THE JOURNAL OF FINANCE • VOL. LXII, NO. 6 • DECEMBER 2007

Measuring Distress Risk: The Effect of R&D Intensity

LAUREL A. FRANZEN, KIMBERLY J. RODGERS, and TIMOTHY T. SIMIN*

ABSTRACT

Because of upward trends in research and development activity, accounting measures of financial distress have become less accurate. We document that (1) higher research and development spending increases the likelihood of misclassifying solvent firms, (2) adjusting for conservative accounting of research and development increases the number of correctly identified distressed firms, and (3) adjusted measures of distress alleviate previously documented anomalously low returns of large, high distress risk, low book-to-market firms. The results hold after updating stale parameters and under various tax assumptions. Our evidence raises concerns about interpretation of extant literature that relies on accounting measures of distress.

THE BANKRUPTCY PREDICTION MODELS proposed by Altman (1968) and Ohlson (1980) are used in many different contexts in both the finance and accounting literatures.[1] These accounting-based models of distress utilize income statement and balance sheet data, making the models sensitive to accounting reporting standards. Evidence of increases in R&D spending over the last 20 years suggests that full expensing of R&D expenditures for financial reporting purposes severely distorts the earnings and book values of R&D intensive firms (e.g., Chan, Lakonishok, and Sougiannis (2001)).[2] We study the effect of this type of distortion on accounting-based measures of distress risk and show that as reporting of R&D spending has increased over time, the effectiveness of accounting-based indicators of distress has deteriorated to the detriment of inferences related to distress risk.

*Franzen is at the University of Texas at Dallas, Rodgers is at New York University, and Simin is at Pennsylvania State University. The authors are grateful for comments from Edward Altman, Diane Denis, Stacie Laplante, Michael Lemmon, Karl Muller, Micah Officer, and the workshop participants at the University of Texas at Dallas, with special thanks to Robert Stambaugh and an anonymous referee.

[1] Studies that use Altman's (1968) bankruptcy prediction model to operationalize financial distress include Pastena and Ruland (1986), Francis (1990), Berger, Ofek, and Swary (1996), Subramanyan and Wild (1996), and Holder-Webb and Wilkins (2000). Studies that use Ohlson's (1980) bankruptcy prediction model include Burgstahler, Jiambalvo, and Noreen (1989), Stone (1991), Han, Jennings, and Noel (1992), Dichev (1998), and Griffin and Lemmon (2002).

[2] Unlike investment in tangible assets that are capitalized to the balance sheet and depreciated over the useful life of the asset, Financial Accounting Standard No. 2 (FAS No. 2) requires a more *conservative* approach for investment in internally developed intangible assets, namely that research and development costs be expensed as incurred. An exception to this rule does exist for software development firms. These firms may capitalize R&D spending after reaching "technological feasibility" (FAS No. 86).

Prior finance research utilizes Ohlson's (1980) measure of the probability of bankruptcy (*O*-score) to rank firms on distress risk to test whether distress risk is priced by the market. This line of research fails to provide consistent evidence that owners of distressed, higher risk firms are rewarded with higher returns. Dichev (1998) finds that firms classified as distressed earn *lower* than average returns. Griffin and Lemmon (2002) find that low returns to high distress risk firms are attributable specifically to highly distressed firms with low book-to-market ratios. These firms have low current earnings but high sales growth, capital expenditures, and R&D spending. Because the effect of fully expensing R&D expenditures is generally lower reported income and net assets relative to a less conservative policy allowing capitalization and amortization of R&D spending, the high distress risk classification increasingly includes solvent, R&D intensive firms.[3] We study the impact of the measurement error from misclassification of solvent firms.

Replicating the results of Griffin and Lemmon (2002), we document how the concentration of R&D intensive firms among the highest distress risk classifications significantly impacts the observed returns to portfolios sorted by distress risk and book-to-market. Adjusting distress risk measures for the effect of the conservative accounting treatment of R&D investment reduces misclassification errors and alleviates the surprisingly low returns documented by Griffin and Lemmon for large firms with high distress risk and low book-to-market. Our adjustments to *O*-scores also reduce the book-to-market effects and eliminate the significant pricing errors noted by Griffin and Lemmon for large firms. However, for small firms with high distress risk and low book-to-market, the anomaly remains. We can provide no explanation consistent with efficiency for the persistent abnormal returns among these firms.

We focus on the distress measure *O*-score. This measure, which is widely used in the finance literature, relies exclusively on accounting data, making it highly susceptible to the trend in R&D spending and the related accounting distortion. Alternative measures such as Altman's *Z*-score and Shumway's (2001) hazard rate model and prediction models suggested by Hillegeist et al. (2004) or Vassalou and Xing (2004) that avoid accounting measures or include additional market data are not useful for our purpose. Relative comparisons of these models are beyond the scope of our paper. Our objective is to demonstrate the influence of conservative GAAP accounting policy for R&D spending on inferences related to distress risk as typically measured by accounting ratios. Whether or not we adjust for potential tax and stale parameter effects, our results suggest caution in applying traditional accounting-based measures over time without adjusting for the treatment of R&D under GAAP.

Given the popularity of these accounting-based measures, our results should be of interest to a wide audience of academics, practitioners, and regulators. While we focus on the work of Griffin and Lemmon (2002) to demonstrate the influence of accounting for R&D on measures of distress risk, researchers

[3] For firms in steady state, expensing R&D would have the same effect on income as capitalizing and amortizing the R&D asset. When R&D spending is growing, fully expensing R&D leads to lower reported net income than capitalizing and amortizing the R&D spending.

in corporate finance have also long used accounting-based performance measures to compare firms across industries over time. Empirical results relating market-to-book or earnings-based performance measures to capital structure, securities issuance, corporate governance, ownership structure, merger and acquisition activity, or managerial turnover over time are also potentially affected by changes in accounting standards and conservative reporting policies. We show that given the mandatory requirement to expense R&D and the increasing importance of R&D activity for the economy, the effect of accounting for R&D spending must be controlled for when measuring financial distress with accounting data.

The paper proceeds as follows. In Section I, we review the evidence on the upward trend in research and development activity and motivate a simple adjustment to the traditional accounting-based prediction models. In Section II, we discuss details of the data and methodology. Section III presents empirical results and Section IV concludes.

I. Motivation and Literature Review

Our investigation of the relation between R&D intensity and measures of financial distress is motivated by evidence that increasing R&D spending over time considerably affects accounting-based indicators of performance. Upward trends in both R&D investment and market-to-book ratios contrast with contemporaneous downward trends in profitability and an increasing frequency of reported losses (i.e., negative earnings).[4] The downward trend in profitability and increase in reported losses extends over periods of economic growth and prosperity, suggesting that recent reported losses may not be a good indicator of a firm's financial performance (Givoly and Hayn (2000), Franzen (2002), Joos and Plesko (2005)).

The evidence on the trend in research and development activity suggests that R&D spending is increasing over time both because existing firms are increasing their investment in R&D and because the type of firms issuing equity has changed. Zingales (2000) notes an increase in the number of initial public offerings of firms composed of purely human, intangible capital, such as consulting and technology firms. Chan et al. (2001) document an increase over time in the number of firms in intangible-intensive industries. They find that across all firms R&D expense as a percent of earnings has more than doubled from 1975 to 1990. Chan et al. estimate that the magnitude of unrecorded R&D capital as a percent of book value of equity for firms engaged in R&D activity has increased from approximately 11% of book value in 1975 to 29% of book value in 1995.[5]

[4] Numerous studies document the increased frequency of losses. For example, see Hayn (1995), Collins, Maydew, and Weiss (1997), Collins, Pincus, and Xie (1999), Givoly and Hayn (2000), and Joos and Plesko (2005). The documented frequency with which losses (negative accounting earnings) are reported has increased from 14% of firms in 1980 to approximately 40% of firms by 2000.

[5] R&D capital is not reported as an asset on a firm's balance sheet. Under current accounting standards, periodic R&D spending is reported as current-period expense and therefore no R&D capital is reported on the balance sheet (i.e., the R&D capital is "unrecorded").

The effect of requiring that all R&D spending be expensed as incurred is generally lower reported income and net assets relative to a less conservative policy that would allow for the capitalization of R&D investment. Lower reported income and net assets that are a result of an accounting convention rather than the performance of the firm confounds accounting-based measures of financial distress. Therefore, we investigate the effect of adjusting for the conservative treatment of R&D spending under GAAP. We follow the adjustments to income statement and balance sheet measures suggested by Lev and Sougiannis (1996) and Chan et al. (2001). Specifically, we reconstruct the accounting-based measures of distress contained in Ohlson's (1980) bankruptcy prediction model as if R&D spending had been capitalized to the balance sheet and amortized over an assumed useful life of 5 years.

II. Data and Methodology

Our sample consists of all domestic NYSE, AMEX, and NASDAQ common stocks for which the requisite CRSP and Compustat data are available. Specifically, we require that sufficient data be available to compute the accounting-based measures of financial distress, R&D intensity, and portfolio returns. Prior studies that investigate distress risk check the validity of accounting-based measures of financial distress using CRSP performance delistings. In order to provide a nonaccounting-based metric of financial distress and to provide evidence relevant to studies that investigate bankruptcy prediction methodologies, we collect bankruptcy filings and classify firms as either bankrupt or not bankrupt in each year.

Using Lexis Nexis, we identify a preliminary sample of 2,262 bankruptcy filings from Bankruptcy DataSource Index. We verify each bankruptcy filing by searching press announcements via Lexis Nexis and Factiva. Because we cannot verify nonevents with certainty, it is possible that we miss some bankruptcy filings. Any inappropriate "not bankrupt" code would likely be found among smaller firms lacking press coverage. The filings span the period from February 1981 through October 2004, though coverage is sparse in the earliest years.[6] Table I shows that of the initial sample, 1,498 bankruptcies appear on the CRSP tapes and of these, 929 have complete Compustat data. While the necessary restriction to listed firms reduces the number of filings by roughly half, the general pattern of filings across years is preserved, that is, the correlation between the samples is 0.97.

Several bankrupt firms delist prior to formally filing. Because we are concerned primarily with the fact that they default (that is, given we do not compute announcement returns), there is no need to exclude such firms, provided Compustat provides their prebankruptcy accounting data. For the 231 firms that

[6] The original Altman and Ohlson prediction models were estimated in a more liquidation-oriented bankruptcy regime prior to Title 11. While the focus of our paper is on fundamental changes in the right-hand side of these prediction models, it is important to note that the bankruptcy event itself may also have changed. Because our entire sample period follows the change in code, our analysis is not subject to any potential problems associated with this change.

Table I
Sample of Bankruptcies

The table reports the frequency distribution of sample firms over time. Column 2 contains the overall number of firms in the intersection of the CRSP and Compustat universes with complete data. Column 3 contains the number of firms in Column 2 known to file for bankruptcy (total 929) and column 4 contains the percentage.

Filing Year	Firms with Complete Data	# of Firms with Complete Data That File for Bankruptcy	% of Firms with Complete Data That File for Bankruptcy
1981	3,370	2	0.06
1982	3,523	15	0.43
1983	3,539	12	0.34
1984	3,821	19	0.50
1985	3,893	22	0.57
1986	3,941	26	0.66
1987	4,011	20	0.50
1988	4,144	28	0.68
1989	4,063	36	0.89
1990	4,022	52	1.29
1991	4,012	62	1.55
1992	4,032	39	0.97
1993	4,158	37	0.89
1994	4,445	25	0.56
1995	4,757	35	0.74
1996	4,915	28	0.57
1997	5,228	30	0.57
1998	5,248	58	1.11
1999	5,029	58	1.15
2000	4,725	89	1.88
2001	4,521	119	2.63
2002	4,186	57	1.36
2003	3,854	46	1.19
2004	3,512	14	0.40

delist prior to filing bankruptcy, we use the delisting date rather than the bankruptcy filing date in classifying the firm. This convention is not likely consequential since we rely on annual Compustat data and the firms that delist prior to filing do so less than a year in advance.

In our empirical analysis, we compute annual buy-and-hold returns for portfolios of firms ranked on measures of distress and book-to-market. We form portfolios at the end of June each year using the most recent publicly available financial statement information. We assume that financial statements are publicly available by the sixth month following the fiscal year-end. We conservatively assume a 6-month lag rather than the traditional 4-month lag because evidence in Ohlson (1980) indicates that financials of distressed firms may be delayed in their release. We compute delisting returns as in Shumway (1997).

As in other bankruptcy samples, we find a relatively large number of filings in the oil & gas industry (SIC 13), which are fairly evenly distributed over time. We also observe clusters in industries classified as R&D intensive by Chan et al. (2001).[7] This is consistent with the notion that firms in R&D intense industries file bankruptcy with increased frequency, especially in periods in which the market is less optimistic about future growth prospects (i.e., the bursting of the so-called technology "bubble"). Griffin and Lemmon (2002) find that highly distressed firms with low book-to-market ratios have low current earnings, but high R&D spending. To investigate whether R&D intensive firms are more likely to declare bankruptcy we measure R&D intensity as the level of R&D expense deflated by total assets.

III. Empirical Results

A. O-score Components and Classification

Ohlson identifies nine accounting measures typically indicative of financial distress. Four of the nine measures include net income. We expect that these income-based indicators of distress are affected by the accounting requirement of full expensing of R&D spending. The additional bankruptcy prediction variables used in Ohlson's model are balance sheet measures, which are also likely affected by increasing R&D intensity.

In Panel A of Table II, we report the mean and median values of the nine variables used in computing the *O*-score for our sample of firms across the sample period (1980 to 2004). The most notable change over time is in the mean and median values of financial ratios that contain net income. The mean ratio of net income to total assets (NITA) becomes negative in 1983 and ranges from 0.053 in 1980 to −0.225 in 2002. Median net income to total assets also declines over time. The ratio of funds from operations to total liabilities (*ffotl*), which is computed as pre-tax income before depreciation to total liabilities, has predominately negative mean values from 1987 to 2004.

The mean values for "*intwo*," an indicator variable equal to one if the firm has negative income in the prior 2 years, indicates that more firms are reporting consecutive losses in the more recent years of the sample. The evidence in Panel A of Table II shows that downward trends in accounting indicators of financial distress extend across periods of economic growth and prosperity. This suggests that firms ranked in the highest *O*-score portfolios, that is, those that are the most likely to declare bankruptcy, may include solvent firms that have conservative financial reporting related to investment in R&D activity.

[7] Chan et al. classify the following SICs as R&D intense: 737 computer programming, 283 drugs, 357 computers, 38 measuring instruments, 36 electrical, 48 communications, and 37 transportation equipment. We find 48 bankruptcy filings by communications firms in 2001 to 2002; 36 filings by electronics firms in 2001 to 2003; 10 filings by firms in transportation equipment in 2001 to 2002; 28 filings by firms in computer equipment in 1990 to 1994; 10 filings by firms in measuring instruments in 2001 to 2002; and 70 filings by firms in the 7300 SIC code (business services including computer programming and software) in 2001 to 2003.

Table II

Ohlson's (1980) Bankruptcy Metrics and R&D Intensity

Panel A reports mean and median values for each variable employed by Ohlson's bankruptcy prediction model over fiscal years 1980 to 2004. Panels B and C report mean and median values, respectively, of all Ohlson inputs and of R&D scaled by total assets and market-to-book, each by *O*-score quintiles. All variables are as defined in the Appendix.

Panel A: Mean and Median Values by Year

	Means										Medians									
Year	*O*-score	*size*	*tlta*	*wcta*	*clca*	*nita*	*ffotl*	*intwo*	*oeneg*	*chin*	*O*-score	*size*	*tlta*	*wcta*	*clca*	*nita*	*ffotl*	*intwo*	*oeneg*	*chin*
1980	−0.804	4.278	0.538	0.277	1.329	0.053	0.265	0.035	0.006	0.060	−0.996	4.149	0.544	0.288	0.500	0.060	0.258	0.000	0.000	0.086
1981	−0.954	4.292	0.529	0.278	1.303	0.042	0.338	0.030	0.006	0.004	−1.011	4.172	0.535	0.285	0.496	0.056	0.242	0.000	0.000	0.044
1982	−0.988	4.192	0.510	0.279	1.297	0.024	0.269	0.043	0.010	0.039	−1.073	4.051	0.516	0.287	0.487	0.052	0.228	0.000	0.000	0.061
1983	−0.514	4.124	0.510	0.262	1.343	−0.009	0.151	0.060	0.011	−0.112	−0.803	3.969	0.516	0.273	0.487	0.040	0.192	0.000	0.000	−0.033
1984	−0.585	4.087	0.488	0.284	1.320	−0.007	0.091	0.087	0.013	0.051	−0.977	3.916	0.489	0.290	0.472	0.041	0.201	0.000	0.000	0.069
1985	−0.641	4.059	0.495	0.280	1.268	−0.017	0.118	0.114	0.013	0.084	−0.967	3.837	0.499	0.288	0.484	0.045	0.208	0.000	0.000	0.095
1986	−0.294	4.033	0.509	0.266	1.347	−0.056	0.031	0.122	0.021	−0.065	−0.690	3.822	0.515	0.278	0.490	0.036	0.178	0.000	0.000	0.000
1987	−0.060	4.035	0.510	0.277	1.382	−0.058	−0.049	0.128	0.019	−0.008	−0.568	3.860	0.523	0.277	0.483	0.029	0.156	0.000	0.000	0.024
1988	−0.019	4.039	0.515	0.281	1.245	−0.043	−0.074	0.156	0.021	0.050	−0.620	3.882	0.528	0.280	0.489	0.031	0.158	0.000	0.000	0.071
1989	0.008	4.073	0.531	0.265	1.599	−0.050	−0.014	0.166	0.029	0.048	−0.547	3.927	0.533	0.264	0.512	0.033	0.156	0.000	0.000	0.079
1990	0.005	4.117	0.540	0.253	1.886	−0.049	0.029	0.182	0.031	−0.004	−0.462	3.963	0.543	0.254	0.520	0.031	0.155	0.000	0.000	0.038
1991	−0.023	4.203	0.538	0.242	1.516	−0.044	0.026	0.169	0.031	−0.013	−0.489	4.047	0.541	0.241	0.531	0.028	0.146	0.000	0.000	0.015
1992	0.040	4.274	0.536	0.238	1.804	−0.070	−0.387	0.165	0.033	−0.040	−0.512	4.084	0.522	0.252	0.521	0.024	0.147	0.000	0.000	0.003
1993	−0.220	4.425	0.509	0.265	2.267	−0.048	0.023	0.152	0.030	0.019	−0.736	4.210	0.496	0.264	0.498	0.027	0.163	0.000	0.000	0.048
1994	−0.341	4.474	0.494	0.278	1.299	−0.059	−0.029	0.159	0.025	0.047	−0.805	4.259	0.482	0.268	0.485	0.029	0.162	0.000	0.000	0.065
1995	−0.377	4.541	0.492	0.269	1.824	−0.055	−0.027	0.163	0.022	0.089	−0.898	4.338	0.490	0.253	0.501	0.035	0.171	0.000	0.000	0.090
1996	−0.457	4.636	0.494	0.271	1.452	−0.046	0.010	0.163	0.021	0.038	−0.879	4.443	0.492	0.258	0.504	0.034	0.172	0.000	0.000	0.071
1997	−0.549	4.722	0.476	0.292	1.140	−0.061	−0.055	0.154	0.020	0.010	−0.936	4.518	0.465	0.275	0.478	0.031	0.167	0.000	0.000	0.054
1998	−0.358	4.809	0.486	0.287	2.017	−0.078	−0.089	0.162	0.026	0.023	−0.925	4.599	0.475	0.272	0.474	0.028	0.158	0.000	0.000	0.057
1999	−0.327	4.980	0.498	0.273	1.135	−0.075	−0.091	0.177	0.028	−0.020	−0.811	4.784	0.491	0.256	0.489	0.025	0.146	0.000	0.000	0.025
2000	−0.354	5.135	0.498	0.266	1.134	−0.073	−0.109	0.190	0.026	−0.013	−0.752	4.953	0.498	0.244	0.496	0.022	0.136	0.000	0.000	0.027
2001	−0.066	5.277	0.485	0.274	1.139	−0.146	−0.313	0.202	0.027	−0.055	−0.727	5.130	0.468	0.251	0.481	0.015	0.117	0.000	0.000	0.000
2002	0.484	5.334	0.501	0.251	1.311	−0.225	−0.397	0.221	0.038	−0.143	−0.585	5.179	0.462	0.239	0.494	0.002	0.089	0.000	0.000	−0.088
2003	0.261	5.399	0.510	0.246	1.888	−0.160	−0.271	0.283	0.035	0.001	−0.696	5.277	0.470	0.241	0.502	0.007	0.110	0.000	0.000	0.032
2004	−0.756	5.562	0.487	0.269	0.743	−0.075	−0.032	0.324	0.029	0.131	−1.205	5.438	0.460	0.255	0.476	0.021	0.138	0.000	0.000	0.102

(*continued*)

Table II—*Continued*

O-score Quintiles	*O*-score	*size*	*tlta*	*wcta*	*clca*	*nita*	*ffotl*	*intwo*	*oeneg*	*chin*	*MTB*	*RD/TA*
Panel B: Mean Values for Each *O*-score Quintile												
1	−4.659	4.687	0.259	0.443	0.332	0.110	1.101	0.035	0.000	0.232	2.846	0.035
2	−2.068	5.160	0.429	0.313	0.495	0.061	0.332	0.052	0.000	0.170	2.090	0.025
3	−0.918	5.004	0.528	0.252	0.615	0.034	0.176	0.072	0.003	0.088	1.817	0.020
4	0.281	4.387	0.605	0.210	0.742	−0.005	0.035	0.136	0.014	−0.039	2.313	0.023
5	4.295	3.095	0.675	0.152	4.005	−0.318	−1.017	0.338	0.075	−0.271	5.156	0.092
Panel C: Median Values for Each O-score Quintile												
1	−3.968	4.530	0.253	0.451	0.295	0.100	0.797	0.000	0.000	0.114	2.021	0.008
2	−2.046	5.008	0.435	0.318	0.429	0.061	0.324	0.000	0.000	0.099	1.509	0.002
3	−0.922	4.858	0.543	0.255	0.514	0.041	0.191	0.000	0.000	0.072	1.342	0.000
4	0.243	4.253	0.618	0.193	0.604	0.022	0.113	0.000	0.000	0.020	1.316	0.000
5	2.502	3.003	0.685	0.141	0.714	−0.130	−0.104	0.000	0.000	−0.233	1.690	0.000

Panel B of Table II displays mean levels of each input variable by sample *O*-score quintiles. The firms in the highest *O*-score quintile (*O*-score quintile 5) have the highest estimated probability of bankruptcy in the next year. It is not surprising that these firms are smaller, on average, than firms in the other *O*-score quintiles, as it has been documented that smaller firms are more likely to declare bankruptcy. In fact, all of the mean values of the variables reported for firms in *O*-score quintile 5 are in line with expectations for financially distressed firms. These firms are smaller, have higher liabilities to assets, smaller working capital to assets, lower net income to total assets, and are more likely to have consecutive losses and negative book value of equity.

In Panel B of Table II, we also provide evidence on how variables related to financial reporting vary across *O*-score quintiles. We report research and development intensity (measured as *R&D expense to total assets*) across levels of financial distress (*O*-score quintiles). The effect of fully expensing R&D spending is an understated book value of equity on the balance sheet. Therefore, market-to-book (*MTB*) measures reflect this accounting effect as well as all other unrecorded investment in intangibles that lead to lower book values. Consistent with evidence in Griffin and Lemmon (2002), firms in *O*-score quintile 5 have the highest mean market-to-book ratio of 5.16 and the highest mean ratio of R&D to total assets of 0.09.

Evidence provided in Table III shows that, indeed, firms in the *O*-score quintile 5 classification are most likely to declare bankruptcy in the next year. The number of bankruptcy filings in year $t+1$ are higher for firms in *O*-score quintile 5 (364 total bankruptcy filings) than in any other quintile and, in most years, the number of filings increases across the *O*-score quintile classifications. The results are qualitatively similar when performance delistings are used instead of bankruptcy filings. Also, the results are qualitatively similar when we identify bankruptcy filings in year t. When we use bankruptcy filings in year $t+2$, the number of bankruptcy filings is highest in *O*-score quintile 4 for most years. This evidence on bankruptcy filings in $t+1$ is similar to evidence presented in Dichev (1998) and Griffin and Lemmon (2002).

However, evidence that bankruptcies and delistings increase across *O*-score quintiles does not disprove the notion that solvent R&D intensive firms are increasingly misclassified among the most distressed firms (i.e., *O*-score quintile 5 firms). Bankruptcy filings (as well as performance delistings) are rather infrequent, occurring in at most 2.63% of the sample firm-years (reported in Table I). Therefore, we investigate firms in *O*-score quintile 5 that have *not* filed for bankruptcy. We first present evidence on how trends in R&D spending and market-to-book over time affect *O*-score measures. We, then investigate how the classification of distressed firms (*O*-score quintile 5 firms) that do not become bankrupt is related to R&D intensity.

B. R&D Intensity: Relation to O-score and Misclassification

Table IV reports mean and median values of R&D intensity (*RD*/*TA*) and *MTB* by year. The reported means of R&D to total assets indicate a distinct

Table III

O-scores and Bankruptcy over Time

Each row displays the number of firms found in each *O*-score quintile in year *t* (given in column 1) and the number of these firms that file for bankruptcy in the following year (t+1). Column 2 contains the number of firms in *O*-score quintile 1 in year *t* and column 3 contains the number of firms in *O*-score quintile 1 in year *t* with bankruptcy filings in year t+1, and so on. For instance, of the 674 firms found in *O*-score quintile 2 in 1981, one firm filed for bankruptcy.

	O-score 1		*O*-score 2		*O*-score 3		*O*-score 4		*O*-score 5	
Year	Firms	Filed	Firms	Filed	Firms	Filed	Firms	Filed	Firms	Filed
1981	674	0	674	1	674	2	674	2	674	10
1982	705	0	704	1	705	1	704	2	705	8
1983	708	0	708	1	707	3	708	5	708	9
1984	764	1	764	0	765	2	764	7	764	12
1985	779	0	778	1	779	5	778	8	779	12
1986	788	1	788	3	789	2	788	6	788	7
1987	802	1	803	0	802	4	803	9	802	13
1988	829	1	829	3	829	6	829	9	829	15
1989	813	1	812	6	813	4	812	21	813	19
1990	804	2	805	4	804	10	805	25	804	20
1991	802	1	803	4	802	5	803	15	802	12
1992	806	3	807	4	806	5	807	7	806	16
1993	832	2	831	2	832	3	831	11	832	6
1994	889	1	889	3	889	7	889	5	889	14
1995	951	0	952	2	951	7	952	11	951	8
1996	983	2	983	2	983	5	983	9	983	12
1997	1,046	1	1,045	5	1,046	8	1,045	14	1,046	29
1998	1,050	3	1,049	2	1,050	12	1,049	19	1,050	20
1999	1,006	2	1,006	7	1,006	14	1,006	23	1,006	40
2000	945	3	945	9	945	20	945	41	945	44
2001	904	0	904	5	905	6	904	23	904	20
2002	837	3	837	3	838	5	837	20	837	13
2003	771	0	771	0	770	4	771	5	771	5
2004	702	0	703	0	702	0	703	0	702	0
Total		28		68		140		297		364

increase in R&D spending over time. In 1980, mean RD/TA is 0.015 and by 2004 the mean is 0.067. The median values of RD/TA are zero until 1998. Because firms are required to report R&D spending as R&D expense, we set R&D expense to zero for the many Compustat firms that do not report the R&D spending. The mean and median values of market-to-book do not reveal any distinct pattern over time.

We hypothesize that the changes in R&D intensity observed in Table IV are related to the changes in *O*-score factors observed in Table II resulting in greater misclassification of nondistressed R&D intensive firms as financially distressed. Indeed, the evidence reported in Figure 1 supports our conjecture. Figure 1B contains plots of median levels of R&D intensity across *O*-score quintiles over time for firms with nonzero R&D spending. Figure 1A plots median

Table IV

R&D Intensity and MTB Across Time

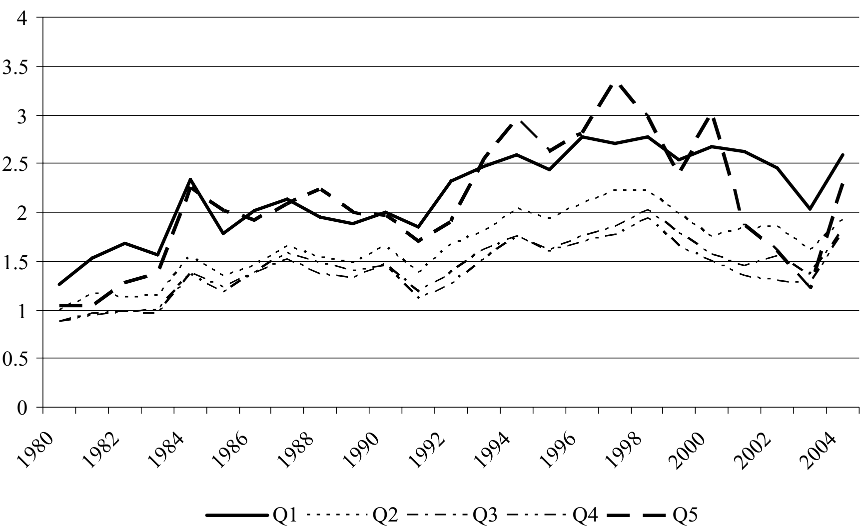
This table reports means and median R&D intensity and market-to-book over time. *MTB* stands for the market-to-book equity ratio, computed as the end-of-period price per share multiplied by the number of shares outstanding to the book value of equity, and *RD/TA* for research and development expense scaled by total assets.

	MTB		*RD/TA*	
Year	Mean	Median	Mean	Median
1980	2.365	0.997	0.015	0.000
1981	2.919	1.120	0.017	0.000
1982	2.438	1.218	0.020	0.000
1983	2.328	1.165	0.025	0.000
1984	3.200	1.732	0.026	0.000
1985	3.109	1.487	0.032	0.000
1986	2.369	1.586	0.037	0.000
1987	4.555	1.761	0.038	0.000
1988	3.249	1.659	0.037	0.000
1989	2.771	1.551	0.041	0.000
1990	2.804	1.672	0.042	0.000
1991	3.474	1.376	0.043	0.000
1992	4.527	1.624	0.045	0.000
1993	3.344	1.875	0.047	0.000
1994	3.152	2.115	0.049	0.000
1995	3.141	1.941	0.055	0.000
1996	1.212	2.136	0.055	0.000
1997	4.739	2.287	0.057	0.000
1998	3.830	2.331	0.067	0.001
1999	3.150	2.006	0.073	0.001
2000	5.308	1.962	0.065	0.002
2001	3.247	1.728	0.068	0.005
2002	2.882	1.710	0.080	0.008
2003	4.072	1.531	0.082	0.008
2004	4.332	2.046	0.067	0.007

market-to-book values across *O*-score quintiles for all firms. Figure 1A reveals that median market-to-book is highest in *O*-score quintiles 1 and 5 in most of the sample period. Recall that *O*-score quintile 1 firms should consist of the financially healthiest firms and *O*-score quintile 5 firms should consist of the most financially distressed firms.

Griffin and Lemmon (2002) document that distressed firms (high *O*-score firms) contain both high and low market-to-book firms. We observe similar evidence here in that *O*-score quintile 5 firms are not comprised solely of those firms with the lowest market-to-book ratios. We note that a firm's market-to-book ratio falls with its stock price. However, for some of those firms, book value may approach zero or even turn negative. Since equity value will never be negative (equity becomes option-like when the firm is distressed), the market-to-book ratio can be very high in some cases. A noncompeting explanation for

A *Market-to-Book*



B *Research and Development*

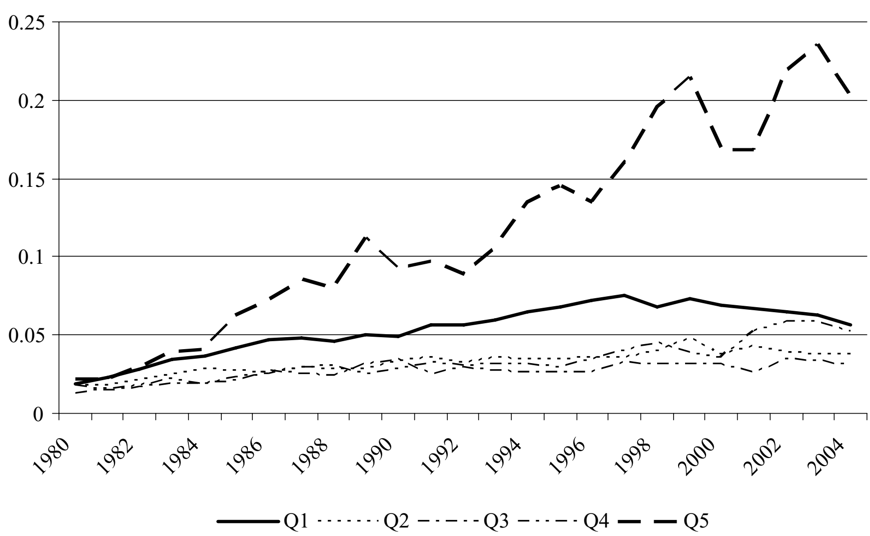


Figure 1. R&D intensity and MTB by *O*-score quintiles. These figures plot median levels of market-to-book and R&D scaled by total assets by *O*-score quintiles over time. Specifically, Figure 1A sorts firms into *O*-score quintiles and reports median market-to-book values in each quintile over time, and Figure 1B sorts firms into *O*-score quintiles and plots median *RD*/*TA*.

high market-to-book firms in the high O-score quintile is that conservative accounting deflates the book value of equity of these firms.

In Figure 1B, we plot the median RD/TA ratio across O-score quintiles for firms with positive R&D spending. Median RD/TA is highest in O-score quintile 5 and is increasing over time. The evidence suggests that firms with high R&D spending relative to total assets have higher O-scores, which are unlikely to reflect financial distress. We investigate whether these R&D intensive firms with high O-scores do in fact file bankruptcy and/or earn higher returns as a result of increased distress risk.

Figure 2 provides misclassification errors across levels of R&D intensity and market-to-book. In Figure 2A, we plot the percentage of nonbankrupt, O-score quintile 5 firms in each year that have the highest (quintile 5) and lowest (quintile 1) market-to-book. In Figure 2B, for only those firms with positive R&D spending, we plot the percent of nonbankrupt firms in the O-score quintile 5 ranking with the highest and lowest R&D to total assets.

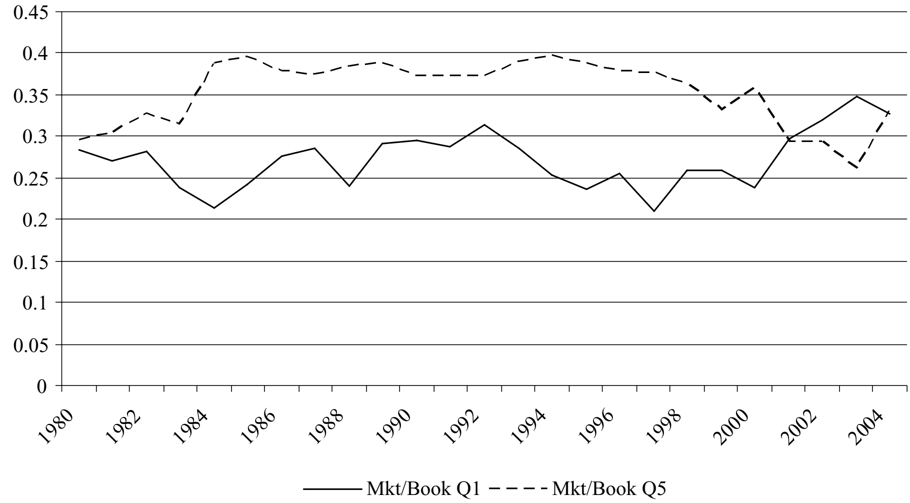
Because fully expensing R&D erodes book value, R&D intensive firms in Panel A are likely to be those in the top market-to-book quintile (Q5) annually. The evidence suggests that from approximately 1980 to 2001, the percentage of high market-to-book firms (Q5) among the nonbankrupt O-score quintile 5 classification is higher than the percentage of low market-to-book firms (Q1). That is, as expected, high market-to-book firms are indeed more likely to be classified as distressed but not to go bankrupt.

In Panel B, we classify firms with positive R&D into quintiles by RD/TA for each year such that firms in the top quintile (Q5) are those most affected by accounting distortions. Figure 2 suggests that firms affected by accounting distortions are more likely to be misclassified as likely to file for bankruptcy.

Table V provides evidence that the number of firms with positive R&D expense is significant in O-score quintile 5 and is increasing over time. The percent of firms classified in O-score quintile 5 with positive R&D spending increases from 34.68% of firms in 1980 to 75.62% in 2003. We observe that positive R&D spending is increasing over time in general (not just in O-score quintile 5), but we should not expect these firms to be more likely to be distressed (classified in O-score quintile 5) over time. Indeed, in untabulated results the frequency of bankruptcy filings among firms in O-score quintile 5 without R&D spending is higher than that among firms in O-score quintile 5 with R&D spending in 22 of 24 years.

Given the univariate relationship between R&D intensity and the misclassification of distress risk described above, we investigate the effect of applying the Ohlson model with income statement and balance sheet measures adjusted for the effects of fully expensing R&D spending. We expect that adjusting O-score computations for the conservative reporting of R&D expense will improve the identification of distressed firms. That is, we expect fewer misclassifications of solvent R&D intensive firms as financially distressed.

A *Market-to-Book*



B *Research and Development*

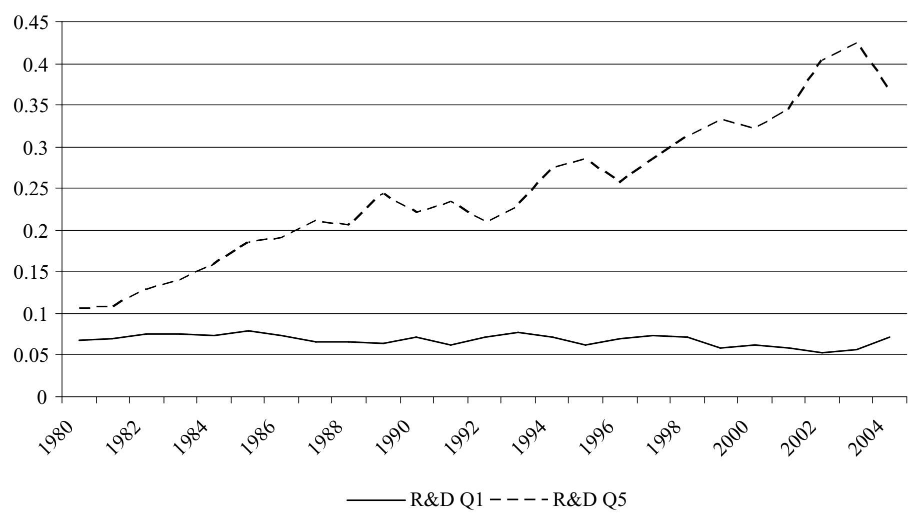


Figure 2. Solvent firms in *O*-score quintile 5. These figures plot the percent of nonbankrupt firms in *O*-score quintile 5 that fall in the top and bottom quintiles of R&D and market-to-book. Specifically, Figure 2A plots the percent of nonbankrupt, *O*-score 5 firms in the top and bottom market-to-book quintiles, and Figure 2B plots the percent of nonbankrupt, *O*-score 5 firms in the top and bottom nonzero RD/TA quintiles over time. Nonbankrupt is defined as not filing for bankruptcy in the year following the *O*-score ranking.

Table V

Research and Development in High *O*-Score Firms

For fiscal years 1980 through 2003, this table reports the total number of firms classified by the *O*-score as most likely to file for bankruptcy (*O*-score quintile 5), the percentage of this group reporting positive R&D expense, and the percentage of this group found in the (independently classified) highest quintile of R&D expense.

	# Firms in *O*-score Quintile 5	# Firms with MTB Data	# of Positive R&D Firms	Positive R&D Expense (%)	Q5 R&D Expense (%)
1980	669	663	232	34.68	10.61
1981	674	672	241	35.76	10.68
1982	705	705	266	37.73	12.62
1983	708	708	276	38.98	13.84
1984	764	763	327	42.80	15.84
1985	779	776	349	44.80	18.36
1986	788	786	363	46.07	18.91
1987	802	801	390	48.63	21.20
1988	829	828	392	47.29	20.63
1989	813	811	404	49.69	23.99
1990	804	802	414	51.49	21.89
1991	802	801	425	52.99	23.07
1992	806	805	421	52.23	20.72
1993	832	832	454	54.57	22.72
1994	889	889	493	55.46	27.33
1995	951	951	552	58.04	28.29
1996	983	983	526	53.51	25.43
1997	1,046	1,044	593	56.69	27.72
1998	1,050	1,050	634	60.38	30.95
1999	1,006	1,006	617	61.33	32.11
2000	945	944	615	65.08	31.43
2001	904	903	623	68.92	34.18
2002	837	837	630	75.27	40.38
2003	771	771	583	75.62	42.28

C. Adjusted O-scores Reduce Misclassification

The adjustment process of Lev and Sougiannis (1996) allows R&D expenditures to be treated as an intangible asset, capitalized to the balance sheet, and amortized over an assumed useful life of 5 years. This leads to the following adjustments to net income and total assets:

$$\begin{aligned} \textit{Adj. Net Income} &= \textit{Net Income} + \textit{RD expense} \\ &\quad - .2 * (RD_{it-1} + RD_{it-2} + RD_{it-3} + RD_{it-4} + RD_{it-5}) \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Adj. Total Assets} &= \textit{Total assets} + RD_{it} + .8 * RD_{it-1} + .6 * RD_{it-2} \\ &\quad + .4 * RD_{it-3} + .2 * RD_{it-4}. \end{aligned} \tag{2}$$

These adjustments result in tax effects. We make two assumptions related to the potential tax effects of our adjustment process. First, we assume that firms choose to expense research and development spending for tax purposes.[8] Second, we assume that there is no tax effect for firms with negative net income.

Our first assumption results in recognizing a deferred tax liability in the amount of $(RDCapital * (t))$ as a result of the capitalization of R&D for financial reporting purposes (but not for tax reporting purposes). We make the assumption that firms take advantage of available current tax savings. Our second assumption arises because we do not want to bias our adjusted bankruptcy prediction model in favor of identifying bankrupt firms.[9] Firms without positive net income are also unlikely to have positive taxable income.[10] Because tax effects serve to lower our income measures and increase liabilities, if we assume tax effects where none exist (due to negative taxable income in the current period and foreseeable future), we would bias our bankruptcy prediction model in favor of identifying bankrupt firms. Therefore, we assume that there is no tax effect for negative earnings firms. In Section E, we present evidence that our results do not rely on our treatment of tax effects.

The assumptions outlined above lead to the following adjustments. Where net income is negative, after-tax adjustments result in no change from the specification above. Where net income is positive, after-tax (AT) adjustments to our adjusted O-score are:

$$\begin{aligned} &AT\_Adjusted\ Net\ Income \\ &\quad = Net\ Income + (RD\ expense - RD\ amortization) * (1 - t), \end{aligned} \tag{3}$$

where

$$RD\ amort = 0.2 * (RD_{it-1} + RD_{it-2} + RD_{it-3} + RD_{it-4} + RD_{it-5}),$$

$$Adjusted\ Total\ Assets = Total\ assets + RD\ Capital, \tag{4}$$

where

$$RD\ Capital = RD_{it} + 0.8 * RD_{it-1} + 0.6 * RD_{it-2} + 0.4 * RD_{it-3} + 0.2 * RD_{it-4},$$

[8] For federal income tax purposes, there are three alternatives available for research and development expenditures: (1) Expense in the year paid or incurred (IRC §174(a)); (2) capitalize and amortize the costs ratably over a period of 60 months or more (IRC §174(b)); or (3) capitalize and write off the costs only when the project is abandoned or becomes worthless (IRC §174(b)).

[9] Accounting for income taxes under GAAP changed during our sample period. SFAS 109 (effective December 15, 1992) changed the criteria for recognizing and measuring deferred tax assets. However, this change in accounting for income taxes is not significant in terms of its effect on the results in this paper.

[10] Hanlon (2003) details the noise inherent in inferring a firm's taxable income from financial statements. However, recent studies document that pre-tax book income exceeded taxable income for U.S. firms on average during most years from 1983 to 2001 (U.S. Department of the Treasury (1999), Hanlon, Laplante, and Shevlin (2005)). Managers have numerous incentives to report higher income for financial reporting purposes, but for tax purposes, managers have incentives to report lower taxable income to maximize after-tax returns to investors.

$$AT\_Adjusted\ Total\ Liabilities = Total\ liabilities + Deferred\ Tax\ Liability(DTL), \tag{5}$$

where

$$DTL = RD\ Capital * t.$$

Here, t is the appropriate annual statutory tax rate: 46% over the 1980 to 1986 period, 40% in 1987, 34% over 1988 to 1992, and 35% over 1993 to 2005.

We use these after-tax adjusted net income, adjusted total assets, and after-tax adjusted liabilities where applicable in Ohlson's bankruptcy prediction metrics. The adjustment process results in the following adjusted metrics: adjusted size (*a_size*), after-tax adjusted total liabilities to total assets (*at_a_tlta*), adjusted working capital to total assets (*a_wcta*), after-tax adjusted negative owners' equity dummy (*at_a_oeneg*), after-tax adjusted net income to total assets (*at_a_nita*), after-tax adjusted funds from operations to total liabilities (*at_a_ffotl*),[11] after-tax adjusted dummy for consecutive losses (*at_a_intwo*), and after-tax adjusted change in net income (*at_a_chin*). All variables are defined in the Appendix.

In Table VI, we report mean and median levels for Ohlson's bankruptcy prediction variables and for levels of R&D intensity across adjusted *O*-score quintiles. We find that the results across adjusted *O*-score quintiles are qualitatively similar to those reported under the original *O*-score rankings in Table II, Panel B. That is, firms in the highest adjusted *O*-score quintile are still the smallest firms; have the highest total liabilities to total assets, the lowest working capital to total assets, the highest current liabilities to current assets, and the lowest net income to total assets; and have a higher incidence of negative book value of equity. These results are as expected for financially distressed firms. The purpose of the adjustment process is to reduce misclassification errors due to conservative accounting for the expensing of R&D. That is, the adjustment process should reduce the likelihood that nondistressed R&D intensive firms are in the highest *O*-score quintile, and therefore incorrectly identified as distressed.

We find that median RD/TA increases from 0.008 in *O*-score quintile 1 under the original *O*-score rankings (reported in Table II, Panel C) to 0.016 in *O*-score quintile 1 under the adjusted *O*-score rankings. Our adjustment process results in the reclassification of firms with R&D spending as expected. In untabulated results, we find that 12.4% of the firm-years in *O*-score quintile 5 are reassigned to lower *O*-score quintiles through the adjustment process.

C.1. Reclassified O-scores

In Figure 3, we present for comparison purposes median levels of MTB and R&D intensity across the original *O*-score quintile rankings (originally

[11] Adjusted funds from operations is defined as pre-tax income plus R&D expense plus depreciation expense. Consistent with adding back depreciation, we do not deduct the estimated R&D amortization expense from the pre-tax income in computing adjusted funds from operations.

Table VI

Ohlson's Bankruptcy Metrics and R&D Intensity across Adjusted *O*-score Quintiles

Panels A and B present mean and median values, respectively, of all Ohlson inputs and of R&D to total assets and market-to-book, each by adjusted *O*-score quintiles. All variables are as defined in the Appendix.

Adj. *O* Quintiles	Adj. *O*-score	*Size*	*tlta*	*wcta*	*clca*	*nita*	*ffotl*	*intwo*	*oeneg*	*chin*	*MTB*	*RD/TA*
Panel A: Mean Values by Adjusted *O*-score Quintile												
1	−4.892	4.657	0.250	0.432	0.317	0.127	1.194	0.035	0.001	0.220	2.908	0.055
2	−2.300	5.097	0.407	0.309	0.473	0.070	0.392	0.052	0.003	0.158	2.064	0.037
3	−1.135	5.014	0.509	0.246	0.598	0.042	0.216	0.070	0.004	0.101	2.149	0.027
4	0.003	4.514	0.589	0.197	0.736	0.008	0.086	0.114	0.014	−0.009	2.212	0.026
5	3.263	3.319	0.681	0.109	4.065	−0.205	−0.601	0.287	0.075	−0.268	4.883	0.051
Panel B: Median Values by Adjusted *O*-score Quintile												
1	−4.229	4.503	0.246	0.430	0.282	0.114	0.899	0.000	0.000	0.110	2.076	0.016
2	−2.271	4.929	0.416	0.311	0.417	0.070	0.381	0.000	0.000	0.093	1.548	0.005
3	−1.133	4.842	0.525	0.248	0.505	0.047	0.221	0.000	0.000	0.073	1.366	0.000
4	−0.035	4.364	0.607	0.183	0.604	0.029	0.134	0.000	0.000	0.032	1.324	0.000
5	1.931	3.191	0.692	0.103	0.758	−0.073	−0.027	0.000	0.000	−0.251	1.490	0.000

A *Market-to-Book*

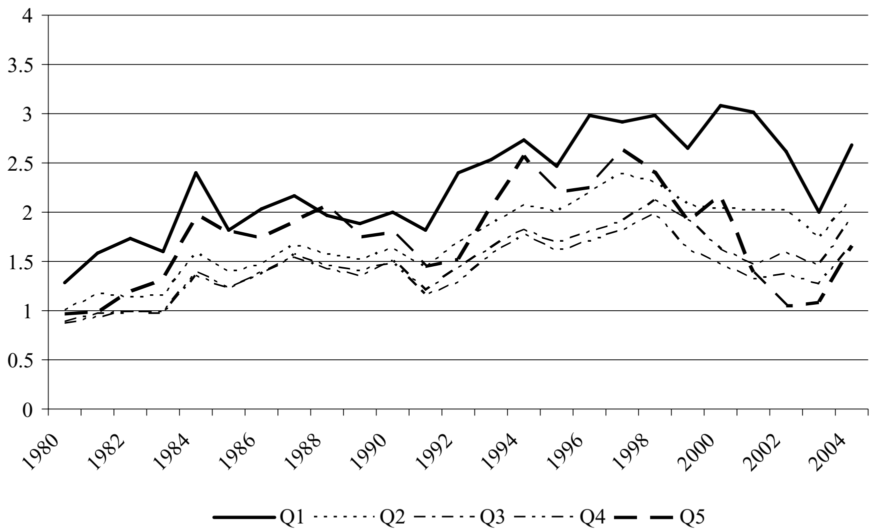


Figure 1A Market-to-Book (unadjusted)

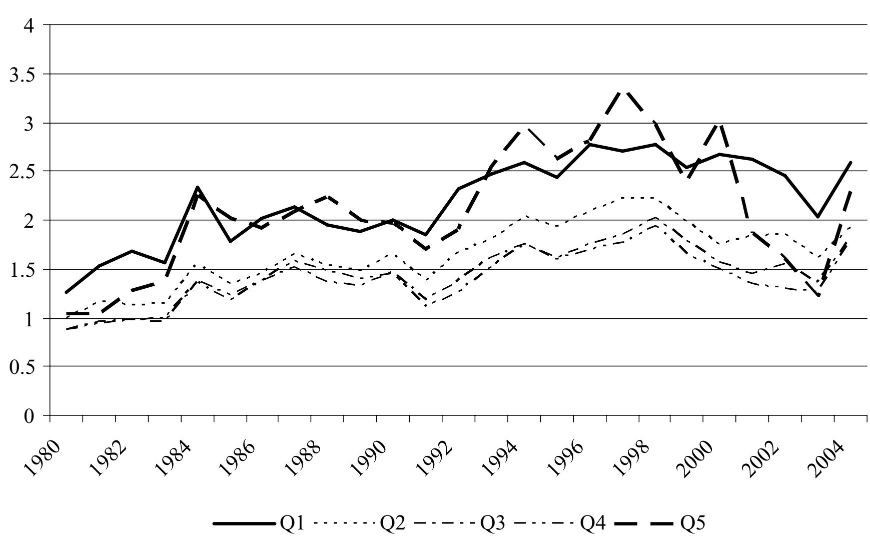


Figure 3. R&D and MTB by adjusted *O*-score quintiles. Firms are sorted into *adjusted O*-score quintiles and then median levels of market-to-book and RD/TA in each quintile are plotted over time. Figures based on unadjusted *O*-scores (Figure 1) are displayed here for comparison.

B *Research and Development*

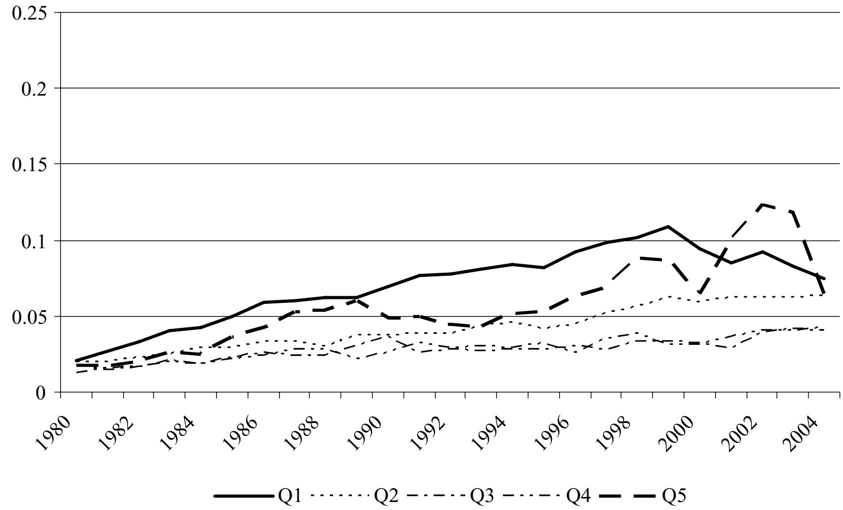


Figure 1B Research and Development (unadjusted)

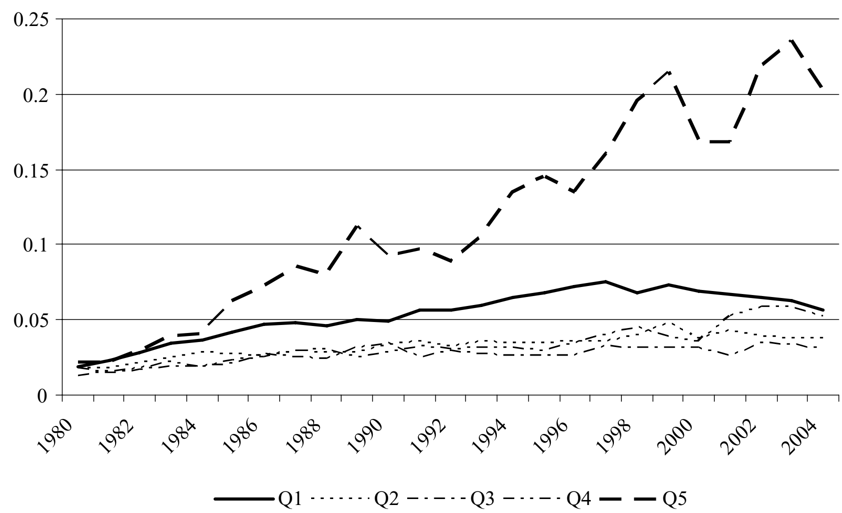


Figure 3. *(Continued)*

presented in Figure 1) with those for the adjusted *O*-score quintile rankings. In Panel A, we find that our *O*-score adjustments lead to yearly median market-to-book ratios in *O*-score quintile 5 that are predominately below the median market-to-book ratios for *O*-score quintile 1 firms. The adjustment process results in median market-to-book ratios across *O*-score quintiles that are more consistent with O-scores sorting firms based on financial distress (rather then levels of accounting distortions). Finally, Panel B suggests that the adjustment process results in lower median RD/TA in adjusted O-score quintile 5 firms and a less pronounced increase over time in the median RD/TA in adjusted O-score quintile 5 firms.

In Figure 4, we provide comparative evidence over time on how the percent of high and low quintiles of MTB and R&D intensity vary among firms misclassified as distressed from the original O-score 5 classification (presented in Figure 2) to the adjusted O-score 5 classification. We find that the adjustment process reduces the disparity between the percent of firms in O-score quintile 5 with high levels of R&D versus low levels of R&D. In Figure 4, Panel B, we find that the percent of firm-years in which O-score quintile 5 firms that do not declare bankruptcy is highest for firms with the highest R&D spending. However, the increasing trend observed in Figure 2, Panel B under the original O-score classification is no longer present. The adjustment process reduces the percentage of nonbankrupt R&D intensive firms in the O-score quintile 5 classification.

Figure 5 shows the cumulative difference over time in the number of bankruptcies occurring in the following 1 and 2 years after ranking by the original O-score quintile 5 classification versus the adjusted O-score quintile 5 classification.[12] The figure confirms that the adjustment process results in additional bankruptcy filings identified under the adjusted O-score classification. Under the adjusted O-score ranking, we identify 417 (718) total bankruptcy filings in the following 1 year (2 years) in O-score quintile 5, which is an additional 53 (92) bankruptcies from the figure reported under the original O-score ranking (see Table III). This represents a 14.6% (14.7%) improvement in identifying bankruptcies over the sample period. We find that the number of additional bankruptcies correctly identified by the adjusted O-score increases sharply in the 1990s.

In contrast, note the similar plot of the cumulative difference between the original Altman's Z-score quintile 5 and the adjusted Z-score quintile 5. It appears that the inclusion of the market value of equity makes the Z-score more robust to the changes that distort the O-score.[13]

$$Z\text{-}score = -1.2 * wcta - 1.4 * reta - 3.3 * Ebitta - 0.60 * mvliab - 0.999 * sata \tag{6}$$

$$\begin{aligned} Adj.\ Z = & -1.2 * (a\_wcta) - 1.4 * (a\_reta) - 3.3 * (a\_Ebitta) \\ & - 0.60 * mvliab - 0.999 * (a\_sata). \end{aligned} \tag{7}$$

[12] We look for firms that file for bankruptcy within the following 1 and 2 years since, as noted by Ohlson (1980), the time between the date of the fiscal year or the last relevant report and bankruptcy can be upwards of 13 months.

[13] This definition is consistent with the application of the Z-score in Hillegeist et al. (2004). The signs of the original coefficients have been changed so that the Z-score is increasing in the probability of bankruptcy (consistent with O-scores). Also, all of the coefficients except *SATA* are multiplied by 100 as in Dichev (1998).

A *Market-to-book*

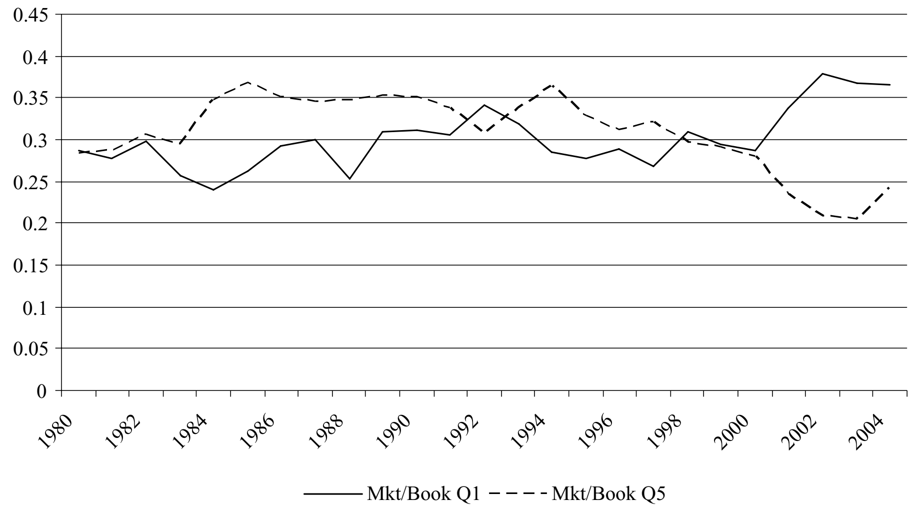


Figure 2A Market-to-book (unadjusted)

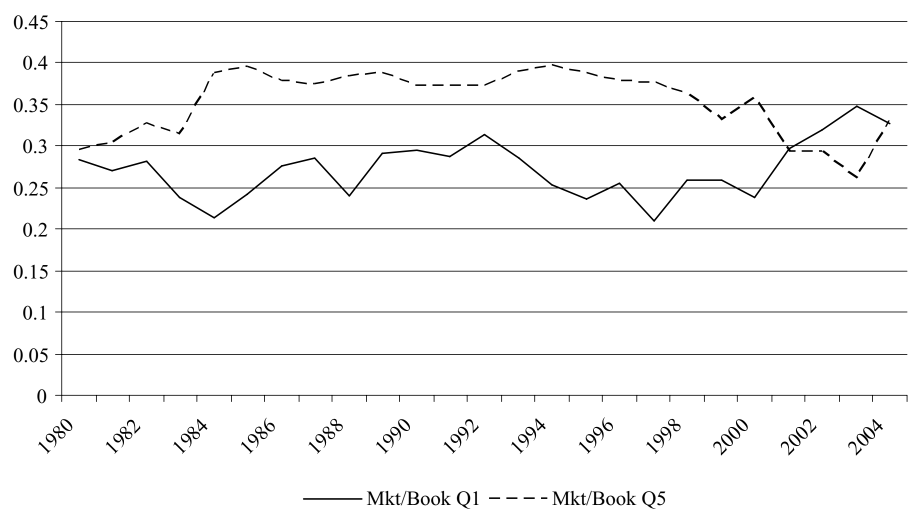


Figure 4. Solvent firms in adjusted *O*-Score quintile 5. These figures plot top and bottom quintiles of market-to-book and R&D to total assets for the subset of firms in adjusted *O*-score quintile 5 that did not file bankruptcy in the following period. Specifically, Figure 4A plots top and bottom market-to-book quintiles and 4B plots RD/TA over time. Figures 2A and 2B are again displayed here for comparison.

B *Research and Development*

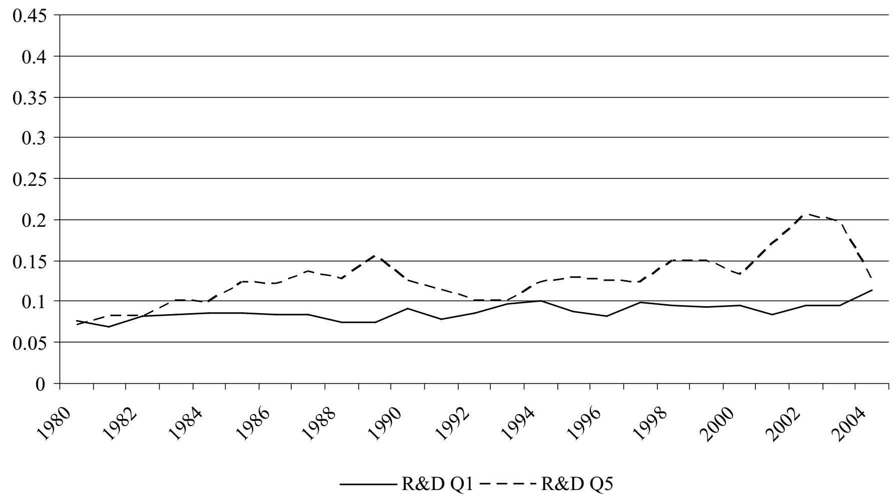


Figure 2B Research and Development (unadjusted)

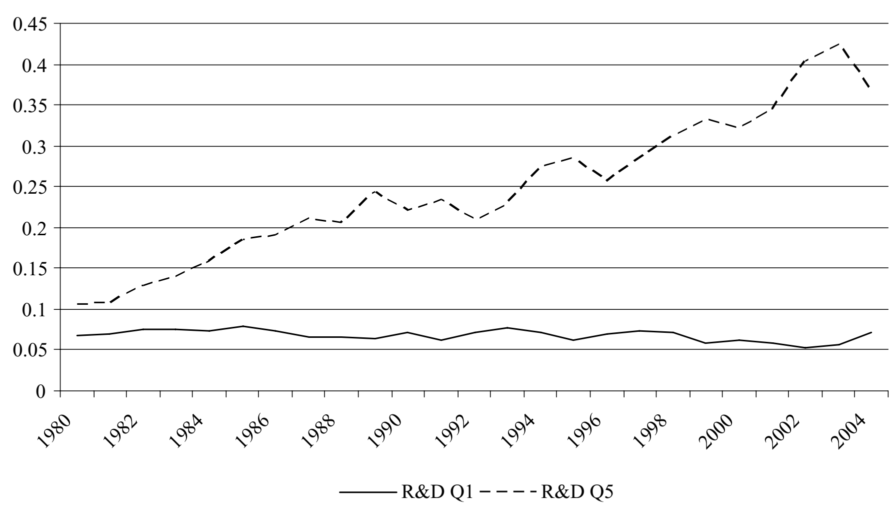


Figure 4. *(Continued)*

Adjusting Ohlson's accounting-based bankruptcy prediction model for the effects of R&D intensity improves related distress risk measures (employed by Dichev (1998) and Griffin and Lemmon (2002)) and reduces the likelihood that R&D intensive firms are confounding the results for samples of firms identified as distressed. In untabulated results, we investigate how the conservative accounting treatment of R&D spending affects the Altman Z-score, a measure that is not purely based on accounting indicators of distress. We find that, on

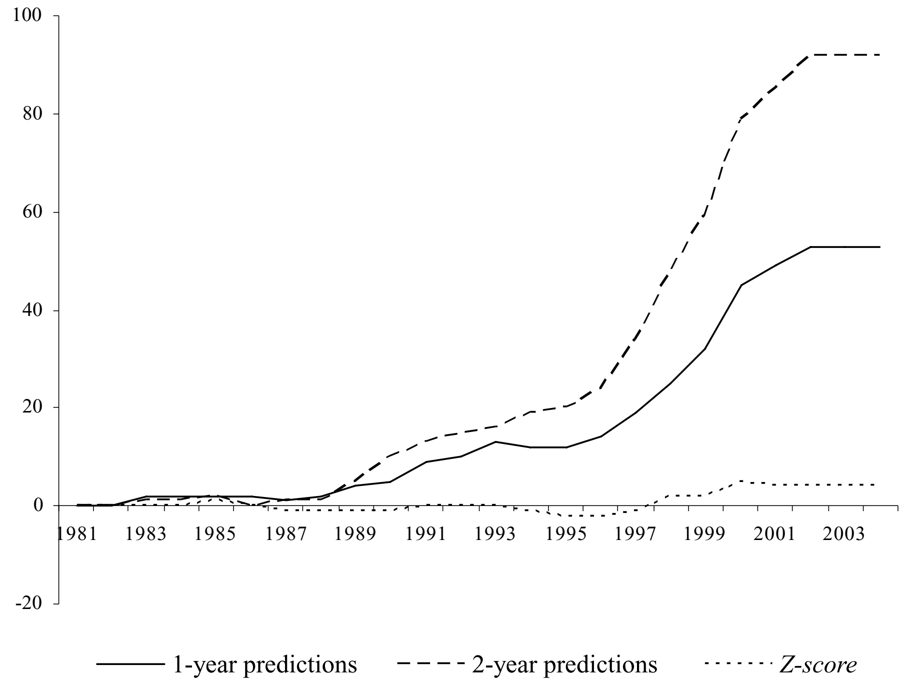


Figure 5. Cumulative differences in correct identification: After-tax adjustments. The solid (dashed) line plots the cumulative difference between the number of firms that filed for bankruptcy in the year (2 years) after being ranked in the top after-tax adjusted O-score quintile and in the top O-score quintile. The dotted line plots the cumulative difference between the number of firms that filed for bankruptcy in the year after being ranked in the top after-tax adjusted Z-score quintile and in the top Z-score quintile.

average across our sample period, R&D intensive firms that are classified under Z-scores as the most financially distressed are not more likely to be misclassified. However, from 1998 to 2003, we do find evidence-using Z-scores that R&D intensive firms are more likely to be misclassified as distressed and that adjustments to the Z-score measure for the conservative treatment of R&D do improve the ability of Z-scores to identify financially distressed firms.

We highlight the relative improvement in predictive ability from our simple adjustment for full expensing of R&D in three ways. First, we use the accuracy ratio developed by Moody's and utilized by Vassalou and Xing (2004).[14] This measure of predictive ability provides a single summary of accuracy for both Type I and Type II errors. Unfortunately, the accuracy ratio is only descriptive so we also include a formal test of predictive accuracy based on a matched sample contingency table. To assess the economic impact of using adjusted rather than unadjusted O-scores we compare the results from a simple bankruptcy score-based trading strategy.

[14] See Sobehart, Keenan, and Stein (2000).

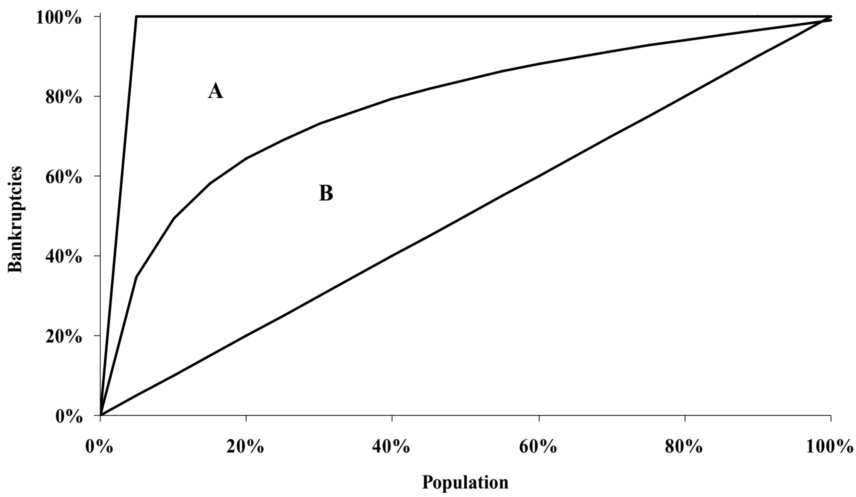


Figure 6. Empirical cumulative distributions of predictive ability. The kinked line is the empirical *CDF* in the case in which the *O*-score perfectly predicts bankruptcy. The straight line is the empirical *CDF* when the *O*-score contains no predictive content. The curved line is the empirical *CDF* of *O*-scores with some predictive ability.

C.2. The Accuracy Ratio

The intuition of the accuracy ratio (*AR*) is straightforward. For a given model we sort all firms by *O*-score from highest to lowest and divide the sorted *O*-scores into 100 equally sized bins. For each bin we find the percentage, $y(x)$, of firms that defaulted within the next year whose *O*-score is less than or equal to the largest *O*-score in the bin. A plot of the cumulative sum of these percentages is the empirical cumulative distribution function (*CDF*) of predictive accuracy. If the *O*-score worked perfectly, then the first bin would contain 100% of the bankrupt firms and the *CDF* would look like the kinked line in Figure 6. If the *O*-score contained no information, the bankruptcies would be evenly dispersed among the bins and the *CDF* would look like the straight line. If the *O*-scores have some predictive content, then the *CDF* would be the curved line.

The *AR* is the ratio of the area marked A to the sum of the areas of A and B in the figure and falls between zero and one, where an *AR* close to zero indicates an *O*-score ranking with little advantage over a random assignment of *O*-scores, while an *AR* near one indicates almost perfect foresight. The *AR* value is defined as

$$AR = \frac{2\int_0^1 y(x)\,dx - 1}{1 - f}, \tag{8}$$

where f is the fraction of defaults within the whole sample.

Panel A of Table VII contains the *AR*s for unadjusted and adjusted *O*-scores where each year we use the model rankings to predict bankruptcy in the

Table VII

Measuring Predictive Ability

Panel A displays accuracy ratios by year for rankings formed on *O*-score (*O*), adjusted *O*-score (*AO*), and the difference between the accuracy ratios. The top portion of Panel B contains the summary statistics for the simple trading strategy outlined in the text. The lower portion of Panel B gives the certainty equivalents over a range of absolute risk aversions (*ARA*).

Panel A: Accuracy Ratios

Year	*O*	*AO*	*AO-O*
1980	0.621	0.631	0.010
1981	0.583	0.587	0.004
1982	0.636	0.641	0.005
1983	0.544	0.538	−0.006
1984	0.532	0.553	0.021
1985	0.494	0.521	0.028
1986	0.410	0.441	0.032
1987	0.530	0.511	−0.019
1988	0.446	0.443	−0.004
1989	0.420	0.445	0.025
1990	0.411	0.420	0.009
1991	0.447	0.504	0.057
1992	0.380	0.385	0.005
1993	0.337	0.381	0.044
1994	0.428	0.409	−0.019
1995	0.375	0.417	0.042
1996	0.372	0.429	0.057
1997	0.451	0.495	0.043
1998	0.429	0.478	0.049
1999	0.477	0.561	0.084
2000	0.436	0.477	0.042
2001	0.466	0.511	0.045
2002	0.422	0.412	−0.010
2003	0.508	0.594	0.086
Mean	0.465	0.491	

Panel B: Value Weighted Spread Portfolios

	OH-OL	*AOH-AOL*
N	41	41
Mean	0.342	0.271
Median	0.278	0.305
Std. Dev.	0.583	0.388
Min	−0.531	−0.474
Max	2.981	1.631
Skewness	2.521	0.739
Kurtosis	12.095	5.303
Sharpe	0.587	0.699
ARA	Certainty Equivalents	
1	0.172	0.197
1.5	0.088	0.160
2	0.003	0.122

following year. While both models produce *AR*s that are on average below 50, the average *AR* from the model using conservatism-adjusted input data (49.1) is greater than the average *AR* using unadjusted data (46.5).[15] In 19 of the 24 years, adjusting *O*-scores produces a more accurate ranking and by this measure, a clearer picture of firm solvency.

C.3. A Formal Test

Since the model produces a probability of default used to sort firms into portfolios rather than a prediction of a value in a future period standard tests

[15] While the *AR*s might seem small, they are in line with those reported in Vassalou and Xing (2004), whose bankruptcy prediction model produces an *AR* of 0.59.

of predictive ability along the lines of Diebold and Mariano (1995), West and McCracken (1998), and Giacomini and White (2005) are not applicable. To circumvent this problem, we utilize a variant of McNemar's classical pair-wise contingency table test.

To form the contingency table, we first define a prediction as correct when the model's O-score sorts the firm into the highest O-score quintile and the firm files for bankruptcy within 2 years *or* the firm is sorted into any of the lower four O-score quintiles and the firm does not file within 2 years. Likewise, we define a prediction as incorrect when the model's O-score sorts the firm into the highest O-score quintile and firm does not file for bankruptcy within 2 years *or* the firm is sorted into any of the lower four O-score quintiles and the firm files within 2 years. Thus, based on these definitions, we can fill in the contingency table below, where n_{ij} is a count.

	Adj-O Predicts Correctly	Adj-O Predicts Incorrectly
O predicts correctly	n_{11}	n_{12}
O predicts incorrectly	n_{21}	n_{22}

The hypothesis of whether one method of ranking firms dominates in terms of predictive accuracy is equivalent to testing for symmetry in the above table. In particular, it is straightforward to show that the statistic

$$\frac{(n_{12} - n_{21})^2}{n_{12} + n_{21}} \sim \chi_1^2 \tag{9}$$

can be used to test H0: $p_{12} = p_{21}$, where p_{ij} is a probability.[16] In our sample $n_{12} =$ 2,863 and $n_{21} = 3{,}044$, producing a test statistic of 5.55 with a p-value of 0.019, which strongly rejects equal predictive ability. Together with the results that the adjusted O-score selects more firms that eventually file for bankruptcy, this test indicates that adjusting the O-score provides a more accurate prediction of distress.[17]

C.4. Certainty Equivalents

The accuracy ratio provides a summary of the informational content of the rankings provided by a given measure of bankruptcy, but it does not provide the economic cost of using one measure over another. In this section, we compare

[16] See Antoch and Hanousek (1999) for the formal derivations.

[17] Because the parameter estimates for the Ohlson model are constant for each firm-year prediction, the values of n_{21} and n_{12} may contain correlated data. Beginning in 1981, we re-estimate the parameters for the model each year using 1 year of historical data and recalculate the test. In this case $n_{12} = 3{,}792$, $n_{21} = 3{,}946$, and we reject equal predictive ability with a test statistic of 3.065, p-value $= 0.08$.

the results of a simple trading strategy whereby a fictional constant absolute risk aversion utility-maximizing investor purchases high probability of default firms and sells low probability of default firms, where the rankings of firms are made using adjusted and unadjusted *O*-scores. Each year our fictional investor purchases those stocks in the 90th percentile of the previous year's *O*-score ranking and shorts stocks in the lowest 10th percentile. Panel B of Table VII contains the summary statistics for this strategy based on both unadjusted and adjusted *O*-score rankings.

While the strategy based on the unadjusted *O*-score rankings has a higher expected return it also has more risk. The Sharpe ratio for the strategy based on adjusted *O*-scores is 20% higher, indicating a better investment opportunity for a risk-averse investor. The last three rows contain the certainty equivalents for three levels of absolute risk aversion. The certainty equivalent is the amount of return on a risk-free asset that produces the same level of utility as the risky investment.[18] Assuming our investor has a CARA normal utility function and invests all of her wealth, the range of risk aversion coefficients is reasonable based on the work of Mehra and Prescott (1985). As with the Sharpe ratios, the certainty equivalents indicate that the strategy based on adjusted *O*-scores dominates the strategy that uses unadjusted *O*-scores.

D. Distress Risk and Stock Returns

Griffin and Lemmon (2002) document the following findings for the returns of portfolios ranked separately on *O*-scores and book-to-market: (1) High *O*-score firms have return differentials between high and low book-to-market securities that are more than twice those of firms in the lowest *O*-score quintile (i.e., a large book-to-market effect), (2) firms with the highest *O*-scores and lowest book-to-market exhibit very low returns (one-half as large as any of the other portfolios returns), and (3) firms with the highest *O*-scores and lowest book-to-market have significant Fama–French (1993) three-factor model pricing errors. We demonstrate that for large firms in our sample, all three of these results are partially due to misclassification of low book-to-market firms as highly distressed due to conservative accounting of R&D activity.

In Table VIII, we replicate the results in Griffin and Lemmon (2002, Table II, page 2323). We sort firm-years into value-weighted portfolios based on *O*-score and book-to-market and present the annual buy-and-hold returns for both small and large firms following Griffin and Lemmon (hereafter G&L).[19] Panel A contains results based on unadjusted *O*-scores. These results are qualitatively similar to those reported in G&L. We find a large book-to-market effect for all *O*-score quintiles and spreads across book-to-market portfolios that are significant for all *O*-score rankings for small firms. In our sample the high *O*-score/low

[18] See Pratt (1964) and Mehra and Prescott (1985).

[19] We follow G&L and delete negative book value firms. For sorting we define book-to-market as total common equity divided by the value weighted return on the broad market index. Since our sample period differs from that used in G&L, we confirm, but do not report, that our results are qualitatively similar over the 1965 to 1996 period used in their study.

Table VIII

Average Buy-and-Hold Returns Sorted on *BE/ME* and *O*-score

The table presents the percentage value-weighted annual buy-and-hold returns over the period 1981–2003 for NYSE, NASDAQ, and AMEX firms for portfolios formed on original and adjusted *O*-score and book-to-market equity (*BE*/*ME*). Stocks are also ranked into two size groups. Groupings are based on breakpoints calculated using all securities. The three book-to-market equity groups are based on the 30 and 70 percentile breakpoints. The tests for statistical differences between groups are based on the time series of monthly returns. The high-minus-low *BE*/*ME* portfolio differences are calculated within distress groups by forming a portfolio that is long the high *BE*/*ME* portfolio and short the low *BE*/*ME* portfolio. Similarly, differences in financial distress portfolio returns are calculated using returns from a high distress minus low distress portfolio within each *BE*/*ME* grouping.

Panel A: *O*-score Sorts (1981–2003)

	BM of Small Firms						*BM* of Large Firms				
O	1	2	3	3-1	*p*-val	*O*	1	2	3	3-1	*p*-val
1	0.12	0.23	0.22	0.10	0.01	1	0.15	0.12	0.17	0.02	0.54
2	0.10	0.22	0.24	0.14	0.00	2	0.15	0.17	0.17	0.02	0.50
3	0.10	0.18	0.24	0.14	0.00	3	0.11	0.14	0.16	0.05	0.08
4	0.05	0.17	0.23	0.18	0.00	4	0.11	0.17	0.16	0.05	0.13
5	0.03	0.16	0.24	0.22	0.00	5	0.02	0.16	0.14	0.12	0.06
5-1	−0.09	−0.07	0.03			5-1	−0.13	0.04	−0.03		
p-val	0.10	0.09	0.51			*p*-val	0.00	0.38	0.68		

Panel B: *AT* Adjusted *O*-score Sorts (1981–2003)

	BM of Small Firms						*BM* of Large Firms				
Adj. *O*	1	2	3	3-1	*p*-val	Adj. *O*	1	2	3	3-1	*p*-val
1	0.13	0.24	0.26	0.13	0.00	1	0.16	0.13	0.17	0.02	0.62
2	0.16	0.23	0.26	0.09	0.35	2	0.14	0.17	0.18	0.04	0.27
3	0.07	0.18	0.25	0.17	0.00	3	0.13	0.14	0.17	0.05	0.14
4	0.06	0.16	0.22	0.15	0.00	4	0.07	0.17	0.17	0.10	0.01
5	0.00	0.14	0.21	0.21	0.00	5	0.09	0.15	0.12	0.03	0.67
5-1	−0.14	−0.10	−0.05			5-1	−0.06	0.02	−0.05		
p-val	0.00	0.00	0.32			*p*-val	0.33	0.70	0.40		

book-to-market portfolio also has very low returns (again, less than one-half as large as any other portfolio's returns for both large and small firms) and the 5-1 spread is significantly negative for low book-to-market firms. In untabulated results, the Newey-West t-statistic of the Fama and French (1993) model intercept for small (large) firms with high O-scores and the lowest book-to-market is −3.20 (−1.96).

In Panel B we report returns for the portfolios sorted using adjusted O-score and book-to-market portfolios. We find that sorting on adjusted O-scores dramatically affects the inferences drawn from buy-and-hold returns for large firms. Focusing on large firms, for the high O-score quintile, the significant book-to-market effect is eliminated. For the high O-score and low book-to-market portfolio we still find low returns, but the returns have increased from 2% to 9%, an increase that is significant at the 1% level. We also find that the spread between high and low O-score portfolios for the low book-to-market portfolio is cut in half and is no longer significant, and that the Fama and French model pricing error for this portfolio now has a t-statistic of -1.11.

Interestingly, adjustments to O-score classifications for the effects of conservative accounting of R&D activity have little impact on the inferences drawn from buy-and-hold returns for small firms. We still find a large book-to-market effect across all O-score quintiles and the returns for the high O-score, low book-to-market portfolio are marginally lower based on sorts using the adjusted O-score. Our results suggest that the observed returns for small firms with low book-to-market do not reflect misclassification of solvent R&D intensive firms. While the results reported by G&L may be overstated for large firms, they still reflect an unexplained anomaly. There should be no way to classify firms into portfolios with predictably different returns after controlling for risk. If the Fama–French factors control for priced risk, sorting firms into additional portfolios (O-score or otherwise) should not result in predictably different returns.

E. Tax Considerations

To provide evidence that our tax assumptions are not driving our results, we present evidence without any tax effects for all firms. In particular, we adjust O-score measures using equations (1) and (2) in Section C. Figure 7 shows that by simply adjusting O-score measures for the capitalization and amortization of research and development spending, bankruptcy prediction is improved. Thus, the improved predictive performance of our adjusted O-score measure is not due solely to our assumptions related to tax effects. We confirm, but do not report, that the results for all the measures of predictive accuracy in Table VII hold for this version of our adjustment.

F. The Issue of Stale Parameters

Our results clearly indicate less reliable prediction as R&D activity increases. However, it is possible that the trend of less reliable prediction is due to increasing staleness of the model parameters, regardless of the pervasiveness of certain accounting policies. As parameter estimates become stale over time, the deterioration in reliable prediction should manifest as both increased Type I and Type II errors, that is, we expect to increasingly misclassify bankrupt firms as solvent, and solvent firms as bankrupt. Table III shows instead that the increase in misclassifications over time is due to an increased propensity to incorrectly predict the bankruptcy of solvent firms.[20]

[20] The number of bankrupt firms that are incorrectly misclassified as solvent (lower O-score quintiles) remains fairly constant, and actually decreases in percentage terms over time.

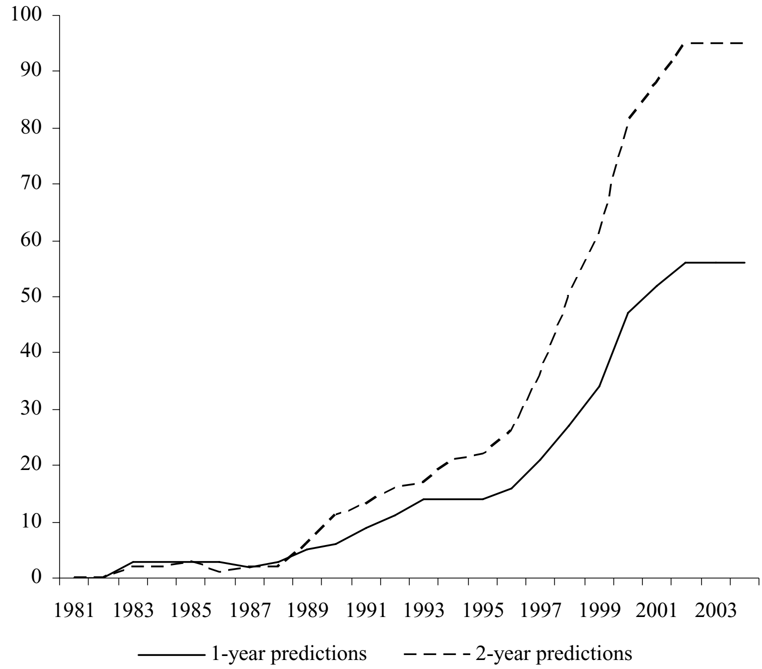


Figure 7. Cumulative difference in correct identification: Pre-tax adjustments. The solid (dashed) line plots the cumulative difference between the number of firms that filed for bankruptcy in the year (2 years) after being ranked in the top adjusted *O*-score quintile and in the top *O*-score quintile. The adjusted *O*-scores do not account for any tax implications.

Our results support the hypothesis that this one-sided deterioration in prediction accuracy is the result of an increase in R&D intensity and the method of accounting for such investment. The conservative GAAP treatment of R&D reduces net income (a fundamental input in accounting-based bankruptcy prediction models) to the point that (1) its mean and median values deteriorate even through periods of economic expansion (see Table II) and (2) re-estimating the *O*-score parameters results in counterintuitive estimates. We expect that accounting for R&D spending increases (decreases) the likelihood of incorrectly predicting bankruptcy (solvency) of solvent (bankrupt) firms. The data suggest this is the case.

To directly address the extent to which our results are driven by changes in accounting distortions as opposed to stale parameters, we re-estimate the Ohlson model parameters each year using 1 year of historical data and we use the most current parameter estimates to predict bankruptcies in the subsequent year. The rolling estimations guard against stale parameters, while using only 1 year of data per firm guarantees timely estimates.[21] Figure 8

[21] In six of the subsamples the presence of a small number of extremely large values in the financial ratios caused convergence problems. To deal with these cases, we Winsorize the independent data, except for the dummy variables, by setting observations beyond the 99.5 and 0.05 percentiles to the 99.5 and 0.05 percentiles.

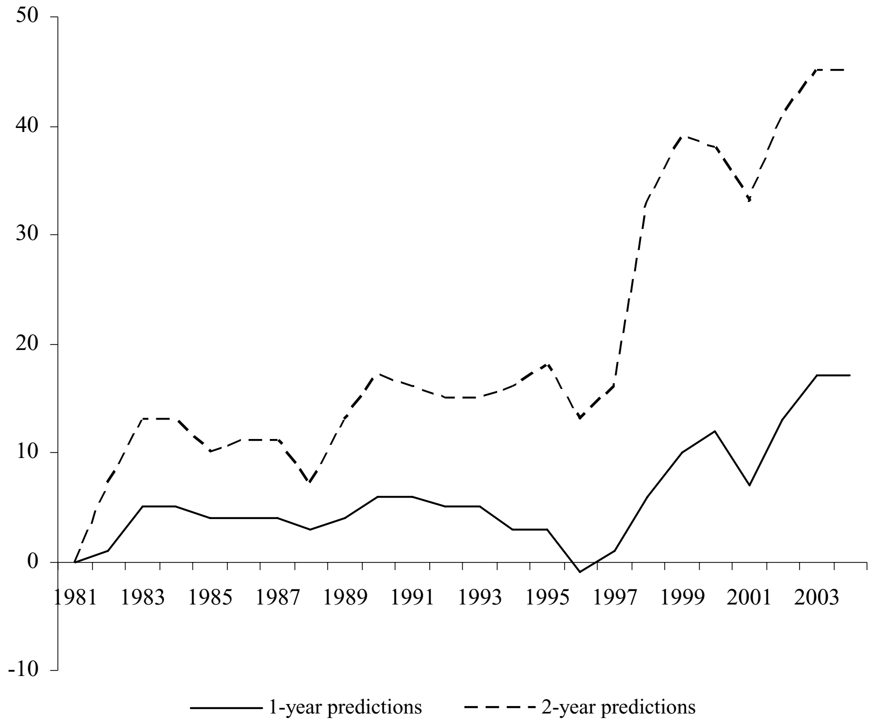


Figure 8. Cumulative differences in correct identifications, updated parameters. The solid (dashed) line plots the cumulative difference between the number of firms that filed for bankruptcy in the year (2 years) after being ranked in the top adjusted *O*-score quintile and in the top *O*-score quintile. Each year the parameters of the model are estimated using the previous one year of data and *O*-scores are recalculated.

contains the cumulative difference over time in the number of bankruptcies identified from the original *O*-score quintile 5 classification to the adjusted *O*-score quintile 5 classification. The lower line is the cumulative difference predicting bankruptcy in the following year. The upper line is the cumulative difference predicting bankruptcy within the following 2 years.

The difference in the success of adjusting for the full expensing of R&D between Figures 6 and 8 shows the impact of the forecast error due to using stale parameters. The cumulative difference is smaller in Figure 8 due to the removal of the errors attributable to stale parameters. Still, our adjustments improve in the latter years, when the effects of R&D intensity are most pronounced.

IV. Conclusion

We investigate the effect of R&D intensity on measures of distress risk based on Ohlson's (1980) *O*-score employed by Dichev (1998) and Griffin and Lemmon (2002). We find that accounting-based distress measures less accurately classify firms as R&D intensity increases over time. Specifically, otherwise healthy firms with higher R&D expenses are more likely to be misclassified as distressed. We report simple adjustments to correct the distorted *O*-score. We find that adjusting for conservative accounting treatment of research and development spending and the associated tax effects increases the number of correctly identified distressed firms over our sample period. Further, we find that adjusted measures of distress alleviate the previously documented low return and pricing error anomalies of large high distress risk firms with low book-to-market. We also document the impact of our adjustment beyond the effect of stale parameters. Our evidence raises concerns about results that rely on accounting measures of distress that incorrectly predict or control for distress risk.

The primary purpose of our paper is to demonstrate the effect of the conservative accounting treatment of R&D on ubiquitous accounting ratios over time—not to horse race bankruptcy prediction models. Simple models based on intuitive accounting ratios will likely remain the staples used among most academics, practitioners, and MBA classrooms. One source of improvement for the more complicated option pricing-based models put forth by Hillegeist et al. (2004) and Vassalou and Xing (2004) may be independence from changes in GAAP and accounting choices of the firm. For readers interested in a meaningful horse race of bankruptcy prediction models, our results provide a simple adjustment to models based on accounting measures.

While we focus on bankruptcy prediction to highlight distortions attributable to conservative reporting of R&D spending, researchers and practitioners rely on accounting ratios in a host of other contexts. Our results raise questions about the impact of accounting distortions in those lines of research as well. Empirical results relating market-to-book or earnings-based performance measures to capital structure, securities issuance, corporate governance, ownership structure, M&A activity, or managerial turnover across industries over time are also potentially affected by pervasive accounting treatments.

Finally, recognizing certain benefits of conservative financial reporting suggested by previous researchers, we do not prescribe less conservative accounting policies generally, nor do we advocate changes in the regulatory environment. Instead, we caution investors and researchers relying on the *O*-score, we suggest simple adjustments to this measure, and we note to corporate management this additional consideration when preparing financial statements and otherwise communicating with investors, analysts, customers, and suppliers.

Appendix A: Variable Definitions

MTB is the market-to-book equity ratio computed as end of period price per share (Compustat annual data item 199) multiplied by the number of shares outstanding (Compustat annual data item 25) to book value of equity (Compustat annual data item 60).

RD/TA is R&D expense (Compustat annual data item 46) divided by total assets (Compustat annual data item 6).

$$O\text{-}score = -1.32 - 0.407 * size + 6.03 * tlta - 1.43 * wcta + 0.0757 * clca - 2.37 * nita - 1.83 * ffotl + 0.285 * intwo - 1.72 * oeneg - 0.521 * chin. \tag{A1}$$

Size is the log of total assets (Compustat annual data item 6).
Tlta is total liabilities (Compustat annual data item 181) divided by total assets.
Wcta is working capital defined as current assets (Compustat annual data item 4) less current liabilities (Compustat annual data item 5) divided by total assets.
Clca is current liabilities (Compustat annual data item 5) divided by current assets (Compustat annual data item 4).
Nita is net income (Compustat annual data item 172) divided by total assets (Compustat annual data item 6).
Ffotl is funds from operations defined as pretax income (Compustat annual data item 170) plus depreciation (Compustat annual data item 14) divided by total liabilities (Compustat annual data item 181).
Intwo is a dummy variable equal to 1 when the firm has negative net income (Compustat annual data item 172) in the 2 prior years and 0 otherwise.
Oeneg is a dummy variable set equal to 1 if the firm has negative book value of equity (if total liabilities exceed total assets) and 0 otherwise.
Chin is change in net income (Compustat annual data item 172) defined as (net income$_t$ − net income$_{t-1}$)/(|net income$_t$| + |net income$_{t-1}$|).

$$Adjusted\ O\text{-}score = -1.32 - 0.407 * (a\_size) + 6.03 * (a\_tlta) - 1.43 * (a\_wcta) + .0757 * clca - 2.37 * (a\_nita) - 1.83 * (a\_ffotl) + 0.285 * (a\_int\ wo) - 1.72 * (a\_oeneg) - 0.521 * (a\_chin). \tag{A2}$$

Adjusted net income is net income (Compustat annual data item 172) plus R&D expense (Compustat annual data item 46) minus R&D amortization defined as 0.2 times the sum of the previous 5 years of R&D expense.

Adjusted total assets is total assets plus R&D capital defined as

$$RD_t + 0.8 * RD_{t-1} + 0.6 * RD_{t-2} + 0.4 * RD_{t-3} + 0.2 * RD_{t-4}.$$

A_size is the log of adjusted total assets.
A_tlta is liabilities divided by adjusted total assets.
A_wcta is working capital divided by adjusted total assets.

A_nita is adjusted net income divided by adjusted total assets.

A_ffotl is (pretax income plus R&D expense plus depreciation expense) divided by total liabilities.

A_intwo is a dummy variable equal to 1 when the firm has negative adjusted net income in the 2 prior years and 0 otherwise.

A_oeneg is 1 if adjusted total assets minus total liabilities is less than zero and 0 otherwise.

A_chin is (adjusted net income$_t$ − adjusted net income$_{t-1}$)/(|adjusted net income$_t$| + |adjusted net income$_{t-1}$|).

After-tax Adjusted O-score

$$\begin{aligned} &= -1.32 - 0.407 * (a\_size) + 6.03 * (at\_a\_tlta) - 1.43 * (a\_wcta) \\ &\quad + .0757 * clca - 2.37 * (at\_a\_nita) - 1.83 * (at\_a\_ffotl) \\ &\quad + 0.285 * (at\_a\_intwo) - 1.72 * (at\_a\_oeneg) - 0.521 * (at\_a\_chin). \end{aligned} \tag{A3}$$

After-tax adjustments are made for those firm-years with positive net income (Compustat annual data item 172). For firm-years with negative net income, the adjusted (pre-tax) model is applied.

After-tax adjusted net income is adjusted net income times (1 minus the tax rate).

After-tax adjusted total liabilities is total liabilities plus deferred tax liability defined as R&D capital times the appropriate annual statutory tax rate: 46% in the period 1980–1986, 40% in the year 1987, 34% in 1988–1992, and 35% in 1993–2005.

At_a_tlta is after-tax adjusted liabilities divided by adjusted total assets.

At_a_nita is after-tax adjusted net income divided by adjusted total assets.

At_a_ffotl is the sum of pretax income, R&D expense and depreciation expense divided by after-tax adjusted total liabilities.

At_a_intwo is a dummy variable equal to 1 when the firm has negative after-tax adjusted net income in the 2 prior years and 0 otherwise.

At_a_oeneg is 1 if the difference between adjusted total assets and after-tax adjusted total liabilities is less than zero and 0 otherwise.

At_a_chin is (after-tax adj. net income$_t$ − after-tax adj. net income$_{t-1}$)/(|after-tax adj. net income$_t$| + |after-tax adj. net income$_{t-1}$|)

$$Z\text{-}score = -1.2 * wcta - 1.4 * reta - 3.3 * Ebitta - 0.60 * mvliab - 0.999 * sata \tag{A4}$$

Wcta is working capital to total assets where working capital is current assets (Compustat annual data item 4) less current liabilities (Compustat annual data item 5).

Reta is retained earnings (Compustat annual data item 36) divided by total assets (Compustat annual data item 6).

Ebitta is earnings before interest and taxes (Compustat annual data item 170 plus Compustat annual data item 15) divided by total assets (Compustat annual data item 6).

Mvliab is market value of equity defined as end of period price per share multiplied by the number of shares outstanding (Compustat annual data item 199 times Compustat annual data item 25) divided by total liabilities (Compustat annual data item 181).

Sata is sales revenue (Compustat annual data item 12) divided by total assets (Compustat annual data item 6).

$$\begin{aligned} \textit{Adjusted Z-score} = &-1.2 * (a\_wcta) - 1.4 * (a\_reta) - 3.3 * (a\_Ebitta) \\ &- 0.60 * mvliab - 0.999 * (a\_sata) \end{aligned} \tag{A5}$$

A_wcta is working capital divided by adjusted total assets.

A_reta is the ratio of retained earnings plus adjusted total assets minus total assets to adjusted total assets.

A_Ebitta is the sum of adjusted net income, interest, and taxes divided by adjusted total assets.

A_sata is sales revenue divided by adjusted total assets.

REFERENCES

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589–609.

Antoch, Jaromir, and Jan Hanousek, 1999, A specification test for discrete choice models, Working paper, Prague Center for Economic Research and Graduate Education—Economic Institute.

Berger, Philip G., Eli Ofek, and Itzhak Swary, 1996, Investor valuation of the abandonment option, *Journal of Financial Economics* 42, 257–287.

Burgstahler, David, James Jiambalvo, and Eric Noreen, 1989, Changes in the probability of bankruptcy and equity value, *Journal of Accounting and Economics* 11, 207–224.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431–2457.

Collins, Daniel W., Edward L. Maydew, and Ira S. Weiss, 1997, Changes in the value-relevance of earnings and book values over the past forty years, *Journal of Accounting and Economics* 24, 39–67.

Collins, Daniel W., Morton Pincus, and Hong Xie, 1999, Equity valuation and negative earnings: The role of book value of equity, *Accounting Review* 74, 29–61.

Dichev, Ilia D., 1998, Is the risk of bankruptcy a systematic risk? *Journal of Finance* 53, 1131–1147.

Diebold, Francis X., and Roberto S. Mariano, 1995, Comparing predictive accuracy, *Journal of Business and Economic Statistics* 13, 253–263.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Francis, Jennifer, 1990, Corporate compliance with debt covenants, *Journal of Accounting Research* 28, 326–347.

Franzen, Laurel, 2002, The nature of losses and the value relevance of earnings, Working paper, University of Texas, Dallas.

Giacomini, Raffaella, and Halbert White, 2005, Tests of conditional predictive ability, *Econometrica* 74, 1545–1578.

Givoly, Dan, and Carla Hayn, 2000, The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics* 29, 287–320.

Griffin, John M., and Michael L. Lemmon, 2002, Book-to-market equity, distress risk, and stock returns, *Journal of Finance* 57, 2317–2336.

Han, Bong H., Ross Jennings, and James Noel, 1992, Communication of nonearnings information at the financial release date, *Journal of Accounting and Economics* 15, 63–86.

Hanlon, Michelle, 2003, What can we infer about a firm's taxable income from its financial statements? *National Tax Journal* 56, 831–863.

Hanlon, Michelle, Stacie Kelley Laplante, and Terry Shevlin, 2005, Evidence for the possible information loss of conforming book income and taxable income, *Journal of Law and Economics* 48, 407–442.

Hayn, Carla, 1995, The information content of losses, *Journal of Accounting and Economics* 20, 125–153.

Hillegeist, Stephen A., Elizabeth K. Keating, Donald P. Cram, and Kyle G. Lundstedt, 2004, Assessing the probability of bankruptcy, *Review of Accounting Studies* 9, 5–34.

Holder-Webb, Lori M., and Michael S. Wilkins, 2000, The incremental information content of SAS No. 59 going concern opinions, *Journal of Accounting Research* 38, 209–219.

Joos, Peter, and George A. Plesko, 2005, Valuing loss firms, *The Accounting Review* 80, 847–870.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization and value relevance of R&D, *Journal of Accounting and Economics* 21, 107–138.

Mehra, Rajnish, and Edward C. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145–161.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Pastena, Victor, and William Ruland, 1986, The merger/bankruptcy alternative, *Accounting Review* 61, 288–301.

Pratt, John W., 1964, Risk aversion in the small and in the large, *Econometrica* 32, 122–136.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Shumway, Tyler, 2001, Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business* 74, 101–124.

Sobehart, Jorge R., Sean C. Keenan, and Roger M. Stein, 2000, *Benchmarking quantitative default risk models: A validation methodology* (Moody's Investors Service).

Stone, Mary, 1991, Firm financial stress and pension plan continuation/replacement decisions, *Journal of Accounting and Public Policy* 10, 175–206.

Subramanyan, K. R., and John J. Wild, 1996, Going-concern status, earning persistence, and informativeness of earnings, *Contemporary Accounting Research* 13, 251–273.

U.S. Department of the Treasury, 1999, *The problem of corporate tax shelters: Discussion, analysis and legislative proposals* (U.S. GPO, Washington, D.C.).

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831–868.

West, Kenneth D., and Michael W. McCracken, 1998, Regression-based tests of predictive ability, *International Economic Review* 39, 817–840.

Zingales, Luigi, 2000, In search of new foundations, *Journal of Finance* 55, 1623–1653.