EQUILIBRIUM
Quarterly Journal of Economics and Economic Policy
2017 VOLUME 12 ISSUE 4, December
p-ISSN 1689-765X, e-ISSN 2353-3293
www.economic-policy.pl

ORIGINAL PAPER

Citation: Berent, T., Bławat, B., Dietl, M., Krzyk, P., & Rejman, R. (2017). Firm's default — new methodological approach and preliminary evidence from Poland. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 12*(4), 753–773. doi: 10.24136/eq.v12i4.39

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Received: 13 March 2017; Revised: 14 September 2017; Accepted: 9 November 2017

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Firm's default — new methodological approach and preliminary evidence from Poland

JEL Classification: *C53; E47; G33*

Keywords: *default; bankruptcy; default probability; prediction accuracy; informational capacity*

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. 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.
Purpose of the article: 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 understanding default itself.
Methods: We critically appraise the bankruptcy research literature for its methodological variety and empirical findings. Default definitions, sampling procedures, in and out-of-sample testing and accuracy measurement are all scrutinized. In an empirical part, we use a double stochastic Poisson process with multi-period prediction horizon and a comprehensive database of some 15,000 Polish non-listed companies to illustrate the merits of our new approach to default modelling.
Findings & Value added: In the theoretical part, we call for the construction of a single unified default forecasting platform estimated for the largest dataset of firms possible to allow testing the utility of various sources of micro, mezzo, and macro information. Our preliminary empirical evidence is encouraging. The accuracy ratio amounts to 0.92 for t = 0 and drops to 0.81 two years ahead of default. We point to the pivotal role played by the information on firm's liquidity (alternatively in profitability) and — in contrast to Altman's tradition — hardly any contribution to predictive power of other financial ratios. Macro data is shown to be critical. It adds, on average, more than 10 p.p. to accuracy ratio. In the future, we hope to integrate listed and non-listed firms data into one model, ideally at higher frequency than annual, and include the information on firm's competitiveness position.

Introduction

Corporate default is too an important research topic to be identified with the forecast accuracy (in the estimation sample in particular) only. 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 first corporate default forecast models were developed in the late 1960s. Altman's Z-score (1968) using discriminant analysis, with more than 95% correct designations, was very accurate. It also proved an incentive for further research around the world, e.g. Emel *et al.* (2003) in Turkey, Galvao *et al*. (2004) in UK, Yim and Mitchell (2005) in Japan, Sandin and Porporato (2008) in Argentina.

With his O-score model, Ohlson (1980) was first in default forecasting to use the logistic regression. Lin and Piesse (2004) used it to distinguish between distressed and non-distressed firms in the UK. Altman & Sabato (2007) — to model credit risk of US SMEs, Lieu *et al.* (2008) examined Taiwanese firms, Bhimani *et al*. (2013) applied it to SMEs in Portugal.

Probit models, pioneered by Zmijewski (1984), are natural candidates for default modelling. For example, Gray *et al.* (2006) examined the impact of various financial and industry variables on credit ratings among Australian firms.

Other techniques such as k-nearest neighbors (k-NN), classification trees, support vector machines (SVM), mathematic programming, evolutionary algorithms or neural networks have also been used. Kim and Sohn (2010) and Ribeiro *et al.* (2012) used SVM. Neural networks were pioneered by Odom and Sharda (1990), Fernandez and Olmeda (1995) and Wilson and Sharda (1992). Zhang *et al.* (1999) used them in US, Becerra *et al.* (2005) in UK. In Poland, the model was used by e.g. Witkowska *et al.* (2004–2005).

In the structural models the probability of default is computed based on the analysis of the dynamics in a firm's equity. These dynamics is usually mimicked by a specific stochastic process like Wiener (cf. Hirsa & Neftci, 2014) or its specific forms like Brownian motion (cf. Karatzas & Shreve, 1988; Nelson, 2001). The approach was used by Black and Scholes (1973) and by Merton (1973, 1974). Despite some criticism from Boyarchenko and Levendorskii (2002), Brigo *et al.* (2010), Cherubini *et al.* (2004) and Nelsen (2006), it was Black-Scholes and Merton that inspired Vasicek, who jointly with Kealhofer and McQuown, built their KMV model (Vasicek, 1987). HKC model was proposed by Hillegeist *et al.* (2004). According to Agarwal and Taffler (2008), it favourably compared against Altman’s Z–score and Black–Scholes model.

The real economy as well as firms are driven by multi-period processes. Models of Altman (1968), Ohlson (1980) or Zmijewski (1984), which had won their wide acceptance in academia and industry, do not follow the underlying nature of the modelled process. Shumway (2001), focusing on survival analysis, was the first to note that. His model was shown to be superior to Altman and Zmijewski’s one. Kingman (1993), Javaheri (2005) and Mikosch (2009) recommended a Poisson process for risk and insurance applications. Lando (1998) was the first to model default with Cox process. The biggest advantage of the model was its ability to model multi-period probabilities or recurring defaults. Other model based on a jump process is Duffie *et al.* (2007).

Chava and Jarrow (2004) were among the first to introduce industry effects resulting from different levels of competition and different accounting conventions. Berkovitch *et al.* (1998) showed that firms in mature industries were more likely to file for bankruptcy. Maksimovic and Phillips (1998) proved default was associated with industry demand conditions. Opler and Titman (1994) focused on adverse impact of leverage on default, more pronounced in concentrated industries. Shleifer and Vishny (1992) showed sector-wide default implications. Lang and Stulz (1992) studied the contagion and competitive intra-industry effects of bankruptcy announcements. Acharya *et al.* (2003) showed that seniority and collateral of the defaulted securities, together with industry conditions at the time of default, were important determinants of the recovery rates.

The objective of the paper is to provide the theoretical argument for the need of the approach switch away from maximizing prediction to measuring the utility of the information used. This would help not only avoid overfitting problem that has plagued the academic research in the area for too long, but also focus research on what really matters: the causes of default. We provide here the preliminary empirical evidence that this approach may yet to lead to considerable breakthroughs.

The novelty of our approach consists in the attempt to change the research paradigm. Rather than compare different default studies, adopt different models, estimated for different regions and time-periods, thus rendering the comparison of the results rather dubious, we call for the construction of one all-embracing model for a vast dataset of firms, which would be fed with various and diverse sources of information. Here, we use a database on some 15,000 Polish non-listed firms and publicly available macroeconomic information. The adoption of a doubly stochastic Poisson process, which enables multi-period forecasting is also new in the context of the Polish market. We attempt to capture the dynamic aspect of the data using differences in dependent variable levels on top of the levels themselves. In the future, we plan to integrate other sources of information, e.g. on the strategic position and competitive strength of a firm.

In the next section, we provide an extensive literature review in which we argue that the current focus of default research is misplaced. Then, in the methodological section, we explain what we mean by a new approach to research and subsequently, in the results section, we provide some preliminary evidence that the construction of the big model using low-quality data on non-listed firms can be useful when properly handled and assisted by other sources of information.

Research gap

The greatest achievements of the default literature, as illustrated by the wealth of tools and techniques, have been made in econometric modelling. 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 default. 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 levels of the variable, 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[1]. 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[2]. 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 over-fitting 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 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

[1] An asset turnover ratio used is one of the two components that determine the operating profitability, also used in Altman's model. This in turn affects net profitability of retained earnings - also present in the model. Berent and Jasinowski (2012) show that equity to debt ratio used by Altman is the least frequently used debt ratio in the leverage literature.

[2] This has occurred even though in the original model there is only one parameter related to the market value.

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 in 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 — a total error rate TER. This is the weighted average of TPR and TNR (a true negative rate, or a specificity, equal to 1 — a 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 — an 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 the 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, 2013), while an accuracy ratio is computed as twice the area between the ROC curve and the no-discrimination line (Duan *et al*., 2012)[3]. Many other ROC-related measures can also be used[4]. 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 (2015) 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) has 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

[3] Note, this accuracy ratio is different from previously mentioned accuracy rates (two versions) even if the share the same acronym AR.

[4] Gini Coefficient or Mann-Whitney Statistics are just few examples. It is also possible to look at a specific region of the ROC curve rather than at the whole curve and compute partial AUC only.

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 the largest dataset of companies possible, ideally both listed and non-listed. 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.

In the relevant literature, evidence is provided for the notion that the default forecast prediction power increases after sector relevant information is included, cf. Chava and Jarrow (2004), Lang and Stulz (1992), Shleifer and Vishny (1992), Opler and Titman (1994), Maksimovic and Phillips (1998) and Berkovitch *et al*. (1998). Bławat (2015) shows that in the emerging market context, after company specific variables are properly redefined, financial data quality and hence their information capacity improves. Adding even textual information can improve the model. This is also true for highly developed markets where inclusion of additional (non-financial) information improves default forecast prediction power. As Bhimani *et al.* (2013) show even non-financial information from company surveys can be valuable.

In the future we also 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 e.g. GDP, investments, exports, exchange rates, risk-free interest as well as peer sector default probability rates and other indicators e.g. oil prices. However, what will eventually distinguish 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 plan to construct the in-house developed Index of Market Attractiveness and Index of Competitive Strength. The data required will be secured from the survey and subsequently refined via face-to-face interviews with executives — the process that may take time to complete, but promises to deliver valuable feedback in the future. 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 ultimate objective of the study is to create a single unified default forecasting platform (ideally 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 and Platt (2002).

The corporate financial information is sourced from a leading business information provider Coface Poland Credit Management Services[5]. The database covers some 116,000 individual annual records on over 15,000 companies (joint stock companies, private limited liability companies, partnerships limited by shares) spanning from 2006-2015. In the future, we also intend to make use of some 42,000 interim (quarterly and half-yearly, sparingly of other frequency) records available in the data-base. 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 backtracked 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). When listed companies are integrated into the system at a later stage, data are planned to be sourced from the Warsaw Stock Exchange (GPW) and the OSIRIS database compiled by Bureau van Dijk. Some computational results will be also 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 periods (cf. Duffie *et al*., 2007; Duan *et al*., 2012). An i-th firm's life is governed by a set of independent double sto-

[5] 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".

chastic 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:

$$P_S = E_t\left[e^{-\int_t^{t+\tau}(\lambda_{iu}+\alpha_{iu})du}\right], \tag{1}$$

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

$$P_D = E_t\left[\int_t^{t+\tau} e^{-\int_t^{t+\tau}(\lambda_{iu}+\alpha_{iu})du}\lambda_{is}ds\right]. \tag{2}$$

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 $\alpha_{it} \equiv g_{it}(\tau)$:

$$f_{it}(\tau) = e^{\beta_0(\tau)+\beta_1(\tau)x_{it,1}+\beta_2(\tau)x_{it,2}+\cdots\beta_k(\tau)x_{it,k}}, \tag{3}$$

and

$$g_{it}(\tau) = f_{it}(\tau) + e^{\overline{\beta}_0(\tau)+\overline{\beta}_1(\tau)x_{it,1}+\overline{\beta}_2(\tau)x_{it,2}+\cdots\overline{\beta}_k(\tau)x_{it,k}}. \tag{4}$$

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.

At some stage, the model is hoped to be fed with quarterly data even though financial data on non-listed firms tends to be annual. Frequency will be increased using regression featuring listed firms and macro data (cf. Kim *et al*., 2012). Modelling the impact of unobservable variables will be done using Duffie and Lando (2001) and Frey and Schmidt (2009). The data collected and processed will be cleaned up and winsorized when necessary (cf. Chambers *et al*., 2000).

Backward selection of predictors will be performed algorithmically, but the final decision which variables are selected will be taken after a careful analysis of the model content. (cf. Bławat, 2015; Tian & Yu, 2013; Sjostrand, 2005). Some variables may be positioned in relation to the sector median. During every loop, selection results will be recorded in terms of values of critical benchmarks. Maximization of pseudo log likelihood function is the main principle, but several other criteria, e.g. the p-value, statistical significance, will also be adopted. Stability of the model over longest time possible, with minimum p-value jumps, and the consistency of estimated coefficients' signs with the theoretical framework will also be observed. In the next step, macro indicators will be included. Necessary steering dummy variables, critically important to enable switching and testing the model in different configurations of variables, will be added. In order to assess the model predictive power, accuracy ratio of the number of forecasted defaults to the actually observed ones will be computed. Type 1 and type 2 errors will be appraised together with Spiegelhalter tests for normality against symmetric alternatives (cf. Spiegelhalter, 1977; 1986). Finally, the traffic light test (cf. Coppens *et al*., 2007) will diagnose the relevance of our model for practitioners. Most of the analyses performed during model development and refining, will be in-sample type followed by out-of-sample tests.

Results

Below, we present our preliminary empirical results. Using a double stochastic Poisson process-based model, estimated with the help of Matlab environment, we receive multi-horizon default prediction for t = 0, t = 1, and t = 2. At this stage, only annual data over 2007–2014 on a large number of Polish non-listed companies, supplemented by macro information, is used. 2006 and 2015 are eliminated due to low quality and/or use of variable differences. To bring outliers into the frame, instead of winsorizing, which would result in the loss of already sometimes patchy data, we opted for the use of hyperbolic tangent sigmoid curve transformation. Table 1 describes the number of complete data companies each year. It ranges from 12,011 in 2014 to 14,834 in 2010. The number of bankrupt companies is 252 over the entire period.

We use five groups of micro financial ratios: liquidity, profitability, rotation, leverage and size. Each group is represented by two different ratios. Their definitions are in Table 2. In addition, following Duan (2012), each financial ratio is represented by two forms — levels and trends. Macro data are represented by GDP (nominal), gross investments and exports growths. To summarize, we first estimate 31 ($2^5 - 1$) different models using all subsets of five micro financial ratios groups to see which micro information matters most. Then we add macro data and finally check if the addition of micro data trends adds anything. As a result, we estimate as many as 124 models and observe how switching between the different groups of data affects the model prediction power. The simple change in accuracy ratio — understood as AUC — resulting from the switches between the models is for now our major metric used.

The choice of both micro and macro variables at this stage is quite arbitrary but, as emphasized before, pushing for the highest prediction is not our goal. Still, we believe the choice is well balanced and representative to serve its purpose — gauging the marginal contribution of different data sets.

Our best model which features both the full set of micro financial ratios and macro data, i.e. micro & macro model, produces accuracy ratio of 0.92 for t = 0, which, given rather poor quality of data for non-listed companies, is more than satisfactory. The accuracy drops by 5 p.p. to 0.87 for t =1 and by another 6 p.p. to 0.81 for t = 2, one and two years prior default respectively (see Figure 1). The drop in prediction power as time goes on is robust across all models. The drop in accuracy is on average 11 p.p. for all the models, with 4 p.p. credited to the first year and 7 p.p. to the second.

Table 3 summarizes the most relevant results of our study. The best model beats the one with the liquidity information alone, i.e. the liquidity model, only marginally inter alia. Profitability as a stand-alone predictor is a bit worse than liquidity. The addition of other financial ratios, i.e. on rotation, leverage and size adds merely 1–2 p.p. to accuracy ratio. This result goes against the Altman-motivated research where liquidity (or profitability) is just a component of overall score. Although our conclusion merits closer attention, the result is robust across all the models. Only when macro data is missing — just like in the case of Altman's models — some evidence exists that profitability ratios do have some marginal information capacity above what is offered by liquidity — accuracy ratio increases from 0.77 for the liquidity model to 0.80 for the model with both liquidity and profitability, see Table 3.

Macro information seems to be pivotal. Not only does it render redundant all other information than liquidity (or alternatively profitability), but the very size of its marginal contribution is rather big — the increase in the accuracy ratio ranges from 9 to 13 p.p. (see Table 3). The result is more than robust across all models estimated. Actually, the average increase is as big as 16 p.p. for both t = 1 and t = 2, and 13 p.p. for t = 2. This probably results from the fact that the models quoted in Table 3 have the highest predictive power among all the models. Poorer information on micro is hence substituted by macro data. Figure 2 illustrates the pivotal role played by the information on liquidity (the lowest curve) on the one hand and macro environment (the highest curve) on the other.

Surprisingly, the best model described above does not include the information on the trends in micro variables. We are somewhat puzzled by this outcome which we believe may result from poor quality of data, i.e. each missing value eliminates two rather than one record (as in the case of the levels). The result is again consistent across most models, the only exception being models with initially low predictive power — the addition of trends is then a bonus. There is also some evidence that the inclusion of trends in micro data is a proxy for the inclusion of macro data. The analysis of the importance of the differences (trends) variables deserves a closer look in the future.

Conclusions

Although it is corporate default forecasting that is the field of our research, we do not 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 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 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.

Our preliminary results are encouraging. The Duan model works in the context of Polish big data-set of non-listed companies, hence poorer quality information, quite well, producing accuracy ratio of 0.92 for $t = 0$, 0.87 for $t = 1$ and 0.81 for $t = 2$. The information on firm's liquidity (or profitability as its "substitute") is shown to possess highest capacity to predict default for all time horizons. Moreover, we demonstrate that when liquidity (or profitability) data is collected, most of other sources of micro data seems redundant. This stands in clear contrast to the Altman tradition of modelling. We also document the pivotal role of macro information. The inclusion of macro data improves the predictive power by more than 10 p.p. Wherever there is any semblance of significance of other than liquidity information, it vanishes altogether the moment macro data is added. Macro information seems to act as a substitute for the poor quality of the data for non-listed firms. We plan to verify this conclusion at a later stage for listed companies and the conjecture that the effect will be weaker. We are somewhat puzzled by our preliminary finding that the inclusion of trends in micro data, in contrast to static levels of financial ratios, adds little. After all, default is more a process rather than an event. This merits more detailed analysis in the future.

Ultimately, we hope to be able to construct one model for all listed and non-listed firms which — on top of the information used here — will include the information on firm's strategic positioning and competitive strength. We also hope to integrate patchy, yet information-rich, quarterly data into the system. We concede the task is ambitious. Given the sample size 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, quality of data especially for non-listed firms etc.). Our preliminary results, based on some 15,000 companies, make us 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.

References

Acharya, V. V.; Bharath, S. T., & Srinivasan, A. (2003). *Understanding the recovery rates on defaulted securities.* Centre for Economic Policy Research. doi: 10.2139/ssrn.442901.

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance*, *32*(8). doi: 10.1016/j.jbankfin.2007.07.014.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4). doi: 10.1111/j.1540-6261.1968.tb00843.x.

Altman, E. I., & Sabato, G. (2007). Modelling credit risk for SMEs: evidence from the US market. *Abacus*, *43*(3). doi: 10.1111/j.1467-6281.2007.00234.x.

Becerra, V. M., Galvão, R. K., & Abou-Seada, M. (2005). Neural and wavelet network models for financial distress classification. *Data Mining and Knowledge Discovery*, *11*(1). doi: 10.1007/s10618-005-1360-0.

Berent, T., & Jasinowski, S. (2012). Financial leverage puzzle–preliminary conclusions from literature review. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, *271*(1).

Berkovitch, E., Israel, R., & Zender, J. F. (1998). The design of bankruptcy law: a case for management bias in bankruptcy reorganizations. *Journal of Financial and Quantitative Analysis*, *33*(04). doi: 10.2307/2331127.

Bhimani, A., Gulamhussen, M. A., & Lopes, S. D. R. (2013). The role of financial, macroeconomic, and non-financial information in bank loan default timing prediction. *European Accounting Review*, *22*(4). doi: 10.1080/09638180.2013.770967.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3). doi: 10.1086/260062.

Boyarchenko, S. I., & Levendorskii, S. Z. (2002). *Non-Gaussian Merton-Black-Scholes theory*. Wspc. doi: 10.1142/4955.

Brigo, D., Pallavicini, A., & Torresetti, R. (2010). *Credit models and the crisis: a journey into CDOs, copulas, correlations and dynamic models*. Wiley: The Wiley Finance Series. doi: 10.1002/9781118374733.

Bławat, B. (2015). Modeling default with sector positioned variables. *Global Credit Review* (forthcoming).

Boritz, J., Kennedy, D., & Sun, J. (2007). Predicting business failures in Canada. *Accounting Perspectives*, *6*. doi: 10.1506/G8T2-K05V-1850-52U4.

Chambers, R., Kokic, P., Smith, P., & Cruddas, M. (2000). Winsorization for identifying and treating outliers in business surveys. In *Proceedings of the Second International Conference on Establishment Surveys*.

Chava, S., & Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, *8*(4). doi: 10.1093/rof/8.4.537.

Cherubini, U., Luciano, E., & Vecchiato, W. (2004). *Copula methods in finance*. Wiley. doi: 10.1002/9781118673331.

Coppens, F., González, F., & Winkler, G. (2007). The performance of credit rating systems in the assessment of collateral used in Eurosystem monetary policy operations. *ECB Occasional Paper*, *65*. doi: 10.2139/ssrn.1687537.

Duan, J.-C., Sun, J., & Wang, T. (2012). Multiperiod corporate default prediction – a forward intensity approach. *Journal of Econometrics*, *170*(1). doi: 10.1016/j.jeconom.2012.05.002.

Duffie, D., & Lando, D. (2001). Term structures of credit spreads with incomplete accounting information. *Econometrica*, *69*(3). doi: 10.1111/1468-0262.00208.

Duffie, D., Saita, L., & Wang, K. (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics*, *83*(3). doi: 10.1016/j.jfineco.2005.10.011.

Emel, A. B., Oral, M., Reisman, A., & Yolalan, R. (2003). A credit scoring approach for the commercial banking sector. *Socio-Economic Planning Sciences*, *37*(2). doi: 10.1016/S0038-0121(02)00044-7.

Fernández E., & Olmeda I. (1995). Bankruptcy prediction with Artificial Neural Networks. In J. Mira & F. Sandoval (Eds). *From natural to artificial neural computation. IWANN 1995. Lecture notes in computer science, vol 930*. Berlin, Heidelberg: Springer. doi: 10.1007/3-540-59497-3_296.

Frey, R., & Schmidt, T. (2009). Pricing corporate securities under noisy asset information. *Mathematical Finance*, *19*(3). doi: 10.1111/j.1467-9965.2009.00374.x.

Galvao, R. K., Becerra, V. M., & Abou-Seada, M. (2004). Ratio selection for classification models. *Data Mining and Knowledge Discovery*, *8*(2). doi: 10.1023/B:DAMI.0000015913.38787.b3.

Gray, S., Mirkovic, A., & Ragunathan, V. (2006). The determinants of credit ratings: Australian evidence. *Australian Journal of Management*, *31*(2). doi: 10.1177/031289620603100208.

Grice, J. S., & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research*, *54*. doi: 10.1016/S0148-2963(00)00126-0.

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, *9*(1). doi: 10.1023/B:RAST.0000013627.90884.b7.

Hirsa, A., & Neftçi, S. (2014). *An introduction to the mathematics of financial derivatives*. Elsevier.

Javaheri, A. (2005). *Inside volatility arbitrage: the secrets of skewness*. Wiley.

Karatzas, I., & Shreve, S. E. (1988). *Brownian motion and stochastic calculus*. Springer Verlag. doi: 10.1007/2F978-1-4684-0302-2.

Kim, B., Duan, J.-C., Kim, C., Kim, W., & Shin, D. (2012). Default probabilities and interest expenses of privately held firms. Technical report. *Working Paper, Risk Management Institute at National University of Singapore*.

Kim, H. S., & Sohn, S. Y. (2010). Support vector machines for default prediction of SMEs based on technology credit. *European Journal of Operational Research 201*(3). doi: 10.1016/j.ejor.2009.03.036.

Kingman, J. F. C. (1993). *Poisson processes (Oxford studies in probability)*. Oxford University Press.

Lando, D. (1998). On Cox processes and credit risky securities. *Review of Derivatives Research*, *2*(2-3). doi: 10.1007/BF01531332.

Lang, L. H., & Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: an empirical analysis. *Journal of Financial Economics*, *32*(1). doi: 10.1016/0304-405X(92)90024-R.

Lieu, P.-T., Lin, C.-W., & Yu, H.-F. (2008). Financial early-warning models on cross-holding groups. *Industrial Management & Data Systems*, *108*(8). doi: 10.1108/02635570810904613.

Lin, L., & Piesse, J. (2004). Identification of corporate distress in UK industrials: a conditional probability analysis approach. *Applied Financial Economics*, *14*(2). doi: 10.1080/0960310042000176344.

Maksimovic, V., & Phillips, G. (1998). Asset efficiency and reallocation decisions of bankrupt firms. *Journal of Finance*, *53*(5). doi: 10.1111/0022-1082.00063.

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance*, *29*(2). doi: 10.2307/2978814.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, *41*(5). doi: 10.2307/1913811.

Mikosch, T. (2009). *Non-life insurance mathematics: an introduction with the Poisson process*. Springer. doi: 10.1007/978-3-540-88233-6.

Nelsen, R. B. (2006). *An introduction to copulas*. Springer Verlag. doi: 10.1007/978-1-4757-3076-0.

Nelson, E. (2001). *Dynamical theories of Brownian motion*. *Vol. 17*. Princeton University Press.

Odom, M. D., & Sharda, R. (1990). *A neural network model for bankruptcy prediction*. 1990 IJCNN international joint conference on neural networks. San Diego. doi: 10.1109/IJCNN.1990.137710.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1). doi: 10.2307/2490395.

Opler, T. C., & Titman, S. (1994). Financial distress and corporate performance. *Journal of Finance, 49*(3). doi: 10.1111/j.1540-6261.1994.tb00086.x.

Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: reflections on choice-based sample bias. *Journal of Economics and Finance*, *26*. doi: 10.1007/BF02755985.

Ribeiro, B., Silva, C., Chen, N., Vieira, A., & Carvalho das Neves, J. (2012). Enhanced default risk models with SVM+. *Expert Systems with Applications, 39*(11). doi: 10.1016/j.eswa.2012.02.142.

Roman, L. (2009). Quality of earnings and earnings management. *Journal of AICPA*.

Sandin, A. R., & Porporato, M. (2008). Corporate bankruptcy prediction models applied to emerging economies: evidence from Argentina in the years 1991-1998. *International Journal of Commerce and Management*, *17*(4). doi: 10.1108/10569210710844372.

Shleifer, A., & Vishny, R. W. (1992). Liquidation values and debt capacity: a market equilibrium approach. *Journal of Finance*, *47*(4). doi: 10.1111/j.1540-6261.1992.tb04661.x.

Shumway, T. (2001). Forecasting bankruptcy more accurately: a simple hazard model. *Journal of Business*, *74*(1). doi: 10.1086/209665.

Sjostrand, K. (2005). *Matlab implementation of LASSO, LARS, the elastic net and SPCA. Informatics and mathematical modelling*. Technical University of Denmark, DTU.

Spiegelhalter, D. (1977). A test for normality against symmetric alternatives. *Biometrika, 64*(2). doi: 10.1093/biomet/64.2.415.

Spiegelhalter, D. J. (1986). Probabilistic prediction in patient management and clinical trials. *Statistics in Medicine, 5*(5). doi: 10.1002/sim.4780050506.

Tian, S., & Yu, Y. (2013). Variable selection for international bankruptcy forecasts. in *Innovation Conference (SIIC).* Suzhou-Silicon Valley-Beijing International. doi: 10.1109/SIIC.2013.6624162.

Vasicek, O. (1987). Probability of loss on loan portfolio. *KMV Corporation*, *12*(6). doi: 10.1002/9781119186229.ch17.

Wilson, R., & Sharda, R. (1992). *Neural networks*. OR/MS Today.

Witkowska, D., Mazur, A., & Staniec, I. (2004-2005). Classification of borrowers: artificial neural networks and classification function. *Folia Oeconomica Stetinensia*, *3-4*(11-12).

Yim, J., & Mitchell, H. (2005). Comparison of country risk models: hybrid neural networks, logit models, discriminant analysis and cluster techniques. *Expert Systems with Applications*, *28*(1). doi: 10.1016/j.eswa.2004.08.005.

Zhang, G., Y Hu, M., Eddy Patuwo, B., & C Indro, D. (1999). Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research*, *116*(1). doi: 10.1016/S0377-2217(98)00051-4.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, *22*. doi: 10.2307/2490859.

Annex

Table 1. The sample size

	Number of firms in the sample
2007	12.753
2008	13.690
2009	14.641
2010	14.839
2011	14.666
2012	14.637
2013	13.637
2014	12.011

Table 2. Micro financial ratios

Group of ratios	Ratio
Liquidity	Short-term financial assets / total assets Current assets / current liabilities
Profitability	EBIT / net sales Net profit/ total assets
Rotation	Net sales / total assets Net sales / short-term receivables
Leverage	Net debt / EBIT Net debt / equity
Size	Total assets Net sales

Table 3. Accuracy ratios for different sets of micro data

	Levels of micro data			Level of micro data & macro data			Level of micro data & macro data & trends		
Micro data	t = 0	t = 1	t = 2	t = 0	t = 1	t = 2	t = 0	t = 1	t = 2
Liquidity only	0.77	0.73	0.69	0.90	0.86	0.80	0.88	0.85	0.79
Liquidity & Profitability	0.80	0.77	0.71	0.91	0.87	0.80	0.90	0.84	0.80
All micro	0.82	0.77	0.72	0.92	0.87	0.81	0.91	0.84	0.70

Figure 1. ROC curves for the micro & macro model (no trends) and t = 0, 1, 2

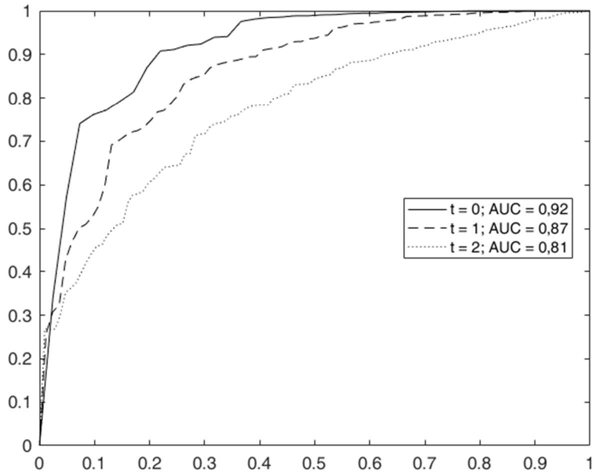

Figure 2. ROC curves for the liquidity, micro data, and micro & macro data models and t = 0