Financial Distress Models: How Pertinent Are Sampling Bias Criticisms?

Robert F. Hodgin
University of Houston-Clear Lake

Roberto Marchesini
University of Houston-Clear Lake

The finance literature shows that over-sampling of distressed companies, time-period selection, cross-industry variation and choice of distress indicator can bias estimating model predictive accuracy. We address those arguments using a sample of high-leverage companies where loan default is the indicator variable. We separately test the predictive accuracy of two published multivariate financial distress models by Zmijewski and Marchesini. The predictive accuracy for both models was generally comparable for the new dataset. Further, each model's predictive accuracy was comparable to that found in their respective original datasets. These comparative results raise doubt regarding the relative importance of sample bias criticisms.

INTRODUCTION

Recent economic down-cycles have spurred academic and practitioner interest in models that more accurately predict corporate financial distress. The current generation of financial distress models evolved over the past forty years of research, beginning with early works by Beaver and Altman (1968) on bankruptcy prediction. Over the ensuing forty-year period, the research focus moved from predicting the bankruptcy event to forms of financial default prediction, a more subtle dimension of financial distress. Simultaneously, financial institutions sought earlier and more accurate predictions of financial distress to permit intervention prior to an actual distress event, including bankruptcy.

Attention in the academic finance literature stresses sampling biases, estimating model form, time period selection, breadth of industry type and distress indicator choice as potentially affecting the predictive accuracy of the financial distress prediction model. We explore those assertions by comparing the predictive accuracy of two relatively recent models applied to a data set of known high-risk companies. The logit model, by Marchesini, Perdue and Bryan (2004), originally derived from a sample of bond defaulting versus non-defaulting firms while the probit model, by Zmijewski (1984), originally derived from a sample of bankrupt versus non-bankrupt industrial firms.

LITERATURE

Financial distress researchers seek accurate predictions from well-specified models predicated on theory, and which, ideally, derive their parameter estimates from appropriately selected samples. Early research on corporate bankruptcy and financial distress emphasized the role of diminished cash flow as a sign of financial trouble (Dambolena, 1988), a direct link to meeting scheduled payments as well as other debt covenant criteria. In the 1980s, logistic model specifications came into favor. In her work, Lau (1987) used a multinomial logit model to estimate a five-state financial distress model with good predictive accuracy as tested on a hold out sample. In his probit model study and methodological review of financial distress models, Zmijewski (1984) criticized the sampling approach used by Lau, suggesting it over-sampled distressed firms and favored firms with complete data. He shows that the overall predictive accuracy, across default and non-default categories, is not affected. The sampling bias manifests in the sub-categories with asymptotically biased estimators when the sample proportion of defaulted firms differs from the proportion of the population.

Grice and Dugan (2001) reviewed the bankruptcy prediction literature and reaffirmed long-held criticisms on sampling bias. Their assessment further suggests that weaknesses in model estimations include a lack of model testing on samples over different time-periods, across different industries and with dependent variables different from those in the original model estimation. They directly criticize Zmijewski's (1984) widely used probit model, asserting that there is not yet any empirical evidence for its general applicability, most notably across industries. Grice and Dugan also claim, as did Zmijewski, that testing a model using hold out samples creates an upward bias in prediction results. Further, they assert that hold out samples provide no evidence regarding the original model's cross-industry predictive power.

Ignoring the finance literature's criticisms above, Tseng (2009) adopts an expert systems approach to estimating financial distress, reducing the effort to data fitting without regard to sample characteristics. His approach to modeling uses predictive accuracy as the sole criterion on the sample for evaluation. Of the four mathematical forms tested, the radial bias function network generally showed better predictive accuracy when compared to the logit and quadratic interval probit models.

Chava and Roberts (2008) recently explored the theoretical link between debt covenants, where a violation invokes the creditor's inspection and often affects corporate investment timing. In particular, the covenant violation elicits a creditor's threat to accelerate the loan, slowing corporate investment. They highlight the logical link from loan covenant violations to financial leverage and potential distress, especially in those firms where agency and information problems exist.

Marchesini, Perdue and Bryan (2004) explored corporate high-yield bond defaults among high-risk firms. They derived a multivariate logit model for bond default using a sample drawn from the Chase High-Yield Database for debt instruments issued by firms across nineteen industries between 1997 and 2000. Their financial data sample used candidate companies from the default event year and the two immediate preceding years. To test for time-dependence in the sample, they re-grouped the original sample that spanned the three years into subsets based on the year of bond issuance, and re-tested with similar results, suggesting there is no time dependence in their model.

In the next two sections, we discuss the test using the MPB and ZMI models as originally specified, on a new sample data set comprised of approximately equal counts of non-defaulting and loan defaulting high-leverage companies. A default occurs at the first loan covenant violation. The question is whether the degree of sample bias inherent in the original model materially affects the predictive accuracy when applying the models to new data. We find that the two models selected predict similarly across different time-periods and across industries, in general. The two models show improvement in predictive accuracy as the event year approaches. More, the predictive accuracy for each model was generally comparable to the predictive accuracy reported in their respective original studies. These findings cast doubt on the relative importance of criticisms regarding the choice of estimation technique and sample bias.

DATA SAMPLE

The investigation uses a new data sample, different by risk class, time-period, indicator variable and industry composition from the original samples used to derive each of the two models. Company sample data selected for the test come from the Credit Suisse/First Boston Global Leverage Finance Annual Review institutional report. That report includes a database of new and defaulted institutional leveraged (high-risk) loans for companies during 2000-2003. The first defaulted loan gets the company listed in the

Credit Suisse/First Boston Global exceptions list. A loan default during 2000-2003 qualified the company as a candidate for analysis. The data collection time-period also overlays the 11-month recession of 2000-2001.

As reported by Credit Suisse/First Boston Global, during 2000-2003, 149 of the leveraged companies defaulted and became sample analysis candidates. Sample mortality occurred for the following reasons: 1) each company must be in the Compustat database, 2) only public companies were eligible, to the exclusion of foreign and privately held companies and 3) candidate companies must have complete accounting data for the two years prior to the loan default year. The final sample count was 91 defaulting high-risk companies. We then randomly drew the non-defaulting company sample from the Leverage Loan Index database, published in the Credit Suisse/First Boston Global Leverage Finance Annual Review, being sure to match industries where at least one default had occurred over the same three-year period. Table 1 data show the industry breakdown for the entire sample of defaulting and non-defaulting companies.

TABLE 1
COMPANIES BY INDUSTRY (n = 206)

Industry	Count
Aerospace	5
Chemicals	8
Consumer Durables	2
Consumer Non-Durables	15
Energy	2
Food & Drug	6
Food & Tobacco	7
Forest Products	4
Gaming & Leisure	6
Healthcare	21
Housing	3
Information Technology	11
Manufacturing	14
Media & Communications	51
Metals & Minerals	5
Other*	2
Retail	5
Services	16
Transportation	18
Utilities	5
*One each in Consumer Products and Financial	

RESULTS

We applied the MPB (Marchesini et al, 2004) logit model, as originally derived from the 2004 bond bankruptcy study and the original ZMI (Zmijewski,1984) probit model article to the two data subsets: loan defaults and no loan defaults in each period T-0 (the default year), then T-1 and T-2 (one and two years immediately prior to the default year). Using the acceptance criterion of 50 percent probability, as the division between likely (over 50 percent) or unlikely (below 50 percent), we calculated the correct predictions as a percentage of the total predictions in each classification subset (likely to default and unlikely to default) and then for the overall predictive accuracy of the combined classification subsets. The original published versions of both models appear below.

ZMI Model:
IND = 14.3 – 4.5 NITA + 5.7 TDTA - .004 CACL
where: NITA = net income/total assets; TDTA = total debt/total assets; CACL = current assets/current liabilities and, IND = overall index

MPB Model:
I(B) = 3.65 -1.04 LOGTA – 3.67 TETA + 4.57 EBITSALES – 22.05 CFOSALES – 4.39 CFOTA + 0.11 EBITINTEX
where: LOGTA = log of total assets; TETA = total equity/total assets; EBITSALES = EBIT/Sales; CFOSALES = Cash flow/Sales; CFOTA = Cash flow/Total Assets; EBITINTEX = EBIT/Interest Expense

Data in Table 2 show the predictive accuracy for the MPB and ZMI models for the loan default year and the two immediately preceding years. Table 3 data show the predictive accuracy of the MPB and ZMI models for the Media/Communications industry alone, an industry subset of the original sample, for the loan default year and two preceding years.

For results shown in Table 2, the "All Correct Predictions" percentages across default and non-default categories and time-period are similar for both models. Predictive accuracy for the "Unlikely to default" percentages across time-periods also are similar. The predictive accuracy for the "Likely to default" percentages in time periods T-2 and T-3 are disparate with the MPB model showing the higher accuracy rate. In sum, both model's predictive accuracy rates are similar to the MPB model reflecting the higher accuracy rate in the "likely to default" category.

TABLE 2
ALL FIRMS CORRECTLY ESTIMATED BY PREDICTION CATEGORY AND TIME-PERIOD

ZMI Model	Period T-0		Period T-1		Period T-2	
Prediction Category	Count	Percent	Count	Percent	Count	Percent
Likely to default	56/86	65%	34/89	38.2%	24/79	30.4%
Unlikely to default	73/86	85%	73/84	86.9%	68/81	84%
All Correct Predictions	129/172	75%	107/173	61.8%	92/160	57.5%
MPB Model	Period T-0		Period T-1		Period T-2	
Prediction Category	Count	Percent	Count	Percent	Count	Percent
Likely to default	55/86	64%	45/88	51%	34/77	44%
Unlikely to default	72/86	84%	72/84	85.7%	63/82	76.8%
All Correct Predictions	127/172	74%	117/172	68%	97/159	61%

For the results shown in Table 3, the MPB model's predictive accuracy regarding Media companies compared to the MPB model for all companies in Table 2, the correct prediction percentages across default and non-default categories together and time-period are similar, with one exception. For the likely to default category in period T-0, the MBP model's predictive accuracy falls to 52 percent for the Media industry, versus 64 percent for all industries. The MPB model's predictive accuracy results for Media companies compared to the MPB model for all companies for non-default companies across time-periods are similar. These comparative results suggest that industry-level predictive accuracy of the MPB model, originally estimated from a multi-industry bond default sample, may not be sensitive to the choice of industry.

TABLE 3
MEDIA & COMMUNICATIONS FIRMS CORRECTLY ESTIMATED BY PREDICTION CATEGORY AND TIME-PERIOD

ZMI Model	Period T-0		Period T-1		Period T-2	
Prediction Category	Count	Percent	Count	Percent	Count	Percent
Likely to default	16/23	70%	16/25	64%	11/21	52%
Unlikely to default	15/19	79%	16/19	84%	14/18	78%
All Correct Predictions	31/42	74%	32/44	73%	25/39	64%
MPB Model	Period T-0		Period T-1		Period T-2	
Prediction Category	Count	Percent	Count	Percent	Count	Percent
Likely to default	12/23	52%	17/25	68%	11/20	55%
Unlikely to default	16/19	84%	16/19	84%	16/18	89%
All Correct Predictions	28/42	67%	33/44	75%	27/38	71%

Across time-periods the predictive accuracy of both the ZMI and MPB models for the "likely to default," the more difficult but important category, is lower than the predictive accuracy for the "unlikely to default" category. More, as the default event draws closer in time, the predictive accuracy of default increases, with the exception of the MPB model in period T-0. Correctly predicting default during the year of default excludes effective intervention. Indeed, the ZMI models predictive accuracy for the "likely to default" category is below 40 percent until the default year, where it rises to 65 percent. Yet, the MPB model's predictive accuracy for "likely to default" is near 70 percent for the year prior to the default.

It is instructive to present the predictive accuracies reported in their respective original studies for the two models we applied in the current study. The overall accuracy reported in the MPB original bond default study was 79.6% one year prior to default, 72.6 two years prior to default and 68.2% three years prior to default. The percentage of firms correctly classified overall by the ZMI model from 1972 to 1978, ranged from 71.7% to 72.2% overall, 52.5% to 54.6% for the complete data and 83.1% to 82.5% for the incomplete data. We suggest that the general conformity of these results to those reported in Table 2 and Table 3 at least raises some doubt as to the effect of sample bias in statistical models classifying financially distressed companies.

We do not deny the presence of sampling bias in either model, as developed in Zmijewski's article. Those biases alone do not appear to explain the few relatively large disparities in predictive accuracy between the models for the important "likely to default" category where the bias would manifest either upward or downward. Nor does sample bias influence seem consistent with the general uniformity of predictive accuracy shown by both models across all industries compared to predictive accuracy for the Media industry alone.

In particular, the MPB logit model directly addresses the biases due to time-period, indicator variable choice and industry sensitivity noted by Grice and Dugan. The MPB model derived originally from a bond default data applied here to loan defaulting firms generated good overall predictive accuracy. The researchers had tested the time independence of the MPB model when originally estimated. Finally, the MPB model predictive accuracy is comparable for the single industry tested, media and communications, and across industries.

SUMMARY AND CONCLUSIONS

We conducted a comparative test of predictive accuracy on loan defaults, using two models from the financial distress literature, and applied to a new sample of high-risk companies. Each model had been derived using a different estimation technique, a different sample set, in a different time-period and using a different distress indicator. We then applied each model to a new sample of leveraged high-risk companies drawn from a different time-period, across multiple industries and sample mortality rate of one-third due to the restriction to public companies and incomplete data. We found that both models yielded similar overall correct prediction rates for the default period and two immediate periods prior to default, but showed some disparity in the "likely to default" sub-category. Further, the results also show generally comparable predictive accuracy rates for specific industry (media/communications) predictions using the all-industry version of each model.

The predictive accuracy similarities from two default prediction models from a sample of high-risk companies cast doubt on the relative influence of literature criticisms regarding 1) missing data bias, 2) time-period bias, 3) distress indicator choice bias and 4) industry range bias, made by other investigators in the literature. The findings further suggest that logit and probit models applied to carefully collected datasets may yield usefully accurate and relatively consistent predictions of pending corporate financial distress.

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