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THE USEFULNESS OF SHARE PRICES AND INFLATION FOR CORPORATE FAILURE PREDICTION

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Abstract

The present paper critically appreciates the usefulness of share prices for corporate failure prediction and suggests utilising macro-economic variables such as inflation to improve the predictive ability of existing models. The results indicate that the predictive ability of share price prediction models improves when adjusted for inflation, in addition, an assessment of the usefulness of the model derived through this research when inflation is omitted shows that only 50% of companies can be predicted as likely to fail more thn four quarters prior to the actual event. (JEL: G33)

Previous research on corporate failure prediction has examined the financial statements and the behaviour of share rates of return of firms some years before failure. Virtually, most of the models predicting corporate failure from financial statements have focused on one ratio (univariate analysis), have analysed a combination of financial ratios (multivariate analysis), or have used logistic analysis. In essence, the major criticism of univariate analysis is that it fails to analyse the interrelationships between different financial ratios.

Next, multivariate analysis utilises discriminant analytic techniques to examine the interrelationships between financial ratios and defines the best combination of weighted financial ratios that explains the financial profile of failed firms. Such analysis is resulted in the now-famous "Z-score" models of Altman [(1968), (1983) and (1984a,b)], Taffler and Tisshaw (1977), and Taffler (1982). These assess the likelihood of a firm failing by comparing the computed Z-score of the firm to the sample average score. In general, the predictive ability of these models was two to three years before failure actually occurred.

However, it should be noted, that there are several studies addressing the methodological or/and statistical problems associated with the use of multivariate analysis for failure prediction, including the following: Joy and Tollefson (1975), Eisenbeis (1977), Moyer (1977), Altman, et al. (1980), Zmijewski (1984), Jones (1987), and Piatt and Piatt (1990, 1991).

Finally, logistic analysis employs a firm's financial ratios, weights each of the ratio value by its respective coefficient and sums those products to produce a specific probability of failure for that firm (for example, Ohlson (1980), Zavgren (1985), and Peel and Peel (1987, 1988)). Note that the restrictive assumptions of discriminant analysis are not required and interpretation of individual coefficients is appropriate in the logit model. Nevertheless, several studies (for example, Ohlson (1980), and Casey and Bartczak (1985)) indicate that the utilisation of logit techniques does not bring significantly greater overall predictive power than the use of multivariate discriminant analysis.

To this end, the market-based models for failure prediction involve the examination of the behaviour of security rates of return some years before failure and then assess to what extent such a behaviour can provide useful signals (for example, successive abnormal losses) of a possible financial collapse. The examination of the behaviour of the rates of return of failed firms is of interest for a variety of reasons. Firstly, market based studies utilise continuous variables (that is, rates of return) rather than discrete variables (that is, financial ratios calculated from annual financial statements). Secondly, market based variables incorporate information beyond the financial information provided by firms. Thirdly, the examination of market data of failed firms provides an insight into the timing of failure, whereas financial ratio based models cannot provide. Finally, the share price is set regardless of the accounting method employed by the firm, while the financial information analysed is extracted from accounting statements. The latter, however, are not necessarily prepared on the same accounting base for each firm.

The particular focus of this study is to investigate how accurately corporate failure can be predicted by using share prices. Towards that end, two different models are employed for testing this hypothesis, these being, a single-index model and a multi-index model which includes expected inflation and unexpected inflation as two additional explanatory variables in the single-index model. There has been no previously published study utilising inflation in a multi-index model to predict corporate failure.

The paper is organised as follows: The first section reviews previous research on predicting corporate failure using share prices. The next section presents the data and the research methodology employed. The empirical results are analysed and compared to previous studies in the third and fourth sections. Th fifth and final section contains a summary of the paper.

1. A Critique of the Predictive Ability of Previous Market-based Models

By way of introduction, we might note that studies examining the behaviour of rates of return of failed stocks report that the capital market revises downward its valuation of those companies about to fail. Essentially, this downward revision shows a trend of losses in the share value which is not due of the movement of the market, these are called abnormal losses and the traditional methodology employed to pin-point when they occur is described in Section II. Obviously, the length of time before corporate failure occurs determines the predictive ability of the models used in previous studies. A summary of these studies is presented in Table 1.

Focusing on Column 5 of Table 1, we immediately see that the predictive power of previous share price models range from 1.25 years to 5.0 years prior to corporate failure, whereas Clark & Weinstein (1983) accurately predict corporate failure 1-3 days prior to the liquidation announcement. It might be useful at this point to note that the following factors may explain the differences in predictive ability shown in Table 1:

i. All studies analysed failures occuring over different time periods. In particular, Castagna and Mataloscy (1981) found that the predictive ability of share price models was better in times of economic stability than of economic instability.

ii. Theobald and Thomas (1982) explained that quarterly data produces a better predictive model because of a reduction in non-trading and non-synchroniation problems. When a firm's shares are not traded, a zero return is recorded and this in turn results in a biased data input to the ordinary least squares analysis. This bias is less when the observation interval is quarterly rather than monthly. On the other hand, non-synchronisation problems occur when the share price does not reflect business which has been done within the trading period and this problem becomes more acute as the time period shortens.

iii. Castagna and Matalocsy (1981) found that the difference in reporting times between Australia and the United States may account for some of the discrepancies between the times when the market shows a down turn in the share prices.

iv. Nearly all previous research has examined a sample of firms in a single industry category. However, it can be easily seen that due to the stock market experience in the high-risk computer industry, an analyst might predict corporate failure at an earlier date than in the engineering industry.

v. The methodology employed in each study is different in various respects. This may suggest that some studies' methodology is correct while others may require improvement.

Before leaving the present section, we think it is important to provide a brief assessment of the above factors. Indeed, the first factor indicated that macro-economic variables affect the length of time during which the market shows a downturn in the share price. No previously published research has incorporated such macroeconomic variables into a share price model in order to predict corporate failure. The second factor, helps explain some of the inaccuracies of monthly share price prediction models. Having said this, it may be better to assess the predictive ability of share price models in a period which is measured by the number of observations performed before corporate failure and not by the actual time scale.

Next, the third factor may explain some of the prediction differences between different countries but this does not explain the striking differences between studies conducted in the same country. Finally, the fourth factor may help to explain some of the differences between studies focusing on different industry categories.

Based on what has been said in this section, it was decided to analyse the results of the share price prediction model during periods of relatively high and relatively low inflation and to compare the results with those produced using the unadjusted market model.

II. Samples and Research Methodology

The London Share Price Database (1991) provided the necessary data for this study. We define failed firms as those that were liquidated, wound up by court order, or to which a receiver was appointed. We focused our attention to continuously listed firms in order to have the same number of observations. The discussion is continued by noting that the first sample for this study is selected according to the following criteria:

i. To minimise zero-return observations, firms must show little non-trading over the ten year period prior to corporate failure;

ii. To test predictive ability in periods of relatively high and lelatively low inflation the sample must contain both firms which had failed before 1980 (higher inflation) and those which became failed after 1980 (lower inflation); and

iii. To minimise the effect to differing industry trends, firms must be in the same industry category.

It should be noted that of the firms that failed during the period 1975-83, 40 fulfilled the second criterion, 25 fulfilled the first and second criteria and 20 fulfilled all three criteria together. More importantly, the sample of 20 firms shows minimal non-trading.

The second sample chosen is cimprised of 17 firms which failed during the period 1986-93. In essence, the second sample is used to examine how far the results related to the first sample are replicable on a different data set.

The methodology used to test the ability of share price information to predict corporate failure is similar to that of Theobald and Thomas (1982). Quarterly share returns are analysed by employing the market model:

$$\ln R_{jt} = \alpha_j + b_j \ln R_{mt} + e_{jt}$$

where

$\ln$ = the natural logarithmic operator

R_{jt} = the rate of return on security j for period t.

a_j = the intercept coefficient.

b_j = the measure of systematic risk or beta. It is equal to the covariance between the rates of return of j and m divided by the variance of the returns on m.

R_{mt} = the rate of return on the market index for period t.

e_{jt} = a residual reflecting the portion of share j's rate of return which is independent of the market index' rate of return. It is assumed that it has zero mean and constant variance. It is also assumed that the residual terms of different securities are independent of each other.

It is worth emphasising that the parameter values a_j and b_j must remain stable for the linear relationship of the market model to hold in every period under consideration. However, there is sufficient evidence indicating that UK security betas obtained from the market model exhibit instability over time (see Dimson (1979) and Diacogiannis (1987)). To cope with the problem of parameter instability, a 20 quarter moving average can be utilised in the ordinary least squares analysis.

The residual, e_{jt}, is the difference between the realized return on the security, InRjt, and the return obtained from their estimated equation, aj - bjInR$_m$t (where the market proxy m was represented by the FT-500 Share Index):

$$e_{jt} = \text{InRjt} - aj - 6j\ \text{InR}_m, \quad (1)$$

It is appropriate to note here that a special case of Equation (1) results when aj = 0 and Bj = 1. Nevertheless, this case will not be utilised in the present work since it seems intuitively unlikely that the mean beta of a small sample of failed firms will equal one. An alternative market model that is employed in previous studies (for example, Altman and Brenner (1981)) is a two-factor model that is consistent with the form of the two-parameter capital asset pricing model. However, Green (1986) concluded that the mean-variance inefficiency of a proxy generates benchmark errors. In this instance, the factor model used is clearly misspecified, a situation which will have the effect of biasing the residuals. Since there is not empirical evidence in UK indicating the validity of a two-factor models this model has not been employed in the present research.

Going still further, the analysis uses the Cumulative Average Residuals test pioneered by Fama, Fisher, Jensen and Roll (1969). The average residual, during period t, AR(t), is calculated for each period relative to the event date (period 0) as follows:

$$AR(t) = 1/N \sum^{N} e_{jt} \quad (2)$$

where

N = the number of firms in the sample in period t.

t = the time period which is measured relative to the event date.

The cumulative average residual for period t is obtained in the following manner:

$$CAR(t) = \sum_{t=-m}^{-1} AR(t) \quad (3)$$

where -m means m periods prior to the event date and -1 means the last period before the event date. The average residual neutralises firm-specific price variation unrelated to the event under consideration because that event did not occur at the same time for the firms in the sample.

In short, the cumulative average residual, CAR(t), can be interpreted as the cumulative deviation, in period t, of the rates of return of securities from their normal relationships with the rates of return of the index. Quite clearly, there is a gain if the value of the cumulative average residual is positive and a loss if the value of cumulative average residual is negative.

Finally, the following methodology adjusts the market model for inflation. The retail/consumer price index is used to measure inflation and the following formula computes the change in inflation per period:

$$IR_t = Inl_{t+1} - Inl_t$$

where

IR_t = the inflation rate in period t.

l_nI_t, l_nI_{t+1} = the retail/consumer price ondex' value in period t and t+1, respectively.

The stock returns should be significantly affected by two parts of inflation:

i. Expected inflation, $E(IR_t)$, it is measured as the inflation rate either in period t-1 pr t-2, and

ii. Unexpected inflation, $U(IR_t)$, where $U(IR_t) = IR_t - E(IR_t)$

Before leaving this section, note that the residual differences in returns at period t are calculated according to the following equation:

$$e_{jt} = InR_{jt} - \hat{a}_j - \hat{b}_{1j}InR_{mt} - \hat{b}_{2j}E(IR_t) - \hat{b}_{3j}U(IR_t) \quad (4)$$

where E(IRt) is lagged 1 and 2 periods. The cumulative average residual, in period t, can be calculated by using Equations (4), (2) amd (3).

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III. The Empirical Results Using a Sample of 20 Firms

A. Initial Tests

Univariate normality is measured in terms of the studentized range, skewness and kurtosis (see Fama (1976), p. 36, and Smith (1975)). The results (not reported here for considerations of space) revealed that fifteen of the twenty distributions of security returns exhibit statistically significant normality at the 95% level of confidence. However, seven distributions had computed studentized range, skewness and kurtosis value which only marginally exceeded the corresponding critical values at the 95% level of confidence. Additionally, the unexpected inflation's distribution exhibited non-normal behaviour due to the abnormal inflation rates. Since the main part of the inflation variable is $E(IR_t)$, the abnormal inflation rates should not disturb the calculation of the cumulative average residuals.

Next, Theobald and Thomas (1982) attempted to minimise the effects of non-trading problems in their analysis by using the Scholes and Williams (1977) estimator for alphas and betas. Casual inspection of Table 2 shows that there is very little difference in the calculation of residuals by the Scholes and Williams technique or by the traditional ordinary least squares method. As a consequence of this fact, there is no reason to employ the Scholes and Williams technique for this study.

The computed R^2 value for the relationship between the FT-500 and the inflation indices is marginally above 1%. This indicates, of course, that there is little multicollinearity between the two indices and gives sufficient justification to include the inflation variable in the sample.

B. Analysing the Estimated Parameter Values

The mean estimated parameter values from the ordinary least squares analysis are reported in Table 3 in which "REG A" represents the model without the inflation variables; "REG B" represents the model with the inflation variables, where expected inflation is measured as the inflation rate at quarter t-1; and "REG C" represents the model with the inflation variables, where expected inflation is measured as the inflation rate at quarter t-2.

In particular, the beta estimates are higher for the period ending well before liquidation. This suggests that stocks move less with the market and inflation as liquidation approaches and the residual term becomes more important. As quarter 0 approaches, the beta values are conistently below 1 indicating that failing stocks, on average, do not move strongly with the market and inflation.

Next, as failure approaches the alpha estimates are consistently negative. This results from liquidating stocks having maintained some abnormal losses in the period prior to evantual liquidation. Now, perusing the R^2 values presented in Table 3 we see that there is hardly any difference between "REG A", "REG B" and "REG C" from quarter -9 downwards. To be in a position to make more precise statements about the statistical significance of "REG A", "REG B" and "REG C" over time, we must use the F-test. The computed F value for the test of significance are displayed in Table 4.

Casual examination of Table 4 clearly reveals that there is a singificant relatiosnhip, at the 95% level of confidence, for "REG A" over the quarters -20 to -8 and for "REG B" and "REG C" over the quarters -20 to -6. More importantly, over the quarters -16 to -11 "REG B" and "REG *C"* are significant at the 99% level of confidence, whereas "REG A" is not. This may be explained by the fact that quarters -16 to -11 coincide with the beginning of the oil crisis in 1974. In consequence, the returns on the sample securities are better explained by the expected inflation, the unexpected inflation and the market index than by the market index alone over the period 1974-1978.

Note carefully that over the quarters -12 to -7 the statistical significance of "REG A" deteriorates becoming statistically insignificant at 95% level of confidence over quarters -6 to 0. Of course, the indicates that the specific risk of the firm plays a greater role in its final demise from quarter -6 until the corporate failure date. Between quarters -11 and -9 the explanatory power of "REG B" is less than "REG C" and towards quarter -8 the explanatory power of "REG B" is the greatest. This may happen because a firm which begins to experience severe financial distress will have less time to offset inflationary effects since management is preoccupied with saving the firm. This means that inflation will have a more immediate effect on the financial position of the firm as corporate failure approaches since management becomes unable to offset the short-term inflationary effects. Finally, it is worth noting that the economic period representing the sample quarters -10 to 0 is characterised by lower inflation and therefore, the significance of "REG B" may increase as corporate failure approaches under more detrimental inflationary conditions.

C. Analysis of the Cumulative Average Residuals

The time has come to turn to an analysis of the cumulative average residuals. In effect, Figure 1 depicts the cumulative average residuals for all firms during the twenty quarter periods before corporate failure.

Looking at "REG A" in Figure 1 it appears that the market begins marking down share prices of failing firms at least 3 years prior to corporate failure. This compares well with Castagna and Matalocsy (1981) and EI Hennaway and Morris (1983). Indeed, looking at the steep downward sloping line respresenting "REG A" it is little wonder that previous researchers have found the market model to be a very glamorous way of predicting corporate failure. However, as emphasised earlier, "REG B" and "REG C" best explains the security movements between quarters -16 and -11. Therefore, although "REG A" looks dramatic, "REG B" and "REG C" must be used to predict corporate failure for this sample.

At this stage note that "REG B" and "REG C" show, on average, abnormal losses commencing at quarter -9. Looking at the trends it must be said that even at quarter -3 there is a minor upward movement towrds the zero cumulative average residual level. This upward movement indicates that the risk of severe financial distress may be avoided and corporate failure cannot be clearly predicted until 2 quarters before it happens.

Next, the cumulative average residuals' trends for pre-1980 failures and post-1980 failures are shown graphically in Figures 2 and 3.

By referring to Figure 2 we see that under periods of relatively high inflation the market seems to consistently mark down share prices at quarter -1. Moreover, all other cumulative average residuals' values gravitate towards zero over the time period. "REG B" and "REG C" does not show any conclusive predictive ability over the last 20 quarters. There is, therefore, no conclusive evidence that corporate failure can be predicted under periods of relatively high inflation.

As can be seen by inspection Figure 3, "REG B" and "REG C" follow a very similar trend. This is presumably because the post-1980 era is associated with slowing inflation. Towards this end, there is less need to manage the effects of inflation and a sready trend emerges.

D. Analysis of the Cumulative Residuals

The trends of each individual company were analysed in the manner described in part C and tested according to whether there was a continuous downturn of results in the comulative residuals for at least 4 quarters prior to corporate failure.

Having analysed the trends, the average cumulative residual value of each firm was compared to the sample average cumulative residual and the cumulative average residual at corporat failure. Specifically, the sample average cumulative residual of the failed firms over the quarters -8 to 0 is -0.25 (post-1980) and -0.302 (pre-1980). On the other hand, the cumulative average residual at corporate failure is -0.43 (post-1980) and -0.45 (pre-1980). The tests are outlined as follows:

i. Any firm which has an average cumulative residual over the 8 quarter period prior to corporate failure lower that the sample average cumultive residual is in financial distress.

ii. If the average cumulative residual for any period over th last 8 quarters prior to corporate lailures is lower than the cumulative average residual at corporate failure, then there is a high probability that the firm will fail.

The results of the above analysis, shown in Table 5, convey the poor predictive ability for both pre- and post- 1980 failures. It should be recognised that the prediction accuracy increases under a mean comparison but it is doubtful whether an investment analyst would be able to predict corporate failure without analysing a trend of the share return residuals.

The Results Using a Sample of 17 Firms

The purpose of this section is to investigate how far the results presented earlier are replicable on a different data set. We use rates of returns for 17 firms which had failed between the years of 1986 and 1993. Once again, parameter estimates (not reported here for considerations of space) were generated by the ordinary least squares method using quarterly data defined in continuous time frame. For "REG A", "REG B" and "REG C" the estimates for alpha were consistently negative and the beta estimates were consistently below 1 as the eventual collapse approaches.

In effect, these results are quite consistent with those presented earlier in

Section III. We now turn our attention to the coefficient of determination. Specifically, the R^2 for "REG B" and "REG C" was relatively higher than that of "REG A" over the quarters -20 to -11. F tests indicates that at the 99% level the returns on the sample securities were marginally better explained by "REG B" and "REG C" rather than "REG A". Moreover, "REG B" and "REG C" reveal abnormal profits over the quarters -8 to 0. However, corporate failure can be clearly predicted 3 quarters before it happens (see Figure 4 for a graphical exposition of the cumulative average residuals).

One final point is that having applied similar tests to those presented in Section III, part D, the analysis revealed that failure can be predicted for only 58% of the firms under consideration. This, predictive ability is notably poor, a conclusion similar to that reported earlier.

V. Conclusions

The conslusion to be drawn from the analysis of the behaviour o share return residuals of 20 firms that failed during the period 1975-83 are as follows:

i. Considering the model without the inflation variables, companies which failed have established, on average, negative excess returns at least three years prior to failure. Based on a graphical analysis of the individual company cumulative residuals the predictive ability of the model seems to be much less attractive than the steep downward sloping line of cumulative average residuals. Additionally, this analysis predicted corporate failure for only 50% of firms (post-1980) and 16% of firms (pre-1980). This predictive ability is notably poor. Based on a comparison of the average cumulative residuals with the sample average cumulative residual the ability of the model to predict corporate failure increases. The question to be asked is whether an investment analyst would make a definite prediction on such a comparative basis without looking at the underlying trend of the share price residuals for the individual firm.

ii. Inflation is justifiably employed to predict corporate failure even though previous research has not published this finding. In effect, the market model plus expected inflation plus unexpected inflation (where expected inflation is measured as the inflation rate at period t-2) is the best explanation of the variation in the sample security returns over quarters -16 to -11. This indicates that the further the form is from corporate failure the better it can hedge the effects of inflation and therefore the significance of inflation increases as the period of lag is increased to 2 periods.

iii. Looking at the models with the inflation variables and utilising the cumulative average residuals for all firms, abnormal losses are being made, on average, commencing at quarter -9. However, failure cannot clearly be predicted until two quarters before it happens.

Finally, the present work employs a second sample of 17 firms which failed between 1986 and 1993 and concludes approximately similar results to those derived using the first sample of 20 firms.

* The authors are greatful to I. Lamour who has provided helpful suggestions on the topic.

TABLES 1
Market Anticipation of Corporate Failure: A Summary of Previous Studies

Author(s)/ Country / (Year)	Period	No of Companies	Time Interval Used	Trend of Abnormal Losses Before Failure
Beaver/US/ (1968)	1954-64	79	month	2.45 years
Westerfield/US/ (1970)	1957-67	20	quarter	5.00 years
Gooi/UK/ (1974)	1964-69	26	quarter	1.25 years
Pettway/US/ (1980)	1972-76	20	month	2.00 years
Aharony et al/US/ (1980)	1970-78	45	quarter	4.50 years
Altman and Brenner/ US/(1981)	1960-63	92	month	4.00 years
Castagna & Matalocsy/ Aus/(1981)	1962-78	42	month	2.50 years
Theobald & Thomas/ UK/ (1982)	1972-77	24	quarter	1.50 years
Clark & Weinstein/ US/ (1983)	1962-79	25	day	1-3 days
El Hennaway & Morris /UK/(1983)	1960-71	20	quarter	5.00 years

TABLE 2
Average Residuals for a Sample of 20 Firms Utilising the Ordinary Least Squares and Scholes & Williams Methods (the Model is not for inflation)

Quarter Before Failure	Average Residuals	
	Ordinary Least Squares	Scholes & Williams
-20	-0.022	-0.026
-19	-0.040	-0.043
-18	0.018	0.020
-17	-0.026	-0.023
-16	-0.025	-0.022
-15	-0.040	-0.039
-14	-0.013	-0.013
-13	-0.024	-0.025
-12	-0.031	-0.032
-11	-0.017	-0.016
-10	0,049	0.038
-9	0.006	0.005
-8	-0.082	-0.083
-7	-0.050	-0.042
-6	-0.083	-0.082
-5	-0.102	-0.092
-4	-0.116	-0.132
-3	-0.054	-0.063
-2	-0.047	-0.058
-1	-0.017	-0.015
0	-0.012	-0.014

TABLE 3
The Mean Estimated Parameter Values from the Ordinary Least Square

Quarter Before Failure	a	"REG A" B	R^2	a	"REG B" B	R^2	a	"REG C" B	R^2
-20	0.043	0.953	0.23	0.033	0.503	0.37	0.063	0.453	0.38
-19	0.043	1.023	0.24	0.023	0.453	0.38	0.043	0.483	0.36
-18	0.033	1.013	0.25	0.043	0.473	0.43	0.023	0.493	0.42
-17	0.033	1.023	0.26	0.033	0.423	0.46	0.053	0.513	0.45
-16	0.023	1.093	0.27	0.023	0.523	0.49	0.073	0.543	0.50
-15	0.023	1.043	0.26	0.033	0.653	0.47	0.023	0.553	0.48
-14	0.033	1.033	0.24	0.053	0.783	0.41	0.043	0.633	0.43
-13	0.013	1.063	0.23	0.083	0.883	0.36	0.063	0.673	0.37
-12	0.013	1.083	0.15	0.093	0.923	0.35	0.073	0.723	0.36
-11	0.013	1.123	0.15	0.103	0.983	0.29	0.093	0.853	0.30
-10	0.003	1.183	0.14	0.083	0.963	0.23	0.103	0.953	0.25
-9	-0.013	1.033	0.14	0.053	0.853	0.15	0.043	0.823	0.17
-8	-0.023	0.953	0.13	0.073	0.873	0.16	0.033	0.873	0.15
-7	-0.023	0.963	0.13	0.043	0.833	0.16	0.063	0.813	0.16
-6	-0.033	0.873	0.12	0.023	0.773	0.15	0.013	0.763	0.16
-5	-0.033	0.863	0.12	0.013	0.853	0.14	0.013	0.833	0.14
-4	-0.043	0.773	0.09	-0.023	0.943	0.10	0.023	0.733	0.09
-3	-0.043	0.653	0.07	-0.033	0.713	0.09	-0.033	0.693	0.10
-2	-0.043	0.543	0.07	-0.043	0.763	0.08	-0.053	0.653	0.08
-1	-0.053	0.653	0.07	-0.053	0.793	0.07	-0.063	0.693	0.07
0	-0.053	0.663	0.08	-0.063	0.723	0.05	-0.063	0.643	0.05

TABLE 4
F-Test of Significance for the
"REG A", "REG B" and "REG C"*

Quarter Before Failure	"REG A"	"REG B"	"REG C"
-20	7.40	4.32	3.50
-19	7.63	4.64	3.65
-18	7.44	4.72	3.80
-17	7.43	4.92	4.56
-16	7.20	5.39	5.44
-15	7.10	5.36	5.40
-14	6.76	5.34	5.38
-13	6.45	5.31	5.32
-12	6.32	5.30	5.30
-11	5.10	5.23	5.27
-10	5.01	5.21	5.01
-9	4.63	5.04	4.78
-8	3.92	4.52	4.62
-7	3.73	4.64	3.54
-6	3.53	3.02	3.05
-5	3.64	3.13	3.16
-4	3.83	2.96	3.02
-3	3.95	2.87	2.98
-2	4.03	2.66	2.86
-1	4.07	2.65	2.83
0	3.92	2.72	2.74

Based on the degrees of freedom and an observed quantity of 20 the critical values are:

LEVEL OF CONFIDENCE	"REG A"	"REG B"	"REG C'
95%	4.41	3.16	3.16
99%	8.29	5.29	5.29

If the computed Value of F exceeds the critical F - value at x percent level of confidence, then the model significantly explains the variation in the dependent variable

TABLE 5
The Usefulness of Share Price Residuals for Corporate Failure Prediction

	% Accurately Predicted As Failed	
Period	Trend	Mean Comparison
Pre 1980	16%	33%
Post 1980	50%	50%

	% Accurately Predicted As in Financial Distress	
Period	Trend	Mean Comparison
Pre 1980	16%	50%
Post 1980	50%	50%

Figure 1: Cumulative Average Residuals for All Firms Based on a Sample of 20 Firms

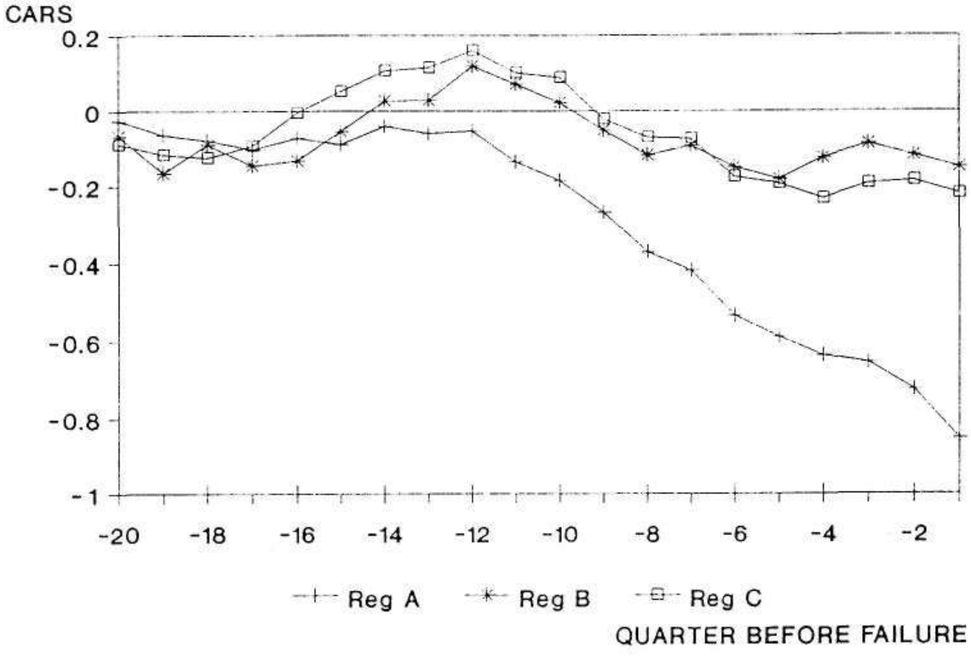


Figure 2: The Cumulative Average Residuals for the Pre-1980 Failures

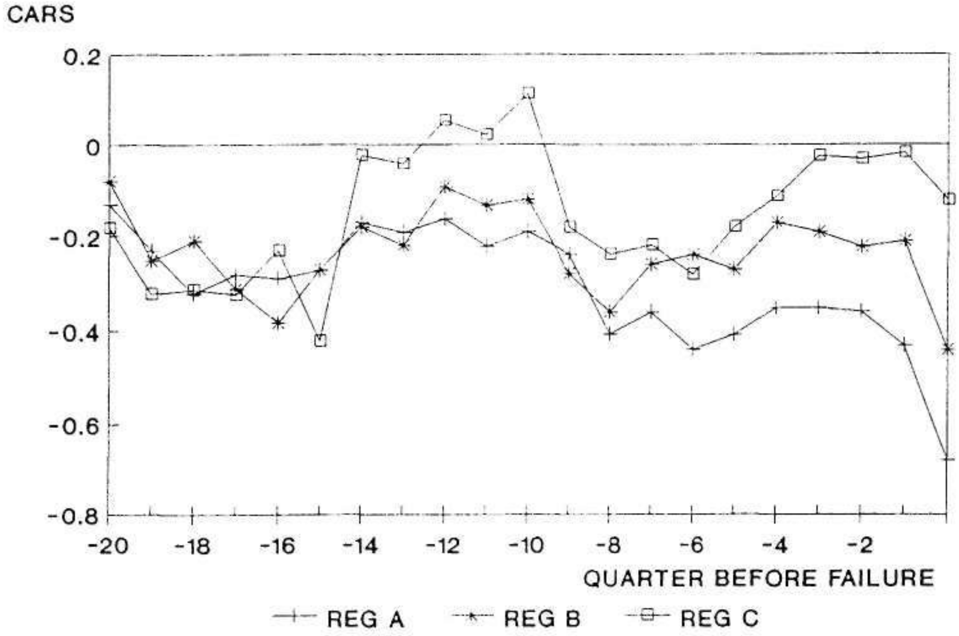


Figure 3: Cumulative Average Residuals for the Post-1980 Failures

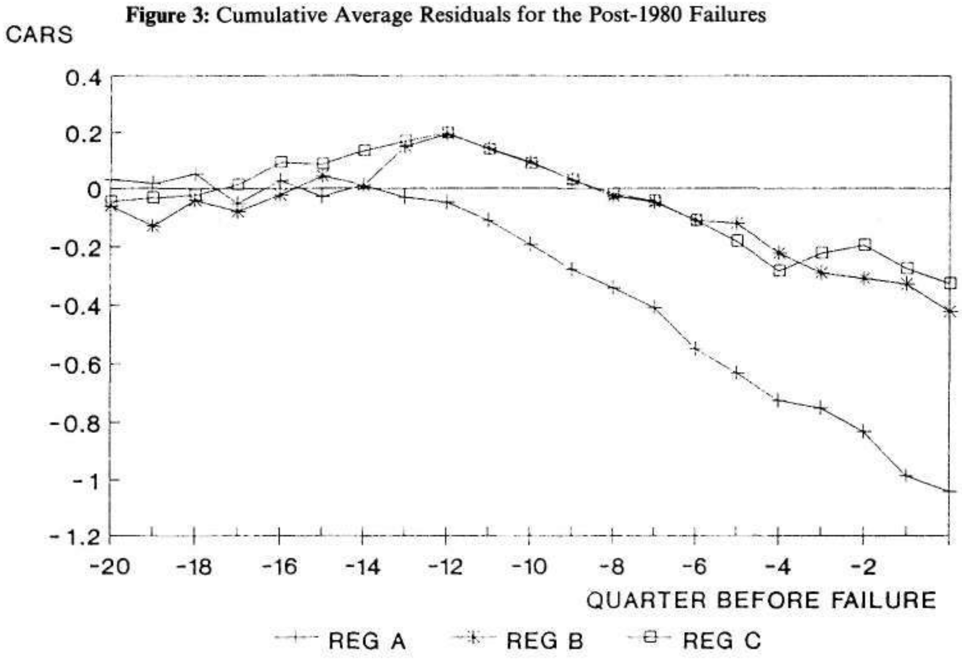
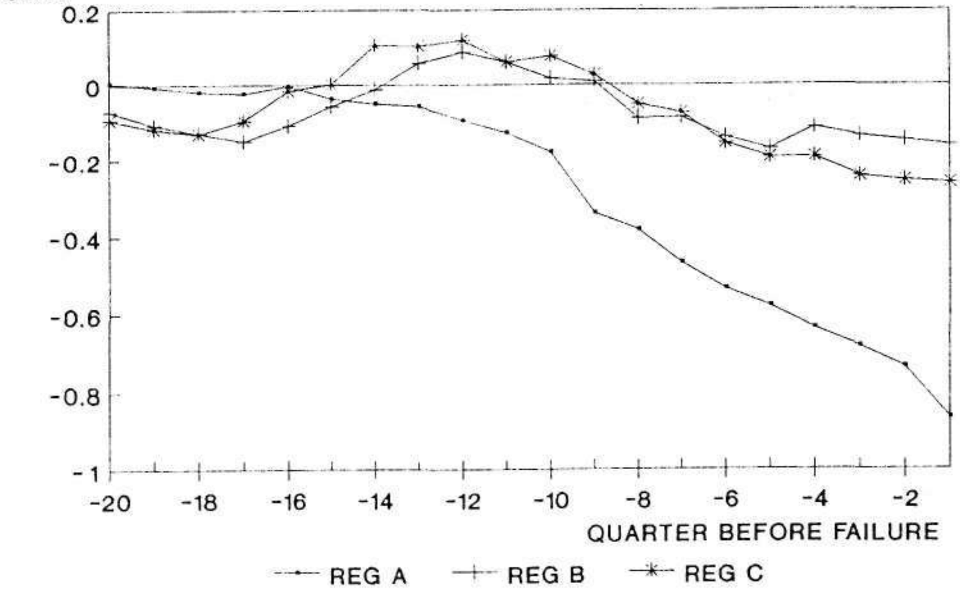


Figure 4: Cumulative Average Residuals for All Firms
Based on a Sample of 17 Firms



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