A Probit Model for Insolvency Risk among Insurance Companies

Leo de Haan*

Jan Kakes†

Abstract

We estimate a probit model of insolvency risk, using a dataset of about 400 Dutch insurance companies during the period 1995-2005. The results suggest that surplus capital, company size, profitability, long-tailed business and being a mutual insurer reduce the risk of insolvency. The model can be used to identify insurers with high insolvency risk one year ahead. It is shown that the choice of the threshold above which an insurer is classified as having high insolvency risk, is an important determinant of the relative occurrence of type I and type II prediction errors. We use a loss function to find the optimal threshold given the supervisor's relative preference with respect to missing insolvencies and false alarms.

Keywords: Probit model, Insolvency risk, Insurance
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* Corresponding author. E-mail: l.de.haan@dnb.nl. Phone: +31 20 5243539. Fax: +31 20 5242514. De Nederlandsche Bank, Economics and Research Division, Amsterdam, The Netherlands.

† De Nederlandsche Bank, Financial Stability Division, Amsterdam, The Netherlands.

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1 - Introduction

For a supervisor of the insurance sector, it may be useful to have a statistical tool to assess the insolvency risk of insurance companies. This paper presents a probit model to investigate the determinants of insolvency.

Earlier applications of classification techniques for financial institutions usually distinguish bankrupt from non-bankrupt companies (see, e.g., BarNiv and McDonald, 1992, for a survey). Most of these studies use US data, where bankruptcies occur frequently. Since bankruptcies among Dutch insurance companies are very rare, other classification criteria have to be used for a sensible statistical analysis. Instead of actual defaults, we therefore use a broader concept that also includes near insolvencies. To identify these, we use an objective classification criterion based on the solvency ratio, which is defined as the actual capital-to-assets ratio of an insurance company divided by the required capital-to-assets ratio that is prescribed by the supervisor.

Besides the fact that we focus on a European country, an important value-added of our paper is that we have a comprehensive dataset. Our dataset comprises the entire Dutch insurance industry – about 400 Dutch life and non-life insurers – and covers a long period (1995-2005) including a full business cycle. So, peculiarities due to specific insurers or a specific year are unlikely to drive our results.

The estimation results suggest that surplus capital, company size, profitability, long-tailed business and being a mutual insurer reduce the risk of insolvency. The model can be used to identify insurers with high risk of insolvency one year ahead. It is shown that the choice of the threshold above which an insurer is classified as having high insolvency risk, is an important determinant of the relative occurrence of type I and type II prediction errors. We use a loss function to find the optimal threshold given the supervisor's relative preference with respect to missing insolvencies and false alarms.

The outline of the paper is as follows. After a literature review in Section 2 to put our contribution in perspective, the model is presented in Section 3. Section 4 discusses the data. The estimation results are discussed in Section 5, after which Section 6 shows how the model can be used for predicting insolvencies. Section 7 concludes.

2 - Literature review

The modeling of insolvencies dates back to the early literature on corporate bankruptcy, including the seminal work by Altman (1968) who used discriminant analysis. Later on, logit or probit models were found to be superior (e.g. Ohlson, 1980; Lennox, 1999). These models assume that the probability of bankruptcy can be predicted by a set of company characteristics and other variables. Discriminant analysis is criticized for its restrictive distributional assumptions, specifically that the variables' distributions are normal and that their variance-covariance matrices are the same for both non-bankrupt and bankrupt firms. Logit and probit models do not impose such assumptions. Moreover, logit and probit models directly give a probabilistic prediction whereas discriminant analysis produces a score, such as the Z-score or the Taffler-score, which has to be converted into a probabilistic measure, being an additional source of error (Ohlson, 1980). A different approach is the Merton (1974) model, which imposes assumptions on the value of firms' underlying assets and capital structure. A firm's default is determined by the market value of its assets relative to its liabilities. While attractive because of its strong theoretical underpinning, the Merton model has been criticized because of the underlying assumptions of perfectly liquid markets, absence of transaction costs and irrelevance of a firm's financial structure.[1] To take into account these weaknesses, the basic Merton model has been extended and modified, while as an alternative reduced form models have been developed, initiated by Jarrow and Turnbull (1995).

These different methodologies to model insolvencies have also been applied to insurance companies, which have a number of special characteristics compared to other firms. Because of the nature of their activities, insurers tend to be sensitive to financial market sentiment, whereas they use specific tools – like re-insurance – to mitigate their risk. Furthermore, like banks, insurers are subject to prudential regulation and supervision. Most studies on insurers' financial structure and the prediction of failures are based on US data. Several of these studies examine the performance of the US regulator's risk-based solvency rules, which were introduced in the early

[1] Furthermore, the estimation of the Merton model requires high-frequency data on share prices for the assessment of market volatility to deduce default probabilities. The outcomes may therefore be largely driven by excessive price fluctuations rather than market fundamentals. In addition, this information is not available for our sample of mostly non-listed insurance companies.

1990s. BarnNiv and McDonald (1992), Cummins et al. (1995, 1999), Grace et al. (1998) and Pottier and Sommer (2000) analyse insolvencies in the property-liability insurance industry. BarNiv and Hershbarger (1990) investigate different models to predict failures of US life insurers. A general finding of these studies is that the risk-based capital ratio used by US regulators can be improved as a leading indicator of failures. Cummins et al. (1999) conclude that cash-flow variables enhance the explanatory power of this static ratio, while Pottier and Sommer (2000) find that ratings by a private agency outperform the risk-based ratio.

Another strand of empirical literature focuses on the actual capital-to-assets ratio of insurers instead of insolvency risk. See, for example, Harrington and Niehaus (2002), Cummins and Nini (2002) and Klein et al. (2002) for the US. De Haan and Kakes (2010) find that Dutch insurers' capital-to-asset ratios can be related to risk characteristics and tend to be significantly higher than the regulatory minimum.

Analyses on solvency of European insurers are scarce, exceptions being Kramer (1996, 1997) for Dutch non-life insurers and Schmeiser (2004) who uses data of a single German insurance company. These studies typically look at a subset of insurers and consider only a brief period. Apart from data limitations, it is difficult to test the performance of indicators of insurer failures in Europe, for the simple reason that insurer defaults hardly ever occur in most European countries including the Netherlands. Because of the lack of bankruptcies in the Netherlands, Kramer (1996, 1997) investigates under what circumstances Dutch insurers are classified as 'strong', 'moderate' or 'weak' according to assessments by the supervisor. His dataset comprises about 200 Dutch non-life insurance companies in a single year (1992). Using an ordered logit analysis, as well as artificial intelligence techniques (neural network, expert system), his classification matches the supervisor's own qualitative assessments in about 90 percent of the cases. Some important explanatory variables – in particular insurers' solvency and profitability – are in line with our results. By contrast, he does not find that organisation type (mutual or stock) is a significant factor while we conclude it is relevant.

3 - The model

We estimate a probit model that classifies insurers into two groups, one with high and the other with low insolvency risk, respectively. Contrary to Kramer (1996, 1997), our classification criterion is based on an objective measure: the solvency ratio, which is defined as the actual capital-to-assets ratio of an insurance company divided by the required capital-to-assets ratio that is prescribed by the supervisor.[2] Our dataset is also much larger, comprising 400 Dutch life and non-life insurers during the period 1995-2005.

The probit model, as introduced by Bliss (1935), assumes that

$$P(Y=1 \mid X=x)=\Phi(x'\beta), \tag{1}$$

where P denotes the probability, $Y \in (0,1)$ is a binary outcome variable which – in the present study – is 1 if an insurer runs high insolvency risk and 0 if insolvency risk is low, X is a vector of explanatory variables, Φ is the cumulative distribution function of the standard normal distribution, and β is a vector of parameters. Hence, the probability of high insolvency, given certain values x for the explanatory variables, is a function of these values multiplied by a set of parameters. The parameters β are typically estimated by maximum likelihood. This will be done in Section 4. But first, we discuss the data and define the variables that will be used.

4 - Data

We use confidential data on individual insurers for the period 1995-2005, gathered for supervisory purposes and published only in aggregated form in the *Statistical Bulletin* of De Nederlandsche Bank.[3] The unbalanced panel consists of around 400 insurance companies from all lines of business.

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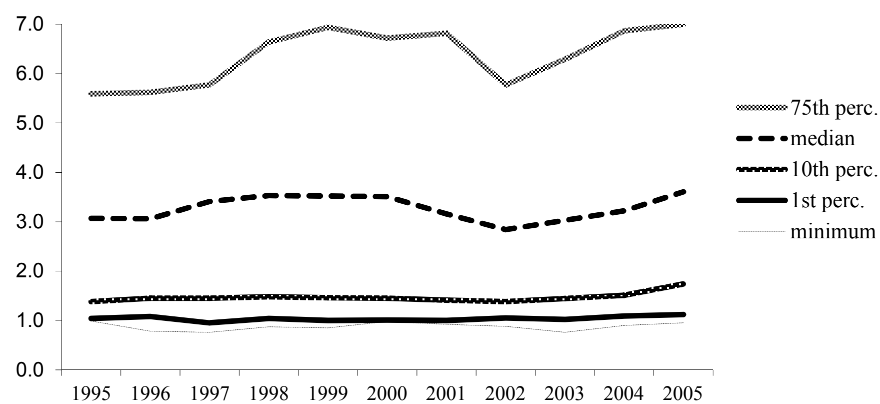
[2] The required solvency ratio is based on an insurer's performance and activities in recent years. For life insurers, the required solvency ratio is largely based on gross technical provisions. For non-life insurers, the required solvency ratio is largely based on premium income and incurred losses over recent years. See De Haan and Kakes (2010) for a more extended discussion of solvency requirements for Dutch insurers.

[3] The dataset used in this study was discontinued after 2005 because of a change in the supervisory reporting framework.

Insurers' financial soundness is often measured by the capital-to-assets ratio. However, the actual capital-to-assets ratio gives only limited information on the financial position of insurers as it does not take account of the risk profiles of their insurance obligations. For example, if a high-risk company and a low-risk company have identical capital-to-assets ratios, the former may be undercapitalized while the latter is overcapitalized. Therefore, insurers' solvency positions are usually presented in terms of the solvency ratio, defined as the actual capital-to-assets ratio of an insurer divided by the required capital-to-assets ratio that is prescribed by the supervisor. The availability of supervisory data on the required capital-to-assets ratio of individual insurers makes our dataset unique and enables us to use the solvency ratio.

Figure 1 shows the percentile distribution of the solvency ratio for each year, including the minimum solvency ratio observed. The median indicates that half of the population has at least thrice the required amount of capital; for the third quartile this is five times or even more. De Haan and Kakes (2010) find that Dutch insurers hold more capital than required because regulatory requirements do not sufficiently take risk factors into account.

Figure 1. Percentile distribution of solvency ratio



Note: The solvency ratio is the actual capital-to-assets ratio divided by the required capital-to-assets ratio.

The dependent variable in our model is the binary outcome variable 'insolvency', which we set equal to 0 if the solvency ratio is greater than 1.5

and equal to 1 if the solvency ratio is less than or equal to 1.5. The frequency distribution of insolvency is given in Table 1. Around 12% of the sample runs high insolvency risk according to this criterion. The hurdle rate of 1.5 reflects supervisory practice at the time and ensures that sufficient observations of high insolvency risk are included, which obviously is essential for a statistically sensible analysis.[4]

Table 1. Frequency distribution of insolvency, by year

	Insolvency = 0		Insolvency = 1		Total number of observations
	Number of observations	Percent of total	Number of observations	Percent of total	
1995	326	86.0	53	14.0	379
1996	345	88.0	47	12.0	392
1997	340	86.1	55	13.9	395
1998	357	87.9	49	12.1	406
1999	354	88.3	47	11.7	401
2000	324	88.3	43	11.7	367
2001	305	86.4	48	13.6	353
2002	289	84.8	52	15.2	341
2003	292	87.4	42	12.6	334
2004	283	89.3	34	10.7	317
2005	278	93.0	21	7.0	299
Total	3493	87.7	491	12.3	3984

The following explanatory variables are considered:

[4] The main results of the probit analysis proved to be not particularly sensitive to this particular choice of hurdle rate. Lower hurdle rates gave less significant outcomes though, due to the fact that there remain too few observations in the insolvent group, which diminishes the discriminatory power of this type of model.

(1) *Surplus capital*, defined as the actual capital-to-assets ratio minus the required capital-to-assets ratio. We expect the probability of insolvency to be lower, the higher the surplus in the preceding year.

(2) *Company size*. Presumably, as large insurers have more scope for diversification than small insurers, their total losses are more predictable. Hence, large firms probably run less risk of insolvency. The size of the company is measured by the natural logarithm of total assets.

(3) *Profitability*. A profitable firm has more internal funds at its disposal that can be hoarded as a buffer, so higher profitability will lead to higher solvency ratios. This is consistent with Kramer's (1996) finding for Dutch insurers that high profitability is one of the significant variables that reduce the probability of insolvency. Profitability is measured by annual return on assets.

(4) *Reinsurance*. If a company reinsures the bulk of its risks elsewhere, lower capitalization is required to achieve a given level of insolvency risk. Hence, we would expect a negative relationship between the use of reinsurance and capital. However, it is also conceivable that reinsurers demand a certain minimum level of capitalization from their clients, leading to a positive relationship between the use of reinsurance and capital. The effect of reinsurance on insolvency risk is therefore ambiguous. The use of reinsurance is measured by the proportion of reinsurance premiums paid in total premiums earned.

(5) *Portfolio risk*. The proportion of equity in the investment portfolio is a standard measure for the risk profile of the insurer's asset portfolio. The more volatile assets are held by the firm, for a given solvency ratio, the more vulnerable it is for asset price fluctuations that could lead to insolvency. Indeed, Kramer (1996) finds that for Dutch insurers, a higher proportion of equity increases the probability of insolvency.

(6) *Long-tailed business*. The ratio of loss reserves over incurred losses is a proxy for the time lag between policy issuance and the payment of the claims, with higher ratios indicating longer tailed business. As this ratio increases, the insurer's management is in control of the policyholders' funds for a longer time, which increases liquidity and thus diminishes the risk of insolvency.

(7) *Underwriting risk*. Underwriting risk is measured by the standard deviation of the loss ratio per firm (the ratio of losses incurred to premiums earned), which is frequently used in the insurance literature (e.g. Meyers, 1989; Guo and Winter, 1997; Lamm-Tennant and Starks,

1993). This measure captures the risk on the insurance portfolio, while portfolio risk (introduced above) measures the risk on the investment portfolio. We expect a positive relation with insolvency risk.

(8) *Herfindahl index*. This index measures the degree to which an insurer is diversified across different lines of business (as measured by the written premiums). Considered lines of business are health, car, transport, fire, other non-life, mixed non-life, and life insurance. Insurers with more diversified underwriting portfolios are expected to run less insolvency risk (e.g. Klein et al., 2002; Cummins and Nini, 2002). Lower Herfindahl indices imply higher diversification and, consequently, we expect a positive relation with insolvency risk.

(9) *Mutual*. This is a binary variable taking a value of 1 for mutual and 0 for stock companies. A priori, this variable's impact on a firm's solvency is ambiguous. Agency theory (Jensen and Meckling, 1976) predicts lower capitalization needs for mutual insurers because of the elimination of the owner-policyholder conflict. However, according to the pecking order hypothesis (Myers and Majluf, 1984) mutual insurers have a greater tendency than stock insurers to hoard capital because of their limited ability to access capital markets.[5]

(10) *Line of business*. A binary variable for each line of business taking the value of 1 if the company in that year is predominantly (i.e. more than half of its written premiums) in that particular line of business and 0 if it is not. This dummy variable should capture any remaining unobservable, time-invariant effects related to the line of business of an insurer.

(11) *Year*. A year dummy for each sample year. This dummy variable captures the effects of macro-economic trends, which are common to all insurers.

Table 2 presents summary statistics for the continuous variables.

[5] See De Haan and Kakes (2010) for a more detailed explanation of the underlying theories.

Table 2. Summary statistics, 1995-2005

	Median	Mean	Standard deviation	Number of observations
Surplus capital	0.228	0.288	0.294	3985
Company size	10.210	10.443	2.354	3915
Profitability	0.020	0.028	0.051	3912
Reinsurance	0.135	0.235	0.266	3284
Portfolio risk	0.129	0.185	0.197	2688
Long-tailed business	2.895	8.563	12.240	3005
Underwriting risk	0.116	0.972	4.565	3808
Herfindahl	1.000	0.881	0.237	3993

5 - Estimation results

The estimation results of the probit model including all explanatory variables are presented as 'model 1' in Table 3. Several variables are not statistically significant. Moreover, many of these insignificant variables have missing values for various company-years, so that they limit the number of observations that can be used in the model estimation. Therefore, the model is re-estimated dropping the statistically insignificant variables one by one in order of significance. This backward elimination procedure results in a model with seven statistically significant variables (model 2).[6] A positive side effect of dropping insignificant variables is that it increases the sample size substantially, which makes the results more representative for the population of insurance companies. Despite the dropping of explanatory variables, the model fit, as measured by the pseudo-R^2, improves, from 0.374 to 0.390. Moreover, all coefficients of the selected variables keep their sign and do not substantially alter in magnitude, and some of them become statistically more

[6] Backward elimination involves starting with all candidate variables and than deleting them one by one in order of statistical significance. This is one approach in stepwise regression; other approaches are forward selection or combinations of the two. See, e.g., Hocking (1976).

Table 3. Estimation results. Dependent variable is Insolvency risk

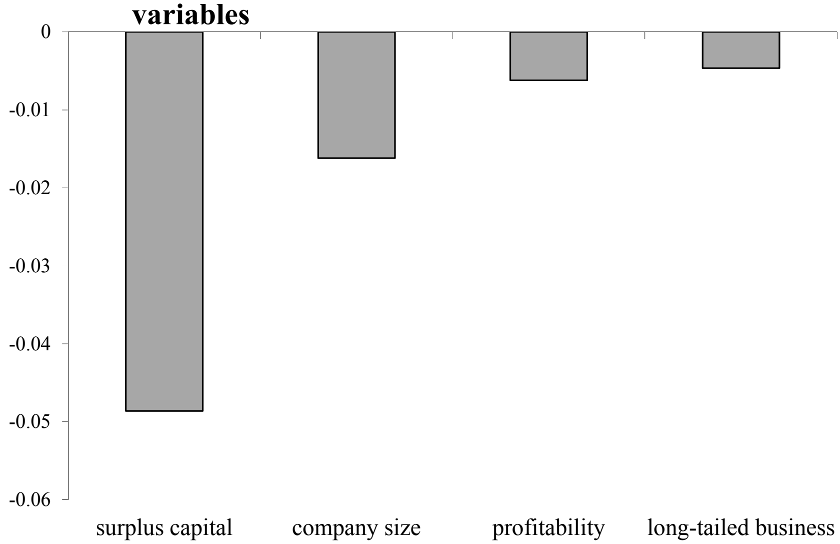
	Model 1			Model 2		
	Coefficient	Standard error	Effect	Coefficient	Standard error	Effect
Continuous variables:						
Surplus capital $_{t-1}$	-7.684**	2.600	-0.112	-7.837**	1.444	-0.177
Company size $_{t-1}$	-0.303**	0.057	-0.004	-0.317**	0.040	-0.007
Profitability$_{t-1}$	-9.210**	1.722	-0.134	-5.759**	1.211	-0.130
Reinsurance $_{t-1}$	-0.162	0.465	-0.002			
Portfolio risk $_{t-1}$	0.171	0.416	0.002			
Long-tailed business $_{t-1}$	-0.017	0.010	-0.0002	-0.017**	0.006	-0.0004
Underwriting risk $_{t-1}$	0.025	0.022	0.0004			
Herfindahl $_{t-1}$	0.050	0.660	0.0007			
Dummy variables:						
Mutual company	-0.510	0.291	-0.006	-0.619**	0.181	-0.012
Health insurance	0.386	0.346	0.008	0.542**	0.169	0.020
Car insurance	0.306	0.441	0.006			
Transport insurance	-0.676	0.392	-0.005			
Fire insurance	-0.167	0.455	-0.002			
Mixed non-life ins.	-0.335	0.539	-0.004	-0.434*	0.182	-0.007
Pseudo R^2	0.374			0.390		
Number of observations	1649			2476		
Number of insurers	277			401		

Explanatory note: Reported effects are marginal effects for continuous variables and fixed effects for dummy variables. Standard errors of the coefficients are calculated using the Huber/White/sandwich estimator and allowing for correlation of observations for the same company. Suffixes * and ** indicate statistical significance at the 5% and 1% level, respectively.

significant. Hence, the estimation results are fairly robust to the selection of variables.

We now turn to the economic interpretation of our selected model. The (‘fixed’) effect of mutual is -0.012, indicating that a mutual insurer’s probability of high insolvency risk is 1.2 percentage points lower than a stock insurer’s. The effects of line of business are in the same order of magnitude (+2 percentage points for health insurers, -0.7 for mixed non-life insurers). The economic interpretation of the (‘marginal’) effects for the continuous variables is less straightforward, as these represent the effects for an infinitesimal change in the explanatory variables. For ease of interpretation, Figure 2 therefore plots the probability effects for these variables. The bars give the partial effects on the probability of high insolvency risk of a one-standard-deviation increase for each explanatory variable. The solvency surplus in the previous year is the most important probability reducer, followed by company size, profitability, and long-tailed business. These outcomes are consistent with the expectations expressed in Section 3.

Figure 2. Probability effects of selected explanatory variables



Note: Partial effect of one-standard-deviation increase in explanatory variable on probability of high insolvency risk.

6 - Model use

A prudential supervisor may wish to use the model to predict, one year ahead, whether or not an insurer runs high risk of falling into the class of companies with high insolvency risk. The performance of a probit model, or any other model or indicator used to predict a dichotomous variable, can be considered in terms of a two by two matrix, as shown in Table 4.[7] A signal is considered *good* (cell A) if it is followed by insolvency and *bad* (cell B) if it remains solvent. If there is no signal and insolvency follows, this is denoted as a *missed signal* (cell C) while a situation in which no signal is followed by no insolvency is a *good silent signal* (cell D).

In standard statistical terms, using type I and type II errors, let the null hypothesis (H0) be equal to insolvency and the alternative hypothesis (H1) be no insolvency. From Table 4, H0 is equal to A+C and H1 is equal to B+D. A type I error is rejecting H0 while H0 is true, which is a missing signal. The proportion of missing signals is equal to C/(A+C). Similarly, a type II error is not rejecting H0 when H0 is false, which is a false signal. The proportion of false signals is equal to B/(B+D).

Table 4. Performance evaluation matrix

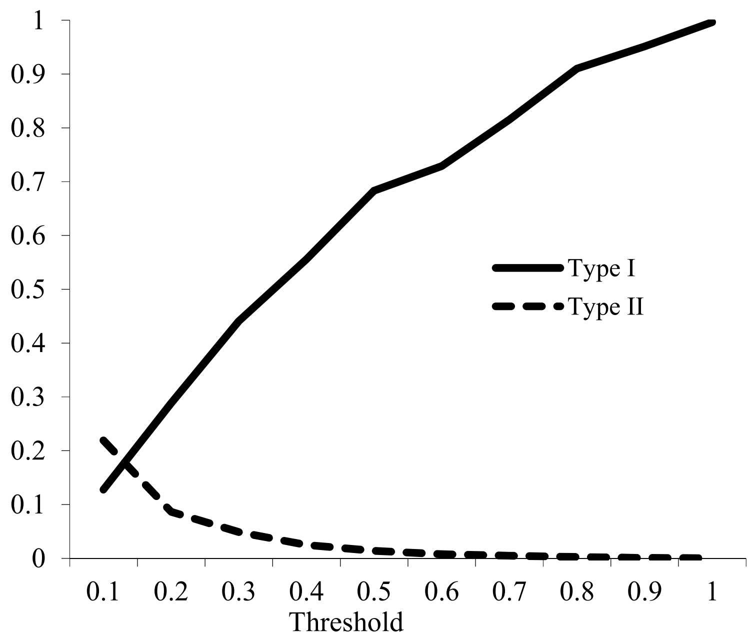
	Insolvency next year	Solvency next year
Signal issued	A	B
No signal issued	C	D

When using a probit model for predictions, one has to choose a threshold for the probability of an event. The model will give a signal if this threshold is crossed. A high (low) value for the threshold decreases (increases) the number of signals issued. Consequently, the choice of the threshold will affect the relative frequencies of type I and II errors. The latter are drawn in Figure 3 for

[7] See, e.g. Kaminsky and Reinhart (1999), Edison (2003), Alessi and Detken (2011).

our estimated model for different thresholds. The figure shows, firstly, that the higher the threshold, the higher is the proportion of missing signals (type I error) and the lower the proportion of false signals (type II error). Secondly, it shows that this trade-off is asymmetric. The type II curve begins at 0.219 for a threshold of 0.1 and quickly bends off towards zero for thresholds higher than 0.5, while the type I curve nearly linearly rises from 0.128 for a threshold of 0.1 to 0.996 for a threshold of 1.0.

Figure 3. Relative frequencies of Type I and Type II errors, by threshold



Note: Following Table 4, Type I = C/(A+C), Type II = B/(B+D).

At face value, one might be inclined to choose a threshold between 0.1 and 0.2 where the two lines intersect at a proportion of 0.185 for both types of errors. However, in that case one assumes that both types of errors are equally important. Alessi and Detken (2011) argue that, when choosing the threshold value, one has to incorporate the relative risk aversion of the model user with

Table 5. Losses for different probability thresholds, given θ

θ =	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Threshold									
0.1	0.210	0.201	0.192	0.182	**0.173**	**0.164**	**0.155**	**0.146**	**0.137**
0.2	0.107	0.127	**0.147**	**0.167**	0.187	0.207	0.228	0.248	0.268
0.3	0.088	**0.127**	0.166	0.205	0.244	0.284	0.323	0.362	0.401
0.4	**0.078**	0.131	0.184	0.237	0.290	0.343	0.396	0.449	0.502
0.5	0.081	0.148	0.215	0.282	0.349	0.415	0.482	0.549	0.616
0.6	0.080	0.152	0.224	0.296	0.368	0.440	0.512	0.584	0.656
0.7	0.086	0.167	0.248	0.329	0.410	0.419	0.572	0.653	0.734
0.8	0.093	0.184	0.274	0.365	0.456	0.547	0.637	0.728	0.819
0.9	0.095	0.190	0.285	0.381	0.476	0.571	0.666	0.761	0.856
1.0	0.100	0.199	0.299	0.398	0.498	0.598	0.697	0.797	0.896

Note: θ is the relative risk aversion between missing signals and false alarms. Minimum losses per θ have been printed in bold.

respect to type I and type II errors. Therefore, they define the following loss function:

$$L = \theta \frac{C}{A+C} + (1-\theta)\frac{B}{B+D} \qquad (2)$$

where $0 \le \theta \le 1$ is the parameter revealing the relative risk aversion between type I and type II errors. The loss can be interpreted as the weighted sum of both types of errors. A θ smaller than 0.5 reveals less aversion towards missing a signal than towards receiving false alarms, a θ greater than 0.5 reveals the opposite risk attitude.

Alessi and Detken (2011) apply (2) to the case of a central banker who uses an indicator of costly asset boom/bust cycles to determine whether or not to ‘lean against the wind’ with monetary policy. They argue that a θ smaller than 0.5 is a realistic description of central bankers’ loss functions, as the economic cost of reacting to a false signal is higher than missing a signal. In our case, where we take the perspective of a supervisor, matters are different. The supervisor uses the model to earmark insurers one year ahead as running a high risk of getting insolvent. A signal from the model may lead to additional supervisory scrutiny of the insurer in question. Hence, the cost of a false alarm is the cost of the additional supervisory effort. The cost of a missing signal, on the other hand, is relatively large, as insolvency may lead to a failure. Hence, we argue that a θ larger than 0.5 is a realistic description of a supervisor's loss function.

Given the relative risk preference θ, one may find the threshold that minimizes the loss using loss function (2). Table 5 gives all possible losses for different thresholds and θ. The optimal threshold is 0.4 for $\theta = 0.1$, 0.3 for $\theta = 0.2$, 0.2 for $\theta = 0.3$ and $\theta = 0.4$, and 0.1 for $\theta \geq 0.5$. Hence, assuming that a supervisor's θ is larger than 0.5, a threshold of 0.1 should be chosen.

7 - Conclusion

We estimate a probit model for insolvency risk among Dutch insurance companies, using a much larger dataset covering a longer sample period than previous studies for the Netherlands. The model relates the probability of high insolvency risk for an insurance company to several of its characteristics. The results suggest that surplus capital, company size, profitability, long-tailed business and being a mutual insurer reduce the risk of insolvency. The model can be used to predict one year ahead which insurance companies are running high insolvency risk. It is shown that the choice of the threshold above which an insurer is classified close to insolvency, is an important determinant of the relative occurrence of type I and type II prediction errors. We use a loss function to find the optimal threshold given the supervisor's relative preferences with respect to missing insolvencies and false alarms.

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