Corporate Failure Prediction Modeling: Distorted by Business Groups' Internal Capital Markets?

Nico Dewaelheyns*

Cynthia Van Hulle§

Revised Version: April 2005

Abstract – Most models in the bankruptcy prediction literature implicitly assume companies are stand-alone entities. However, in view of the importance of business groups in Continental Europe, ignoring group ties may have a negative impact on predictive reliability. We find that models encompassing both bankruptcy variables defined at subsidiary level and at group level have a substantially better fit and classification performance. Furthermore we find that the group's support causes improved survival chances for subsidiaries, especially when these subsidiaries belong to the group's core business. Overall our results are consistent with existing theoretical and empirical findings from the internal capital markets literature.

* (Corresponding author) K.U.Leuven Centre for Applied Economic Research (CTEO) – AFI Leuven Research Centre, Naamsestraat 69, 3300 Leuven, Belgium; tel. +32 16 326766; e-mail: nico.dewaelheyns@econ.kuleuven.ac.be

§ K.U.Leuven Centre for Applied Economic Research (CTEO) - AFI Leuven Research Centre, Naamsestraat 69, 3300 Leuven, Belgium; tel. + 32 16 326734; e-mail: cynthia.vanhulle@econ.kuleuven.ac.be

Acknowledgements – We would like to thank Marc Deloof, Marie Dutordoir, Dirk Heremans, Nancy Huyghebaert, Frederiek Schoubben and Linda Van de Gucht for useful comments and suggestions.

1. INTRODUCTION

A reliable assessment of a company's failure probability is useful to a large number of economic agents, including potential investors, lenders, clients, suppliers, etc. This explains the constant attention paid to bankruptcy prediction modeling in the finance and accounting literature ever since the pioneering work by Beaver (1966). Because of the growing availability of data and the development of improved econometrical techniques, the number of bankruptcy prediction models has increased exponentially, especially during the 1980s and 1990s. Most of this work has been strongly influenced by a small number of early papers (e.g. Altman, 1968; Ohlson, 1980; Zavgren, 1985) on U.S. quoted companies. Consequently, prediction models typically include accounting proxies for liquidity, leverage, past and current performance, efficiency and size of individual sample firms. This type of modeling implicitly introduces the assumption that sample companies are stand-alone firms. However, over the last decade, research on ownership and control has documented that in many countries, business groups play an important role. In an international study on ownership structure of quoted companies, La Porta et al. (1999) conclude that dispersed ownership is only generally present in the U.S., the U.K. and some of the smaller Anglo-Saxon countries. Elsewhere, they find that firms are often part of a business group controlled by large corporate owners. These findings have been confirmed by many studies (for a survey, see Denis and McConnell, 2003). Moreover, it has been shown that in such groups resources and risk are reallocated across firms through internal capital markets (e.g. Shin and Stultz, 1998). For bankruptcy prediction models this raises the question whether using only variables defined on individual firm level is appropriate.

A few bankruptcy prediction studies have attempted to account for intra-group effects. One rudimentary way to control for group related factors is the inclusion of a dummy variable representing group membership. Using this approach, Heiss and Köke (2004) empirically examine the impact of control structure on ownership changes and failure in Germany. Their evidence only weakly supports the notion that pyramidal ownership and failure are linked. However, as the authors point out, this may be the result of lack of power, due to the very low number of failing firms in their sample. Bechetti and Sierra (2003) include a group membership dummy in a prediction model estimated on a large sample of Italian manufacturing firms, and find a negative relationship between probability of failure and business group membership between 1992 and 1997. Ooghe et al. (1991) incorporate a "group relationships" ratio for mostly small, but also medium and large sized Belgian private companies. This ratio is defined as the portion of assets committed by the sample firm to other group member companies and proves to be negatively related to survival chances. For a sample of mostly non-quoted Belgian medium and large sized firms, Dewaelheyns and Van Hulle (2004) show that the performance of existing bankruptcy prediction models such as Ooghe et al. (1991) or an Altman Z"-model (see e.g. Altman, 1993) can be improved by adding the Altman Z"-score of the group as a whole, implying that the quality of information contained in the accounting ratios typically used as bankruptcy predictors is not the same for group member companies as compared to stand-alone firms. Moreover, as medium and large sized firms have to release more information than small ones, the "group relationships" ratio from Ooghe et al. (1991) could be refined to reflect the net effect of commitments received from and given to other group members instead of only encompassing given commitments.

Using the same sample as in Dewaelheyns and Van Hulle (2004), this paper shows that the use of "double" prediction models, i.e. models that combine company and group level predictors, increases fit and classification performance to a much larger extent than the group adjustment attempts made thus far in the literature. The data also indicate that private business groups support struggling subsidiaries. Especially when these groups are financially sound, bankruptcy of a distressed subsidiary becomes unlikely. However, once group profitability turns negative, groups tend to terminate support to weak subsidiaries in non-core activities. Support to core subsidiaries is often continued until the group as a whole runs out of financial resources.

The sample has several interesting features. First, as in other Continental European countries, private business groups play a crucial role in the Belgian economy.[1] Contrary to the case of U.S. conglomerates (e.g. Gertner et al., 1994), member firms of a business group may – in addition to using the internal capital market – also directly access the external market. Hence, next to the group perspective, also the individual firm's financing decisions remain important. Therefore, the behavior of business groups towards distressed subsidiaries and the way this affects the likelihood of subsidiary bankruptcy, is a matter of direct concern for all providers of external capital. This of course adds a dimension to the problem of bankruptcy prediction. Furthermore, almost all sample companies (i.e. 98.7% of all included firms) are privately held, while the vast majority of internal capital market, business group and bankruptcy prediction studies are limited to quoted firms – often due to data availability problems. Consequently, access to equity capital should be relatively more difficult for the companies in our sample, so that for each subsidiary the use of the internal capital market is likely to be an important part of its financial management. Deloof (1998) empirically confirms this for large non-quoted Belgian companies.

The remainder of the paper is organized as follows: section 2 describes the potential impact of the presence of a group on the informational content of important bankruptcy prediction variables, section 3 describes the sample, section 4 contains some methodological issues, section 5 reports the test results and section 6 concludes.

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[1] Of the 27 industrialized countries examined in La Porta et al. (1999), Belgium has the highest presence of pyramids and controlling shareholders. Becht et al. (2001) conclude that due to corporate ownership via pyramids, cross participations, and voting blocks held by holding firms and families, Belgium is a prototype of an 'insider system'. Simultaneously, external capital markets are relatively underdeveloped, increasing the importance of internal resources. Equity market capitalization at the end of September 2002 was 49.1% of GDP for Belgium, compared to 98.5% for the United States and a European Union average of 65.7%. The value of outstanding corporate debt securities equaled 9.8% of GDP (US: 22.9%, EU: 9.5%).

2. BANKRUPTCY PREDICTION VARIABLES AND BUSINESS GROUPS

Membership of a business group may affect the informational content of the main bankruptcy prediction variables in the literature. More specifically, adding group level data may be useful for measures of:

Liquidity – Using data on Japanese keiretsu and bank relationships, Hoshi et al. (1991) show that liquidity constraints of group member firms are weaker than those of stand-alone companies. If access to cash is less restricted within a group, this could lead to a situation where companies belonging to a business group pay less attention to liquidity as compared to stand-alone companies, as the latter have no choice but to resort to expensive short-term financing in case of liquidity shortages. Deloof (2001) empirically confirms this for private Belgian companies. For a firm belonging to a business group, low liquidity need therefore not necessarily reflect a higher probability of failure.

Performance (past and current) – A business group may decide to keep a subsidiary afloat, even if it incurs severe losses and has been doing so for several years. This may be an economically sound decision, based on strategic, taxation, control or other group-specific reasons. Alternatively, internal capital markets may cause "socialism" within a group or conglomerate (i.e. stronger divisions subsidize weaker ones), as discussed in Scharfstein and Stein (2000). Empirical evidence of these phenomena is reported in Scharfstein (1998), Claessens et al. (2002) and Lamont (1997), among others. The latter shows that US oil companies subsidized underperforming non-oil activities during the early 1980s when profits from oil operations were extremely high. After the oil shock of 1986, subsidized non-oil investments were significantly reduced or stopped altogether. Preceding findings and arguments imply that adding information on group level performance could be useful for bankruptcy prediction purposes. Specifically, strong group performance should positively affect survival chances of subsidiaries.

Leverage – High firm leverage may be less important for the survival chances of group member companies as compared to those of stand-alone firms. Hoshi et al. (1990) argue that the costs arising from information asymmetries at debt renegotiations are smaller within business groups. These decreased potential costs of financial distress allow group members to ex ante take on more debt, thus realizing more tax gains and avoiding relatively expensive equity issues (cf. Myers and Majluf, 1984). A coinsurance effect across activities in diversified groups could further decrease costs of debt, but according to Berger and Ofek (1995), this should be of rather limited importance. Furthermore, an intra-group optimization process may take place via the internal capital market to reduce costs at all levels (cf. Faccio et al., 2001; Bianco and Nicodano, 2002), again increasing ex ante optimal leverage. Finally, the subsidiary may also receive intra-group debt guarantees which could increase debt bearing capacity even more.

Size – Ceteris paribus, larger companies have a higher capacity to bear debt throughout difficult business periods and should have a lower risk of failure (Rajan and Zingales, 1995). Because of the close ties between the different group members, group size may better measure the size effect then the size of the subsidiary proper. This is empirically confirmed by, for instance, Manos et al. (2001). These authors find that the size of Indian group affiliates has no impact on their capital structure, but that group size does. Belonging to a – preferably large – business group may also have other non-quantifiable beneficial effects: the group's reputation may change perception and behavior of banks and other creditors, thus increasing access to external finance in times of need (cf. Schiantarelli and Sembenelli, 2000).

Efficiency – Following Altman (1968), managerial efficiency in the bankruptcy prediction literature is often defined as sales-generating ability (proxied by a capital turnover ratio). Ceteris paribus, the more efficient a business group, the better its performance. As argued above, this may have positive effects on the survival chances of the subsidiary.

Overall, the preceding discussion implies that (a) a failure prediction model based on the classic prediction variables may be less effective for group member firms as compared to stand-alone companies, and (b) that adding group level data may improve performance of bankruptcy prediction models.

3. DATA AND SAMPLE DESCRIPTION

The data set contains externally audited information on all non-financial Belgian limited liability corporations filing complete financial accounts for at least one year between fiscal years 1996 and 2001. Because only companies that are sufficiently large have to file such accounts, the sample consists of medium sized and large firms.[2] Accounting information was obtained from the electronic databases BelFirst and Amadeus produced by data provider Bureau Van Dijk Electronic Publishing. Accounts for company years not included in these data sets were obtained from the National Bank of Belgium. Information on ownership and legal status were gathered from the same sources. All companies filing for bankruptcy (cf. U.S. Chapter 7 bankruptcy) or judicial composition (cf. U.S. Chapter 11 bankruptcy) are termed "failing". Following common practice, separate models are estimated to predict failure occurring within one and three years after the closing of a fiscal year. As pointed out by Ohlson (1980), the use of information released after a company has filed for bankruptcy may artificially increase performance of prediction models. Therefore, since in our sample the typical lag between the fiscal year end and the filing of accounts in the population of companies equals 7 months[3], year t-1 is defined as the fiscal year ended between 7 and 19 months prior to failure. Year t-3 is defined as two fiscal years before t-1. For reasons of

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[2] Under Belgian Accounting Law, "large" (de facto large and medium sized) companies are required to file complete (unconsolidated) accounts if they meet at least two of the following criteria: total assets exceeding 3.125 million euro, operating revenue exceeding 6.25 million euro, 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.

[3] Seven months is also the legally allowed maximum publication lag in Belgium.

comparability across prediction lengths, we consider only firms for which information for both years t-1 and t-3 is available (cf. Zavgren, 1985).[4] Applying these criteria, we collect information on 156 companies that filed for bankruptcy protection between January 1st, 2000 and December 31st, 2002. Three companies were deleted due to company specific reasons.[5] The thus selected 153 failed companies are randomly paired with an equal number of non-failing firms with data from the same fiscal years.[6]

Next, the ultimate corporate owners of the sample companies are identified. For each company, a parent firm that directly or indirectly holds more than 50% of the shares is classified as the controlling owner. Continuing the same reasoning, if this parent firm itself is controlled (+50%) by another company, this third corporation ultimately controls the sample firm. Working through the control chain in this way, we define the ultimate corporate owner (UCO) of the sample firm as the controlling company for which there is no incorporated majority shareholder. It is assumed that this UCO controls the business group to which it belongs. Hence UCO level information is used as proxy for group characteristics. Whenever available, consolidated statements are used, as these should give the most realistic view of the group's financial situation.[7] Occasionally, the sample firm is the UCO's only or dominant operational asset. In such a case the UCO is considered to be a shell company and sample firms with such a parent are reclassified as stand-alone.[8] Data on the UCO is obtained from

[4] As a robustness check against a potential data availability bias, we dropped this requirement and used all available data. The main results and findings remain the same.

[5] Lernout & Hauspie Speech Products failed in the wake of a major accounting scandal; Sabena and Durobor were State controlled firms.

[6] Alternatively, firms could be matched based on e.g. size or industry. However, controlling for these effects directly in the models is the procedure preferred in the literature (cf. Ohlson, 1980).

[7] Consolidated accounts are available for 62.4% (t-1) and 52.3% (t-3) of all UCOs. As a robustness check, models were rerun on the sub sample of companies for which consolidated accounts are available. Conclusions remain unaffected.

[8] 23 companies in the t-1 sub sample and 20 companies in the t-3 sub sample are in this situation. To reclassify a UCO as a shell company the following decision rule is applied: the ultimate corporate owner is only one level above the sample firm, it has a NACE-BEL code identifying it as a holding company, its sales are less than 10% of total assets, its total assets are lower than the total assets of its subsidiary and consist for 90% or more of financial assets and/or real-estate. The same rule is applied to classify intermediate level owners as ultimate corporate owner, i.e. if an intermediate corporate owner has a parent company which meets the aforementioned

the previously mentioned sources, or from Datastream. All companies for which no UCO can be identified according to the preceding procedure are classified as stand-alone.[9]

Table 1 contains some details of the sample composition. In panel A, all 153 failed and 153 non failed firms are split into two sub-samples of stand-alone or group member companies. The large proportion of sample firms with a UCO (about 45%) confirms the relative importance of business groups in the Belgian economy. Note that due to a change in ownership, a few companies shifted from one sub-sample to the other between t-3 and t-1.

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Table 1 about here

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Table 1 Panel B reports the sample's industry distribution.[10] The industry distributions of the failed and non failed sub-samples are rather similar. In both sub-samples the most important industries are manufacturing & construction (43.8%) and distribution (31.4%). The set of the

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criteria, that intermediate owner is considered to be the ultimate corporate owner. This approach is conceptually similar to Pagano et al. (1998) who, in their research on initial public offerings in Italy, classify a subsidiary of a holding firm that concentrates its assets mainly in the ownership of one company as a stand-alone firm as opposed to a carve out or subsidiary of a business group.

[9] To ensure that the procedure classifies all firms in the sample, we consider all companies without a UCO to be stand-alone. Consequently, some of the latter firms may have limited group ties. However, robustness checks showed that this does not cause any important distortions, and this mainly because of the extremely high ownership concentration in private business groups on the one hand and the low level of corporate ownership in the sub-sample of stand-alone firms on the other. In particular, in the group sub-sample, the median UCO owns 99.99% of the sample company (both at t-1 and t-3), while the average ownership equals 93.26% (t-1) and 92.86% (t-3). Of the firms classified as stand-alone, the majority (100 out of 165 at t-1 and 121 out of 176 at t-3) has no incorporated shareholder at all. As discussed in footnote 8, a number of the remaining stand alone firms (23 for t-1 and 20 for t-3) have a UCO but are classified as stand-alone because this UCO is a shell company. Hence at t-1 there are 165-100-23 = 42 firms that have a registered corporate shareholder with ownership below 50%. Of these 42 firms, 15 have shareholders that are shell companies, 8 have shareholders that are venture capitalists while 3 have corporate owners with only a small stake (less than 20%). Similarly at t-3 there are 176-121-20 = 35 companies with a corporate minority shareholder. Of these firms 8 have shell companies as corporate owners, 10 have owners that are venture capitalists and 4 have corporate owners with only a limited ownership stake. This leaves in the stand-alone sample 16 (t-1) and 13 (t-3) companies with a corporate owner holding between 20 and 50% of the shares. With respect to these latter firms two robustness checks have been performed. First, the companies in question were deleted from the sample. Second, by lowering the classification threshold from 50% to 20% ownership, these firms were transferred from the stand-alone to the group member sub-sample. Findings are robust for both of these changes.

[10] If a sample company is active in multiple industries it is categorized according to its primary activity (i.e. the first reported industry code).

failed firms comprises somewhat more companies from the former industry, while the set of the non failed firms includes more distribution firms. Potential industry effects are considered in the next section.

The definition of the variables as well as their expected relationship with the probability of failure – as previously discussed – are given in Table 2. For each of the main predictor variable classes, we include a ratio computed at company level and a similar ratio computed at UCO level. To keep information requirements as low as possible we only use standard ratio definitions. We also introduce two dummy variables similar to those previously used in the literature to account for group membership. Finally, we reduce the impact of extreme observations by winsorizing all explanatory variables at 5% and 95%.

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Table 2 about here

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4. METHODOLOGICAL ISSUES

Before we turn to the results, we briefly discuss some important methodological issues, viz. the estimation technique, model performance comparison and industry adjustments.

Estimation Technique – Many of the more recent studies on bankruptcy prediction examine the usefulness of different estimation techniques (see Atiya, 2001 for a survey). As our goal is to achieve better performance through the addition of extra information, instead of through technical improvements, we opt for a standard binary classification technique. The most popular techniques worldwide still are multivariate discriminant analysis (MDA) and logistic regression (Altman and Narayanan, 1997). MDA assumes that the variance-covariance matrices of the predictors are the same for the failed and the non-failed group and that all predictors are normally distributed. The latter assumption would be a particularly important problem for our test design, as by definition the UCO level variables are zero for stand-alone companies.[11] Logistic regression, on the other hand, does not need assumptions about the distribution of the predictors or the prior probabilities of bankruptcy and provides better scope to perform standard significance tests (cf. Ohlson, 1980).

Performance Comparison – Numerous researchers have attempted to create R^2 equivalents for binary logistic regressions (e.g. Cox & Snell R^2, Nagelkerke R^2, McFadden R^2, etc.). In this paper, the squared Pearson correlation coefficient ($=\rho^2$) is used as an R^2 equivalent. ρ^2 expresses in a straightforward way how close the model's predictions are to the observed values and has fewer shortcomings than some of the likelihood based R^2 measures (Hosmer and Lemeshow, 2000).

We also report the percentage of successful classifications, both in sample and for leaving-one-out approaches (quasi-jackknife). However, classification success is only a very crude approximation to bankruptcy prediction – for any company it can but take the values 1 or 0. In practice, companies are subject to subtly different degrees of bankruptcy risk and a continuous variable may be more appropriate.[12]

Finally, following Hillegeist et al. (2004), we statistically compare models with respect to informational content. Specifically, we use an extension of the Vuong (1989) test that examines the significance of differences in performance of non-nested logit models. This test uses the log likelihood statistics of two models and checks which model is closest to the 'true' distribution according to the Kullback–Leibler Information Criterion.

Industry Adjustment – Leverage, credit mix, asset mix, liquidity needs, etc, may differ across industries. Therefore, industry adjusted predictor ratios may improve model performance. Platt and Platt (1991) divide the ratios of each sample firm by their industry

[11] As a robustness check, the analyses for the group sub-sample was repeated with stepwise MDA (optimizing Wilk's Lambda). The same variables as those obtained with logistic regression proved to be significant predictors of bankruptcy.
[12] 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).

average and conclude this approach leads to improved stability of the model's coefficients and better predictive abilities. Other authors, including Cudd and Duggal (2000), criticize the adjustment of financial ratios based only on a measure of central tendency as this may not sufficiently capture departure from the industry norm. We therefore adjust for industry by subtracting the industry median ratio from the unadjusted ratio and dividing by the industry's ratio inter-quartile range (IQR), both for company as UCO level variables.[13] A stepwise selection technique determines whether an adjusted or a non-adjusted ratio is included in the model.

5. TESTS AND RESULTS

(i) Univariate Tests

Table 3 reports medians for all continuous predictor variables, one and three years before failure. The Table also contains median equality tests for failing and non-failing firms within the full sample and the sub-samples of stand-alone and group member firms. Additional summary statistics (means and standard deviations) can be found in Appendix.

Consistent with the literature, median liquidity (LIQ), past and present performance (PP and ROA), leverage (LEV) and sales generating efficiency (EFF) are considerably worse for failed firms. The only variable which is not significantly different between failing and non-failing firms is size (SIZE). However, this may be explained by the fact that the sample contains only companies that have to publish complete financial accounts, so that smaller firms are excluded. By contrast, when group member firms are compared to stand-alone

[13] The industry correction of group level variables is less straightforward than that of company level variables. First of all, many UCOs have an industry classification (NACE) code which identifies them as a holding company. As in Pagano et al. (1998), we examine the activities of their most important operating subsidiaries and changed the UCO's NACE code accordingly. Another problem arises from the fact that some of the UCOs are foreign companies and it is not clear which industry statistics should be used (home country, international?). We assume that industry performance and ratios across industrialized countries are sufficiently similar and always industry-adjust the UCO level variables using Belgian industry statistics.

companies, the size of the former is significantly larger than the size of the latter, both for failing and non-failing companies.[14] This finding indicates that, even within our sample of larger firms, ownership structure is significantly linked to size. The data also show that for group member companies, problems may have been present for a relatively long time before bankruptcy. Specifically, already at t-3, efficiency (EFF) and leverage (LEV) are significantly worse for failing group firms as compared to failing stand-alone companies.[15] Most striking however, is the finding that groups with a failing subsidiary are in significantly worse financial health as compared to groups without failing subsidiaries. Both at t-1 and t-3, groups with a bankrupt subsidiary have worse median values for all ratios. Also, at the group level, size does play a role: groups with a failing subsidiary are significantly smaller than those with healthy subsidiaries.

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Table 3 about here

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Overall, the univariate tests are consistent with the bankruptcy prediction literature, as well as with the hypothesis that group level characteristics matter for the survival chances of group member companies.

(ii) Multivariate Prediction Models and the Group Effect

Table 4 reports optimized prediction models for t-1 and t-3. The models have been estimated on the total sample, and hence comprise both stand-alone firms and group member companies. To establish a benchmark, models containing only ratios calculated at the level of individual sample companies are estimated (models A and B).[16] Basically, these models

[14] Not reported in table 3. t-1: Wilcoxon T-statistic of 2.46 across failing and 2.55 across non-failing companies; t-3: Wilcoxon T-statistic of 2.74 across failing and 1.81 across non-failing firms.

[15] Wilcoxon T-statistic of 1.66 for LEV and 2.06 for EFF.

[16] These benchmark models were also reported in Dewaelheyns and Van Hulle (2004).

ignore the existence of business groups and internal capital markets. Next, models A' and B' add variables as suggested thus far in the bankruptcy prediction literature to account for group phenomena. Finally, fully extended models that allow for the inclusion of all company and group level variables are presented in A'' and B''. Model variables are selected using a stepwise estimation technique that optimizes the likelihood ratio (i.e. fit). Because of their high correlation, the selection process was constrained to only include either leverage (LEV) or past performance (PP).[17] The process also takes into account whether or not a variable should be industry adjusted (cf. Section 4). Industry adjusted variables are indicated with the subscript IA. It should be noted however that industry adjustment only increases the predictive power of the sales generating efficiency measure (EFF). This is in line with Altman (1993), who reports that in his Z and ZETA models, the asset turnover ratio is the variable most influenced by differences across industries.

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Table 4 about here

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Considering one year before bankruptcy prediction first, the results in column A for the benchmark model without group adjustments are comparable to those of existing models in the literature (cf. Altman and Narayanan, 1997). As could be expected from the univariate results, the better performing and more efficient a company, the lower its risk of failure. However, again consistent with the univariate results, SIZE is not included. Even this relatively unsophisticated model achieves a ρ^2 of 0.548 and allows classifying 83.0% (quasi-jackknife corrected) of all sample companies correctly one year before the filing for bankruptcy. As indicated above, in model A' the selection procedure is also allowed to include

[17] The Pearson correlation coefficient between PP and LEV in the full sample equals –0.69 (t-1). A similar restriction is put on the inclusion of the UCO level variables GPP and GLEV.

variables used so far in the literature to account for group membership. The first of these variables is simply a dummy for membership of a corporate group (UCO). The second is a dummy (NCOM) representing strong intra-group commitments – i.e. loans and guarantees – made to the firm by affiliated companies.[18,19]

Both UCO and NCOM prove to be highly significant, which is in line with earlier findings by Bechetti and Sierra (2003) and Ooghe et al. (1991). Ceteris paribus, group members and especially companies that have received substantial commitments from the group, have a lower probability of failure. By including these dummies, ρ^2 improves from 54.8% to 56.7% while classification performance remains virtually unchanged. A Vuong test of relative information content shows that model A' significantly outperforms model A at the 1% level. The importance of group membership and commitments may be explained by asymmetric information problems between the majority (group) shareholders and external debt providers, which should be relatively important in our sample of mostly non-quoted companies. One could hypothesise that the limited liability of each member of a group offers more scope for the controlling corporate shareholders to extract benefits at the expense of external debt holders, i.e. 'milk' a subsidiary and then shed it through bankruptcy (cf. Bianco

[18] Belgian Accounting Law uses the term group "affiliation" instead of group membership. It assumes group affiliation or control over a firm to exist when a parent owns more than 50% of the shares or the votes in another firm, or when the parent can appoint the majority of the board or make strategic decisions. This control can also be the result of company bylaws, contracts or the existence of a consortium.

[19] As mentioned before, Ooghe et al. (1991) compute a group relationships ratio which is defined as the portion of total assets which is committed to affiliated companies. Our data allows us to extend this to both in- and outflows, which leads to a ratio which expresses the importance of net commitments made to affiliated companies (NCAC). This ratio could be added as a continuous variable, but the relationship between the continuous ratio and the probability of failure is not necessarily clear-cut. The fact that a company has to provide commitments to affiliated companies could point either to problems within the group, or to the fact that the subsidiary is strong and has no need for all of its resources, or that those resources can be more profitably used elsewhere. A solution to this ambiguity is not apparent. On the other hand, receiving commitments can be an indication of difficulties at the subsidiary level, or an indication that the subsidiary presents interesting investment opportunities. Whatever the underlying reason, elevated levels of received commitments can be seen as a strong signal of the importance of a specific company for the group. This leads us to a strong commitments dummy (NCOM), where we put the cut-off at 1/3 of assets based on predictive performance. Findings are robust for changes in the cut-off to e.g. 20 or 40% of assets. Virtually all companies with a value of 1 for NCOM are part of the group sub-sample. However, there are a small number of firms in the stand-alone sample that also have an NCOM value of 1 (8 companies for t-1, 9 for t-3). The reason is that a few firms have a corporate majority owner but are economically stand-alone because the owner is only a shell company (see footnote 8). A robustness check shows this is of little importance.

and Nicodano, 2002). Rational external debt providers anticipate this and will demand security and commitments from other companies within the group, thereby intensifying intra-group ties. This is consistent with evidence from, for instance, Chang and Hong (2000) who show that debt guarantees are a widely used cross-subsidization technique between Korean chaebol members. Allowing a subsidiary to fail may then have a severe negative impact on the relationships between the parent and its lenders as well as on the group's reputation in general, and result in an increased cost of capital (Bebchuk et al., 2000).

An even more substantial increase in fit and classification performance is obtained in model A", where the set of selectable variables is further extended to include prediction ratios defined at group or ultimate owner level. ρ^2 increases to 65.9% and prediction accuracy to 87.3% (quasi-jackknife corrected). Consistent with our expectations, firms belonging to more liquid (GLIQ), less levered (GLEV) and more profitable groups (GROA), have better chances for survival. In line with the univariate tests, size only plays a role at the group level (GSIZE) as subsidiaries of larger groups or UCOs are less likely to fail. Furthermore, the UCO and NCOM dummies are no longer included in the optimized specification, which indicates that their explanatory content is subsumed by the group level ratios. Vuong tests confirm that model A" strongly outperforms both the unadjusted benchmark model A and the "first pass" adjusted model A'.

It goes without saying that both fit and classification accuracy decline as the prediction period lengthens. Three years before failure, the benchmark model B only has a ρ^2 of 20.1% and classifies 69.0% (quasi-jackknife corrected) of all observations correctly. Relative to the one year ahead prediction model, adding the dummies UCO and NCOM (model B'), brings about a more marked improvement both in terms of ρ^2 (increases from 20.1% to 25.7%) and in terms of classification performance (increases from 69% to 72.9%). Especially the NCOM dummy is highly significant. These results indicate that, ceteris paribus, belonging to a group also has an important positive impact on medium term survival chances. However, the increase in performance from including more detailed group information is not as strong as in the case of one year ahead prediction (cf. Vuong tests). As compared to model B', the ρ^2 of model B" only increases from 25.7% to 27.4% while quasi-jackknife corrected classification performance slightly drops from 72.9% to 71.6%. Nevertheless, although only group size (GSIZE) and group leverage (GLEV) have a significant impact, these group level variables still subsume the explanatory power of the UCO and NCOM dummies in model B'.

In sum, the results from Table 4 demonstrate that group level variables are indeed important for bankruptcy prediction. By incorporating these ratios, performance of prediction models improves significantly. The most marked improvement occurs when bankruptcy of the subsidiary is imminent.

(iii) Sub-Sample Prediction Models

We now turn to the question whether or not the estimation of separate models for stand-alone firms and group member companies offers further improvement in model performance. In fact, the discussion in sections 1 and 2 and evidence by Dewaelheyns and Van Hulle (2004) has indicated that this issue may be important. Model variables are selected with the same stepwise estimation technique as used before. Models C and D in Table 5 are comparable to the benchmark models for t-1 and t-3 from Table 4, but estimated solely on the sub-sample of stand-alone companies. Similarly, models E and F are the benchmark models for the group member sub-sample. E' and F' are fully extended group member sub-sample models (i.e. the variable set encompasses all group level variables), again for t-1 and t-3 respectively.

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Table 5 about here

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Models C and D show that for stand-alone firms, both past (PP) and current performance (ROA) matter, and this for one year ahead as well as for three years ahead bankruptcy prediction. Leverage is not included in the model. As mentioned earlier, past performance is strongly negatively correlated with leverage, so that the optimization process is constrained to select maximally one of these variables. A possible reason why past performance is preferred over leverage in all specifications is that the former not only incorporates information on leverage, but also reflects the firm's past ability to generate profits, and hence contains information on its reputation on that score. The fact that efficiency (EFF) is not significant indicates that the mere generation of sales does not help the firm to survive; activity should also be profitable (ROA and PP are significant). Notice that, contrary to the full sample results, liquidity (LIQ) is a significant predictor of bankruptcy in the stand-alone sub-sample. This should not be surprising, as stand-alone firms cannot rely on an internal capital market to fill liquidity shortages.

Looking first at one year before bankruptcy prediction for the group sample (models E and E'), we observe that, next to past (PP) and current performance (ROA), efficiency (EFF) does matter for the survival of group subsidiaries. This could mean that these firms are supported by their group as long as they are capable of generating sufficient sales. As expected, company level liquidity is not included in the optimized models for the group sample. At the group level, liquidity (GLIQ) is important, as well as size (GSIZE), current performance (GROA), and leverage (GLEV). For t-3, the findings are similar, except that past performance loses its significance at the subsidiary level. This could indicate that the support of the group lowers the importance of the subsidiary's leverage or profit generation track record. Contrary to the earlier results from the full sample estimations, liquidity at group level (GLIQ) remains in the model. Furthermore, current group performance (GROA) drops out.

This is in line with the findings from Table 4 that showed that group performance becomes especially important when bankruptcy of the subsidiary is imminent.

When comparing model performance across sub-samples, it is clear that predicting bankruptcy is more difficult for stand-alone firms than for subsidiaries, at least once group effects for the latter are taken into account. Specifically, for stand-alone companies at t-1, ρ^2 amounts to 0.627, while the percentage of correct classifications equals 84.8% (quasi-jackknife corrected). For group subsidiaries these values equal 0.766 and 90.1% respectively, which reflects very high model performance. A similar picture arises for the medium term prediction models: once group effects are accounted for, bankruptcy is easier to predict for subsidiaries than for stand-alone firms. If groups support their subsidiaries and only bankrupt them if the financial situation of the group itself is troublesome, this finding is not surprising. If such a strong degree of support is present, one would expect that group level variables add valuable information. This is confirmed by the Vuong tests: the group adjusted model specifications significantly outperform their non-adjusted benchmark models.

(iv) Do Parents Have a Pecking Order in (Terminating) the Support of Subsidiaries?

Our evidence thus far only documents the existence and importance of group support in general, and does not allow us to determine the underlying motivation of business groups' behaviour. Some extra insights can be gained from examining two potential factors which may influence a group's behaviour towards a distressed subsidiary, viz. the separation between ownership and control and whether or not the UCO and the subsidiary are active within the same industry.

If the subsidiary is part of a pyramidal structure, the percentage of cash flow rights may diverge from the ownership percentage. As the gap between ownership and control widens, the scope and incentive for expropriation of minority shareholders increases as well (i.e. ‘milking’ behavior). Another factor that may influence the degree of support a subsidiary receives is its activity. If the subsidiary is active in the core industry of the group, letting it fail is likely to have a severe impact on the group’s reputation and may even have direct operational consequences for other group firms. For subsidiaries in non-core activities, these effects should be less important. In sum, the subsidiary support process may be different depending on the degree of cash flow rights or the subsidiary’s activities. To test this, we construct interaction terms that allow the impact of the group level prediction variables to differ depending on whether or not (a) the cash flow rights (CFR) are not fully owned by the UCO (dummy variable D_{CFR})[20] or (b) the subsidiary is active in the same industry as the UCO (dummy variable D_{Ind}).

The results of the stepwise optimized model allowing the use of all company level, UCO level and interaction variables are given in column E” in Table 5. A first observation that can be made is that none of the interaction terms with the cash flow rights dummy are included in the model specification, which is not surprising in view of the high ownership concentration in our sample. Two of the interaction terms between the same industry dummy and group level variables are significant predictors of bankruptcy at t-1, viz. GSIZE*D_{Ind}, with a negative sign, and GROA*D_{Ind}, with a positive sign. The first one shows that, ceteris paribus, larger groups support their core activity subsidiaries more strongly. The interpretation of the second term requires some more explanation. For non-core subsidiaries, GROA*D_{Ind} is zero, so that only the highly negative coefficient for GROA remains. This shows that if the group has weak profitability, it is more likely to terminate support of non-core subsidiaries. The latter finding is completely analogous to the earlier mentioned results of Lamont (1997), who studies the use of free cash flows within U.S. conglomerates and

[20] Because of the very high ownership concentration (median ownership of 99.99% at t-1 and t-3), we have opted for a dummy indicating whether or not the parent has full ownership, instead of using the actual ownership percentage. D_{CFR} has a value of 1 if the UCO directly or indirectly holds less than 95% of the cash flow rights. An alternative cut-off value of 75% was used as robustness check, but this did not change results.

reports that if cash flow production decreases, these conglomerates stop channeling resources to non-core businesses and sell them instead. For subsidiaries in the same sector as the parent, the global effect of group profitability is the sum of the coefficients of GROA and GROA*D_{Ind}. A Wald test for joint significance shows that this sum is not significantly different from zero ($\chi^2 = 1.690$). Or, for subsidiaries within the core activity, support does not depend upon the global current profitability of the group. Next to size, only the group's liquidity and debt position seem to play a role. This is consistent with the notion that parents support their core business until their own lack of financial resources forces them to stop. In fact, ex post analysis shows that the majority of UCOs with a failing subsidiary in their core activity fail themselves within a year. However, if the bankrupt group member company does not belong to the core business, only a small minority of the parents fail.[21] Overall, these findings support the notion that reputation and intra-group ties with core subsidiaries are important drivers of parent behaviour. As bankrupting a core business subsidiary is likely to cause much more damage to the group as compared to the failing of a non-core group member, the pecking order of termination of group support shown by the data is rational.

Including these refinements again increases model performance both in terms of ρ^2 (+ 0.039) and of classification performance (+1.4% quasi-jackknife corrected). The significance of the increase in information content is confirmed by the Vuong test. For the longer prediction horizon, neither incorporating cash flow rights nor the subsidiary's activity can improve failure prediction, which again confirms that group information is especially useful for the shorter prediction horizon.

As a final check on relative prediction performance for the full sample, ρ^2 has been calculated for a combination of the optimal stand-alone sample models and the optimal group

[21] Almost all of the UCOs (12 out of 13) that are active in an industry different from their failing subsidiary survive, while the survival rate of UCOs in the same industry is only 32% (30 out of 44). T-tests show that the UCO failure rates of 8% and 68% respectively are significantly different from each other (t = -5.777). For groups with a non-core failing subsidiary, the failure rate is significantly lower than 50% (t = -5.500), while for groups with a failing subsidiary in the core business, the failure rate is significantly higher than 50% (t = 2.559).

sample models (models C and E” for t-1 and models D and F' for t-3). Table 6 shows that in this combined model ρ^2 attains 71.7% for the short term and 31.0% for the median prediction length. This compares favourably to the best performing models estimated on the full sample (an extra +5.8% and +3.6% respectively). As mentioned before, the most important contribution to fit at t-1 is produced by incorporating group level predictors, while at t-3 the more basic adjustments (i.e. dummies) already perform relatively well. The total difference in fit between the basic prediction models – that ignore group effects – and the optimal separate sub-sample approach is very substantial for both prediction lengths (+16.9% for t-1 and +10.9% for t-3).

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Table 6 about here

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6. CONCLUSIONS

Even though academic interest in the implications of the presence of business groups in Continental Europe is steadily growing, bankruptcy prediction modeling still largely ignores the existence of intra-group relationships. We combine insights from the literature on bankruptcy prediction, internal capital markets and business groups, and show that these group effects affect the informational content of accounting ratios that are widely used in bankruptcy prediction, such as measures of liquidity, leverage, past and current performance, size and efficiency. The usefulness of approaches to correct for group membership previously applied in the literature, viz. the inclusion of a dummy for group membership and a measure of intra-group commitments, is confirmed. However, we show that including key ratios from the group or ultimate corporate owner increases model performance to a much larger extent. Size, current performance, leverage and liquidity of the group to which a company belongs are shown to have a significant impact on the failure probability of the latter. Vuong relative content of information tests confirm that models containing group related information significantly outperform unadjusted benchmark models. We find that especially financially sound groups support weak subsidiaries, so that the latter have more chances of surving distress. When groups themselves are in a weak financial position, they continue to support subsidiaries in their core activities, but may terminate non-core businesses. Overall these findings are consistent with recent theoretical and empirical work on business groups and internal capital markets.

In view of the concentrated ownership structure of private Continental business groups, their behaviour is unlikely to be driven by empire building or other managerial agency problems. Rather, the strengthening of intra-group relationships through the demand of guarantees by providers of external finance and the paramount importance of group reputation may be more plausible explanations. This is supported by the fact that group support appears to be especially strong if the subsidiary is active in the group's core industry. The findings also indicate that further analysis of the motivation of business groups' behaviour toward distressed subsidiaries, as well as intra-group and extra-group dynamics for distressed versus non-distressed business groups, could be important areas for further research.

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Table 1

Sample Description

Panel A – Failure Rates and Group Membership

		Total # obs.	%	Failed #	Failed %	Failed in '00	Failed in '01	Failed in '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

Panel B – Industry Composition

Industry	*Number of Companies*	*Failed*	*Non-Failed*
Food & Agriculture	16	8	8
Manufacturing & Construction	134	81	53
Distribution (Wholesale & Retail)	96	41	55
Transportation	23	9	14
Services	37	14	23

Table 2

Definition of Variables

Variable Name	*Definition*	*Proxy for*	*E(Relationship) to Prob. of Failure*
Basic Prediction Ratios (Company Level)			
SIZE	$\ln\left(\text{total assets}\right)$	Company Size	–
LIQ	$\dfrac{\left(\text{current assets - inventory and W.I.P.}\right)}{\text{current liabilities}}$	Liquidity	–
PP	$\left(\text{reserves + retained earnings}\right)/\left(\text{total assets}\right)$	Past Performance	–
ROA	$\left(\text{operating profits (losses)}\right)/\left(\text{total assets}\right)$	Current Performance	–
LEV	$\left(\text{ST debt} + \text{LT debt}\right)/\left(\text{total assets}\right)$	Leverage	+
EFF	$\text{sales}/\left(\text{total assets}\right)$	Efficiency	–
Group Adjustment Dummies			
NCOM	dummy variable: 1 if [Net Commitments to Affiliated Companies§] < -1/3 of total assets; 0 otherwise	Strong commitments made by Affiliated Companies	–
UCO	dummy variable: 1 if an Ultimate Corporate Owner is identified; 0 otherwise	Group Membership	–
Basic Prediction Ratios (UCO Level)			
GSIZE	$\ln\left(\text{total assets of UCO}\right)$	Group Size	–
GLIQ	$\dfrac{\left(\text{current assets - inventory and W.I.P.}\right)\text{ of UCO}}{\text{current liabilities of UCO}}$	Group Liquidity	–
GPP	$\dfrac{\left(\text{reserves + retained earnings}\right)\text{ of UCO}}{\text{total assets of UCO}}$	Past Group Performance	–
GROA	$\dfrac{\text{operating profits (losses) of UCO}}{\text{total assets of UCO}}$	Current Group Performance	–
GLEV	$\dfrac{\text{ST debt of UCO} + \text{ST debt of UCO}}{\text{total assets of UCO}}$	Group Leverage	+
GEFF	$\dfrac{\text{sales of UCO}}{\text{total assets of UCO}}$	Group Efficiency	–

§ **Net Commitments to Affiliated Companies (NCAC) =** $\dfrac{\left(\begin{array}{l}\text{commitments(guarantees \& loans) made to affiliated companies}\\ \text{-commitments (guarantees \& loans)made by affiliated companies}\end{array}\right)}{\text{total assets}}$

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*	*F*	*NF*	*F*	*NF*	*F*	*NF*	*F*	*NF*	*F*
SIZE	8.460	8.578	8.330	8.423	8.832	8.989	8.386	8.591	8.265	8.398	8.641	9.029
	(0.09)		*(0.68)*		*(0.31)*		*(1.11)*		*(0.82)*		*(1.20)*	
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	1.627	1.088	1.694	1.208	1.585	1.000	1.673	1.168	1.682	1.365	1.623	0.960
	*(4.58)***		*(2.59)***		*(4.10)***		*(3.87)***		*(2.06)***		*(3.72)***	
GSIZE	–	–	–	–	12.125	11.170	–	–	–	–	11.584	10.234
	–		–		*(3.62)***		–		–		*(3.81)***	
GLIQ	–	–	–	–	0.858	0.504	–	–	–	–	0.957	0.633
	–		–		*(4.45)***		–		–		*(4.13)***	
GPP	–	–	–	–	0.245	0.017	–	–	–	–	0.190	0.032
	–		–		*(5.69)***		–		–		*(4.01)***	
GROA	–	–	–	–	0.054	0.003	–	–	–	–	0.037	0.029
	–		–		*(5.52)***		–		–		*(1.60)*	
GLEV	–	–	–	–	0.554	0.723	–	–	–	–	0.559	0.699
	–		–		*(4.32)***		–		–		*(2.41)***	
GEFF	–	–	–	–	1.155	0.873	–	–	–	–	0.740	0.732
	–		–		*(1.84)***		–		–		*(1.66)**	

Notes:
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

Table 4

Basic and Group-Adjusted Prediction Models (Full Sample)

	t-1			*t-3*		
	A	*A'*	*A''*	*B*	*B'*	*B''*
PP	-6.119***	-6.602***	-7.644***	-2.954***	-3.672***	-3.039***
	(31.442)	*(33.929)*	*(26.902)*	*(18.405)*	*(24.209)*	*(17.714)*
ROA	-14.901***	-14.445***	-15.732***	-4.326***	-5.138***	-4.643***
	(29.614)	*(26.935)*	*(22.828)*	*(6.954)*	*(8.988)*	*(7.021)*
EFF_{IA}	-1.036***	-1.116***	-0.876***	-0.603***	-0.606***	-0.547**
	(12.442)	*(13.080)*	*(7.021)*	*(8.035)*	*(7.790)*	*(5.897)*
NCOM	–	-2.771***	–	–	-1.723***	–
		(7.381)			*(11.690)*	
UCO	–	-0.854**	–	–	-0.483*	–
		(5.677)			*(3.186)*	
GSIZE	–	–	-0.407***	–	–	-0.275***
			(13.126)			*(21.081)*
GROA	–	–	-18.980**	–	–	–
			(5.528)			
GLEV	–	–	7.489***	–	–	3.883***
			(17.411)			*(14.634)*
GLIQ	–	–	-1.172*	–	–	–
			(3.029)			
Intercept	-0.047	0.493	0.492	0.189	0.617	0.519
ρ^2	0.548	0.567	0.659	0.201	0.257	0.274
$CP_{in\ sample}$	83.3	83.0	88.6	69.9	74.2	72.5
$CP_{quasi\text{-}jackknife}$	83.0	82.7	87.3	69.0	72.9	71.6

Vuong tests	*z-statistic*		*z-statistic*
Model A' vs. Model A	2.997***	Model B' vs. Model B	6.199***
Model A'' vs. Model A	11.321***	Model B'' vs. Model B	6.447***
Model A'' vs. Model A'	10.547***	Model B'' vs. Model B'	2.015**

Notes:

Stepwise logistic regressions (likelihood ratio optimizing); variables as defined in Table 2; $_{IA}$ = industry adjusted ratio

A & B = full sample basic prediction models; A' & B' = full sample group-adjusted models (allowing use of data at company level only)

A'' & B'' = full sample group-adjusted prediction models (allowing use of variables at company and UCO levels)

Wald test statistics in parentheses; CP = overall classification performance (in %)

Vuong tests for log likelihood comparison of non-nested logit models (positive z statistic implies the first model reflects more information relative to the second)

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

Table 5

Prediction Models for Stand-Alone and Group Samples

	Stand-Alone Sample		*Group Sample*				
	t-1	*t-3*	*t-1*			*t-3*	
	C	*D*	*E*	*E'*	*E''*	*F*	*F'*
PP	-9.004***	-3.488***	-5.323***	-6.977***	-8.924***	-2.246**	–
	(17.654)	*(10.165)*	*(13.438)*	*(8.378)*	*(7.798)*	*(5.354)*	
ROA	-19.965***	-5.448**	-10.749***	-12.686***	-13.524***	-5.605**	-8.495***
	(17.225)	*(5.192)*	*(8.820)*	*(6.783)*	*(6.397)*	*(5.266)*	*(9.069)*
EFF_{IA}	–	–	-1.935***	-2.273***	-2.906***	-1.354***	-1.527***
			(13.571)	*(9.859)*	*(10.624)*	*(12.618)*	*(12.349)*
LIQ	-0.955*	-0.530*	–	–	–	–	–
	(2.928)	*(3.296)*					
GSIZE	–	–	–	-0.604***	-0.452**	–	-0.434***
				(10.506)	*(4.435)*		*(13.352)*
GROA	–	–	–	-15.642*	-69.526**	–	–
				(3.156)	*(4.460)*		
GLEV	–	–	–	6.844***	8.974***	–	2.204*
				(10.137)	*(10.911)*		*(3.436)*
GLIQ	–	–	–	-1.688**	-1.843**	–	-0.524**
				(4.199)	*(4.247)*		*(4.514)*
$GSIZE*D_{Ind}$	–	–	–	–	-0.287**	–	–
					(4.932)		
$GROA*D_{Ind}$	–	–	–	–	57.119*	–	–
					(2.701)		
Intercept	1.384	1.038	-0.686	3.203	2.895	-0.210	3.876
ρ^2	0.627	0.225	0.523	0.766	0.805	0.244	0.419
$CP_{in\ sample}$	86.7	68.2	84.9	92.2	94.3	76.2	76.9
$CP_{quasi\text{-}jackknife}$	84.8	66.5	83.0	90.1	91.5	73.8	74.6

Vuong tests	*z-statistic*		*z-statistic*
Model E' vs. Model E	11.118***	Model F' vs. Model F	7.015***
Model E" vs. Model E	11.397***		
Model E" vs. Model E'	7.885***		

Notes:
Stepwise logistic regressions (likelihood ratio optimizing); variables as defined in Table 2; $_{IA}$ = industry adjusted ratio
C & D = stand-alone sample basic prediction models; E & F = group sample basic prediction models
E' & F' = group-adjusted prediction models (allowing use of variables at company and UCO levels)
E" = group-adjusted prediction model (allowing use of variables at company and UCO levels and interactions between UCO level variables and a cash flow rights dummy or a same industry dummy)
Wald test statistics in parentheses; CP = overall classification performance (in %)
Vuong tests for log likelihood comparison of non-nested logit models (positive z statistic implies the first model reflects more information relative to the second)
* denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level

Table 6

Model Performance Comparison

	t-1	*Δ*	*t-3*	*Δ*
ρ^2 – Basic	0.548		0.201	
ρ^2 – Simple Adj.	0.567	+0.019	0.257	+0.056
ρ^2 – Group Adj.	0.659	+0.092	0.274	+0.017
ρ^2 – Basic + Group Adj.	0.717	+0.058	0.310	+0.036
		+0.169		+0.109

Notes:
Basic = basic prediction model (full sample; Table 4 models A & B)
Simple Adj. = group-adjusted model with adjustment for group effects using company level data only (Table 4 models A' & B')
Group Adj. = group-adjusted prediction model model with adjustment for group effects using company level and UCO level data (full sample; Table 4 models A" & B")
Basic + Group Adj. = combination of basic prediction model for the stand-alone sample (Table 5 models C & D) and group-adjusted prediction model using company level and UCO level data for the group sample (Table 5 models E” & F')

Appendix

Summary Statistics (continued)

		t-1						*t-3*					
		Full Sample		*Stand-Alone Sample*		*Group Sample*		*Full Sample*		*Stand-Alone Sample*		*Group Sample*	
		NF	*F*	*NF*	*F*	*NF*	*F*	*NF*	*F*	*NF*	*F*	*NF*	*F*
SIZE	Mean	8.705	8.696	8.377	8.513	8.974	9.003	8.578	8.691	8.362	8.483	8.816	9.043
	St.Dev.	*1.167*	*1.001*	*0.972*	*0.886*	*1.252*	*1.112*	*1.157*	*1.010*	*0.992*	*0.823*	*1.281*	*1.191*
LIQ	Mean	1.200	0.732	1.160	0.657	1.234	0.858	1.204	0.890	1.213	0.843	1.195	0.970
	St.Dev.	*0.706*	*0.533*	*0.624*	*0.385*	*0.768*	*0.703*	*0.805*	*0.699*	*0.840*	*0.618*	*0.770*	*0.819*
PP	Mean	0.149	-0.266	0.193	-0.278	0.113	-0.244	0.118	-0.055	0.146	-0.048	0.087	-0.066
	St.Dev.	*0.211*	*0.420*	*0.206*	*0.458*	*0.210*	*0.349*	*0.225*	*0.213*	*0.214*	*0.217*	*0.233*	*0.208*
ROA	Mean	0.062	-0.120	0.064	-0.154	0.060	-0.062	0.048	-0.013	0.056	-0.013	0.039	-0.014
	St.Dev.	*0.083*	*0.213*	*0.073*	*0.252*	*0.091*	*0.103*	*0.088*	*0.101*	*0.088*	*0.101*	*0.087*	*0.103*
LEV	Mean	0.631	0.867	0.605	0.877	0.652	0.849	0.662	0.763	0.647	0.745	0.678	0.792
	St.Dev.	*0.234*	*0.243*	*0.254*	*0.249*	*0.216*	*0.235*	*0.227*	*0.181*	*0.223*	*0.171*	*0.232*	*0.194*
EFF	Mean	1.872	1.355	1.868	1.493	1.875	1.123	1.792	1.358	1.760	1.463	1.827	1.182
	St.Dev.	*1.264*	*1.116*	*1.231*	*1.232*	*1.296*	*0.847*	*1.042*	*0.874*	*1.040*	*0.934*	*1.051*	*0.736*
GSIZE	Mean	–	–	–	–	12.298	10.463	–	–	–	–	11.916	10.110
	St.Dev.	–	–	–	–	*2.802*	*1.834*	–	–	–	–	*2.657*	*1.648*
GLIQ	Mean	–	–	–	–	1.089	0.589	–	–	–	–	1.330	0.728
	St.Dev.	–	–	–	–	*0.881*	*0.585*	–	–	–	–	*1.082*	*0.745*
GPP	Mean	–	–	–	–	0.255	0.031	–	–	–	–	0.222	0.089
	St.Dev.	–	–	–	–	*0.203*	*0.185*	–	–	–	–	*0.192*	*0.164*
GROA	Mean	–	–	–	–	0.066	-0.001	–	–	–	–	0.059	0.035
	St.Dev.	–	–	–	–	*0.069*	*0.047*	–	–	–	–	*0.061*	*0.046*
GLEV	Mean	–	–	–	–	0.532	0.678	–	–	–	–	0.527	0.627
	St.Dev.	–	–	–	–	*0.209*	*0.162*	–	–	–	–	*0.253*	*0.216*
GEFF	Mean	–	–	–	–	1.315	0.978	–	–	–	–	0.778	0.588
	St.Dev.	–	–	–	–	*0.942*	*0.448*	–	–	–	–	*0.650*	*0.577*

Notes:
Variables as defined in Table 2; F = failed companies; NF = non-failed companies