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Firms' Default - from Prediction Accuracy to Informational Capacity of Predictors

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**Firms' Default – from Prediction Accuracy to
Informational Capacity of Predictors**

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Abstract

Research background: Bankruptcy literature is populated with scores of (econometric) models ranging from Altman's Z-score, Ohlson's O-score, Zmijewski's probit model to k-nearest neighbors, classification trees, support vector machines, mathematical programming, evolutionary algorithms or neural networks, all designed to predict financial distress with highest precision.

Purpose of the article: We believe corporate default is too an important research topic to be identified with the prediction accuracy only. Despite the wealth of modelling effort, a unified theory of default is yet to be proposed. Due to the disagreement, both on the definition and hence the timing of default as well as on the measurement of prediction accuracy, the comparison (of predictive power) of various models can be seriously misleading. The purpose of the article is to argue for the shift in research focus from maximizing accuracy to the analysis of the information capacity of predictors. By doing this, we may yet come closer to understand default itself.

Methodology/methods: We have critically appraised the bankruptcy research literature for its methodological variety and empirical findings. Default definitions, sampling procedures, in and out-of-sample testing and accuracy measurement have all been scrutinized. We believe the bankruptcy models currently used are, using the language of Feyerabend, incommensurable.

Findings: Instead of what we call the population of models paradigm (the comparison of predictive power of different models) prevailing today, we propose the model of population paradigm, consisting in the estimation a single unified default forecasting platform for both listed and non-listed firms, and analyze the marginal contribution of the different information sources. In addition to classical corporate financial data, information on both firm's strategic position and its macroeconomic environment should be studied.

Introduction

Corporate default is too an important research topic to be identified with the forecast accuracy (in the estimation sample in particular). Despite many advances within theoretical studies, several issues i.e. the very definition of default, the moment it materializes, the nature and the size of bankruptcy (direct and indirect) costs, the interplay between different stakeholder groups - to name just a few, are yet to be resolved. No surprise, no unified theory of default has been formulated to date. We believe it may partly be because the focus of the empirical research is misplaced. Rather than concentrating on maximizing the model accuracy, research should focus on the study of the information relevant to the default process.

The wealth of tools that have been deployed since the late 1960s in econometric modelling of financial default is the greatest achievement of the bankruptcy literature. Apart from the classic MDA-driven Z-score of Altman (1980), logistic regression-led O-score of Ohlson (1984) and probit model of Zmijewski (1984), there are countless other techniques e.g. k-nearest neighbours, classification trees, support vector machines, mathematic programming, evolutionary algorithms or neural networks. Sectorial and geographic cover of the empirical work is also impressive. Still, it is by no means clear how much insight one can gain from these models on the very nature of bankruptcy. The models are frequently arbitrarily defined, one-period, dominated by corporate financial data. The change of the variable levels (data dynamics), as opposed to statically conceived level of the variable itself, is also a rarity. There have usually been no attempts to accommodate for a potential profit management either. The issue is particularly important when examining (accounting) variables ‘under the control’ of a distressed firm.

Indeed, the arbitrary selection of variables is still a significant weakness of most models. Altman's classic model, using several interconnected financial indicators, is the best example. The need for a different model for non-listed firms, as the original one for the listed companies proved useless in the new context, is also symbolic. In general, the models estimated in one period for a given set of companies tend to underperform when re-estimated for a different firm sample. The sometimes-dramatic drop in the predictive power when the models are used in a different setting without re-estimation is also well documented (Grice & Ingram, 2001).

All this may not only hinder the understanding of the very process of going under but may even question the rationality of the inter-model comparisons.

As the dominant criterion is still model's prediction power, the risk of overfitting is real. We believe there are many reasons why various models should not be compared with each other at all. Firstly, they usually describe default differently. The existence of so many similar terms e.g. bankruptcy, default, financial distress may already send a warning signal. To make it worse, each of these concepts can be defined/understood in so many different ways. Narrowly speaking, a default is a judicial decision declaring a company insolvent. In the US, it is often identified with the creditor's or management's filing for e.g. Chapter 10 or Chapter 11 protection. This definition is sometimes broadened to include other forms of voluntary or forced reorganization (Boritz et al. 2007), deferral of payments of corporate liabilities, a government rescue support, a forced merger or change of control following a collateral execution (Altman et al., 1977), failure to meet listing requirements or even a dividend omission (Duffie et al. 2007).

Different definitions of the "object researched" determines the moment of registering it. Failure to pay interest on time is certainly something else than filing for bankruptcy. However, even in the unlikely case of the event studied being identically defined in two papers, the research setting may still make the results incomparable. As some papers fail to check the exact dates of a) the default event registration and b) the release of financial data, it is not uncommon that financial data released after the default event are used as independent predictor variables (sic!). This leads effectively to "back rather than fore-casting" (Ohlson, 1980). If defining the moment of bankruptcy proves tricky, what about the time the company faces financial troubles? Platt and Platt (2002, p. 185) regret that "while there is abundant literature describing prediction models of corporate bankruptcy, few research efforts have sought to predict corporate financial distress".

Secondly, to compare the predictive power of various models one should adopt similar (if not the same) predictive power (or model efficiency) measures. The issue is probably even more important as, in contrast to the challenges stemming from the default definition ambiguity, the differences and interrelation between different efficiency measures do not attract much attention in default literature. For example, an accuracy rate, defined as the percentage of correctly designated ratings, of 95% may indicate both a very poor model performance in the case of a big, representative sample of thousands of firms with, say, 3% of bankrupt companies, as well as quite an achievement for a model with matched pairs. The almost unprecedented richness of terminology used in a binary classification is not helpful either. Most models quote the percentage of properly identified bankrupt companies, referred to as a true positive rate TPR (the probability of detection, a sensitivity, or a recall), equal to $1 -$ a false negative rate FNR (or a miss rate)

(e.g. Zmijewski, 1984). Others, especially Polish authors, quote the total of all (failed and healthy) correctly identified firms – the measure known as an accuracy rate, or $1 - \text{TER}$. This is the weighted average of TPR and TNR (a true negative rate, or a specificity, equal to $1 - \text{false positive rate}$, the probability of false alarm, or a fall-out). Some authors (e.g. Altman & Sabato, 2007) take an arithmetic average of TPR and TNR. This measure, equal to $1 - \text{average error rate}$, is again referred to as accuracy rate (sic!). Needless to say, its reading may be different from that provided by the “weighted” version. We have listed but a few examples of terms used. There are many more potentially confusing names e.g. a positive predictive value, or a precision; a false discovery rate; a false omission rate; a negative predictive value. Even the classic terms such as type I and II errors may lead to confusion (not debated in the default literature): type I error to Altman (1968) is the misclassification of a failing firm as not failing, while to Ohlson (1980) it is the opposite: a non-failing firm misclassified as failing (sic!). Other efficiency measures originate from the ROC (receiver operating characteristics) curve which illustrates the change of model efficiency with the change of the cut-off point. An AUC ratio (area under curve) is calculated as the area below ROC (Tian & Yu, 2013), while an accuracy ratio is computed as twice the area between the ROC curve and the no-discrimination line (Duan et al., 2012). Many other ROC-related measures can also be used. We believe the measurement of predictive power of default models deserves a separate treatment.

The misclassification (error) costs is another critical issue. Surely, the (economic) cost of branding a bankrupt firm as going concern is different from the case when a healthy firm is recognized as financially distressed. Although the issue of misclassification costs is sometimes mentioned (Altman et al., 1977), it has been hardly invoked in the relative performance of different models debate. The issue is ever more important as the weight of misclassification errors may influence the cut-off point and affect the size of both errors.

Another issue critical to a meaningful comparison of various studies is the way the sample used has been selected. This concerns both the size of the sample as well as the way it was selected. The small size may not necessarily be an artefact of small computing power of the past. It is true that e.g. Tian & Yu (2013) uses several thousands of firms in a recent paper but Sandin and Porporate (2008), in a not much older one, use only 22. What concerns the way the sample is drawn, “it is by no mean obvious what is really gained or lost by different matching procedures, including no matching at all” (Ohlson, 1980, p. 112). What we know though is that the use of balanced samples of defaulted and surviving firms may carry a risk of artificially increasing the

efficiency of the model. Zmijewski (1984) proved that "(...) group error rates are associated with sample frequency rates and provide at least a partial explanation for the divergent distressed firm error rates reported in previous financial distress studies". Apart from this choice-based sample bias, he described a sample selection bias resulting from the selection of a complete data sample. A company with financial problems is clearly more likely to have incomplete dataset.

Finally, if the predictive efficiency of any model is to be taken seriously, it is out-of-sample precision that should be quoted and subsequently compared to the (out-of-sample) precision of other models. Paradoxically, we may be here somewhat too optimistic. Out of dozens of papers we have reviewed, only around half do it. For example, having admitted that the comparison between various models would require fresh data, Ohlson (1980) fails to provide out-of-sample validation due to lack of data. He went on to explain that it should not matter as he was "not indulging in any data dredging" (sic!) (p.126). Even when performed, it is not clear how exactly the out-of-sample testing was done (e.g. Shumway 2001). It matters as there are many different out-of-sample validations procedures: e.g. "matched" vs. random, the same vs. future period etc. It is by no means clear what the pros and cons of these procedures are.

To summarise, we are concerned that because of different default definitions, different prediction power measures, different sample selection procedures and the lack of out-of-sample validations, the comparison of the predictive power of different default models is at least dubious. Indeed, one can even claim the models compared are, using the language of Feyerabend, simply incommensurable. Despite this, the comparison between the predictive power of models, typically estimated with the help of small samples, based on predominantly corporate financial ratios, is still very popular. We brand such an attitude - **the population of models paradigm**. In the next section, we propose an altogether different methodological approach to the default research.

Research methodology

We believe our research proposal offers an alternative and potentially very rewarding approach. In contrast to the population of models paradigm, our methodology, referred to as **the model of population**, consists in the estimation of one model for all listed and non-listed companies. To do it successfully, we intend to use an extensive database of Polish firms and diverse sources of (micro, mezzo and macro) data used as predictors. Instead of focusing on the maximization of the prediction power, our research is

aimed at quantifying the incremental change in the model accuracy. Thanks to some econometric tools, we hope to be able to 'switch' between different subsets of information and hence capture their marginal contribution. It is **marginal predictive efficiency of the model**, conditional on the data set used, rather than the maximization of a prediction rate that matters here. In short, we intend to measure information capacity of different data within one model rather than compete with other models on the overall accuracy.

We plan to use extensive financial accounting data with an emphasis on input that is more likely to be manipulated by the firm in the face of financial troubles. Macroeconomic data will include GDP, exchange rates, risk-free interest as well as peer sector default probability rates and other indicators e.g. oil prices. However, what distinguishes our dataset most is the extensive use of the data on the firm's competitive position and attractiveness of the market in which it operates. Two firms characterized by identical financial indicators but with different strategic positioning could be in a completely different situation as far as default risk is concerned. For this reason we intend to construct the in-house developed Index of Market Attractiveness and Index of Competitive Strength. Data required will be secured from the survey and subsequently refined via face-to-face interviews with executives. By using various sources of information, the model is hoped to be useful even when the quality of corporate financial data (for non-listed companies in particular) is poor.

To sum up, the objective of the study is to create a single unified default forecasting platform for both listed and non-listed firms, which, in addition to corporate financial information, would include data on firm's mezzo (sector level) and macro environment. Nominal levels of input as well as their dynamics are expected to be used as independent variables (Duan et al., 2012). The model will be a multi-period one, so that we should be able to see not only the events of default, but the whole process of approaching (or avoiding) it. We believe, our approach, although far from trying to create a theory of default, may explain the importance of various sources of information, and thus move us closer to understanding the very causes of default. This may ultimately help us move away from the research on bankruptcy to a broader theme of financial distress as postulated by Platt & Platt (2002).

The corporate financial information is sourced from a leading business information provider Coface Poland Credit Management Services¹. The

¹ The database was financed by the National Science Centre (NCN) as the part of the OPUS 9 project "The Quality and Scope of Information in the Context of Corporate Default Prediction".

database covers some 116000 individual annual and some 42000 interim (quarterly and half-yearly, sparingly of other frequency) records on over 15000 companies (joint stock companies, private limited liability companies, partnerships limited by shares) spanning from 2006-2015. Only companies maintaining comprehensive bookkeeping, with at least 10 employees, with annual sales of at least the equivalent of € 2 mln (in 2006) are included. Firms declaring financial activity as their main focus (section K in Polish Industry Classification, or PKD) are excluded. The data provided by Coface originate either from the National Court Register (KRS) or is collected by Coface via direct surveys. The database includes information about 35 different KRS-registered categories of legal actions related to different debtor protection schemes recognized under the Polish law, including notions filed and court decisions taken on creditor arrangement, recovery, bankruptcy and reorganization. The default definition followed in this project covers court decisions to open the above-mentioned proceedings or dismiss a creditor arrangement proceeding notion on the grounds of insufficient debtor's net worth. The very moment of default will be back-tracked to the date of filing the notion initiating a respective court-approved proceeding.

The macro and financial market data are taken from the Central Statistical Office of Poland (GUS) and Warsaw Stock Exchange (GPW) respectively. Data on listed companies were collected from the OSIRIS database compiled by Bureau van Dijk. Some computational results will be compared and tested against probabilities of defaults datasets provided by Credit Research Initiative, Risk Management Institute, National University of Singapore.

The model is based on a double stochastic process with multi-period prediction horizon up to 3 years (cf. Duffie et al., 2007; Duan et al., 2012). An i -th firm's life is governed by a set of independent double stochastic Poisson processes with their own stochastic intensities. Every intensity is a function of some state variables X_i . We distinguish between default, with the stochastic intensity λ_{it} , and other exit (of dissolving, M&A etc.), with the stochastic intensity a_{it} – both only known at or after time t . For the company to survive any period $u = [t, t + \tau]$ the probability equals:

$$P_S = E_t \left[e^{-\int_t^{t+\tau} (\lambda_{iu} + a_{iu}) du} \right],$$

and the probability of default in period $s = [t, t + \tau]$, having survived u , equals:

$$P_D = E_t \left[\int_t^{t+\tau} e^{-\int_t^{t+\tau} (\lambda_{iu} + a_{iu}) du} \lambda_{is} ds \right].$$

We let the dependence of default or other exit be any kind of function of state variable X_{it} as long as they are nonnegative and the default intensity (at

the future time τ) $\lambda_{it} \equiv f_{it}(\tau)$ is no greater than the combined other exit intensity $\alpha_{it} \equiv g_{it}(\tau)$:

$$f_{it}(\tau) = e^{\beta_0(\tau) + \beta_1(\tau)x_{it,1} + \beta_2(\tau)x_{it,2} + \dots + \beta_k(\tau)x_{it,k}},$$

and

$$g_{it}(\tau) = f_{it}(\tau) + e^{\bar{\beta}_0(\tau) + \bar{\beta}_1(\tau)x_{it,1} + \bar{\beta}_2(\tau)x_{it,2} + \dots + \bar{\beta}_k(\tau)x_{it,k}}.$$

Following Duan et al. (2012), we do not specify the dynamics of the state variable X_{it} . In this sense the model resembles the model of Duffie et al. (2007) as long as $\tau = 0$, it is when the forward intensity is equal to the spot intensity.

Conclusions

Although it is corporate default forecasting that is the field of our research, we do not intend to focus on the forecasting accuracy but on the information used in the forecasting process. In particular, we focus on the analysis of how the scope and quality of information used, hereafter referred to as information capacity, influence the default forecast prediction power. Marginal contribution of different information sets to predicting default is what in our opinion ultimately matters. Reaching close to 100% forecasting accuracy, which can be relatively easily achieved with the use of advanced econometric techniques and statistical modelling in large data sets (in the test sample in particular), is therefore not our ultimate goal. Although a skilful design of a model, employing input variables significantly broadening the information set used, will by itself increase the prediction power, such an increase will be a by-product rather than an objective of the approach. We believe an information set containing only corporate financial data (as it is the case in most bankruptcy models referred to in the literature), especially in their static form, is too poor to both accurately forecast the probability of default as well as the marginal informational capacity of the data used, for the non-listed firms in particular. Only after the information on strategic positioning and on its macroeconomic environment are incorporated into the model, the model is able to properly describe the default probability.

We concede the task is ambitious. Given the sample size (over 15000 companies) and the extensive dataset of micro, mezzo, and macro information, the model to be estimated may yet prove too difficult to yield unambiguous answers (due to the inadequacy of e.g. model specification, variables definitions, estimation procedures etc.) We believe the challenge is worth taking though as the switch in the mindset, moving away from small models and inter-model accuracy comparisons, typical of the population of models paradigm, towards the study of marginal contribution of information

used, in line with the model of the population paradigm, should eventually prevail.

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