

**Marek Gruszczyński**

# Sample bias in the research on corporate bankruptcy

**Quantitative studies on bankruptcy and financial distress in Poland have more than twenty years of history. There is another 30 years from the world's first works on this subject. Studies at the international level are still ahead of us, mostly because they are created directly by the research community in the field of corporate finance and accounting.**

In Poland, such an understanding of empirical research in finance and accounting is not frequent; valuable research in this scope are the domain of methodologists (statisticians, econometricians, data analysts, etc.). What is more, it is rare to communicate the results of these studies in English and to participate in the worldwide scientific discourse. I mean, for example, such leading journals as: "Accounting Review" (45 points on ministerial list A in Poland), "Journal of Business, Finance and Accounting" (20 points), "Journal of Empirical Finance" (25 points), "Journal of Corporate Finance" (40 points), "Contemporary Accounting Research" (40 points), "Journal of Accounting Research" (45 points), "Journal of Accounting and Economics" (50 points), "Review of Accounting Studies" (35 points). We are also rarely present in international journals of slightly lower rank.

We have extensive national literature on the subject of studies on insolvency, bankruptcy and financial distress, which is not particularly well-known in the world. At the same time, we commit a variety of methodological mistakes in

these studies, which we often point out to ourselves, and which is also the subject of discussion in this elaboration. The article is devoted to one of the methodological problems that occur when using classical models of bankruptcy, meaning the models estimated on the basis of non-random samples of companies. It is about the biases resulting from sample selection and their influence on the estimation of bankruptcy probability.

The following sections present comments on sampling in the research on bankruptcy in Poland, a comment on the possible errors related to sample selection, a method of correction of the logit model of bankruptcy, a general relation between a biased and unbiased probability of bankruptcy of a single company, as well as variants of this relationship for models other than the logit model. The article ends with comments on classification models and a summary.

## **Sample election in the studies on bankruptcy and financial distress in Poland**

The reports on the results of research on bankruptcy or financial distress of companies in Poland are released often or very often. A few last monographs – with comments on the choice of the research sample – are presented below.

In the book edited by A. Adamska and E. Mączyńska [2013], the methodological part included four texts: W. Rogowski, K. Duleba [2013], M. Ciszewska [2013], M. Tymoszuć [2013], P. Antonowicz, M. Zwierzyńska [2013]. In the first of them [Rogowski, Duleba, 2013], the "classic"

models of research on bankruptcy in Poland for the data from companies of the Warsaw Stock Exchange (WSE), which filed bankruptcy applications in the years 2005-2010 were used. The study revealed pretty good quality of the known discriminant models for completely new data. In her article, M. Ciszewska [2013] analyses 16 companies of the WSE, including eight, which announced bankruptcy proceedings, or declared bankruptcy in 2010, and eight, which did not announce it. For these 16 companies, the normality of the distribution of independent variables in the potential bankruptcy model has been verified, and then the discriminant analysis has been applied. Apart from other weaknesses of this research, sample choice itself and the sample size are difficult to accept. In the article of M. Tymoszuk [2013], the Author's own model is based on the assumption that the sample consists of the companies that have declared bankruptcy in the years 2007-2010, and whose assets are in the range of PLN 30 million-435 billion. "Healthy" companies were added to them at the ratio of 50:50, and in total, the sample comprises in 68 companies. The choice of the non-bankrupt companies was random. Although the Author indicates that the proportion of the bankrupt companies in the population is 18 percent, she claims (allegedly<sup>1</sup> after B. Prusak, 2005), that the sample with the structure corresponding to the population of all companies results in similar effects as the balanced sample. This is not entirely true, but the fact of paying attention to this issue should be commended. By the way, I really do not like the title of this article, which is odd as for a title of a research article.

The book of P. Antonowicz [2015], provides a comprehensive picture of the Polish studies on bankruptcy, including also the methodological comments of the Author. These comments, for example, point

<sup>1</sup> According to B. Prusak, there is no such statement in his book.

out to the quality of data on the companies recognised as insolvent companies in the research samples. In the same book, in its methodological part, the Author does not devote his attention to the subject of the selection of companies to research samples. He focuses on the careful description of his own sample of bankrupt entities. This sample itself, at first consisting of 4,750 companies that were declared bankrupt in the years 2007-2013, is a valuable output of this research. The Author can define it well and specify its weaknesses. But the selection of "healthy" companies to those that have gone bankrupt is not particularly exposed, because it is not even there. The Author used his own collection of data on bankrupt companies in Poland, among others, to show how the data about those companies provide the symptoms of bankruptcy a year, two, etc. before the time of its announcement. The monograph itself is a very valuable work representing a thorough analysis of data on the bankrupt companies in Poland at a specific time and place. It is a pity, that such a rich collection of data on bankrupt entities was not utilized in modelling with the samples of companies that are not financially distressed.

The work of J. Kitowski [2015] is a kind of encyclopaedia of the Polish studies on bankruptcy, based on the method of discriminant analysis. The Author is also reliable in finding inaccuracies in the Polish language works reporting about models constructed in Poland and abroad. The layout of the book does not encourage methodological analysis, concentrating itself on a detailed reporting of subsequent studies on Polish companies. The reader does not learn about the Author's opinion about the sample choice and other topics, for example normality of distribution of independent variables. However, I still pay compliments to the Author for chasing nonsense in the national literature on the bankruptcy and insolvency models.

Apart from these and other monographs, the Polish literature on these subjects includes of course many reports in the form of articles. Some of them constitute kind of benchmarks for the researchers on empirical accounting, and some do not, e.g. a very good model of P. Ciesielski [2005], published in “Rachunkowość”. I have the impression that the articles that are currently produced largely duplicate methodological ideas from the past, trying to adjust them to the newer collections of data. Anyway, our authors and our studies are not visible in the global trend of empirical corporate finance and applied accounting, as mentioned above.

As a reader of national publications on financial distress and bankruptcy, what I miss there are the remarks on the quality of modelling and forecasts in the context of the used sample of bankrupt/distressed companies and the companies that are financially healthy. Hence, the idea to take a closer look at these issues once more, especially because new works appear that question the previous ways of drawing conclusions on the basis of the estimated models.

### Choice-based sample bias and sample selection bias

The basic “inconsistency”, which seems unsolved up to this day to the researchers, results from the low frequency of the event/state of “bankruptcy” in the entire population of companies. Usually, the data on some specific group of bankrupt entities is obtained, and later, various operations of selection of “healthy” enterprises to this already specified group are performed. M. Zmijewski [1984] was the first who drew attention to it. His work was quoted many times in subsequent years after its publication, but in most of the empirical studies the subject of the “problematic sample” was rather overlooked. More important for researchers were good forecasts/classifications obtained from the models.

We will focus on the binary situation, which means modelling the  $Y$  variable representing the bankruptcy – based on the sample of bankrupt and non-bankrupt companies [cf. Gruszczynski, 2012]. Modelling involves the explanation of the  $Y$  variable using the model including the selected independent variables  $X$  (*covariates*). It is the binomial model of the  $Y$  variable, in which it takes two values:  $Y=1$  (bankrupt) or  $Y=0$  (non-bankrupt). Usually, the selected companies do not represent a random sample from the entire population of companies. This causes biases. Two kinds of sample biases present in most of the studies are:

- *choice-based sample bias*, which means selecting the sample on the basis of earlier knowledge on the dependent variable (for example, first the data about the group of bankrupt companies is collected); the probability of entering the sample depends on the features of the dependent variable; for example, the sample is arranged in such a way, that all bankrupt companies are included, and the remaining (healthy) companies are selected using some matching scheme;
- *sample selection bias* occurs when for a specific reason only some of the companies enter the sample; in the case of studies on bankruptcy, it is typical to select only companies for which we have complete data.

The studies of M. Zmijewski [1984] were based on the probit model and indicated that the choice-based selection bias decreases when the sample structure (bankrupt – non-bankrupt companies) approaches the structure that is present in the population, and is completely eliminated when an appropriate method of model estimation is used.

He also showed that the effect of both types of errors is the asymptotic bias of parameter estimates and bankruptcy

probability estimates. At the same time, it turned out that both types of errors did not have a significant impact on the accuracy of the classification and prediction on the basis of the estimated models. However, he indicated that these errors have a clear influence on the estimates related to individual cases, e.g. on the estimates of the probability of bankruptcy of a particular company.

H.D. Platt and M.B. Platt [2002] confirmed the existence of a choice-based sample bias on a single example in the studies on financial distress. The exercise involved multiple estimation of the early warning model for the samples randomly selected from the Authors' own dataset on bankrupt and healthy companies.

To avoid biases resulting from the choice-based samples, some researchers use samples, in which the share of bankrupt companies is close to that in the population, which is very low. For example, J. Chen, et al. [2006] used a sample with 89 bankrupt and 940 non-bankrupt companies. There are also some attempts to select a sample, but not with the proportion of 50:50. For example, H.D. Platt, M.B. Platt, J.G. Pedersen [1994] used 35 bankrupt companies, to which 89 non-bankrupt companies were added. In the newer research, larger samples are used, for example S. Jones et al. [2017] took into account 990 bankrupt companies, and the sample itself included 3,960 observations (company-years) for bankrupt companies and 26,169 observations for non-bankrupt ones (the share of observations for the bankrupt companies was approximately 13 percent).

The awareness of the choice-based sample bias becomes more and more common. Practical applications confirmed findings of M. Zmijewski [1984] about lesser importance of these biases when models aim at the quality of the classification. However, the biases significantly

influence the estimate of the bankruptcy probability of a single company.

### Anderson-Maddala correction for the logit model

There is a case when the bankruptcy model estimated from the choice-based sample can be simply converted to the one for the population. It happens when one uses the binomial logit model and the proportions of selecting companies to the sample are known. In this case the Anderson-Maddala correction might be applied [Anderson, 1973; Maddala, 1983; Gruszczyński, 2012].

How does it work? As previously,  $y=1$  means a bankrupt company, and  $y=0$  a non-bankrupt one. The subject of modelling is the probability  $P(y=1)$ . If we know the proportions of the companies selected to the sample from both groups, we denote them  $p_1$  for companies with  $y=1$  and  $p_2$  for companies with  $y=0$ . Then, in the logit model, after its estimation, the intercept should be diminished by (the correction):

$$\delta = \ln p_1 - \ln p_2 \quad (1)$$

The correction equals zero, when these proportions ( $p_1$  and  $p_2$ ) are identical, for example, for a random sample from both groups together. Let us remind that in the logit model, the dependent variable is the logit. It is a logarithm of the odds, which means a logarithm of the ratio of probabilities:  $P(y=1)$  by  $1-P(y=1)$ . Explanatory variables ( $X$  variables; *covariates*) are the various characteristics of companies selected to the sample. Therefore, on the right-hand side of the model, there is a linear function of  $X$  variables, and an intercept. Exactly this element must be corrected in accordance with the equation (1).

For example [Gruszczyński (ed.), 2012], let us consider 1,000 companies, of which 60 are bankrupt, and 940 are non-bankrupt. Usually, all bankrupt companies (that is 60) are selected to the sample. Then, from 940 non-bankrupt companies, 60 companies are selected at

random. As a result, we obtain a sample in which there are 50 percent of companies from each group. Then  $p_1=1$  (we took into account all bankrupt companies) and  $p_2=60/940$ . After estimating the model on the basis of the sample, we can calculate the estimates (theoretical values) of bankruptcy probabilities for companies in the sample. These are estimates with a sample selection bias. The unbiased estimates are obtained when we take into account the entire population from which we did the sampling. A model for all 1,000 companies is obtained from the model estimated for the sample by reducing the intercept by the value (1) that is by  $\ln(1)-\ln(60/940)$  that is by 2.7515.

If we do not know the population and we do not sample but only have estimates of the values  $p_1$  and  $p_2$ , then the correction should be applied with a relevant comment. In any case, we apply the correction when we make inferences in the context of the entire population and not the sample itself.

The Anderson-Maddala correction gives the result consistent with the Skogsvik's equation for the unbiased bankruptcy probability, which is presented below. Wider practical implications of applying the correction can be found in M. Gruszczynski [2012]. It is worth noting that this exposure is not about the classification problem, but about the estimation of bankruptcy probability, which is the subject of growing demand from analysts in accounting and corporate finance.

### Skogsvik's equation

We will repeat in line with the last paragraph that apart from the model that "properly classifies" bankrupt and non-bankrupt companies, in practice more detailed information might be needed. Such is the unbiased estimate of probability of bankruptcy of a particular company in the sample or outside the sample. For the models based on choice-based samples

such a probability is usually biased due to samples' non-randomness.

K. Skovsik and S. Skogsvik [2013] emphasise that in predicting bankruptcy usually the non-random samples are used, so the bankruptcy probabilities obtained from the bankruptcy prediction models depend on the share of bankrupt companies in the sample, and therefore they are biased. The Authors found a relationship between the biased bankruptcy probability of a given company (from the model – *sample based*), and the unbiased probability, which results from the proportion of bankrupts in the population. This last proportion has been called the *a priori* probability of bankruptcy (in a given year).

The probability of bankruptcy of a given company resulting from the model (from the sample) marked by the Skogsvik's as  $p_{fail}^{prop}$  is therefore biased. It is the function of:

- unbiased probability  $p_{fail}^{\pi}$  (this is what interests us),
- proportion (*prop*) of bankrupt companies in the sample,
- proportion  $\pi$  of bankrupt companies in the population.

The formula (derived from the Bayes theorem [cf. Skogsvik, Skogsvik, 2013]) is as follows:

$$p_{fail}^{prop} = \left[ 1 + \left( \frac{\pi}{1-\pi} \right) \left( \frac{1-prop}{prop} \right) \left( \frac{1-p_{fail}^{\pi}}{p_{fail}^{\pi}} \right) \right]^{-1} \quad (2)$$

Using this relationship, we can calculate the unbiased probability for each company in the sample. It is also shown that  $p_{fail}^{prop} > p_{fail}^{\pi}$ , if  $prop > \pi$  and vice versa. Moreover, the ranking of companies based on probability resulting from the model  $p_{fail}^{prop}$  is the same with the ranking based on probability  $p_{fail}^{\pi}$ .

Important note: in the proof of the equation (2), the Authors assume that the bankrupt companies are selected to the sample at random from the population of

all bankrupt companies, and the same applies to the population of non-bankrupt companies.

What is the use of the Skogsviks' equation? The Authors themselves indicate that although the theoretical probability from the model  $p_{fail}^{prop}$  in general is sufficient to classify the companies (with which we are not dealing here), still specific unbiased probability  $p_{fail}^{\pi}$  is needed, for example in financial risk management, in the valuation of company's equity or company's bonds.

It is worth noting that when  $prop = \pi$ , then  $p_{fail}^{prop} = p_{fail}^{\pi}$ . This means that the sample with the proportion of bankrupt companies equal to that in the population guarantees that the probability of bankruptcy of a given company resulting from the model is unbiased. Hence, it would follow that when we are interested in estimation of bankruptcy probability, the sample should have the proportions corresponding with the proportions of the population.

### Biased and unbiased bankruptcy probability estimate in different models

The result obtained by K. Skogsvik and S. Skogsvik [2013] turns out to be a generalisation of the result of Anderson-Maddala for the logit model, which has been discussed above. Let  $N$  be the size of the entire population, in which  $N_1$  means the number of bankrupt companies and  $N_2$  the number of non-bankrupt companies. Then  $\pi = N_1/N_2$ . There are  $n$  observations in the sample, including  $n_1$  bankrupt and  $n_2$  non-bankrupt companies. It means  $prop = n_1/n$ . In the equation (1) of Anderson-Maddala we have  $p_2 = n_2/N_2$  and  $p_1 = n_1/N_1$ . Using these definitions, the equation (2) can therefore be written as:

$$p_{fail}^{prop} = \left[ 1 + \frac{p_2}{p_1} \left( \frac{1 - p_{fail}^{\pi}}{p_{fail}^{\pi}} \right) \right]^{-1} \quad (3)$$

$$\text{or} \quad \frac{p_2}{p_1} \left( \frac{1 - p_{fail}^{\pi}}{p_{fail}^{\pi}} \right) = \left( \frac{1 - p_{fail}^{prop}}{p_{fail}^{prop}} \right) \quad (4)$$

The equation (4), which is another form of equation (2) shows that the product of  $p_2/p_1$  and the unbiased odds is equal to the biased odds.

Next, we have from (4):

$$\ln\left(\frac{p_2}{p_1}\right) - \ln\left(\frac{p_{fail}^{\pi}}{1 - p_{fail}^{\pi}}\right) = -\ln\left(\frac{p_{fail}^{prop}}{1 - p_{fail}^{prop}}\right)$$

or

$$\ln p_1 - \ln p_2 + \text{logit}(p_{fail}^{\pi}) = \text{logit}(p_{fail}^{prop}) \quad (5)$$

It follows that the logit for the biased bankruptcy probability  $p_{fail}^{prop}$ , that is what we receive from the estimated logit model, must be reduced by the value of  $\delta = \ln p_1 - \ln p_2$  [equation (1)]

to obtain the logit for the unbiased bankruptcy probability  $p_{fail}^{\pi}$ . Thus – the Anderson-Maddala correction is equivalent with the equation of Skogsviks.

The advantage of equation (2) is the possibility to apply it also to estimates of the bankruptcy probability received from other binomial models, e.g. probit or linear probability model (LPM). In the probit model, the (theoretical) estimate of bankruptcy probability cannot be presented in a form of an algebraically closed formula. Naturally, it can be calculated and as  $p_{fail}^{prop}$  substituted into equation (4).

As for the LPM, the (biased) probability is obtained directly from the model as the estimate of the value of the binary dependent variable [cf. Gruszczynski, 2012].

This value is substituted into the equation (4) as  $p_{fail}^{prop}$  and next the unbiased  $p_{fail}^{\pi}$  is calculated, provided that the proportions of  $p_1$  and  $p_2$  are known. If they are equal, it means that the evaluation of bankruptcy probability calculated directly from the model is unbiased.

The relationships (2) or (4) allow for calculating an unbiased estimate of bankruptcy probability for a specific company based on the "standard" models: logit, probit and LPM.

### Effects for classification

If the estimates of bankruptcy probability are only the basis for the classifi-

cation of companies (into bankrupt and non-bankrupt ones), the sample biases may not be significant. It is true, as long as the cut-off value (limit probability for the classification) is appropriately selected.

The forecast principle with the cut-off value of 0.5 should be applied only when the proportion of the bankrupt and non-bankrupt companies in the sample equals 1:1. With other proportions, for example, the Cramer principle can be applied. It assumes the percentage of ones (i.e. bankrupt companies) in the sample as the cut-off value [cf. Gruszczyński, 2001]. Alternatively – the biased bankruptcy probabilities should be transformed into unbiased with the use of relationships discussed in the previous sections [Skogsvik, Skogsvik, 2013].

Some of the bankruptcy models cannot be directly used to estimate bankruptcy probabilities, since they are rather constructed for classification purposes. Such a model is the linear discriminant analysis (LDA). M. Zmijewski [1984] reports that the non-random sampling can be corrected by taking into account the population proportion of “bankrupt and non-bankrupt companies” (choice-based sample in this case affects only the intercept [Morrison, 1990]). The application of LDA is problematic when the assumption of normality of the distribution of  $X$  variables does not hold. The LDA assumes that the independent variables have multivariate normal distribution in the populations of bankrupt and non-bankrupt companies. The financial indicators that are usually used as the  $X$  variables generally do not meet this assumption.

At this point, it is worth to indicate the article of S. Jones, et al. [2017], in which the Authors focus on the new methods of data classification (classifiers) in the modelling of bankruptcy. These methods are based on the concepts deriving from *data mining*, such as the neural networks, sup-

port vector machines, or the new generation statistical learning techniques, such as generalised boosting, AdaBoost and random trees. Classic classifiers, such as logit or LDA turn out to be pretty good for predicting bankruptcy, but the Authors propose the use of new techniques. They are better for the panel data, and, despite the form of a “black box”, they have quite acceptable interpretations. It is worth pointing out that the issues of the sample selection bias are not the subject of comments in the cited article.

Returning to the main topic, if the subject of modelling is finding the unbiased bankruptcy probability (suitable for the risk assessment for a particular company), then the transformations proposed in the above equations should be used. Let us emphasise once more that we do it when we make inferences in the context of the entire population and not the sample itself.

## Summary

Sample selection in bankruptcy modelling is usually the weakest side of the empirical research. The concept of this article is to point to the sample selection biases, their effects for the prediction and classification models, and the ways of dealing with them in practice. In particular, it is about the estimates of the probability of bankruptcy of a single company.

The bankruptcy probability estimates obtained from the models are usually biased due to the inconsistency of the proportions of bankrupt and non-bankrupt companies in the sample and in the population. The central part of the paper is devoted to the analysis of the relations between the biased and unbiased probability, which has been given by Skogsviks [2013]. This equation should be used in practice, if the model is used to estimate the probability of bankruptcy of a single company. It turns out that for the logit model, this equation is consistent with

the Anderson-Maddala correction [Anderson, 1973; Maddala, 1983], as shown in the paper.

Let us add that the subject of quality of the “classic” Polish models of bankruptcy that up to this day are willingly applied to current data, and which – apart from their age – have been estimated with multiple

methodological defects, is rarely raised. There is no reason just now to come back to it, but it is hard to resist the impression that a large part of the Polish authors dealing with finance and accounting do not choose the known, better methodological approaches, especially when the quality of data has significantly improved.

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Prof. dr hab. **Marek Gruszczyński**, Collegium of Economic Analysis, Warsaw School of Economics.

Translated by: mgr Monika Borawska