011						
Mean	3.791	4.235	3.794	3.781	3.707	3.032
St. Dev.	1.311	1.588	1.302	1.340	1.283	0.972
2012						
Mean	3.759	4.258	3.731	3.754	3.659	3.055
St. Dev.	1.392	1.748	1.391	1.399	1.330	1.009
2013						
Mean	3.751	4.277	3.696	3.724	3.614	3.108
St. Dev.	1.304	1.648	1.346	1.375	1.314	0.974
2014						
Mean	3.772	4.077	3.753	3.766	3.670	3.116
St. Dev.	1.197	1.444	1.244	1.228	1.229	0.926
2015						
Mean	3.768	4.226	3.758	3.766	3.680	3.110
St. Dev.	1.197	1.498	1.191	1.214	1.180	0.999
2016						
Mean	3.939	4.352	3.929	3.933	3.854	3.131
St. Dev.	1.262	1.585	1.267	1.282	1.248	1.017
2017						
Mean	3.975	4.481	3.946	3.957	3.882	3.136
St. Dev.	1.282	1.532	1.375	1.323	1.309	1.002

Notes: This table reports descriptive statistics for six different Z-score approaches. *Zs1* is defined in Equation [3]; *Zs2* is defined in Equation [4]; *Zs3* is defined in Equation [5]; *Zs4* is defined in Equation [6]; *Zs5* is defined in Equation [7], and *Zs6* is defined in Equation [8]. All of these are calculated in logarithms. Our final dataset comprises 183 insurers (1,382 observations) operating in the Spanish insurance sector during the period 2010-2017.

Table 6
Correlation coefficients of the different Z-score metrics

	Zs1	**Zs2**	**Zs3**	**Zs4**	**Zs5**	**Zs6**
Zs1	1					
Zs2	0.7853***	1				
Zs3	0.9863***	0.7756***	1			
Zs4	0.9943***	0.7825***	0.9928***	1		
Zs5	0.9821***	0.7688***	0.9910***	0.9841***	1	
Zs6	0.6885***	0.5398***	0.6711***	0.6831***	0.6609***	1

Notes: This table reports the pairwise correlation coefficients for six different Z-score approaches. *Zs1* is defined in Equation [3]; *Zs2* is defined in Equation [4]; *Zs3* is defined in Equation [5]; *Zs4* is defined in Equation [6]; *Zs5* is defined in Equation [7], and *Zs6* is defined in Equation [8]. All of these are calculated in logarithms. Our final dataset comprises 183 insurers (1,382 observations) operating in the Spanish insurance sector during the period 2010-2017. *** indicates significance at the 1 percent level.

Table 7
Root mean squared error for the components of the different Z-score approaches

Z-score	ROA_t,	$ROA_{\mu 3}$	Eq/TA_t	$Eq/TA_{\mu 3}$	σROA_2	σROA_3	σROA_T
Zs1	1.2781		1.2423			1.0464	
Zs2	1.5843		1.5630		1.3402		
Zs3		1.2702		1.2530		1.0219	
Zs4		1.2775	1.2599			1.0297	
Zs5	1.2682			1.2134		1.0484	
Zs6	**0.9729**		**0.9174**				**0.8203**

Notes: This table reports the average root mean squared error (RMSE) for the components of the different Z-score approaches. Our final dataset comprises 183 insurers (1,382 observations) operating in the Spanish insurance sector during the period 2010-2017. *Zs1* is defined in Equation [3]; *Zs2* is defined in Equation [4]; *Zs3* is defined in Equation [5]; *Zs4* is defined in Equation [6]; *Zs5* is defined in Equation [7], and *Zs6* is defined in Equation [8]. All of these are calculated in logarithms. ROA_t is the year *t* value of return on assets; $ROA_{\mu 3}$ is the three-year moving average of ROA; Eq/TA_t is the year *t* value of the equity to total assets ratio; $Eq/TA_{\mu 3}$ is the three-year moving average of Eq/TA; σROA_2 is the two-year moving standard deviation of ROA; σROA_3 is the three-year moving standard deviation of ROA; and σROA_T is the standard deviation of ROA calculated over the whole period. The minimum average RMSE is highlighted in bold.

Table 8
Comparative analysis of the Z-score models

Variables	(1) **Zs1**	(2) **Zs2**	(3) **Zs3**	(4) **Zs4**	(5) **Zs5**	(6) **Zs6**
Size	0.153***	0.157***	0.139***	0.155***	0.128***	0.145***
	(0.039)	(0.044)	(0.039)	(0.040)	(0.038)	(0.039)
Profitability	3.388**	3.906**	2.642	3.213*	0.189	3.982***
	(1.661)	(1.661)	(1.813)	(1.764)	(1.436)	(1.339)
Capitalization	2.697***	2.716***	2.635***	2.743***	2.691***	2.819***
	(0.415)	(0.429)	(0.420)	(0.424)	(0.409)	(0.380)
Reinsurance	-0.198	-0.086	-0.234	-0.238	-0.214	0.345
	(0.299)	(0.297)	(0.311)	(0.315)	(0.297)	(0.277)
Portfolio risk	0.641	0.391	0.691	0.636	0.676	0.574
	(0.490)	(0.553)	(0.476)	(0.495)	(0.470)	(0.427)
Underwriting risk	-0.116	-0.079	-0.140	-0.126	-0.128	-0.221***
	(0.123)	(0.131)	(0.129)	(0.129)	(0.124)	(0.127)
Long-tailed business	0.013	0.025	0.016	0.015	0.017	0.015
	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.024)
Mutual	0.633***	0.662***	0.611***	0.642***	0.596***	0.418***
	(0.202)	(0.205)	(0.203)	(0.205)	(0.199)	(0.190)
Life insurance	0.680***	0.699***	0.691***	0.693***	0.613***	0.719***
	(0.206)	(0.214)	(0.211)	(0.210)	(0.208)	(0.206)
Industry concentration	-0.001	-0.003	0.000	0.000	0.000	-0.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.000)
Constant	-0.046	1.192	-0.412	-0.452	-0.128	-1.123
	(1.263)	(1.647)	(1.316)	(1.332)	(1.263)	(0.972)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Firm	Firm	Firm	Firm	Firm	Firm
Number of obs.	1,382	1,382	1,382	1,382	1,382	1,382
Number of firms	183	183	183	183	183	183
R^2	19.47%	12.99%	18.23%	19.33%	18.64%	32.60%
Adjusted R^2	**18.53%**	**11.97%**	**17.27%**	**18.38%**	**17.69%**	**31.81%**
F-value	7.97 (16,182)	6.85 (16,182)	8.02 (16,182)	8.16 (16,182)	9.06 (16,182)	12.41 (16,182)

Notes: This table reports the ordinary least square (OLS) regressions of different Z-score approaches for the Spanish insurance sector during the period 2010-2017. *Zs1* is defined in Equation [3]; *Zs2* is defined in Equation [4]; *Zs3* is defined in Equation [5]; *Zs4* is defined in Equation [6]; *Zs5* is defined in Equation [7], and *Zs6* is defined in Equation [8].The dependent variable is included in its logarithmic form. See Table 4 for a description of the independent variables. Robust standard errors, which are clustered by firms, are reported in parentheses. Significance levels are indicated as follows: ***= significance at the 1 percent level; **= significance at the 5 percent level; and *= significance at the 10 percent level. The explanatory power of the model is highlighted in bold.

Table 9
Determinants of insurer risk in Spain according to the different Z-score measures

Variables	(1) Zs1	(2) Zs2	(3) Zs3	(4) Zs4	(5) Zs5	(6) Zs6
Lagged dependent	0.581***	0.229***	0.666***	0.615***	0.647***	0.749***
	(0.038)	(0.039)	(0.044)	(0.038)	(0.045)	(0.059)
Size	0.159***	0.186***	0.127***	0.156***	0.126***	0.097***
	(0.056)	(0.071)	(0.044)	(0.056)	(0.048)	(0.019)
Profitability	2.156*	2.294	0.261	2.050	-0.268	2.865***
	(1.294)	(1.956)	(1.329)	(1.430)	(1.344)	(0.377)
Capitalization	1.973***	3.058***	1.638***	1.971***	1.714***	1.158***
	(0.486)	(0.827)	(0.522)	(0.530)	(0.529)	(0.294)
Reinsurance	0.009	-0.247	-0.141	-0.086	-0.096	0.138*
	(0.221)	(0.328)	(0.259)	(0.242)	(0.247)	(0.071)
Portfolio risk	-0.177	-0.499	-0.122	-0.148	-0.076	-0.078
	(0.304)	(0.405)	(0.292)	(0.326)	(0.271)	(0.095)
Underwriting risk	-0.050	0.041	0.003	-0.022	-0.065	-0.023
	(0.104)	(0.197)	(0.126)	(0.116)	(0.122)	(0.069)
Long-tailed business	-0.010	0.016	0.001	-0.003	0.001	-0.009
	(0.023)	(0.034)	(0.019)	(0.023)	(0.020)	(0.012)
Mutual	0.249**	0.402**	0.163	0.254**	0.165	0.159***
	(0.101)	(0.176)	(0.102)	(0.102)	(0.107)	(0.060)
Life insurance	0.358**	0.515*	0.242	0.334*	0.266	0.245**
	(0.166)	(0.269)	(0.172)	(0.176)	(0.190)	(0.112)
Industry concentration	0.001	-0.001	0.001	0.001		-0.001***
	(0.001)	(0.002)	(0.001)	(0.001)		(0.000)
Constant	-2.687	-1.256	-2.520**	-2.925**	-1.754	-1.220***
	(1.183)	(1.658)	(1.014)	(1.189)	(1.073)	(0.441)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
z1	36.24 (9, 182)	5.50 (9, 182)	30.93 (9, 182)	35.01 (9, 182)	31.14 (8, 182)	31.87 (9, 182)
z2	2.29 (7, 182)	2.67 (7, 182)	1.75 (7, 182)	2.15 (7, 182)	1.48 (8, 182)	3.84 (7, 182)
m1	-6.84	-6.71	-6.94	-6.87	-6.86	-2.06
m2	-1.18	0.17	-0.75	-1.12	-0.75	0.85
Hansen	169.26 (204)	165.26 (204)	161.05 (204)	167.22 (204)	163.37 (204)	174.25 (204)
Number of obs.	1,382	1,382	1,382	1,382	1,382	1,382
Number of firms	183	183	183	183	183	183

Notes: This table presents the determinants of insurer risk in the Spanish insurance sector (2010-2017) according to different Z-score measures. *Zs1* is defined in Equation [3]; *Zs2* is defined in Equation [4]; *Zs3* is defined in Equation [5]; *Zs4* is defined in Equation [6]; *Zs5* is defined in Equation [7], and *Zs6* is defined in Equation [8]. The dependent variable is included in its logarithmic form. See Table 4 for a description of the independent variables. We use the system-GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). Except for *Mutual*, *Life Insurance, Industry concentration* and *Year dummies*, all variables are considered endogenous in our model. In model (5), *industry concentration* is dropped due to collinearity. We report heteroskedasticity-consistent asymptotic standard errors in parentheses, and significance levels are indicated as follows: ***= significance at the 1 percent level; **= significance at the 5 percent level; and *= significance at the 10 percent level. z_1 and z_2 are Wald tests of the joint significance of the reported coefficients for the nondummy and dummy explanatory variables, respectively, asymptotically distributed as *F* under the null hypothesis of no significance, with degrees of freedom in parentheses. mi is a serial correlation test of order *i* using residuals in first differences, asymptotically distributed as *N(0,1)* under the null hypothesis of no serial correlation. *Hansen* is a test of the overidentifying restrictions, asymptotically distributed as χ^2 under the null hypothesis of no correlation between the instruments and the error term, with degrees of freedom in parentheses.