Tijdschrift voor Economie en Management
Vol. XLIX, 4, 2004

The Impact of Business Groups on Bankruptcy Prediction Modeling

by N. DEWAELHEYNS and C. VAN HULLE

Nico Dewaelheyns
KULeuven, Department of Applied Economics, (CTEO) – AFI Leuven Research Centre, Leuven.

Cynthia Van Hulle
KULeuven, Department of Applied Economics, (CTEO) – AFI Leuven Research Centre, Leuven.

ABSTRACT

De literatuur over falingspredictie negeert eigendomsstructuren en maakt de assumptie dat alle ondernemingen onafhankelijke economische entiteiten zijn. Door het belang van ondernemingsgroepen gaat die assumptie niet op voor het Europese Continent. In een steekproef bestaande uit middelgrote en grote Belgische ondernemingen tonen we aan dat de verklarende kracht van een aantal vaakgebruikte boekhoudkundige ratio's (vb. winstgevendheid, schuldgraad, liquiditeit en efficiëntie) verschillend is voor ondernemingen die deel uitmaken van een groep dan wel voor zelfstandige bedrijven. Het uitspelen van de relatieve verschillen in verklaringskracht kan de performantie van een falingspredictiemodel verbeteren zonder nieuwe informatie toe te voegen. Verdere verbetering is nog mogelijk door rechtstreeks te corrigeren voor groepsgebonden effecten, bijvoorbeeld door het toevoegen van een maatstaf voor de financiële situatie van de hele groep. Tenslotte wordt aangetoond dat ook de voorspellingskracht van enkele vooraanstaande predictiemodellen kan verbeterd worden door rekening te houden met groepsfactoren.

* * *

The bankruptcy prediction literature generally ignores corporate ownership and assumes companies are independent economic entities. In Continental Europe this latter assumption does not hold, due to the importance of business groups. Using a sample of mostly non-quoted Belgian medium and large sized companies, we show that the predictive power of several accounting ratios that are commonly used in bankruptcy prediction models (e.g. performance, leverage, liquidity and efficiency) is different for group member companies as compared to stand-alone companies. By exploiting these differences in relative importance, model fit can be improved without adding any new information. Performance can be increased further by directly adjusting for group related factors, e.g. by including a measure of financial health of the group as a whole. Finally, it is shown that group adjustments can also improve the fit of some well-known existing prediction models.

I. INTRODUCTION

Ever since the late 1960s, publicly available financial statement data has been actively examined to predict corporate failure. This is hardly surprising given the importance of the topic to many different economic agents: financial institutions and suppliers need to be able to form an opinion on the credit worthiness of a client; institutional investors want to identify acceptable investment risks; auditors are interested in the going concern probabilities of a company; government agencies need a reliable identification tool to grant support to distressed companies, etc. Knowledge of the financial health of a company can benefit individual stakeholders (e.g. clients, employees and managers) as well.

A. *No miracles in the bankruptcy prediction literature*

All bankruptcy prediction models in the literature are build on the basic insights of a small number of pioneering papers: Beaver (1966) who introduces univariate tests on financial ratios, Altman (1968) who is the first to use Multivariate Discriminant Analysis (MDA) in classifying failing versus non-failing companies and Ohlson (1980) who points to statistical problems with respect to MDA and prefers logistic regression as discriminating method.

During the last decades researchers have made continuous efforts to increase predictive performance. Most models select explanatory variables from a large pool of financial ratios, based either on stepwise selection methods or past performance in the literature. Some other studies argue there are theoretical grounds on which to build distress models, for instance cash flow identities (Aziz et al. (1988)) or variations in market returns (Aharony et al. (1980)). Other attempts to improve modeling include refining the definition of distress and incorporating additional information. For example, Lau (1987) distinguishes five different states of distress and uses multinomial logit models and Kluger and Shields (1989) find that changes in information quality due to auditor changes can be helpful in improving predictive performance. In addition, a growing number of niche models are being developed; Huyghebaert et al. (2000), for instance, use a cash flow based model to predict survival of start-up companies. Mossman et al. (1998) compare four different approaches using a single data set and conclude that ratio models do best for short-term prediction (one year before failure) and cash flow models perform adequately as an early warning signal (three years before failure).

Many of the more recent studies on bankruptcy prediction examine the usefulness of more sophisticated estimation techniques. Altman et al. (1994) evaluate the performance of classic (MDA and logit) models versus that of neural networks of varying complexity. They find neural networks are not superior, even when compared to a simple MDA approach. Other methodological issues are raised by e.g. Laitinen and Laitinen (2000), who explore the usefulness of Taylor series expansions in logistic regressions and Shumway (2001), who builds a case for forecasting bankruptcy using hazard models instead of static techniques.

While the majority of models that received most attention in the literature focused on quoted companies in the United States, many researchers have developed models for quoted and/or private companies in their home countries. A survey of these efforts – both in industrialized and in developing countries – is contained in Altman and Narayanan (1997). The survey shows there is no real consensus on which technique best estimates the probability of corporate failure. However, there is much similarity in the selected predictors: measures of past and present performance, liquidity, solvability, efficiency and – depending on the sampling approach – size and industry.

B. *Business group effects: little studied but potentially important*

All of the bankruptcy prediction models discussed above ignore corporate ownership structure. In essence, this is equivalent to making the assumption that all companies are stand-alone, i.e. independent economic entities. However, during the 1990s empirical studies have shown that the classic Bearle and Means (1932) assumption of dispersed ownership is mostly relevant for publicly quoted firms in Anglo-Saxon countries. La Porta et al. (1999), for instance, find that ultimate ownership and control in Continental Europe often belongs to families, financial groups or, in some cases, the State. This control is achieved through pyramidal holding structures, cross-holding constructions and – in countries where this is legal – shares with differential voting rights. Of the 27 industrialized countries examined in La Porta et al. (1999), Belgium has the highest score for the presence of pyramids and controlling shareholders. Becht et al. (1999) confirm that, due to concentrated corporate ownership by holding companies and families, Belgium is a prototype of an 'insider system'.

Links between companies create agency problems that are not as straightforward as those discussed in the literature of the 1970s and 1980s (Bebchuk et al. (2000)). Moreover, the existence of business groups gives rise to the formation of internal capital markets. These enable groups and conglomerates to actively shift resources and risk throughout their structure. Deloof (1998) empirically confirms the importance of intra-group financing for Belgian non-quoted companies.

If a company has access to an internal capital market popular bankruptcy prediction ratios likely are biased. For instance, empirical research has documented that group member companies have lower liquidity constraints and hence maintain lower liquidity levels (Hoshi et al. (1991); Deloof (2001)) than their stand-alone counterparts. The power of liquidity ratios to predict bankruptcy of the former firms may therefore be limited. The information content of leverage ratios may be affected by internal capital markets as well: group membership may increase debt bearing capacity (Hoshi et al. (1990)) while the leverage of individual firms within the group likely is the result of a global cost minimizing intra-group optimisation process (cf. Faccio et al. (2001); Bianco and Nicodano (2002)). Even performance measures – usually the strongest class of predictors – may not have the same predictive ability as they have in the case of stand-alone companies: several studies have shown that groups or conglomerates tend to systematically support weakly performing subsidiaries (Lamont (1997); Claessens et al. (2002)). This type of behavior may be inspired by strategic, taxation or control considerations, but could also be due to inefficiencies sometimes referred to as 'socialism within the group' (Sharfstein et al. (1998)). Furthermore, bankrupting a subsidiary may have a severe negative impact on the relationships between the parent and its lenders and on the group's reputation in general, leading to a group-wide increase in the cost of capital (Bebchuk et al. (2000)).

A limited number of models have attempted to correct for group effects. A straightforward way of doing this is by including a dummy variable representing group membership. Using this approach on a set of Italian SMEs, Bechetti and Sierra (2003) find that, ceteris paribus, group member firms have a lower probability of failure than stand-alone companies. Heiss and Köke (2001) examine the impact of control structure on ownership changes and failure in Germany. They introduce a Herfindahl index for ownership concentration and dummies for the existence of an ultimate owner, pyramid membership and level within the group. Although they report a significant relationship between ownership concentration and occurrence of a control change, they find no evidence of a link between ownership and failure. However, they indicate that this may be a result of lack of power due to the very low number of failing firms in their sample. Finally, in a three-years-before-bankruptcy prediction model developed for Belgian non-quoted small, medium and large companies, Ooghe et al. (1991) introduce a 'group relationship' ratio. This ratio reflects the importance of the commitments (amounts receivable, secured loans, etc.) taken up by a firm to the benefit of affiliated companies.

Using a sample of mostly non-quoted Belgian medium and large sized companies, our paper attempts to further improve bankruptcy prediction model performance by controlling for group membership in a more refined way. First, we estimate separate models for group member and stand-alone companies. This should allow us to examine whether or not the importance of specific prediction ratios differs across different company types. Second, we refine the group relationship ratio of Ooghe et al. (1991) by also taking into account commitments made by affiliated companies in favor of the sample company. Next, whatever the underlying motivation, the extent to which weak subsidiaries can be supported is likely to be related to the financial situation of the group as a whole. We therefore include a measure of the group's financial health (Altman Z" score) as a predictor of the bankruptcy probability of its subsidiaries. Finally, we analyze whether including group control variables increases the performance of some well-known international (Altman (1983)) and Belgian (Ooghe et al. (1991)) prediction models.

The remainder of the paper is organized as follows: section II discusses the sample composition and some methodological issues; section III describes the tests and empirical findings and section IV concludes.

II. SAMPLE AND METHODOLOGY

A. *Data and sample construction*

We start from the set containing all non-financial Belgian limited liability corporations (NV/SA) filing complete financial accounts for at least one year between fiscal years 1996 and 2001. As only companies that meet certain size criteria are obliged to do this, the data set consists of medium sized and large firms.[1] Accounting data and information on ownership and legal status have been obtained from BelFirst (Bureau Van Dijk Electronic Publishing) and the National Bank of Belgium (NBB). In this set, 252 companies are identified as filing for bankruptcy (cf. U.S. Chapter 7) or judicial composition (cf. U.S. Chapter 11) between January 1st, 2000 and December 31st, 2002.

Following the literature, we estimate both short-term (one year before failure) and medium term models (three years before failure). To avoid an artificial increase in predictive performance the use of information published after the bankruptcy filing is minimized. As the average publication lag for Belgian companies is 7 months, year t-1 is defined as the fiscal year ended between 7 and 19 months prior to failure. Year t-3 is set as two fiscal years before t-1. To be able to compare across different prediction lengths, we only include firms with information for both years t-1 and t-3. This implies a loss of 71 data points. Furthermore, 25 observations are lost due to missing data and three more companies were deleted due to company specific reasons.[2] The remaining 153 bankrupt companies are randomly paired with an equal number of non-failing firms with data from the same fiscal years (cf. Ohlson (1980)).

Next, the ownership structure of the sample companies is examined. It is assumed that corporations that directly or indirectly hold more than 50% of another company's shares, have full control over financing decisions. These controlling shareholders are termed corporate owners (CO). If the CO itself is fully controlled (+50%) by another company, this third corporation controls the sample firm as well. We continue to follow this decision rule until the ultimate corporate owner (UCO) is identified. This UCO is thus assumed to control the business group to which it belongs. Setting a lower control threshold (e.g. 20 or 30%) would only have a marginal impact in our setting with highly concentrated ownership.[3] Consolidated statements are used when available, as these should give the most realistic view of the group's financial situation (62.4% of UCOs at t-1 and 52.3% at t-3). If not, UCO level information is used as proxy for group characteristics. Data on the UCO is obtained from the databases mentioned above and from Datastream or Amadeus for international owners. For a number of UCOs (23 at t-1 and 20 at t-3) the sample firm is its only substantial operational asset. In such a case the UCO is likely merely a taxation or limited liability construction instead of the hub of a business group. Therefore their subsidiaries are reclassified as stand-alone firms.

The detailed sample composition is given in Table 1. The 153 failed and 153 non failed firms are split into two sub-samples: stand-alone and group member companies. The importance of business groups in the Belgian economy is confirmed by the large number of group member companies in the sample (more than 46% at t-1). Note that due to some ownership changes, a small number of companies shifted across sub-samples between t-3 and t-1.

Based on the discussion in section I, we compute standard bankruptcy prediction ratios: liquidity (LIQ; quick ratio), past performance (PP; retained earnings), current performance (ROA; return on assets), leverage (LEV; total debt) and efficiency (EFF; asset turnover). More precise definitions and the expected relationship of the variables to the probability of bankruptcy are given in Table 2. The proxy for sales generating efficiency (EFF) is known to be industry sensitive (for instance, the asset turnovers of a retailer and of a metallurgy company are completely different). Therefore, EFF is industry-adjusted by subtracting the industry median ratio first and then dividing by the industry inter-quartile range (cf. Cudd and Duggal (2000)).[4]

A second group of variables defined in Table 2 are meant to control for the presence of business group effects. As discussed above,

TABLE 1
Sample description

				Failed		Failed in		
		Total # obs.	%	#	%	‘00	‘01	‘02
t-1	Stand Alone Companies	165	53.9	96	58.1	34	34	28
	Group Member Companies	141	46.1	57	40.4	15	17	25
	Full Sample	306		153		49	51	53
t-3	Stand Alone Companies	176	57.5	96	54.5	34	35	27
	Group Member Companies	130	42.5	57	43.8	15	16	26
	Full Sample	306		153		49	51	53

these include a dummy for group membership (GROUP), a measure for the net commitments (receivables, guarantees, etc.) the sample company has received from affiliated companies[5] (NCOM) and a measure of the financial health of the group or UCO (GZ). This last variable is the Z" score calculated at the UCO level using the original Altman (1983) coefficients. The very low data requirements enable us to compute a Z" score for both the Belgian and the international owners in our sample.

To reduce the influence of extreme observations, all continuous explanatory variables are winsorized at 5 and 95%.

B. *Methodological issues*

Despite the development of more advanced classification techniques, Multivariate Discriminant Analysis (MDA) and logistic regression (LR) continue to be the most widely used techniques (Altman and Narayanan (1997)). LR has the advantage that it imposes no assumptions on the distribution of the predictors or the prior probabilities of bankruptcy. It also provides better scope to perform standard significance tests. In addition, for reasons of comparability and following Mossman et al. (1998), all models in this paper are estimated using logistic regression, even if originally they have been developed with MDA (e.g. the Altman (1983) model).

In a binomial logistic setting, the (adjusted) R^2 cannot be used for evaluating model performance. In this paper, the squared Pearson correlation coefficient functions as a simple R^2 equivalent. For ρ^2 expresses in a straightforward way the closeness of the model's predictions to the observed values (Hosmer and Lemeshow (2000)). An alternative performance measure is the number of correct classifications. We report the percentage of classification success for the estimated model both in sample and quasi-jack-knife corrected.[6] However, classification success is a very crude approximation to bankruptcy prediction, as, by definition, for any company it can only take on a value of either 1 or 0. In practice, companies are subject to different degrees of bankruptcy risk so that a continuous variable is more appropriate. In credit scoring, for instance, model output (i.e. the actual predicted value, not a 0/1 prediction) is translated into internal risk categories or transformed into bond equivalent ratings (Altman (2002)). Therefore we prefer fit (ρ^2) as the main performance criterion.

TABLE 2

Definition of variables

Variable	Definition	Proxy for	E(Failure Prob.)
Basic Prediction Ratios			
LIQ	(*current asstes – inventory and W.I.P.*) ⁄ (*current liabilities*)	Liquidity	–
PP	(*reserves + retained earnings*) ⁄ (*total assets*)	Past Performance	–
ROA	(*operating profits (losses)*) ⁄ (*total assets*)	Current Performance	–
LEV	(*ST debt + LT debt*) ⁄ (*total assets*)	Leverage	+
EFF	*Industry-adjusted* (*sales* ⁄ *total assets*)	Efficiency	–
Group Adjustments			
GROUP	*dummy variable: 1 if an Ultimate Corporate Owner is identified*	Group Membership	–
NCOM	$\left(\begin{array}{l}\textit{commitments made by affiliated companies}\\ -\textit{commitments made to affliliated companies}\end{array}\right) \Big/ \left(\textit{total assets}\right)$	Net Commitments from Affiliated Companies	–
GZ	*Altman Z" score of Ultimate Corporate Owner*§	Group Financial Health	–

§Z'' = 6.56 AX_1 + 3.26 AX_2 + 6.72 AX_3 + 1.05 AX_4 (see Appendix for definitions of Altman (1983) variables)

III. TESTS AND RESULTS

A. *Summary statistics and univariate tests*

The one and three years before failure median values of all continuous standard predictors and group adjustment variables are shown in Table 3. Statistics are given for the full sample and for the stand-alone and group member sub-samples separately. Wilcoxon tests for equality of medians between failing and non-failing companies are reported in brackets.

As could be expected, median liquidity (LIQ), performance (PP and ROA), leverage (LEV) and sales generating efficiency (EFF) are considerably worse for failing firms as compared to non-failing companies. Univariate tests strongly reject the equality hypothesis for these variables for both prediction lengths and in both sub-samples. When comparing across sub-samples (tests not reported in Table 3), leverage of non-failing group firms is significantly higher than that of non-failing stand-alone companies, both at t-1 and t-3. This is consistent with the argument that debt-bearing capacity (and hence the optimal leverage) of firms belonging to a group is higher. The data also indicate that within groups, problems have been present for a longer time before the bankruptcy filing. Specifically, at t-3, efficiency (EFF) and leverage (LEV) are significantly worse for failing group firms as compared to failing stand-alone companies (tests not reported in Table 3). Another interesting result is that groups with a failing subsidiary are in worse financial health as compared to groups without failing subsidiaries; both at t-1 and t-3 the Altman Z" score at UCO level (GZ) is significantly better for groups without failing subs.

More information on the relative importance of predictors for stand-alone versus group companies can be found in Table 4. The Table reports the fit (ρ^2) of univariate logistic regressions for all standard bankruptcy prediction variables. In general, results are consistent with the discussion of potential group effects in section I. The performance ratios (PP and ROA) have more predictive power in the stand-alone sub-sample, both at t-1 and t-3. The leverage ratio (LEV) does better for stand-alone companies as well, but only at t-1. The largest differences in fit are observed for liquidity (LIQ; very poor performance for group member companies) and for sales generating efficiency (EFF; very strong performance for group members). The latter observation

TABLE 3

Summary statistics and univariate tests

	t-1						t-3					
	Full Sample		Stand-Alone Sample		Group Sample		Full Sample		Stand-Alone Sample		Group Sample	
	NF	F	NF	NF	NF	F	NF	F	NF	F	NF	F
LIQ	1.028	0.637	1.079	0.629	1.001	0.669	0.997	0.735	1.010	0.716	0.974	0.741
	*(7.57)****		*(5.78)****		*(4.35)****		*(4.97)****		*(4.08)****		*(2.75)****	
PP	0.110	–0.110	0.168	–0.089	0.089	–0.142	0.119	–0.009	0.136	–0.001	0.103	–0.017
	*(11.00)****		*(8.75)****		*(6.69)****		*(7.16)****		*(5.62)****		*(4.54)****	
ROA	0.047	–0.051	0.053	–0.064	0.040	–0.044	0.042	0.014	0.047	0.018	0.019	0.005
	*(10.89)****		*(8.28)****		*6.86)****		*(4.87)****		*(4.51)****		*(2.40)***	
LEV	0.659	0.846	0.644	0.853	0.697	0.841	0.696	0.789	0.678	0.776	0.734	0.828
	*(7.73)****		*(5.91)****		*(4.80)****		*(3.90)****		*(3.00)****		*(2.87)****	
EFF	0.102	–0.302	0.108	–0.214	0.101	–0.407	0.083	–0.224	0.080	–0.152	0.108	–0.287
	*(5.51)****		*(3.09)****		*(5.10)****		*(4.35)****		*(2.25)***		*(4.03)****	
NCOM	–	–	–	–	0.009	0.000	–	–	–	–	0.017	0.000
	–		–		*(2.85)****		–		–		*(2.07)***	
GZ	–	–	–	–	2.483	–0.810	–	–	–	–	2.019	0.668
	–		–		*(6.53)****		–		–		*(3.31)****	

Test statistics in parentheses: Wilcoxon (Mann-Whitney) T-statistics for equality of medians; variables as defined in Table 2;
F = failed companies; NF = non-failed companies
* denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

indicates that business groups continue to support their subsidiaries as long as they generate sufficient sales.

B. *Basic prediction models and group adjustments*

Of course, univariate tests alone do not suffice to determine the relative importance of predictors for group and stand-alone companies. In this section we will therefore estimate multivariate logistic regression models for both sub-samples. Variable selection is done by a stepwise optimisation technique (likelihood ratio optimising).

First an optimised model is estimated on the full sample to establish a benchmark. Because of the high correlation between the past performance (PP) and leverage (LEV) ratios, the selection technique is restricted to include maximally one of these two variables. Results are presented in Table 5. For both prediction lengths, the optimal model specification contains the same three variables: PP, ROA (current performance) and EFF (sales generating efficiency). All are highly significant and have the expected signs. Similar to the literature, this very simple model performs quite well and allows classifying 83.0 % (CP quasi-jack-knife adjusted) of all companies correctly one year before bankruptcy. ρ^2 equals 0.548. Not surprisingly, model performance is lower for the longer prediction horizon (ρ^2 of 0.201 and CP of 69.0%).

Next, the same optimisation technique is used to construct models for the stand-alone and group samples separately. Confirming the univariate regression results, the optimal model specification is different

TABLE 4
Performance of individual prediction ratios across sub-samples

	t-1		t-3	
	Stand-Alone Sample	Group Sample	Stand-Alone Sample	Group Sample
LIQ	0.211	0.078	0.067	0.023
PP	0.476	0.317	0.194	0.110
ROA	0.425	0.309	0.124	0.075
LEV	0.230	0.173	0.060	0.063
EFF	0.048	0.190	0.033	0.128

ρ^2 of univariate Logistic Regressions; variables as defined in Table 2.

TABLE 5

Basic Bankruptcy Prediction Models and Group Adjustments

	t-1				t-3			
	Full Sample	Stand-Alone Sample	Group Sample	Full Sample Group Adj.	Full Sample	Stand-Alone Sample	Group Sample	Full Sample Group Adj.
PP	–6.119***	–9.004***	–5.323***	–7.230***	–2.954***	–3.488***	–2.246**	–3.690***
	(31.442)	*(17.654)*	*(13.438)*	*(30.938)*	*(18.405)*	*(10.165)*	*(5.354)*	*(23.573)*
ROA	–14.901***	–19.965***	–10.749***	–16.244***	–4.326***	–5.448**	–5.605**	–5.729***
	(29.614)	*(17.225)*	*(8.820)*	*(26.770)*	*(6.954)*	*(5.192)*	*(5.266)*	*(10.115)*
EFF	–1.036***	–	–1.935***	–0.830***	–0.603***	–	–1.354***	–0.487**
	(12.442)		*(13.571)*	*(6.847)*	*(8.035)*		*(12.618)*	*(4.828)*
LIQ	–	–0.955*	–	–	–	–0.530*	–	–
		(2.928)				*(3.296)*		
GROUP	–	–	–	–0.781*	–	–	–	–
				(3.674)				
NCOM	–	–	–	–2.929***	–	–	–	–2.198***
				(11.536)				*(15.016)*
GZ	–	–	–	–0.544***	–	–	–	–0.174**
				(13.514)				*(5.614)*
Intercept	–0.047	1.384	–0.686	0.465	0.189	1.038	–0.210	0.469
ρ2	0.548	0.627	0.523	0.630	0.201	0.225	0.244	0.282
$CP_{\text{in sample}}$	83.3	86.7	84.9	86.6	69.9	68.2	76.2	72.6
$CP_{\text{quasi-jack-knife}}$	83.0	84.8	83.0	85.9	69.0	66.5	73.8	70.9

Stepwise Logistic Regressions (Likelihood Ratio Optimising); variables as defined in Table 2; Wald test statistics in parentheses; CP = overall Classification Performance (in %)

* denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

depending on the class of company. PP and ROA are included in both sub-samples, but for stand-alone companies LIQ is preferred over EFF. One year before bankruptcy, the fit of the basic prediction model is much better for stand-alone companies (ρ^2 of 0.627) as compared to business group companies (ρ^2 of 0.523). By contrast, for the medium prediction length performance is better in the group sample due to the strong predictive power of the sales generating efficiency proxy. By combining the predicted values made by the separate models, we obtain a ρ^2 for the full sample but based on split sample estimation. These ρ^2s amount to 0.598 (t-1) and 0.242 (t-3) and show that split sample estimation improves model fit by about 0.05 without adding new information.

As an alternative for the split estimation approach, we take the full sample and correct for group effects by adding the group adjustment variables discussed in sections I and II to the pool of variables of the optimisation algorithm. The fourth and eighth columns of Table 5 show the optimised model specification for t-1 and t-3 respectively. For both prediction horizons NCOM and GZ are significant with a negative coefficient. In other words, companies that are net receivers of intra-group commitments and subsidiaries of healthy groups are, ceteris paribus, less likely to file for bankruptcy. At t-1 the GROUP dummy is significantly negative as well, albeit only at the 10% level. The group-adjusted full sample models substantially outperform the benchmark full sample models, both in terms of fit (an increase in ρ^2 of 0.082 at t-1 and of 0.081 at t-3) and of classification performance. The fit of the group-adjusted approach is also higher than that of the split estimation. In sum, the results from Table 5 show that business group business membership matters for the relative importance of individual predictor variables and for overall predictive model performance.

C. *Incorporation of group adjustment variables into existing models*

In this sub-section we turn to the question whether or not group corrections add value to some well known and widely used prediction models.

Undoubtedly worldwide the best known bankruptcy prediction indicators are produced by Edward Altman's Z and ZETA models. Due to the low number of predictor ratios and the limited data requirements to compute those predictors, Z type models are popular with practitioners looking for a first quick assessment of failure probability. For the same reasons, Altman Z scores are often used in the finance and accounting literature as a measure of bankruptcy risk (e.g. Allayanis et al. (2003); Sapienza (2004), among many others). Most appropriate for our sample is the Z" version (Altman (1983)) designed for non-quoted companies. It contains ratios for working capital, past performance, current performance and leverage (see the appendix for definitions). Note that the original Altman models are estimated with MDA. As discussed in section II above, we use Altman (1983)'s variables in logistic regressions.

Results of these regressions are given in Table 6. Under the original model specifications, model fit (ρ^2 of 0.529 for t-1 and 0.184 for t-3) is slightly lower than that of our non-group adjusted basic models from Table 5. Next, the Z" models are group adjusted based on a stepwise optimisation selection process. The general results are very similar to the ones obtained for the basic models. For the one year prediction horizon, the GROUP dummy, net commitments to affiliated companies (NCOM) and the original Z" score of the ultimate corporate owner (GZ) are significant predictors of bankruptcy. At t-3, again only NCOM and GZ are included in the optimised model. The performance improvement obtained by including the group adjustment variables is even more outspoken for the Altman Z" models as compared to our basic prediction models from Table 5: ρ^2 increases by 0.111 (t-1) and 0.104 (t-3), while quasi-jack-knife corrected classification performance rises with 3.2% one year before bankruptcy and 7.5% for the medium term prediction length.

As already mentioned, the ratios of the Altman models require only a limited amount of accounting data. In Belgium, publicly available financial statements are very detailed, even for small private companies. A number of Belgian bankruptcy prediction models have been constructed to exploit this wealth of available data (for a survey, see Ooghe et al. (1995)). Good examples are the Ooghe-Joos-De Vos models. Ooghe et al. (1991) estimate separate models one year and three years before failure. The short term prediction model contains eight factors (see appendix). These include measures of leverage, liquidity and past and current performance. Furthermore, information from the notes to the financial statements is used in computing a secured debt ratio and a dummy for overdue tax and social security payments. The first column of Table 7 shows the results of reestimating the original Ooghe-Joos-De Vos one year model (from here on denoted as OJD1)

TABLE 6
Altman (1983) Z" models

	t-1		t-3	
	Original Specification	Group Adjusted	Original Specification	Group Adjusted
AX_1	0.393	–	0.399	–
	(0.202)		*(0.315)*	
AX_2	–6.030***	–7.325***	–2.745***	–3.198***
	(29.760)	*(31.061)*	*(13.073)*	*(16.293)*
AX_3	–15.690***	–16.952***	–5.226***	–6.733***
	(33.345)	*(28.197)*	*(10.239)*	*(13.839)*
AX_4	–0.586	–1.195***	–0.454**	–0.659***
	(2.599)	*(9.079)*	*(3.385)*	*(7.672)*
GROUP	–	–0.731*	–	–
		(3.193)		
NCOM	–	–3.967***	–	–2.767***
		(17.656)		*(20.777)*
GZ	–	–0.633***	–	–0.170**
		(16.277)		*(5.514)*
Intercept	0.279	1.006	0.414	0.837
ρ^2	0.529	0.640	0.184	0.288
$CP_{in\ sample}$	83.0	86.9	65.4	73.2
$CP_{quasi\text{-}jack\text{-}knife}$	82.4	85.6	64.7	72.2

Logistic Regressions using Altman (1983) variables as defined in the appendix; Wald test statistics in parentheses; CP = overall Classification Performance (in %) * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

on our sample. Note that the dummy for overdue payments ($OJD1X_4$) and the secured debt ratio ($OJD1X_8$) are significant. Therefore, it is not surprising this model outperforms the (non-group adjusted) basic and Altman models from Tables 5 and 6. The second column at the left hand side of Table 7 shows a group adjusted version of the OJD1 model. Net commitments to affiliated companies (NCOM) and the Z" score of the ultimate corporate owner (GZ) are once again included in the optimised specification, but in this case the GROUP dummy is not. Given the fact that fit was already quite high, there is less scope for improvement through group adjustment. Nevertheless, ρ^2 still increases with 0.034 to 0.664.

TABLE 7
Ooghe et al. (1991) Models

t-1			t-3		
	Original Specification	Group Adjusted		Original Specification	Group Adjusted
$OJD1X_1$	–1.594***	–2.485***	$OJD3X_1$	–2.773***	–3.975***
	(9.723)	*(29.570)*		*(12.461)*	*(25.716)*
$OJD1X_2$	–3.662***	–4.867***	$OJD3X_2$	0.001	–
	(13.656)	*(21.035)*		*(1.174)*	
$OJD1X_3$	–7.144**	–9.211***	$OJD3X_3$	1.285**	1.148**
	(6.019)	*(8.908)*		*(5.592)*	*(4.382)*
$OJD1X_4$	2.461***	2.552***	$OJD3X_4$	–6.805***	–7.010***
	(18.222)	*(15.317)*		*(19.265)*	*(19.336)*
$OJD1X_5$	–0.138	–	$OJD3X_5$	1.249*	–
	(0.018)			*(3.170)*	
$OJD1X_6$	–2.977	–	$OJD3X_6$	0.640	–
	(2.249)			*(0.699)*	
$OJD1X_7$	4.288***	4.238***	NCOM	–	–2.273***
	(13.820)	*(14.860)*			*(14.934)*
$OJD1X_8$	1.989**	–	GZ	–	–0.122*
	(5.397)				*(2.703)*
NCOM	–	–1.355*	Intercept	–0.423	0.787
		(2.898)			
GZ	–	–0.713***			
		(18.050)			
Intercept	–0.340	0.817			
ρ^2	0.630	0.664	ρ^2	0.251	0.316
$CP_{in\ sample}$	86.3	86.9	$CP_{in\ sample}$	69.3	72.9
$CP_{quasi\text{-}jack\text{-}knife}$	85.3	85.3	$CP_{quasi\text{-}jack\text{-}knife}$	67.0	72.9

Logistic Regressions using Ooghe et al. (1991) variables as defined in the appendix; Wald test statistics in parentheses; CP = overall Classification Performance (in %)
* denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level

The Ooghe-Joos-De Vos three-years-before-bankruptcy prediction model (OJD3) consists of six factors (see appendix), two of which – the proxies for current performance and overdue payments – were already in OJD1. Other interesting variables are $OJD3X_2$ (the lag between the end of the fiscal year and the publication date of the financial statements; not significant for our sample) and $OJD3X_5$ (commitments made by the sample company to affiliated companies). The latter variable is comparable to our NCOM, but only shows half the picture, i.e. it does not take into account the commitments made by affiliated companies to the sample company. Therefore, it is not surprising that NCOM and not $OJD3X_5$ is included in the optimised model specification. As was the case for the other medium term models, the additional group adjustments have a very positive impact on performance, both in terms of fit and of classification success.

Table 8 summarizes the fit of the different model specifications we evaluated. In addition to the ρ^2 of the standard and group adjusted models from Tables 5, 6 and 7, the fit of a split estimation approach is reported as well. Recall that the split estimation approach entails the estimation of two separate models (one for stand-alone companies and another for business group members) using an optimised mix of standard predictor variables (i.e. without group adjustment variables). It turns out that split estimation increases fit by 0.02 to 0.05 for all models and in both prediction lengths. Given the fact that extra information is used in the group adjusted models, it is not surprising their fit further improves (improvements between 0.034 and 0.111 compared to the standard model specifications).

TABLE 8
Model performance comparison

	t-1	t-3
Basic Prediction Models		
ρ^2 – Standard	0.548	0.201
ρ^2 – Split Estimation	0.598	0.242
ρ^2 – Group Adjusted	0.630	0.282
Altman Z”		
ρ^2 – Standard	0.529	0.184
ρ^2 – Split Estimation	0.552	0.203
ρ^2 – Group Adjusted	0.640	0.288
Ooghe-Joos-De Vos (1991)		
ρ^2 – Standard	0.630	0.251
ρ^2 – Split Estimation	0.650	0.306
ρ^2 – Group Adjusted	0.664	0.316

IV. CONCLUSIONS

The bankruptcy prediction literature tends to ignore ownership structure and implicitly assumes companies are stand-alone entities. On the European Continent this assumption does not hold because many companies are linked through business groups. As these groups likely actively use internal capital markets, the predictive power of classic bankruptcy predictors (such as liquidity, performance, leverage or efficiency) may be different for group companies as compared to stand-alone firms. We show that the univariate performance of liquidity, past performance and current performance ratios is better for stand-alone companies and that sales generating efficiency predicts failure better for group members. Optimised multivariate models confirm these results: sales generating efficiency is only included in a sub-sample consisting of group member companies, while liquidity is only significant for stand-alone firms. By estimating separate models for the sub-samples of companies, global fit in terms of ρ^2 improves by up to 0.05. An even larger improvement, with relative increases of ρ^2 of 40% or more, is achieved by controlling directly for group effects. A dummy for group membership is only useful in some cases. More refined control variables – net commitments made by affiliated companies and the Altman Z" score of the group or the ultimate corporate owner – are significant predictors across all model specifications, both for short-term and medium-term prediction horizons. These group corrections also improve the predictive performance of existing models such as Altman (1983) and Ooghe et al. (1991).

In general, results are consistent with the notion that business groups support poorly performing subsidiaries unless the financial situation of the group prevents them from engaging in this activity (cf. Lamont (1997)). A more detailed analysis of the group's or the ultimate corporate owner's characteristics may shed more light on intra-group behaviour towards distressed subsidiaries.

NOTES

1. Under Belgian Accounting Law, "large" companies are required to file complete (unconsolidated) accounts if they meet at least two of the following criteria: total assets exceeding 3.125 million euros, operating revenue exceeding 6.25 million euros, or more than 50 full time equivalent employees. Companies with on average more than 100 full time equivalent employees are always classified as "large", regardless of assets and revenue. All other ("small") companies are allowed to file abbreviated accounts.

2. Lernout & Hauspie Speech Products, a former NASDAQ quoted company for which accounts allegedly do not reflect economic reality; Sabena, a State controlled airline company; Durobor, a State controlled glass manufacturer.
3. For instance, lowering the control threshold from 50% to 20% increases the number of sample companies identified as business group members from 141 to 157 in the one year before failure sample, and from 130 to 143 in the three year before failure sample. Robustness checks show that results and findings remain unaltered.
4. Following Platt and Platt (1991), computation of industry statistics is based on the 4-digit industry classification code NACE-BEL (the Belgian version of the European standard industry classification system NACE). If there are less than 25 observations in an industry the 3 or 2-digit NACE-BEL is used instead.
5. Under Belgian Accounting Law, all companies which are controlled by or are controlling a corporation are considered to be "affiliated". Control is defined as holding more than 50% of the shares or the votes, or having common controlling shareholders who can appoint the majority of the board or can make strategic decisions. This control can also be the result of company bylaws, contracts or the existence of a consortium. Information on affiliated companies is reported in the comments to the financial statements.
6. Jack-knife correction is a leaving-one-out validation procedure in which an observation is removed from the sample, the model parameters are reestimated and the observation is classified based on the new model parameters. This means the entire procedure consists of estimating as many models as there are observations. To limit computation time, a number of software packages (including SAS) automatically provide a one-step approximation to jack-knife adjusted parameter estimates; hence the term quasi-jack-knife.

REFERENCES

Allayannis, G., Brown, G.W. and Klapper, L.F., 2003, Capital Structure and Financial Risk: Evidence from Foreign Debt Use in East Asia, *Journal of Finance* 58, 6, 2667-2709.

Aharony, J., Jones, C. and Swary, I., 1980, An Analysis of Risk Characteristics of Corporate Bankruptcy Using Capital Market Data, *Journal of Finance* 35, 1001-1016.

Altman, E.I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance* 23, 4, 589-609.

Altman, E.I., Marco, G. and Varetto, F., 1994, Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (the Italian Experience), *Journal of Banking and Finance* 18, 505-529.

Altman, E.I. and Narayanan, P., 1997, An International Survey of Business Failure Classification Models, *Financial Markets, Institutions and Instruments* 6, 2, 1-57.

Altman, E.I., 2002, Corporate Distress Prediction Models in a Turbulent Economic and Basel II Environment, Report, (Stern School of Business, NYU).

Aziz, A., Emanuel, D.C. and Lawson, G.H., 1988, Bankruptcy Prediction – An Investigation of Cash Flow Based Models, *Journal of Management Studies* 25, 5, 419-437.

Berle, A.A. and Means, G.C., 1932, The Modern Corporation and Private Property, (MacMillan, New York).

Beaver, W., 1966, Financial Ratios as Predictors of Failure, *Journal of Accounting Research* 5, suppl., 71-111.

Bebchuk, L.A., Kraakman, R. and Triantis, G., 2000, Stock Pyramids, Cross Ownership and Dual Class Equity: the Creation and Agency Costs of Separating Control from Cash Flow Rights, in Morck, R., ed., Concentrated Corporate Ownership, (University of Chicago Press, Chicago), 445-460.

Becchetti, L. and Sierra, J., 2003, Bankruptcy Risk and Productive Efficiency in Manufacturing Firms, *Journal of Banking and Finance* 27, 2099-2120.

Becht, M., Chapelle, A. and Renneboog, L., 1999, Shareholding Cascades: the Separation of Ownership and Control in Belgium, Discussion Paper, (Tilburg CentER for Economic Research).

Bianco, M. and Nicodano, G., 2002, Business Groups and Debt, Working Paper, (Bank of Italy).

Claessens, S., Fan, J.P.H. and Lang, L.H.P., 2002, The Benefits and Costs of Group Affiliation: Evidence form East-Asia, *CEPR Discussion Paper 3364*.

Cudd, M. and Duggal, R., 2000, Industry Distributional Characteristics of Financial Ratios: an Acquisition Theory Application, *The Financial Review* 41, 105-120.

Deloof, M., 1998, Internal Capital Markets, Bank Borrowing and Financing Constraints: Evidence from Belgian Firms, *Journal of Business Finance and Accounting* 25, 7 & 8, 945-968.

Deloof, M., 2001, Belgian Intragroup Relations and the Determinants of Corporate Liquid Reserves, *European Financial Management* 7, 3, 375-392.

Heiss, F. and Köke, J., 2001, Dynamics in Ownership and Firm Survival: Evidence from Corporate Germany, ZEW Discussion Paper, (University of Mannheim).

Hoshi, T., Kashyap, A. and Scharfstein, D., 1990, The Role of Banks in Reducing the Costs of Financial Distress in Japan, *Journal of Financial Economics* 27, 1, 67-88.

Hoshi, T., Kashyap, A. and Scharfstein, D., 1991, Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups, *Quarterly Journal of Economics* 106, 1, 33-60.

Hosmer, D.W. and Lemeshow, S., 2000, Applied Logistic Regression, 2nd Ed, (John Wiley and Sons, New York).

Huyghebaert, N., Gaeremynck, A., Roodhooft, F. and Van de Gucht, L.M., 2000, New Firm Survival: the Effects of Start-up Characteristics, *Journal of Business Finance and Accounting* 27, 5 & 6, 627-651.

Faccio, M., Lang, L.H.P. and Young, L., 2001, Debt and Corporate Governance, Working Paper.

Faccio, M. and Lang, L.H.P., 2002, The Ultimate Ownership of Western European Corporations, *Journal of Financial Economics* 65, 365-395.

Kluger, B.D. and Shields, D., 1989, Auditor Changes, Information Quality and Bankruptcy Prediction, *Managerial and Decision Economics* 10, 275-282.

Lamont, O., 1997, Cash Flow and Investment: Evidence from Internal Capital Markets, *Journal of Finance* 52, 1, 83-109.

La Porta, R., Lopez de Silanes, F., Shleifer, A. and Vishny, R., 1999, Corporate Ownership Around the World, *Journal of Finance* 54, 2, 471-528.

Lau, A.H.L., 1987, A Five-State Financial Distress Prediction Model, *Journal of Accounting Research* 25, 1, 127-138.

Ohlson, J.A., 1980, Financial Ratios and the Probabilistic Prediction of Bankruptcy, *Journal of Accounting Research* 18, 1, 109-131.

Ooghe, H., Joos, P. and De Vos, D., 1991, Failure Prediction Models, Working Paper (Rijksuniversiteit Gent).

Ooghe, H., Joos, P. and De Bourdeaudhuij, C., 1995, Financial Distress Models in Belgium: the Results of a Decade of Empirical Research, *The International Journal of Accounting* 30, 245-274.

Platt, H.D. and Platt, M.B., 1991, A Note on the Use of Industry-Relative Ratios in Bankruptcy Prediction, *Journal of Banking and Finance*15, 1183-1194.

Sapienza, P., 2004, The Effects of Government Ownership on Bank Lending, *Journal of Financial Economics* 72, 357-384.

Scharfstein, D.S. and Stein, J.C., 2000, The Dark Side of Internal Capital Markets: Divisional Rent-Seeking and Inefficient Investment, *Journal of Finance* 55, 6, 2537-2564.

APPENDIX

Definition of variables in Altman (1983) and Ooghe et al. (1991) models

Variable	Definition	Proxy for	E(Failure Prob.)
Altman Z"			
AX_1	(*working capital*)/(*total assets*)	Working Capital	–
AX_2	(*reserves + retained earnings*)/(*total assets*)	Past Performance	–
AX_3	(*operating profits* (*losses*))/(*total assets*)	Current Performance	–
AX_4	*equity*/(*total debt*)	Leverage	–
Ooghe-Joos-De Vos			
$OJD1X_1$	*dummy variable;* *1 if (net return on total assets before taxes – average interest rate of debt) > 0*	Direction of Financial Leverage	–
$OJD1X_2$	$(\textit{reserves} + \textit{retained earnings}) \Big/ \left\{ \begin{matrix} \textit{equity} + \textit{total debt} - \textit{accrued} \\ \textit{charges} \,\&\, \textit{deferred income} \end{matrix} \right\}$	Past Performance	–
$OJD1X_3$	(*cash + ST investments*)/(*total assets*)	Liquidity	–
$OJD1X_4$	*dummy variable; 1 if (overdue taxes & social security charges) > 0*	Overdue Payments	+
$OJD1X_5$	$\left\{ \begin{matrix} \textit{inventories} + \textit{accounts receivable} - \textit{accounts payable} \\ - \textit{taxes, wage} \,\&\, \textit{socials security debts} - \textit{advances on W.I.P.} \end{matrix} \right\} \Big/ (\textit{total assets})$	Working Capital	–

$OJD1X_6$	*net return on operating assets before taxes*	Current Performance	–
$OJD1X_7$	$(\textit{ST financial debt})/(\textit{ST debt})$	ST Financial Debt	+
$OJD1X_8$	$(\textit{guaranteed debt})/(\textit{total debt})$	Guaranteed Debt	+
$OJD3X_1$	$= OJD1X_2$	Past Performance	–
$OJD3X_2$	*number of days between end of fiscal year and filing of accounts*	Publication Lag	+
$OJD3X_3$	$= OJD1X_4$	Overdue Payments	+
$OJD3X_4$	$(\textit{EBITDA} - \textit{capital investments})/(\textit{total assets})$	Autofinancing Ability	–
$OJD3X_5$	$\left[\left\{\begin{matrix}\textit{amounts receivable from}\\ +\textit{loans guaruanteed for}\\ +\textit{other commitments in favor of}\end{matrix}\right\}\textit{affiliated companies}\right]\Big/(\textit{total assets})$	Group Relationships	+
$OJD3X_6$	$(\textit{total debt})\Big/\left\{\begin{matrix}\textit{equity} + \textit{total debt} - \textit{accrued}\\ \textit{charges} \,\&\, \textit{deferred income}\end{matrix}\right\}$	Leverage	+