A PANEL ANALYSIS OF UK INDUSTRIAL COMPANY FAILURE

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Abstract

We examine the failure determinants for large quoted UK industrials using a panel data set comprising 539 firms observed over the period 1988-93. The empirical design employs data from company accounts and is based on Chamberlain's conditional binomial logit model, which allows for unobservable, firm-specific, time-invariant factors associated with failure risk. We find a noticeable degree of heterogeneity across the sample companies. Our panel results show that, after controlling for unobservables, lower liquidity measured by the quick assets ratio, slower turnover proxied by the ratio of debtors turnover, and profitability were linked to the higher risk of insolvency in the analysis period. The findings appear to support the proposition that the current cash-flow considerations, rather than the future prospects of the firm, determined company failures over the 1990s recession.

JEL Codes*:* G33

Keywords: Company Failure Risk, Unobserved Heterogeneity, Conditional Fixed Effects Logit Model.

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1. Introduction

The innovation in this paper follows from the use of both time-series and cross-section data to model the empirical determinants of company failure on large quoted industrial UK firms observed over the period 1988-93. Numerous studies, employing cross-sectional data and independent variables derived from accounts, have provided models that have proved useful for the identification of poorly performing companies with financial profiles similar to those of firms placed into regimes of legal insolvency. **Taffler and Tisshaw** (1977), **Marais** (1979), **Taffler** (1982), **Goudie** (1987), **Goudie and Meeks** (1991), **Cosh and Hughes** (1995) have modelled financial failure as a classification problem, where the binary response variable falls into one of two classes: failed firms and non-failed firms, and the risk of failure is then quantified using discriminant analysis combined with cross-sectional data and covariates purely based on accounting measures. An alternative approach based on logit, which has been used to model the causal relationship from firm's attributes to the probability of failure was utilised by **Peel, Peel, and Pope** (1986), **Keasey and McGuinness** (1990), and **Morris** (1997). Recent UK work by **Alici** (1995), **Tyree and Long** (1995), and **Wilson, Chong, and Peel** (1995) has employed a newer, but statistically less well defined analytical approach of neural networks to classify the data.[1]

The objective of the present study is to extend existing work by using a panel of UK quoted companies that spans 1988-93 and reflects changes in financial performance over a recession period.[2] This extension to panel data is based on **Chamberlain's** (1980) conditional logit model with a binomial response. Aside from providing larger numbers of observations, which allows one to alleviate the cross-sectional problem of over-sampling the failed category relative to the proportion of failed companies in the population, a panel data set enables one to carry out more sophisticated statistical analysis and to increase the likelihood that valid conclusions regarding found associations between the failure outcome and firm's attributes, are drawn. For instance, we may wish to take account of unobserved heterogeneity across firms by applying fixed and random effects models. While cross-section estimates of company failure determinants are likely to suffer from the problem of omitted variable bias, the use of panel data is one solution to the problem of controlling for underlying additive individual effects. Many company characteristics might tend not to vary over time, especially over short periods. In addition to that, certain firm-specific attributes are simply undetectable in a cross-sectional data set but nonetheless are likely to influence company performance and therefore to be correlated with observable financial ratios. Company failure is a multi-dimensional process. It is likely that the following unobserved individual effects are linked to the probability of failure: the firm's sales exposure to export,[3] organisation and ownership structure,[4] technological and managerial qualities, "know-how" stock, industry-specific influences,[5] aspects of the business location, industrial union power,[6] as well as vulnerability to external shocks explained by a particular type of debt finance that can be issued, for instance, either at fixed rate or at variable-rate.[7] The existence of firm-specific effects seems to be consistent with the view that selection effects of recessions are unevenly spread amongst firms (see e.g. **Geroski and Gregg**, 1996; **Morris**, 1997). In other words, a panel data set may be more robust to incomplete model specifications. Finally, in the panel of UK quoted firms, the data on failing firms are synchronised with the data on companies that survived the economic downturn of 1990-92.

The structure of the paper is as follows. Section 2 introduces the panel dataset. Section 3 turns to the explanatory variables in our model. Section 4 deals with issues of model specification and estimation and section 5 presents the main results.

2. The Sample

We define company failure as the event of entering a legal insolvency regime (administrative receivership, or administration, or winding-up, i.e. liquidation). That allows us to employ in model development a binary response describing the failure outcome, which takes the value 1 in the year the failing company published the last set of accounts and 0 otherwise. The data for the present panel study of company failure consist of company accounts' items and market valuation information for the six-year period 1988-93 and were extracted from the DATASTREAM database in 1997. The data set is a moderately sized unbalanced panel, constituting 539 individual quoted industrial companies, 56 of which discontinued publishing financial records over these six years due to entering a legal insolvency regime. Such short and wide panel appears common of data employed in microeconomic studies (see e.g. **Greene**, 1997), where a relatively large number of individual units is observed over the quite small number of periods. Our panel is unbalanced as we equate the date of failure with the fiscal year, in which, according to the DATASTREAM records, the failing company issues the last set of accounts. Therefore, this calendar year is considered as the firm's last year in the panel. In our sample, a failed company terminates reports from twelve to twenty months before insolvency proceedings commence, while a choice of the particular sample period of 1988-93, is a reflection of those lead times. The years of sample data were arrived at via identification the dates of release of the last accounts of: (i) firms, where formal insolvency was concurrent with the 1990-92 recession, and (ii) companies, where failures might have resulted from operations during the recession, even though the recession phase had actually ended before the date of insolvency.

Transition of companies within the unbalanced panel can be seen in Table 1. Since failing companies exit the panel, the sub-panel of failed firms is unbalanced. In contrast to the failed company category, 483 non-failing firms are being followed over the whole six-year period of the panel, meaning that the resulting sub-panel of non-failed firms is complete and rectangular. Names of 59 quoted industrial companies that entered insolvency state in the early 1990s, have been identified by using various editions of the London Stock Exchange Official Yearbook. Non-failed company names were taken from the DATASTREAM "live" list of quoted industrials as of 13 February 1997.[8] We intend to base the panel analysis upon the fixed effects estimator, from which inference is drawn with respect to the effects that lie within the sample. Therefore it was essential to include in the data set all quoted industrials with consistently available records for the period. We selected 483 non-failed firms with continuos records over the late 1980s and through to mid 1990s. The non-failed category is deliberately "over-sampled" to resemble the actual incidence of insolvencies in the population. Annual rates of failures in the constructed panel vary from 1.01 to 3.34 per cent (Table 1). In terms of company mix, the population of firms selected is restricted by the exclusion of companies from the petroleum, transportation, and financial services sectors. Table 2 shows that more than 80 per cent of non-failed and failed firms come from manufacturing and services sectors.

3. Explanatory Variables

The appropriateness of detecting the important determinants of failure within the framework of traditional binary response statistical models combined with explanatory variables derived from accounting data, is evidential from the apparent *ex ante* predictive ability of such proprietary applications for assessing quoted industrial companies as the UK-based *Z*-score model (**Taffler**, 1995) and the US-based *ZETA*® model (**Altman**, 2000). We use to develop the panel data model, 24 financial statement-based and equity valuation items reported by DATASTREAM for UK quoted industrial firms.[9] Standard financial ratios represent the key dimensions of financial analysis, namely, profitability, turnover, gearing, and liquidity. As the literature on company failure (see e.g. **Cosh and Hughes**, 1995) has documented an important role for company size which may proxy causal effects of youth and inexperience of smaller firms, in this paper we assume that the size factor can be introduced into model development by employing the net sales variable. Market valuation of the firm is proxied by the ratio of market value to book value (premium or discount to net tangible assets), while the influence of dividend policy on failure risk is represented by the payout ratio (a reciprocal of dividend cover). Further, to proxy the firm's net worth, we also included an index for the book value of ordinary shareholders' funds computed as the sum of share capital and reserves less intangibles. This so called "net tangible assets index" is defined as a percentage of the assets figure obtained from the first (in terms of DATASTREAM records) accounts; it is often used for solvency control, and therefore might be important in determining the risk of default. To the company, as a corporate identity, shareholders' funds are usually the only source of funds, other then liabilities, which it can use to finance assets. Changes in ordinary shareholders' funds also matter because a borrower's financial position is a key determinant of the cost of external finance. However, net worth at book values represents a rather crude estimate of the firm's value, because the assets shown in the balance sheet are usually recorded at historic cost (less depreciation) and may differ greatly from their current market values. Finally, the ratio between published tax and published pre-tax profit is used to proxy the tax position of the company. The comprehensive range allows us to implement in the panel data analysis the *general-to-specific* modelling approach[10] and via statistical reduction identify the financial performance variables, explaining failure risk for our data set.

Names and descriptive statistics of independent variables employed in modelling are displayed in Table 3. To handle the problem of non-stationarity in data, the original DATASTREAM values were normalised with respect to means and standard errors of relevant cross-sections for each calendar year of the panel, that is each observation is relative to the year mean and therefore each within year covariate is centred on zero.

4. A Fixed Effects Binomial Logit Model for Panel Data

The model with a binary dependent variable can be formulated in terms of an underlying latent variable. Typically, for a possibly unbalanced panel we would specify:

$$y_{it}^{*} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\varepsilon}_{it}\,, \tag{1}$$

where we observe $y_{it} = 1$ if $y_{it}^{*} > 0$, and $y_{it} = 0$ otherwise.

In (1) we index all variables by an i for the individual cross-sectional unit $(i = 1,\ldots,N)$ and a t for the time period $(t = 1,\ldots,T)$. There are K explanatory variables (financial determinants) in $\mathbf{x}_{it}$, which are observed, not including a constant. This means that effects of a change in $\mathbf{x}$ are the same for all units and all periods, but the average level for individual i may be different from that for unit j.

The α_i captures the effects of those variables that are peculiar to the $i-\mathrm{th}$ individual member of the panel and that are constant over time. Two basic approaches for modelling heterogeneity are a fixed effects treatment and a random effects treatment. The fixed effects approach takes α_i to be a group specific constant term and $\boldsymbol{\varepsilon}_{it}$ is assumed to be independent and identically distributed over individuals and time with mean zero and variance σ_{ε}^{2}:

$$y_{it}^{*} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\varepsilon}_{it}\,, \quad \boldsymbol{\varepsilon}_{it} = \mathrm{IID}(0, \sigma_{\varepsilon}^{2}). \tag{2}$$

A random effects framework specifies that a_i are different but that they can be treated as group specific disturbances, similar to $\mathbf{e}_{it}$, except for each group there is but a single draw that enters the regression identically in each period. The essential assumption is that these drawings are independent of the explanatory variables in $\mathbf{x}_{it}$. That leads to the random effects model where individual-specific constant terms are randomly distributed across cross-sectional units. The error term in this model thus consists of two mutually independent components, which are also independent of $\mathbf{x}_{js}$, namely, a time-invariant component a_i and a remainder component $?_{it}$ that are uncorrelated over time. If we specify that $\mathbf{e}_{it} = a_i + ?_{it}$, the random effects model can be written as

$$y_{it}^{*} = m + a_i + \mathbf{ß}'\mathbf{x}_{it} + ?_{it}, \quad a_i = \mathrm{IID}(0, s_a^2); \quad ?_{it} = \mathrm{IID}(0, s_n^2). \qquad (3)$$

The fixed effects approach is contrasted with the random effects one. Whether to treat the individual effects a_i as fixed or random can make a difference to the estimates of the **ß** parameters when T is small and N is large relative to T (**Verbeek**, 2000). A distinction is that under a fixed effects approach we condition on the a_i's, so that their distribution plays no role. This interpretation makes sense if the individuals in the sample are "one of a kind", such as large quoted companies of the present study, and cannot be viewed as a random draw from some underlying population (**Greene**, 1997). The fixed effects model is thus considered as applying only to cross-sectional units in the sample and, therefore, inferences are with respect to the effects that are in the sample. A random effects approach invokes a distribution for a_i, and individual-specific constant terms are viewed as randomly distributed across cross-sectional units. This is appropriate if we believe that sampled cross-sectional units are drawn from a large population.[11] Thus the random effects approach allows one to make inference with respect to the population characteristics. However, even if one is interested in the larger population of individual units, and a random effects framework seems appropriate, the fixed effects estimator may still be preferred. The reason for this is that it may be the case that a_i and $\mathbf{x}_{it}$ are correlated, in which case the random effects approach, ignoring this correlation, leads to inconsistent estimators due to omitted variables.

Two techniques have been commonly used for modelling heterogeneity on panel data with a binary dependent variable: a fixed effects logit model based on a conditional likelihood approach due to **Chamberlain** (1980) and a random effects probit model that is often referred to as **Butler and Moffitt's** (1982) "equicorrelated" model. Given that both categories of firms in the panel, the failed firms and the non-failed firms, represent a rather large proportion of equities, followed by the DATASTREAM database, and were not sampled randomly, we would expect the fixed effects approach to have some intuitive appeal. More specifically, the 489 non-failed firms in the panel represent 36.8 per cent of equities that were on the "live" DATASTREAM list as of February 1997, while the 56 failed companies account for 50.9 per cent of those quoted companies, that according to the London Stock Exchange Official Year Book entered the insolvency state over the period 1988-93. The list of firms selected for the panel analysis was compiled by excluding transportation, petroleum, and financial services companies due to their specific taxation and accounting policies, and then through unavoidable filtering of companies due to the usual requirement of record completeness and continuity for the period of the analysis. The above might well have resulted in non-random selection of both categories – the failed companies and non-failed companies. Further, in the present study we expect that unobserved individual firm-specific effects, such as, for instance, managerial quality, industry-specific influences, industrial union power, organisation and ownership structure, are likely to be correlated with observable characteristics of corporate performance, captured by financial statement-based and equity market valuation measures. Therefore it would appear reasonable to assume that the fixed effects logit model would yield an appropriate specification for the present panel study.

A fixed effects logit model that accounts for heterogeneity is given by:

$$\mathrm{Prob}(Y = 1\,(Failure)) = \frac{e^{a_i + \boldsymbol{\beta}'\mathbf{x}_{it}}}{1 + e^{a_i + \boldsymbol{\beta}'\mathbf{x}_{it}}}. \tag{4}$$

If we treat a_i in (4) as fixed unknown parameters, we essentially including N dummy variables in the model. Maximising the log-likelihood function with respect to $\boldsymbol{\beta}$ and a_i (i=1,...,N) results in a consistent estimator provided that the number of time periods T goes to infinity. For a short and wide panel, with fixed T and $N \to \infty$, the estimators are inconsistent. The reason is that for fixed T, the number of parameters grows with the sample size N, which results in an "incidental parameters" problem arising in any fixed effects model. That is, any a_i can be only estimated consistently if we have a growing number of observations for individual i, thus we have T tending to infinity. In general, the inconsistency of $\hat{a}_i$ for fixed T will carry over to the estimator for $\boldsymbol{ß}$.

Chamberlain (1980) suggested an approach to estimating a panel data model with a binary dependent variable, where N is large and T is small. He considers the set of T observations for unit i as a group, and then use the likelihood function conditional upon a set of statistics t_i that are sufficient for a_i. This means that conditional upon t_i, an individual's likelihood contribution no longer depends on a_i but still depends upon $\boldsymbol{ß}$.[12] In the fixed effects logit model, $t_i = \bar{y}_i$ is a sufficient statistic for a_i, and consistent estimation is possible by conditional maximum likelihood. That is we discard alternative sets for which $\sum_t^T y_{it} = 0$ or $\sum_t^T y_{it} = T$, because these cross-sectional units never change states and thus contribute zero to the likelihood function. The conditional distribution of $y_{i1},..., y_{iT}$ is degenerate if $t_i = 0$ or $t_i = 1$. The conditional likelihood function is written as

$$L^c = \prod_{i=1}^{N} \text{Prob}(Y_{i1} = y_{i1}, Y_{i2} = y_{i2},..., Y_{iT} = y_{iT} \mid \sum_{t=1}^{T} y_{it}) . \tag{6}$$

With homogeneity $(a_i = a)$, the model can be estimated as a binomial logit model. In order to test the null hypothesis of the homogeneity restriction a Hausman-type test[13] based on the difference between Chamberlain's conditional maximum likelihood estimator ($CMLE$) and the usual logit maximum likelihood estimator (ML), ignoring the individual effects, is performed.

Constructing the difference $\hat{\mathbf{q}} = \hat{\boldsymbol{ß}}_{CMLE} - \hat{\boldsymbol{ß}}_{ML}$

with the variance $$V(\hat{\boldsymbol{\theta}}) = V(\hat{\boldsymbol{\beta}}_{CMLE}) - V(\hat{\boldsymbol{\beta}}_{ML}),$$

$$m = \hat{\boldsymbol{\theta}}'[\mathbf{V}(\hat{\boldsymbol{\theta}})]^{-1}\hat{\boldsymbol{\theta}} \tag{7}$$

can be used as a χ_K^2 statistic under the null, where K is the dimensionality of $\boldsymbol{\beta}$.

Whether the null hypothesis of homogeneity is true or not, Chamberlain's conditional maximum likelihood estimator is consistent, but inefficient under the null, because it fails to use the homogeneity restriction. The usual maximum likelihood estimator is consistent and efficient only under the null of homogeneity and inconsistent under the alternative.

5. Empirical Results

Table 4 presents the results from the logit analysis for three parsimonious models derived from a more general specification that includes all 24 financial variables.[14] Covariates were eliminated using a sequence of independent Likelihood Ratio tests. The failure outcome is denoted by 1 and the opposite state is assigned 0, therefore a positive (negative) coefficient indicates that the factor, expressed by the covariate positively (negatively) correlated with the outcome of company failure. The diagnostics indicate that the panel data models have good overall fit – the Likelihood Ratio test statistics are significant at the 0.1 per cent level for all three models. In all Models 1, 2, and 3, based on the Hausman χ^2 statistics, the null hypothesis of homogeneity of intercepts is rejected at the 5% level and better. As discussed above, this implies that control for the firm-specific effects is necessary and that, therefore, the results of cross-sectional analyses may be biased. Regarding the importance of individual dimensions of company performance, the absence of gearing measures from all the three models is noteworthy. With regard to other dimensions of company performance, profitability, turnover, liquidity, and changes in net worth (measured by the index of net tangible assets at book value) have a strong effect on the probability of failure for the firms in the panel. When the influence of ratios, expressing a profitability factor, is examined, at first glance, the estimate coefficients in Models 1, 2, and 3 seem not all to have the correct sign. For instance, the coefficient for the cumulative profitability ratio and the coefficient of the operating profit margin (in Models 1 and 2) have contra-intuitive positive signs.

The essential implication of positively signed coefficients for the cumulative profitability ratio, significant at the 10% level, is that failing companies are characterised by a greater ratio of revenue reserves relative to total assets employed. Aside from that, Models 1 and 2 link a greater likelihood of failure to higher operating profit margins, but this variable is insignificant. Positive coefficients for the net profit margin (significant at the 10% level and better in Models 1, 2, and 3) appear to provide further support to a "teasing" positive relationship between profitability and the risk of failure. However, coefficients for the pre-tax profit margin (significant at the 10% level and better) are negative.

One possible explanation of the signs of these explanatory variables stems from the definitions of ratios adopted by DATASTREAM. For example, the operating profit margin is calculated before both interest expenses and losses on termination of operations. On the other hand, the pre-tax profit margin ignores pre-tax and after-tax profits of associated companies and undertakings, whereas the net (after-tax) profit margin takes account of amounts of associates' profits attributable to the parent company. Therefore, the fact that the pre-tax profit margin is negative, but the net profit margin is positive, might have to do with the equity method, used in financial reporting of companies, which have subsidiaries, and where financial results of subsidiaries are significant in their overall impact. Under the equity method, the parent company often shows in consolidated accounts proportional profits of its associates attributable to the group. Since profits are attributed it is possible that little or nothing has been received by the group, and its liquidity position has not been improved. In other words, higher profitability as measured by the net profit margin might have no bearing on the liquidity of the business. For further investigation of the "incorrectly" signed net profit margin, more detailed information of cash flow reports and relevant notes is needed, however, financial characteristics reflected in our data preclude our pursuing this aspect of analysis further. As far as the ambiguous sign for the measure of cumulative profitability is concerned, it might be explained by the possible impact that accounting policies might have on the accounting values of retained profits, because attributable revenue reserves of subsidiaries are included into revenue reserves of a parent company, in line with the equity accounting method. Moreover, the positive sign of the operating profit margin, considered together with the negatively signed coefficient for the pre-tax profit margin ratio, might be an indication that failed companies in the sample were productive and economically valuable as they would still be trading and receiving revenue from operations in the years preceding insolvency. At the same time, they are equally likely to suffer greater losses from terminating operations and incurring greater interest expenses as compared with the non-failing group. That tentative interpretation of the subtle interplay between the four profitability ratios, in our view, might reflect certain underlying factors such as shifts in corporate sector indebtedness combined with high nominal interest rates before the 1990-92 recession, such that the high gearing effect is captured by the incidental parameters. Further, "conflicting" signs of profit margins and the cumulative profitability ratio are consistent with the fixed effects specification, as they would appear to accord with the fact that, of the failed category in our panel, many firms are organised as a group or a holding company, and this organisational characteristic might also have been captured by the firm-specific fixed effects.

All three models suggest an appropriate negative relationship between turnover measures and failure risk. The ratio of turnover to net current assets is insignificant in Model 1, while the debtors turnover ratio is significant at the 10% level in all three models, reflecting that before failure there is either a slowdown in trade, due to a fall in demand, or a decline in debtors quality resulting in bad debts, not recognised by provisions. The liquidity dimension is captured by a quick assets ratio, significant at the 5% level and better, that deals with the most liquid assets and is regarded as the best guide to short-term solvency. In all three models, the quick assets ratio suggests the expected negative influence of liquidity on the risk of failure. Lastly, all models yield the net tangible assets index as a failure determinant that is significant at the 5% level and better. As shown in Table 4, a company is more likely to fail if its index of net tangible assets is declining. This result is intuitively logical as the borrower's net worth represents a buffer or a crude margin of long-term solvency between the assets and the liabilities, although, being based on book values and hence historically oriented, this measure depends upon accounting conventions. Moreover, the strong influence of the assets index should be treated with caution as financial reporting policies and practice, which affect book values, might have been inconsistent across companies and years followed by the panel.

6. Conclusions

This paper has reported empirical results on financial ratio-based determinants of company failure obtained with the panel data on large quoted UK industrials for 1988-93. A better understanding of the factors determining corporate financial distress and failure, is important because at the micro level, it is an ingredient of investment decisions, especially in the context of corporate lending, while at the macro level, it is an essential step in designing the inclusive and efficient policies preventing and ameliorating crises, by banks and regulators.

In the unbalanced panel we follow 539 companies of which 56 firms exit the panel due to severe financial distress problems resulted in formal insolvency. The structure of the panel constructed resembles the actual population proportions of the examined categories of failed and non-failed firms. We employ an econometric technique that controls for the unobservable permanent differences across companies, which are likely to affect the propensity to failure of an individual firm. We find evidence of considerable heterogeneity across companies in the panel, which suggests that the panel data estimates are preferable to the cross-sectional estimates.

As for the individual determinants, our analysis provides the following findings. When the fixed individual effects are controlled for, our results with regard to important financial dimensions, suggest that narrowly defined liquidity, profitability, turnover, and changes in net worth (measured as the book value of net tangible assets) are the key determinants of failure for firms in our panel data set. Moreover, modelling with the panel data captures changes in both short-term liquidity and long-term solvency. The documented importance of the liquidity dimension emphasises that the current cash flow considerations, rather than the economic value of the firm based on the future free cash flows, are more pertinent to the explanation of company failure in our panel. That result is consistent the findings reported in the time-series study of the aggregate rate of company insolvency by **Turner, Coutts, and Bowden** (1992), who argue that failure of the banks to extend to distressed companies short-term credit on the basis of the long-term potential is an important structural weakness of the British economy.

The results also show that the event of failure is associated with lower pre-tax profit margins. However, unexpectedly, the analysis also identifies a concurrent and of roughly equal magnitude, positive link between the net profit margin and insolvency risk, which, under the equity method used in financial reporting of groups, might be linked to that fact that profits of associates are attributable to the parent company. This observation appears to be in line with evidence from **Geroski and Gregg** (1996) that holding companies had fared less successfully in the 1990-92 recession. In contrast to existing cross-sectional studies we do not detect in our panel an association between gearing and the probability of insolvency, when models of failure are conditioned on the fixed effects. Lastly, inference presented here was drawn at the costs of the assumption of the fixed effects and must be interpreted with caution since the sample cover just six years and the results are applicable only to companies in the study, not to the additional firms outside the sample range.

TABLES

Table 1: Transition within the Panel of UK Industrial Companies for 1988-93

(Failure is determined as the time of release of the last accounts)

	Unbalanced Panel: 1988-93					
	1988	1989	1990	1991	1992	1993
Total	539	539	521	505	493	488
Companies “live” in the current year and subsequent years of the panel	483	483	483	483	483	483
Companies failing over the current and subsequent years of the panel	56	56	38	22	10	5
Cumulative total of companies failed in preceding years and in the current year	-	18	34	46	51	56
Companies failing in the current year *t*	-	18	16	12	5	5
Companies failing in the current year *t*, per cent	-	3.34	3.07	2.38	1.01	1.02

Table 2: Sectoral Composition of the UK Industrial Company Panel for 1988-93, Breakdown of Observational Units by Economic Group (Percentages in parentheses)

	FT-SE Economic Groups											
	Mineral Extraction		General Industrials		Consumer Goods		Services		Utilities		Total	
Unbalanced Panel: Distribution across 1988-93 (N=539)												
1988 Non-Failed	1	(0.19)	307	(56.96)	80	(14.84)	150	(27.83)	1	(0.19)	539	(100)
1988 Failed	-	-	-	-	-	-	-	-	-		0	(100)
1989 Non-Failed	1	(0.19)	299	(57.39)	78	(14.97)	142	(27.26)	1	(0.19)	521	(100)
1989 Failed	-	-	8	(44.44)	2	(11.11)	8	(44.44)	-	-	18	(100)
1990 Non-Failed	1	(0.20)	289	(57.23)	77	(15.25)	137	(27.13)	1	(0.20)	505	(100)
1990 Failed	-	-	10	(62.50)	1	(6.25)	5	(31.25)	-	-	16	(100)
1991 Non-Failed	1	(0.20)	285	(57.81)	77	(15.62)	129	(26.17)	1	(0.20)	493	(100)
1991 Failed	-	-	4	(33.33)	-	-	8	(66.67)	-	-	12	(100)
1992 Non-Failed	1	(0.20)	282	(57.79)	77	(15.78)	127	(26.02)	1	(0.20)	488	(100)
1992 Failed	-	-	3	(60.00)	-	-	2	(40.00)	-	-	5	(100)
1993 Non-Failed	1	(0.21)	279	(57.76)	76	(15.73)	126	(26.09)	1	(0.21)	483	(100)
1993 Failed	-	-	3	(60.00)	1	(20.00)	1	(20.00)	-	-	5	(100)

Table .3: Descriptive Statistics for UK Quoted Companies in the 1988-93 Panel, 483 Non-failed Companies and 56 Failed Companies with a Maximum of 6 Years of Data on Each Company, Sample Size 3,085 [(488×6)+ (5×5)+ (12×4)+ (16×3)+(18×2)]

continued on next page

	Mean	St. Dev.	Annual Means					
	Original Values, Levels		Original Values, Levels					
	Full Sample: 3,085 obs.		539 firms	539 firms	521 firms	505 firms	493 firms	488 firms
	1988-93		1988	1989	1990	1991	1992	1993
Financial Dimension								
Accounting Variable								
Size								
Total Sales (net of trade discounts (£,m))	546.116	1405.888	424.586	501.920	549.124	565.561	601.056	651.352
Profitability								
Return on Shareholders' Capital (percentage)	10.510	101.743	17.024	16.563	8.034	14.951	9.791	-4.566
Return on Capital Employed (percentage)	15.502	48.046	21.096	21.093	12.131	12.019	12.849	13.072
Return on Net Fixed Assets (percentage)	19.080	99.506	39.119	32.561	20.558	7.612	3.020	8.637
Cumulative Profitability	0.341	2.701	0.401	0.336	0.349	0.226	0.420	
Operating Profit Margin (percentage)	6.746	23.250	9.048	8.751	7.490	6.020	5.630	3.092
Pre-tax Profit Margin (percentage)	5.912	20.287	8.835	7.982	6.385	4.537	4.671	2.585
Net Profit Margin (percentage)	3.537	19.463	5.886	5.034	3.778	2.540	2.925	0.692
Turnover								
Turnover / Fixed Assets	6.409	11.062	6.496	6.179	6.020	5.930	2.741	7.197
Turnover / Net Current Assets	9.908	153.093	25.651	4.062	4.440	12.118	5.960	6.525
Stock Turnover	17.621	105.138	25.802	12.906	12.477	20.242	17.710	16.511
Debtors Turnover	7.431	12.803	7.590	6.983	7.491	7.305	7.392	7.871
Creditors Turnover	5.221	2.424	5.190	5.061	5.194	5.316	5.255	5.337

Table 3:- *Continued*

	Mean	St. Dev.	Annual Means					
	Original Values, Levels		Original Values, Levels					
	Full Sample: 3,085 obs.		539 firms	539 firms	521 firms	505 firms	493 firms	488 firms
	1988-93		1988	1989	1990	1991	1992	1993
Financial Dimension								
Accounting Variable								
Gearing								
Capital Gearing (percentage)	33.221	99.393	25.174	36.902	31.771	37.460	31.269	37.252
Income Gearing (percentage)	9.239	922.089	16.703	18.192	57.520	-50.897	39.138	-28.376
Borrowing Ratio	0.614	5.110	0.504	0.937	0.702	0.356	0.547	0.624
Gross Cash-flow / Total Liabilities	0.098	0.684	0.171	0.101	0.090	0.070	0.093	0.054
Loan Capital / Equity and Reserves	0.336	4.052	0.224	0.596	0.346	0.216	0.324	0.297
Liquidity								
Working Capital Ratio	1.573	0.993	1.651	1.528	-0.080	1.548	1.621	1.585
Quick Assets Ratio	0.987	0.857	1.026	0.937	0.935	0.970	1.036	1.022
Other								
Market Value/Book Value	2.171	6.163	2.646	2.279	1.651	1.623	2.163	2.660
Payout Ratio	0.490	3.198	2.750	0.584	0.559	0.623	0.652	0.157
Assets Index (percentage)	1991.846	15673.119	1924.887	2018.541	1898.274	1997.071	2047.921	2078.299
Tax Ratio (percentage)	26.305	173.176	29.896	29.409	9.461	28.041	24.251	37.233

Table 4: Results from Fixed Effects Binary Logit for the Unbalanced Panel of UK Quoted Companies, the Panel Period 1988-93

Alternative Specifications of Fixed Effects Binary Logit
For the Unbalanced Panel of UK Quoted Companies, for 1988-93,
Failure Times are Defined as Years the Last Accounts Released,
N=539, T=6, Sample Size 3,085 [(488´ 6)+(5 ´5)+(12´ 4)+(16´ 3)+(18 ´2)],
56 Failed Companies

Financial Dimension *Accounting Variable*	**Model 1**		**Model 2**		**Model 3**	
	Coefficient (two-tailed p-value of asymptotic t-statistic)					
Profitability						
Cumulative Profitability	0.314	(0.060)	0.302	(0.075)	-	-
Operating Profit Margin	0.755	(0.155)	0.765	(0.147)	-	-
Pre-tax Profit Margin	-3.484	(0.028)	-3.754	(0.018)	-2.766	(0.070)
Net Profit Margin	2.858	(0.036)	3.107	(0.023)	2.666	(0.061)
Turnover						
Turnover /Net Current Assets	-0.747	(0.166)	-	-	-	-
Debtors Turnover	-3.914	(0.059)	-3.697	(0.067)	-2.902	(0.087)
Liquidity						
Quick Assets Ratio	-3.603	(0.011)	-3.568	(0.009)	-2.622	(0.016)
Net Worth						
Assets Index	-92.028	(0.002)	-99.200	(0.001)	-100.789	(0.001)
Log Likelihood at Convergence	-30.84		-32.28		-34.25	
c^2 statistic of LR Test[15]	65.71		62.83		58.91	
(p-value)	(0.000)		(0.000)		(0.000)	
Hausman Fixed effects Test χ^2 statistic	53.58		33.37		13.01	
(p-value)	(0.000)		(0.000)		(0.023)	
n	3,085					
Per cent Failed	1.8					

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Notes

[1] Fairclough and Hunter (1998) have applied this approach to the classification of target firms, but they bootstrap the output of the solved net to analyse the performance of a model.

[2] It should be noted that although some data are available to analyse the subsequent period such analysis requires pooling due to a dearth of failed companies across the period 1994-2000.

[3] Exports continued to grow during the 1990-92 recession (see the article "The UK Recession 1990-92" in *Economic Briefing,* 6, 1994) and export-oriented firms fared better during the economy downturn (Geroski and Gregg, 1996).

[4] Using data generated from a large-scale survey of how UK firms coped with the 1991 recession, Geroski and Gregg (1996), identify an association in the data between organisation and ownership structure and vulnerability to the recession. Holding companies and firms with highly dispersed share ownership tended to be a little more vulnerable to recessionary pressures than functionally organised and divisionalised firms with a dominant owner (such as foreign owned firms).

[5] See Dickerson, Gibson, and Tsakalotos (1997).

[6] Machin and Van Reenen (1993) employ an explicit measure of industrial unionism in their panel study of UK firms' profitability.

[7] Young (1995) discusses how the types of debt contract might have influenced aggregate company liquidations in the UK in the early 1990s, because a variable-rate debt is a good hedge against inflationary shocks whereas fixed-rate debt is a good hedge against real interest rate shocks. His empirical findings from the time-series study support two reasons for the rise in compulsory and creditors' voluntary liquidations over the early 1990s. The first reason has been an unexpected rise in real interest rates in the late 1980s, and the more important second factor has been that, over the period from the mid-1970s to early 1990s, variable-rate debt was heavily used.

[8] The DATASTREAM code for this equity list was "UKQI". For reasons of space, the list of the sample companies, is not reported here and can be found in Isachenkova (2001).

[9] For a more detailed description of the firm-specific explanatory variables used in this study, see Isachenkova (2001).

[10] A *general-to-specific* approach to modelling has been applied to economic time-series by Davidson, Hendry, Srba and Yeo et al (1978) and in the context of a cross-sectional analysis of company accounts by Hunter and Komis (2000).

[11] Appropriate scaling will help to alleviate such problem, as the differences associated with size, for example, are less pervasive when the data are standardised. However, the micro units in the sample may differ for other reasons, such as for example: industry sector or export sensitivity.

[12] In the panel data model with a binary dependent variable, the existence of a minimal sufficient statistic depends upon the functional form of $F(\cdot)$, that is, depends on distribution of e_{it}. If a sufficient statistic t_i exists, this means that there exists a statistic t_i such that the probability mass function does not depend on a_i, that is $f(y_{i1},...,y_{iT} \mid t_i, a_i, \mathbf{ß}) = f(y_{i1},...,y_{iT} \mid t_i, \mathbf{ß})$. For a probit model no sufficient statistic for a_i exists. Thus in applying the fixed effects models to discrete dependent variables based on panel data, the logit model and the log-linear model seem to be the only choices (Maddala, 1987).

[13] Hausman (1978).

[14] For a full discussion of the findings see Isachenkova (2001).

[15] Note that here the Likelihood Ratios are only a function of the slope parameters and not the fixed effects themselves, which are never estimated.