AGGREGATE ECONOMY RISK AND COMPANY FAILURE:

AN EXAMINATION OF UK QUOTED FIRMS IN THE EARLY 1990s

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Abstract

Considerable attention has been directed in the recent finance and economics literature to issues concerning the effects on company failure risk of changes in the macroeconomic environment. This paper examines the accounting ratio-based and macroeconomic determinants of insolvency exit of UK large industrials during the early 1990s with a view to improve understanding of company failure risk. Failure determinants are revealed from estimates based on a cross-section of 369 quoted firms, which is followed by an assessment of predictive performance based on a series of time-to-failure-specific logit functions, as is typical in the literature. Within the traditional for cross-sectional data studies framework, a more complete model of failure risk is developed by adding to a set of traditional financial statement-based inputs, the two variables capturing aggregate economy risk - one-year lagged, unanticipated changes in the nominal interest rate and in the real exchange rate. Alternative estimates of prediction error are obtained, first, by analytically adjusting the apparent error rate for the downward bias and, second, by generating holdout predictions. More complete, augmented with the two macroeconomic variables models demonstrate improved out-of-estimation-sample classificatory accuracy at risk horizons ranging from one to four years prior to failure, with the results being quite robust across a wide range of cutoff probability values, for both failing and non-failed firms.

Although in terms of the individual ratio significance and overall predictive accuracy, the findings of the present study may not be directly comparable with the evidence from prior research due to differing data sets and model specifications, the results are intuitively appealing. First, the results affirm the important explanatory role of liquidity, gearing, and profitability in the company failure process. Second, the findings for the failure probability appear to demonstrate that shocks from unanticipated changes in interest and exchange rates may matter as much as the underlying changes in firm-specific characteristics of liquidity, gearing, and profitability. Obtained empirical determinants suggest that during the 1990s recession, shifts in the real exchange rate and rises in the nominal interest rate, were associated with a higher propensity of industrial company to exit via insolvency, thus indicating links to a loss in competitiveness and to the effects of high gearing. The results provide policy implications for reducing the company sector vulnerability to financial distress and failure while highlighting that changes in macroeconomic conditions should be an important ingredient of possible extensions of company failure prediction models.

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1 Introduction

The central objective of the present paper is to investigate the impact of aggregate economy risk on company failure in a cross-section sample representative of 369 UK large quoted industrials in 1989-92. We proxy failure by the event of legal insolvency due to debt default, and consequently define failure risk as the potential that a company will enter a formal insolvency state. We refine the analysis of firm-level characteristics by controlling for variations in macroeconomic conditions. The key macroeconomic indicators, augmenting in this study a conventional, accounting ratio-based model of failure risk, were the nominal interest rate and the real effective exchange rate. Results from logit provide evidence that over the years before and during the 1990s recession, unanticipated shifts in the real effective exchange rate and in the nominal interest rate were associated with a higher propensity of industrial company to exit via insolvency. These effects seem to point to the adverse effect of inflation on highly geared firms, to a loss in competitiveness for the firms relying on exports and to a possible decline in performance via reported equity values for the firms with assets denominated in foreign currency.

The determinants of failure risk are of natural interest to investors and lenders. At the macro level, the issue of corporate distress and failure has important implications of financial stability and economic growth. Given the potential severity of economic and social consequences of sharp rises in company failures, the knowledge of factors driving the corporate sector vulnerability to default and insolvency is important for informing forward-looking policies of banks and public bodies. The risk of failure through insolvency can be decomposed into three components: financial risk associated with highly geared capital structure, business risk, inherent in the firm's operations, and aggregate economy risk. At the firm level, conventional quantitative analysis of failure risk involves a detailed examination of a firm's balance sheet, income statement and cash flow, assuming that information on financial and business risks is reflected in financial accounts. However, an analysis of historical statements alone may present the incomplete picture of the relations underlying the failure process. Aggregate economy risk, arising from uncertainty regarding trading conditions due to business and credit cycles and other macroeconomic influences, affects the volatility of cash flows and thus clearly conditions the risk of corporate failure. In order to achieve a better approximation of complex interrelations between factors influencing the failure process, the business environment variables should be incorporated into a modelling framework. Recent academic research and commercial models of credit risk have attempted to take account of the role of macroeconomic conditions in explaining the process of corporate failure due to insolvency (see e.g. Moody's Report ? 53853, 2000; Bhattacharjee, Higson, Holly, Kattuman, 2002).

The next section reviews the literature. Section 3 presents our examination of the role of macroeconomic instability in failure of UK quoted industrial firm in the early 1990s. Section 3.1 defines the proxy for failure and gives details of the data set structure. Section 3.2 describes factors driving failure risk in our model, while the modelling approach is discussed in Section 3.3. The estimation results are presented in Section 3.4 and Section 4 offers our conclusions.

2 Company Failure Theories and Stylised Facts on the Role of Macroeconomic Factors

There is of course a voluminous literature on company failure dating back to Beaver (1966). Much of it argues that, at the firm level, company failure is explained by economic inefficiency, debt financing and management mistakes. Neo-classical economics equates failure to the firm's exit from the market (Mueller, 1991). From this angle, failure is a manifestation of Schumpeterian 'creative destruction' through which the market selects between efficient and inefficient firms. According to neo-classical analysis, insufficient profitability is the main factor that in the long run forces the firm to reduce its presence in the market and exit the industry. Firms that do not supply the product at the competitive price-cost margins face financial difficulties generated by the inevitable discipline of factor and product markets and exit. Obviously, failure in the economic sense need not be accompanied immediately by financial distress arising from liquidity shortages and external financing constraints. Within this framework, the possible exit rout of formal insolvency proceedings can be viewed as a welfare-enhancing device and way of re-allocating industry-specific resources.[1]

In business language, the word ‘failure’ generally means that a company has become involved in certain legal consequences. The company unable to meet or renegotiate the cash claims upon it exercises its right to default, which usually follows by the firm’s creditors instituting legal proceedings whereby all claims against the company are settled. The risk of business failure is associated with debt financing and the lack of liquidity, but ultimately depends on the limits of lenders’ willingness to support the firm. As argued by Armour and Frisby (2001), a rational secured creditor will cease supporting the firm where the returns from enforcement are greater than the returns from negotiations. However, these returns are not directly observable.

Although financial distress does not accurately represents economic failure, it may be caused by economic distress at firm and industry levels. Economic inefficiency is usually not directly observable, while financial distress may straightforwardly be inferred from such outcomes as debt defaults and legal insolvency cases. For ease of tractability debt default and legal insolvency are often used to proxy the state of failure in empirical work. The financial economics emphasises that indebtedness is the main determinant of failure because financial distress is induced by debt and because default is an attribute of a credit asset. However, as the finance literature argues, debt performs an important function of contingent control allocations (Aghion and Bolton, 1992), enabling involved in complex financial contracts creditors to take over control of the firm once default occurs and resolve distress. Viewed in this light, debt is an invaluable controlling device while default and bankruptcy serve as a particular kind of catalyst for restructuring of claims. Consequently financial distress may not necessarily entail exit from the industry and a welfare loss.

The management strand of theories (e.g. Argenti, 1976; Hambrick and D’Aveni, 1988*; The Society of Practitioners of Insolvency Fifth Survey*, 1996) suggests the primary role of management error and poor corporate governance in company failure. If failure is due to bad governance, default may create value by forcing the management to reduce production capacity and rethink operating policy and strategy decisions. Financial distress will also generate value when the firm value is the highest in liquidation and the management is reluctant to liquidate. Thus the insolvency mechanism may help financially distressed but economically viable companies stay in business and facilitate exit of inefficient firms.

Notwithstanding the possibility of potential benefits of distress and bankruptcy, which are yet to be quantified empirically, these processes involve substantial direct costs (legal, administrative and advisory fees) and indirect (opportunity) costs of real resources to the firm and to its stakeholders (see e.g. Wruck, 1990). In a highly geared firm faced with credit constraints, a small decline in performance due to a change in the macro-environment, may adversely affect its liquidity position and capacity to meet interest payments, triggering debt default. Even when the firm is economically viable in the long run, it may not, due to borrowing constraints, escape going bust in the short run. This will generate an additional welfare loss when the firm’s assets are more productive within the firm than when transferred to another owner. At the economy level, inefficiently high rates of failures in a fragile corporate sector can have serious welfare and macroeconomic consequences. Financial distress can lead to inefficient excessive piecemeal liquidations, especially when an industry is hit by the industry-wide or economy-wide shocks. In the situation when losses on corporate loan book are unanticipated, high liquidation rates can, by gradually eroding bank capital, weaken the banking system and trigger a financial crisis. Furthermore, as Vlieghe (2001) points out, a heightened state of financial fragility at a single firm leads to inefficient allocation of resources because a reduction in available credit causes valuable investment opportunities to be missed while resources devoted to renegotiating debt contracts are crowding out resources required for production.

Numerous empirical studies have examined the determinants of corporate failure risk with firm-level information available from historical financial statements. Such analyses are intended to aid understanding the risk of bankruptcy and to facilitate its monitoring of at the firm level as well as to provide appropriate,

[1] It should be noted, however, that a firm might disappear from the industry as a result of merger. Rivals possibly may acquire the successful firm’s assets and expertise and apply it to the products of both firms. In this case exit comes from success.

failure incidence reducing policy responses at the economy level. This said, it should also be noted that the current empirical literature on the determinants of company failure lacks a unifying structural model[2]. Stylised models of company failure, constructed for UK firms have involved multiple discriminant analysis, logit and neural networks as statistical settings for the problem of identifying risk factors. Taffler and Tisshaw (1977), Marais (1979), Taffler (1982), Peel, Peel, and Pope (1986), Goudie (1987), Keasey and McGuinness (1990), Goudie and Meeks (1991), Cosh and Hughes (1995), Alici (1995), and Morris (1997) have modelled failure with cross-sectional data using accounting ratios-based explanatory variables. The competing risks framework has recently been employed for an exploration of the joint influence of firm-specific and macroeconomic factors on bankruptcy risk in Bhattacharjee, Higson, Holly, Kattuman (2002). In relation to the importance of firm-level attributes, observable from financial accounts, these studies have summarily documented that high gearing, declining profitability and insufficient liquidity increase the likelihood of distress and insolvency.

However, the failure process is not completely determined by firm's characteristics alone, being in part related to environmental factors. Failure risk of a geared firm is amplified by macroeconomic instability and therefore the question of failure determinants should be seen in a macroeconomic context. Relevant to our objective of an integrated analysis of impacts of firm-level and aggregate economy factors, are empirical studies on the aggregate liquidation rate based on the experience of UK firms. These studies have produced several stylised facts regarding the strong impact on failure risk of the business cycle, inflation, and movements in interest and exchange rates.

Increases in *inflation and in the nominal interest rate* heighten aggregate rates of failure (Wadhwani, 1986; Davis, 1995; Robson, 1996) consistent with the notion that in the absence of indexed economy and perfect capital markets, firms financed with variable-rate debt may be unable to increase their borrowing and therefore inevitably face cash shortages. Wadhwani (1986) explored the determinants of UK corporate failure with quarterly data on total liquidations and found that declining profitability and the nominal interest rate determined aggregate insolvency rates. Having experimented with both real and nominal interest rates, Wadhwani interpreted the fact that the nominal interest rate was a highly significant determinant as evidence that inflation had driven corporate liquidations in the study period. When debt is not indexed and capital markets are imperfect, price inflation raises nominal interest charges. Due to historical cost accounting, inflation tends to distort the company's valuation worsening its financial position and limiting its ability to raise external funds. Inflation badly affects cash flows for capital allowances are fixed in nominal terms as a proportion of historical costs implying that taxes tend to rise in real terms due to inflation. By affecting negatively interest cover, inflation reduces the firm's chances in obtaining new loan finance. Aside from that, inflation can also engender expectations of a subsequent tightening of macroeconomic policy, leading to a decline in business confidence. Recent empirical findings on the exit behaviour of listed UK firms over 1965-98 presented by Bhattacharjee, Higson, Holly, Kattuman (2002), have corroborated Wadhwani's results that uncertainty in the form of sharp increases of inflation heightened bankruptcy risk.

Analyses of the impact of interest rates on aggregate rates of company failure have also been undertaken in Hudson (1986), who focused on rates of compulsory liquidations and creditors' voluntary liquidations, and in Simmons (1989) for bankruptcies of small, unincorporated businesses. Results from these studies, however, documented the inverse relation between the real interest rate and the liquidation rate, in contrast to the findings of Wadhwani. The inverse relation can be interpreted as evidence for adverse selection in credit markets. At high real rates, credit is likely to be diverted to high-risk borrowers, i.e. distressed firms, which are consequently less likely to fail. Vlieghe (2001) observed the long-run impact of the real interest rate on corporate sector fragility in a recent investigation of the UK over the period 1975-99. Vlieghe also found the short-run effect of the nominal interest rate, suggesting the adverse impact of high inflation upon company cash flows in imperfect capital markets. A modification of Wadhwani's model was tested for the

[2] In academic research, much empirical modelling of company failure determinants at the firm-level has been based on cross-section data and therefore made no attempt of applying analytical approaches typical of analyses of the timing of default problem in the line of Merton (1974). The event of default as such is deduced from the evolution of the firm's market value, for instance, in commercial models of failure risk presented in Crosbie (1998), where of course the analysis question is rather different, related to measuring the probability and time of default.

UK corporate sector during 1969-90 in Davis (1995), who found that rising inflation, the business cycle (recession), and factor prices were as important for explaining business failure rates as gearing.

Bankruptcy risk is procyclical (Turner, Coutts and Bowden, 1992; Davis, 1995). As sales and earnings of companies are directly related to the overall business activity, most defaults occur during or immediately after recessions, which are often coincident with periods of monetary and fiscal constraints. The link from recession to bankruptcy is an increased incidence of technical insolvency – inability to meet current cash obligations. This effect is influential in imperfect capital markets, which prevent companies from being able to borrow as much as they would to cover cash flow shortages resulting from a fall in demand. However, an empirical study of company exit by Bhattacharjee, Higson, Holly, Kattuman (2002), relying on a large panel data set, reported that the business cycle did not emerged as a key factor explaining bankruptcy risk over the period 1965-1998.

Unexpected changes in inflation and interest rates, rather than their levels, are critical as to bankruptcy risk (Young, 1995; Robson, 1996). Since observed values of the interest rate may be to some extent anticipated, then only the unanticipated component represents a 'surprise' impacting adversely on company survival. Evidence on the extent to which *ex post* inflation and real interest rates differ from their expected levels and its relevance to the rate of compulsory and creditors' voluntary liquidations has been provided by Young (1995). Macroeconomic instability, associated with high inflation and rapid, unanticipated movements in the real interest rate and demand, led to a higher liquidation rate of UK companies in 1977-92. Young argued that the firm's response to changes in interest rates depended on the composition of its debt contract.[3] Companies financed by variable-rate debt would be adversely affected by unexpected increases in real interest rates as that reduces the market value of their capital, but does not affect the value of variable-rate debt, causing the firm's net worth to fall. Firms financed at fixed nominal interest rates would be vulnerable to unanticipated reductions in inflation. Young's results show that a rise in nominal interest rates may either increase, decrease or have no effect on the rate of liquidations, depending on whether it corresponds to a rise in real interest rates or inflation, is anticipated or unanticipated, and debt is at fixed rates or variable rates. Rises in long-term interest rates by increasing the cost of capital may increase failure risk by forcing firms to shift their preferences towards riskier investment projects associated with higher rates of expected return required to afford debt finance. Robson's (1996) examination of the influence of macroeconomic factors on the extent of UK businesses' dissolutions for 1980-90, confirmed the findings reported in Wadhwani and Young, but also emphasized the explanatory power of the real interest rate.

As mentioned earlier, creditors' willingness to support the distressed firm is an additional factor for explaining insolvency risk, but information of the relevant motives is hard to come by. Turner, Coutts, and Bowden (1992) highlighted, the prevalence of *short-term cash flow considerations* in deciding distressed companies' fate in their time series study of liquidations over the period 1951-89. The macroeconomic component in their model was represented by the nominal interest rate, the rate of price inflation, the rate of growth of money stock capturing credit market constraints, and the rate of company formation reflecting the age structure of companies. The nominal rather than real rate of interest explained failure probabilities in their data. They concluded that credit markets did not allow firms to adjust their debt levels for inflation, with the overall implication that the short-term, cash flow considerations were dominating creditors' decisions regarding the fate of distressed companies. Similar points emerged from the work of Cuthbertson and Hudson (1996), where compulsory liquidations amongst UK companies over the period 1972-89 were analysed. In their paper income gearing was used as a joint proxy for the nominal interest rate and capital gearing. The observation that income gearing specified in differences was significant has been interpreted as evidence that gearing is a short-run factor, implying creditors' myopia as to the firm future prospects. The result seemed also indicative of the firm's ability to adapt, after time, to high nominal interest rates by reducing borrowing and, in the long run, by cutting input costs.

[3] A company that has borrowed at a floating rate of interest may find that interest rate rises will place real strains on cash flows and profitability. Conversely, a company that has a fixed rate of interest will find that when interest rates are falling it will not enjoy benefits of lower interest charges. To reduce or eliminate the expected component of the interest rate risk, a company may enter into a hedging arrangement, such as forward rate agreements, interest rate options and swaps. However, unanticipated movements in interest rates can present a significant issue for companies that have high levels of borrowing.

The role of *movements in the exchange rate* on failure risk of UK companies has been studied in Goudie and Meeks (1991), in Vlieghe (2001) and in Bhattacharjee, Higson, Holly, Kattuman (2002). The exchange rate had an additional explanatory power in Goudie and Meek's model. Their analysis linked failure risk to the degree of transaction exposure suggesting that failure can be a penalty for producing exports at a time of a soaring exchange rate, especially if the rise is combined with relative price increases leading to a disastrous loss of competitiveness. Notably, previous studies have observed very different effects of the exchange rate on bankruptcy risk. For instance, Bhattacharjee, Higson, Holly, Kattuman (2002) found the adverse impact of a sharp depreciation of the pound-dollar exchange rate on UK quoted firms for 1965-98, noting that this result can reflect the possibility that a fall in the exchange rate disadvantaged domestic business. Freshly listed companies in their sample were more likely to go bankrupt in years, characterized by unfavourable movements in the exchange rates. In contrast, a recent model of liquidation rates, based on variables reflecting the corporate sector financial position and macroeconomic conditions, which was presented in Vlieghe (2001) did not appear to confirm the explanatory role of a trade-weighted real exchange index[4].

The conclusions of studies into aggregate rates of bankruptcy underscore the importance for the corporate sector of a smooth and predictable macroeconomic environment. In addition, these stylised facts seem to bring to the fore the management role in the failure process as they seem to agree with managerial theories of corporate failure highlighting possible inadequacies in risk management in UK companies. Thus it is important to account for these factors in a model of failure risk.

3 Examination of a Sample of UK Quoted Firms in 1989-92

In this study, we have augmented a financial ratio-based model of failure risk with two macroeconomic variables so as to explore the explanatory power of macroeconomic factors and to get a better understanding of the failure process. We use firm-level data on UK large quoted companies, representative of insolvency over the 1990-92 recession. The determinants of failure are evaluated from the estimated results of two sets of logit functions and their associated predictive performance. The prediction functions of the first set rely on traditional, financial ratio-based inputs alone. The second set of models uses both financial ratio-based predictors and two macroeconomic variables, measuring unanticipated changes in the real effective exchange rate and in the nominal interest rate. A single set of models is a series of individual logit functions estimated with data specific to four risk horizons, ranging from one year to four years prior to failure. Multiple observations on financial variables permit to evaluate the extent to which determinants of failure tend to change over time while the pooled cross-sectional structure allows an incorporation of time-series observations on the two macroeconomic indicators.

3.1 Failure Definition and Data Composition

By adopting a purely legalistic criterion, we equate company failure with the event of entering a formal insolvency regime, that is administrative receivership, administration, or winding-up (liquidation). Using information on quoted company insolvency status from the London Stock Exchange Official Yearbook and financial statement data from DATASTREAM, we compile a list of firms[5] going into insolvency over the early 1990s and then create estimation and holdout cross-sections. Since availability of data on insolvent firms is always a limiting factor in developing statistical models of corporate failure, data points comprising a single, year-to-failure-specific cross-section come from several consecutive calendar years. An advantage of the pooled cross-section design is that it provides a temporal dimension to the data, which is of great importance for isolating the influence of macroeconomic factors on failure risk. Annualised financial records were collected for a four-year period prior to insolvency so as to reveal the determinants of failure occurring in one, two, three and four years, allowing for temporal precedence. Therefore the sample companies are subject to at least four consecutive years of complete accounting records. The sub-

[4] Vlieghe (2001) uses a rich specification which contains explanatory variables measuring company indebtedness, profitability, availability of external and internal finance, property prices, corporate bond spreads, factor prices, nominal and real interest rates, the company formation rate, and the real effective exchange rate.

[5] See Table A-1in the Appendix.

set of 53 failing firms defines the estimation period, which in terms of calendar year of insolvency announcement covers 1989-93, corresponding to the period of high default rates in the early 1990s. Records concerning firms' financial conditions concentrate in 1988-91 because of the lag between last accounts and insolvency announcement. Although we use non-random sampling for the failed firm category, 368 company-years based on 316 non-failing firms were drawn randomly, without replacement, from data on industrial firms with complete and consistent DATASTREAM records over the period 1985-95[6]. Non-failed firms in our sample had been continuing in independent existence and were free of insolvency up to 1995. No matching of failed and non-failed companies by criteria such as industry sector or size was used, but to counter-effect modification associated with time, we matched the observations on failing and non-failed firms by the timing of financial records. The sampling scheme has yielded unbalanced cross-sections with the failing firm category accounting for 12.6 per cent of company-years, which seem representative of the quoted company population proportions for failed and non-failed categories.[7] A sample with the prevailing proportion of non-failed firms permits a relatively large number of observations and provides a sounder basis for evaluating models' performance. In this way, we can better approximate the population's insolvency rate to deal with the well known methodological problem of biased estimates where state-based samples are employed in conjunction with estimators and inference procedures that assume random sampling (see e.g. Palepu, 1986).

To perform an 'out-of-sample' validation of the obtained determinants, we create year-to-failure specific holdout samples containing observations on firms entering the insolvency state in 1992-95. These were compiled according to the filters and procedures employed in designing the primary estimation sample[8]. In terms of timing of financial records, the holdout observations are distributed over the period of 1992-94. Holdout samples are also unbalanced, with a 10.4 per cent share of failing firms.

The composition of sample firms by insolvency status and sector are provided in Table A-3 of the Appendix. Companies in transportation and petroleum industries were not included as their capital structure tend to be quite unique and these industries have different taxation regimes, accounting conventions, and the insolvency environment.

3.2 Explanatory Variables

Financial Variables

Information from audited annual accounts is seen in the literature as a critical input to empirical models of company failure, however there exists no dominant or unique set of accounting variables with respect to corporate performance and financial position. Empirical results from Hamer (1983) on comparative power of failure prediction models, show no significant variation in models' performance which can be attributed to alternative definitions of ratios or combinations of ratio-based variables as long as a set of accounting ratios is comprehensive and represents major dimensions of financial analysis. Hamer recommends considering a single set of accounting covariates that minimises the cost of data collection. Therefore we employ a fairly standard range of 25 accounting ratios and market measures based on items provided for

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[6] A primary listing of non-failed firms was tabulated from the DATASTREAM list of UK " live" quoted industrials that consisted of 1,330 equities as of 13 February 1997.

[7] It is impossible to access how accurately the sample mix approximates the proportions of failed and non-failed firms in the underlying population of large quoted industrials, as the necessary data have been hard to acquire. To our knowledge, comprehensive time series on the number of UK quoted companies suffering financial distress or being placed into formal insolvency regimes have not been reported systematically, and only rough and even arbitrary estimates have been used in previous research. Estimates of population proportions for failed and continuing firms vary. Letza (1994) refers to Dun and Bradstreet's estimate of the long run average failure rate of companies in England and Wales at 0.85 per cent. Taffler (1982) drew on subjective estimates of the investment analysts and used an odds ratio (based on the prior probabilities for a failed and non-failed firm) of 1:10. Focusing on the period of 1968-73, his study was concerned with industrial enterprises quoted on the London Stock Exchange, and failure was defined as formal insolvency. Dunne and Hughes (1994) examined death rates over the period of 1980-85 in the sample of 2,149 UK firms that included all quoted and large unquoted companies, and found that, on average, liquidations or receiverships accounted for 3.7 per cent of sample firms.

[8] See Table A-2 in the Appendix.

quoted industrial companies by DATASTREAM. These include: rates of return, profit margins, cumulative profitability, turnover ratios, measures of gearing, liquidity and tax position, total net sales proxying firm's size, the net tangible assets index, which reflects long-term solvency, and the dividend payout ratio. To alleviate the problem of non-stationarity of financial ratios arising in a pooled cross-section data (see e.g. Sudarsanam and Taffler, 1995), values of ratio-based covariates have been standardised using mean and standard deviations from their respective accounting years. Tables A-3 and A-4 in the Appendix show some descriptive statistics of financial ratio-based explanatory variables for each of the four years prior to failure.

Macroeconomic Variables

In modelling the influence of macroeconomic factors we follow the approach used by Young (1995) for representing uncertainty in the macroeconomic environment, in that it is assumed that only unanticipated changes - 'surprises' - in the interest rate and in the exchange rate matter for company viability. Anticipated changes in interest and exchange rates, damaging firms' cash flows and equity values, should be possible to incorporate in strategies for hedging and other business decisions. As pointed out by Wadhwani (1986), the nominal interest rate seems to be an especially relevant explanatory factor in the failure process. The empirical results in Goudie and Meeks (1991) and Bhattacharjee, Higson, Holly, Kattuman (2002) suggest the importance of shifts in the exchange rate on company performance and survival. A real appreciation in the effective exchange rate increases failure risk by adversely affecting profitability and competitiveness of both the exporters, sensitive to external competition, and those firms that compete internally and are therefore sensitive to the level of import penetration. A real depreciation in the effective exchange rate can also adversely affect firms with foreign currency debt. Hunter and Simpson (1995) discuss in greater detail the impact of the conservative government policy on the exchange rate and competitiveness of UK companies over the early 1990s.

Further, we assume a delay in the effect of changes in the two macroeconomic indicators on firm performance and financial position. Due to the certain extent of inertia, it is the last year's mistakes and miss-predictions, which may be critical as a financial distress trigger. The failure process might well be driven by a sequence of such mistakes. Accordingly, in modelling, we utilize lagged unanticipated changes in the annualised values of macroeconomic variables corresponding with the timings of financial records on the sample firms.

As unanticipated changes in macroeconomic variables are not directly observable, they must be proxied. The simplest path to follow is to make a major assumption that the macroeconomic series of interest evolve as a random walk.[9] To measure the underlying economic risks affecting the likelihood of failure, we then assume that the process for a series of observations of the macroeconomic variable u_t is generated by a naive (driftless) random walk:

$$u_t = u_{t-1} + e_t; \quad e_t \sim \mathrm{IID}(0, s^2); \quad t = 1,...,n \quad , \tag{1}$$

where u_t is a value of the macroeconomic variable at time t; and e_t is a random disturbance, not predictable from the history of the process.

Then the conditional mean and variance of the variable at date t, conditional on the initial value u_0 at date 0, is:

[9] As for the nominal interest rate process this assumption is a gross simplification. However, stylised facts concerning time series for the major exchange rates (under floating exchange rate regimes) are that exchange rates are hard to distinguish empirically from a simple random walk (Mussa, 1984; Taylor, 1995). Meese and Rogoff (1988) report that their regression forecasts of log real exchange rates are never significantly better than the driftless random walk. Evidence on real exchange rates stationarity has been presented by Hunter and Simpson (2001).

$$E(u_t \mid u_0) = u_0 + 0 \quad (2)$$

$$Var(u_t \mid u_0) = s^2. \quad (3)$$

That implies that the unanticipated change in the macroeconomic variable equals $(u_t - E(u_t))$, that is the entire change is unanticipated. It is obvious from (1) - (3), that one can approximate the 'surprise' by the one-year lagged change in the macroeconomic variable.

Accordingly, we construct the one-year lagged logarithmic change in the real effective exchange rate, which influences competitiveness in the traded goods sector, and the one-year lagged logarithmic change in the nominal interest rate, which directly impacts on the burden of debt and capacity to raise finance. If financial statement-based independent variables describing an individual firm in the pooled cross-section pertain to year *t*, then the two macroeconomic variables are measured as follows:

$$\text{One - year Lagged Change in the Real Effective Exchange Rate} = [\ln RER(t-1) - \ln RER(t-2)], \quad (4)$$

where the real effective exchange rate, $RER(t)$, is given as an index,[10]

$$\text{One - year Lagged Change in the Nominal Interest Rate} = [\ln IR_n(t-1) - \ln IR_n(t-2)], \quad (5)$$

where the nominal interest rate, IR_n, is given by the 3-month sterling inter-bank rate measured as the annualised percentage rate.[11]

An additional advantage of specifying macroeconomic measures in differences is that the resulting macroeconomic covariates are stationary, complementing the correction made for financial statement-based variables. As noted earlier, the potential for the joint use of cross-sectional financial data and macroeconomic time-series is provided here by the structure of repeated pooled cross-sections allowing the variation of financial covariates over time.

It is important to observe that the expected value of the two macroeconomic variables is zero, implying on average zero response to either the interest rate change or the exchange rate change. One can argue that unanticipated rises both in the exchange rate and in the interest rate had the adverse impact on those companies that would consequently fail, thus to capture the influence of changes in the business climate, a macroeconomic dummy variable is constructed that is equal to 'one' for failed companies. This dummy is then used in interactions with each macroeconomic variable. It follows that the predictions from the model will be conditional on the mistakes in macroeconomic forecasts, the effect of which is measured from their impact on failed firms. Hence, we are looking at the risk of failure conditional on a poor response to changes in macroeconomic conditions[12].

[10] The index is the DATASTREAM item "UKOCREXC". This measure is similar to a trade-weighted exchange rate index employed in Vlieghe (2001).

[11] Young (1995) employed this proxy for the nominal interest rate.

[12] We should also comment on a potential methodological problem of measuring the impact of aggregate macro variables on micro units, when a strategy of merging aggregate data with cross-sectional data is employed (Moulton, 1990). Using an example of the linear model, Moulton cautions that ignoring the correlation of errors within groups, which used to merge aggregate with micro data, can result in spurious downward bias of the usual OLS standard errors, the resulting inflation of test statistics and incorrect inference. It is important to emphasize that in our empirical design no aggregate measure is being used as we combine with financial statement data on firms such economic indicators as the nominal interest rate and the real exchange rate. Moreover, the cost of omitting relevant explanatory variables is inconsistency. Nonetheless, we recognise that in further research it might be desirable to investigate further the implications and solutions of this potential problem when a range of macroeconomic variables used in logit models of failure is expanded by the addition of aggregate macro variables.

3.3 Statistical Model

In the case of conventional, failed/non-failed dichotomy, the dependent variable is a binary response. An outcome is a reflection of the underlying regression, which links the dependent variable $\mathbf{y}$ to the explanatory and control variables gathered in the vector $\mathbf{x}$.

If the logistic density is used to specify the link for the unknown probability that the binary outcome is equal to 'one' than the probability for a company to fail is given by the following expression:

$$\text{Prob}(Y = 1\,(Failure)) = \frac{e^{\mathbf{ß}'\mathbf{x}_i}}{1 + e^{\mathbf{ß}'\mathbf{x}_i}}. \tag{6}$$

Here y_i independently equals 1 or 0 with probabilities p_i or $1\text{-}p_i$. The $\hat{p}_i$ is considered as predicting whether an observation with the covariate vector $\mathbf{x}_i$ will be a failed firm or a non-failed firm, by using the realised prediction rule $\hbar$:

$$\begin{cases} \hbar_i = 1 \text{ if } \hat{p}_i > C_0, \\ \hbar_i = 0 \text{ if } \hat{p}_i \le C_0, \end{cases} \tag{7}$$

for some cutoff point C_0.

The primary test of a constructed model adequacy and its ability to reveal the determinants of failure is whether the model accurately returns response values for future observations, taken outside the estimation sample range and time period.

The classificatory power of the model, fitted to the estimation sample, is commonly defined as the apparent error rate, yielding an estimate of the true error rate of the model (Efron, 1986):

$$\bar{\text{e}}\text{rr} = \#\{\text{y}_\text{i} \ne \hat{\hbar}_i\} / n. \tag{8}$$

Because $\mathbf{y}$ is used for both constructing and assessing the prediction rule $\hbar$, $\overline{\text{err}}$ will usually be biased downwards and as a result the new binary outcome might not be predicted nearly as accurately by the old $\hbar$.

The bias (or the optimism) is the difference between the true error rate and the apparent error rate, hence the purpose of estimating the bias is to construct the estimates of the true error rate, better than the apparent error rate. In assessing the *ex ante* predictive power of the realised prediction rule based on logit, we generate holdout predictions and compute analytic estimates of the optimism in the apparent error rate, using the method proposed by Efron (1986). Efron's solution allows adjusting the overall apparent error rate generated on estimation samples for the optimism. The analytic estimate of the expected downward bias in the apparent error rate is added to the apparent error rate so as to obtain an improved estimate of prediction error, and to infer how well a model predicts the response value of a future observation. A model with better explanatory power will generate lower error rates. It should be noted that it would be inappropriate to compare classificatory accuracy rates for alternative models derived from and assessed on different data sets.

3.4 Results

We interpret the estimated models as describing the conditional expectation of the failure outcome given the selected explanatory variables. The model building approach utilised here is the standard *general-to-*

specific modelling method[13]. To produce a parsimonious model an initial general specification is tested down by eliminating covariates using a sequence of *t*-tests and independent Likelihood Ratio tests. The resulting model should essentially contain a satisfactory proportion of information conveyed by the original general specification, while also being much more parsimonious.

We present two groups of logit estimates: from models explaining failure with financial covariates alone (Tables 1 and 2) and from models incorporating macroeconomic effects (Tables 3 and 4). Estimates are shown separately for the four specified risk horizons, covering one to four years before failure. Tables A-5, A-6, A-7, and A-8 in the Appendix, present the goodness of fit, which is judged by the within-the-estimation-sample classificatory accuracy adjusted for the optimism, and by the models' power to predict fresh, holdout observations. The choice of the relevant cutoff probability value, which influences classification results, has been discussed elsewhere (see e.g. Ohlson, 1980; Palepu, 1986; Maddala, 1992; Greene, 1997; Bayldon and Zafiris, 1999; Cramer, 1999). As pointed out in Cramer (1999), in assessing the within-sample performance of a model derived from the unbalanced sample, the cutoff probability taken from sample frequencies is the appropriate one to use. However, here we follow Ohlson (1980), and evaluate classificatory and predictive accuracy for a wide range of cutoff probability values ranging 0.1 to 0.875.

Basic Models Based on Financial Variables

The overall significance of the four parsimonious models based on financial variables alone (Tables 1 and 2) is acceptable as the χ^2 statistics for the joint significance of model parameters exceed respective critical values at the 0.1% level. The model for the one-year risk horizon shows the best fit in terms of the Likelihood Ratio Index[14] (Table 1). The results for one year prior to failure reflect the information contained in the last accounts released by a failing company, and therefore record the state of severe distress. The estimates indicate that the company with low creditors turnover, high gearing, low liquidity, and a smaller proportion of earnings paid out as dividends, is more likely to fail. The predicted signs for profitability ratios indicate that, in the short run, the failing firm has negative operating profits, which might be interpreted as a sign of economic distress. Failing firms have lower returns on capital employed relative to non-failed firms, but may record higher returns on shareholders' capital. The counterintuitive positive relation of the return on shareholders' capital to failure risk can simply be due to the DATASTREAM specification of the ratio used, with the combination of negative numbers for after-tax profits and negative values for shareholders' funds yielding the positive sign for the ratio.

Using longer time horizons, failure determinants are revealed from models estimated using covariates two, three, and four years prior to failure. Reinforcing the stylised fact that smaller firms exit first (see e.g. Dunne, Roberts, Samuelson, 1989), size appears indicative of insolvency in years two through to four prior to failure. The model predicting failure in two-year time (Table 1) suggests that failing firms generate lower cash flows, have inadequate current assets and reduce dividends as compared with non-failing firms. The results for the three-year risk horizon (Table 2) imply that, in the long run, high gearing, measured by capital and income gearing, distinguishes the likely to fail firms from survivors. A positive relationship is also observed between current assets turnover and the probability of failure, which may be consistent with the view that highly geared and fast growing companies fared least well during the 1990-92 recession. The model specific to the four-year risk horizon (Table 2) seems to confirm chronic liquidity shortages of failing companies. When compared with the healthy company's profile, failing firms appear to have comparatively less long-term debt, but borrow heavily from short-term sources to compensate for insufficient current assets and for low levels of their gross cash flow relative to total liabilities. This is implied in the positively signed borrowing ratio and in the negatively signed ratio of loan capital to equity and reserves. The failing companies' reliance on borrowings with less that one year maturity, is also

[13] See Hendry, Muellbauer and Murphy, 1990.
[14] See McFadden, 1974.

Table 1: Financial Ratio-Based Models:
One and Two Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	**One Year Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Two Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-3.249	(0.000)	-2.517	(0.000)
Size				
Log Total Sales			-0.455	(0.022)
Profitability				
Return on Shareholders' Capital	1.370	(0.006)		
Return on Capital employed	-1.244	(0.001)		
Operating Profit Margin	-0.813	(0.017)		
Pre-tax Profit Margin				
Turnover				
Turnover/Net Current Assets				
Creditors Turnover	-0.450	(0.048)		
Gearing				
Capital Gearing	0.667	(0.001)		
Income Gearing				
Borrowing Ratio				
Gross Cash Flow/ Total Liabilities			-0.705	(0.000)
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio	-1.789	(0.000)	-1.124	(0.000)
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio	-1.312	(0.020)	-0.800	(0.056)
Assets Index				
Tax Ratio				
Log-Likelihood at Convergence	-103.55		-125.85	
c^2 statistic of LR Test (p-value)	111.61 (0.000)		67.00 (0.000)	
Likelihood Ratio Index	0.325		0.179	
n	421			
Per cent Failed	12.6			

Table 2: Financial Ratio-Based Models:
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed *p*-value of asymptotic *t*-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed *p*-value of asymptotic *t*-statistic)	
Constant	-2.263	(0.000)	-2.458	(0.000)
Size				
Log Total Sales	-0.804	(0.000)	-1.020	(0.000)
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin				
Pre-tax Profit Margin				
Turnover				
Turnover/Net Current Assets	0.225	(0.017)		
Creditors Turnover				
Gearing				
Capital Gearing	0.828	(0.000)		
Income Gearing	0.865	(0.023)		
Borrowing Ratio			0.937	(0.007)
Gross Cash Flow/ Total Liabilities			-0.439	(0.005)
Loan Capital/Equity and Reserves			-1.312	(0.002)
Liquidity				
Working Capital Ratio			-0.701	(0.001)
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index			0.368	(0.007)
Tax Ratio			-0.796	(0.050)
Log-Likelihood at Convergence	-134.65		-125.02	
c^2 statistic of LR Test (*p*-value)	49.39 (0.000)		68.64 (0.000)	
Likelihood Ratio Index	0.122		0.185	
n	421			
Per cent Failed	12.6			

consistent with the negative coefficients on the ratio of gross cash flow to total liabilities and on the working capital ratio. The four years prior to failure model suggests the importance of changes in the value of net tangible assets indicating that failing firms had a period of asset growth, which might have facilitated their access to credit, providing that borrowing restrictions were based on book value of equity. In the model for the four-year risk horizon, the tax ratio has a negative sign, indicating that the proportion of tax payments in pre-tax profits is lower for failing firms. However, tax charges are subject to factors unconnected with the current year performance. Notably, no patterns with respect to company profitability are evident in the financial ratio-based models for two, three and four years prior to failure.

As far as the classification and predictive ability of obtained accounting ratio-based models is concerned, the question of interest is to find to what extent the results are coherent. Models predicting short-term risk - within one and two years before failure (Table A-6) - generate relatively robust, with respect to a wide range of cutoff probability values, estimates of the overall error rate adjusted for the optimism. Prediction error estimates vary from 14 percent to 26.1 percent for year one prior (Panel A in Table A-6), and for two years prior to failure they lie between 16.7 percent and 32 percent (Panel B in Table A-6). Roughly similar accuracy is demonstrated in validation. The performance of the four years prior to failure model, in terms of overall prediction error magnitudes and the robustness on both estimation and holdout observations, is remarkably similar to the accuracy levels observed for the one year prior to failure model and two years prior model. If accuracy is judged by the adjusted apparent error rate, the model for the three-year risk horizon is likely to forecast no worse than models for other risk horizons. The estimates of prediction error lie between 17.7 and 36.5 percent (Panel A in Table A-7), although the approximation of holdout observations is rather weak.

Models Incorporating Macroeconomic Variables

Results from modelling the impact of macroeconomic instability are displayed in Tables 3 and 4. A series of risk-horizon-specific models incorporates financial variables alongside one-year lagged, unanticipated changes in the real effective exchange rate and in the nominal interest rate. The initial specification used to test down to more parsimonious models, is more complete than that used for the series of basic models. We allow for a lagged relation between the changes in a macroeconomic variable and the full economic impact of the changes on the firm's performance as reflected in its financial accounts. As noted earlier in Section 3.2, effects of macroeconomic instability on failure risk are modelled by using an interactive dummy, which is set to unity for observations on failing firms. That is we argue that non-failed firms had forecast more accurately the future conditions and were able to better and at lower costs react to 'surprises' in the macroeconomic environment. Hence, in modelling we assume that a failing company's performance is sensitive to one-year lagged unanticipated changes because of miss-predictions by the failing firm or its inability to assess the impact of changes in the future business conditions and take correcting actions. We infer the models' stability and relevance of aggregate economy risks by examining the significance of estimates of the individual coefficients for the interaction terms along with the accuracy of conditional predictions on primary and holdout data points. In holdout tests, outside the estimation period, we assume that all firms are at risk of failure and set the macroeconomic dummy to unity for both failing and non-failed firms.

Results presented in Tables 3 and 4 indicate that the impact of macroeconomic instability is substantial. The overall fit improves markedly. All models, across the four risk horizons, show acceptable overall performance with the Likelihood Ratio c^2 statistics being significant at the 0.1% level. When judged by the Likelihood Ratio Index, the models augmented with the macroeconomic variables explain the failure outcome better than the basic, financial ratio-based models. Clearly, for the sample firms, failure risk is linked to unanticipated shifts in the real effective exchange rate. The coefficient for the unanticipated change in the real exchange rate is significant at the 1% level and better, across all four years preceding failure, being positively signed in the models for years one, two, and three prior to failure, but being negative in the model for four years prior. Overall, this indicates that increases in the real effective exchange rate precipitated company failure during the 1990s recession. These increases might have generated additional risks for exporters as compared with the generality of firms. Unexpected increases in

Table 3: Models Incorporating Macroeconomic Variables:[15]
One and Two Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension / *Variable*	One Year Prior to Failure: Coefficient (two-tailed p-value of asymptotic t-statistic)		Two Years Prior to Failure: Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-5.481	(0.000)	-2.682	(0.000)
Size				
Log Total Sales			-0.540	(0.010)
Profitability				
Return on Shareholders' Capital	3.895	(0.000)		
Return on Capital employed	-3.778	(0.000)		
Operating Profit Margin				
Pre-tax Profit Margin				
Turnover				
Turnover/Net Current Assets				
Creditors Turnover				
Gearing				
Capital Gearing	1.641	(0.000)		
Income Gearing				
Borrowing Ratio			0.548	(0.030)
Gross Cash Flow/ Total Liabilities			-0.727	(0.001)
Loan Capital/Equity and Reserves				
Liquidity				
Working Capital Ratio			-0.980	(0.002)
Working Capital / Assets Employed	-1.222	(0.018)		
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio				
Macroeconomic Variables				
Change in Real Effective Exchange Rate	190.452	(0.002)	35.066	(0.000)
Change in Nominal Interest Rate	31.230	(0.000)		
Log-Likelihood at Convergence	-25.90		-115.69	
c^2 statistic of LR Test (p-value)	266.90 (0.000)		87.31 (0.000)	
Likelihood Ratio Index	0.831		0.246	
n	421			
Per cent Failed	12.6			

[15] Macroeconomic variables enter the model specification as interaction terms, where the binary indicator takes on 'one' for observations on failing firms.

Table 4: Models Incorporating Macroeconomic Variables:[16]
Three and Four Years Prior to Failure; 1988-91 Estimation Period,
53 Failed Companies and 368 Non-failed Company-years (n=421)

Dimension *Variable*	**Three Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)		**Four Years Prior to Failure** Coefficient (two-tailed p-value of asymptotic t-statistic)	
Constant	-2.519	(0.000)	-3.243	(0.000)
Size				
Log Total Sales	-0.651	(0.001)	-0.621	(0.028)
Profitability				
Return on Shareholders' Capital				
Return on Capital employed				
Operating Profit Margin			1.441	(0.045)
Pre-tax Profit Margin			-1.683	(0.034)
Turnover				
Turnover/Net Current Assets				
Creditors Turnover				
Gearing				
Capital Gearing	0.867	(0.000)		
Income Gearing	0.751	(0.043)		
Borrowing Ratio			1.126	(0.025)
Gross Cash Flow/ Total Liabilities				
Loan Capital/Equity and Reserves			-1.374	(0.021)
Liquidity				
Working Capital Ratio			-0.699	(0.036)
Working Capital / Assets Employed				
Other Financial Variables				
Payout Ratio				
Assets Index				
Tax Ratio			-1.478	(0.009)
Macroeconomic Variables				
Change in Real Effective Exchange Rate	32.773	(0.000)	-122.365	(0.000)
Change in Nominal Interest Rate	-26.655	(0.000)	21.104	(0.000)
Log-Likelihood at Convergence	-118.31		-81.04	
c^2 statistic of LR Test (p-value)	82.08 (0.000)		156.63 (0.000)	
Likelihood Ratio Index	0.228		0.472	
n	421			
Per cent Failed	12.6			

[16] Macroeconomic variables enter the model specification as interaction terms, where the binary indicator takes on 'one' for observations on failing firms.

the exchange rate can cause a decline in liquidity due to falling revenues and, over a longer period of time, may inflict a loss of competitiveness. In addition, increases in the exchange rate can have possible detrimental effects on performance measures, especially on the earnings per share, in relation to reported overseas profits. Firms with located overseas and denominated in foreign currency assets may experience deteriorating solvency and face financing constraints when the pound appreciates. However, our findings on the relation between the exchange rate changes and failure risk, contrast somewhat with the conclusions drawn by Bhattacharjee, Higson, Holly, Kattuman (2002) and by Vlieghe (2001).

Further, our results show that unexpected movements in the nominal interest rate are an important determinant of failure for the firms in our sample. In the model for three years prior to failure (Table 4), the coefficient for the nominal interest rate effects is negative. However, results from the models for one-year and four-year risk horizons (Tables 3 and 4) lend support to the stylised fact that unexpected increases in the nominal interest rate exacerbate financial constraints on highly geared firms. Such unexpected increases may apply with particular force to the companies in our sample, which pertain to the early 1990s. A report by The Bank of England suggested that in the early 1990s, subdued equity issues and a fall in short-term interest rates following the stock market crash of October 1987, encouraged companies to issue long-term debt and increase short-term borrowing. The capital gearing of UK industrial and commercial companies rose significantly over the early 1990s being about three times higher than in 1980s (*Bank of England Quarterly Bulletin*, August 1993). A sharp rise in interest rates from 1988 increased companies' debt service costs while the subsequent recession lowered companies' ability to service debt.

The inclusion of the two macroeconomic indicators illustrates the robustness of the estimates of the effects of liquidity and gearing. Similarly to the results from financial ratio-based models, size is a significant explanatory factor at risk horizons of two to four years. Profitability measures are now important both in the short run and in the long run, with rates of return and profit margins explaining failure at one and four years prior to failure. The rate of return on shareholders' capital retains its positive sign and the rate of return on capital employed is negatively signed. In the four years prior to failure model (Table 4), coefficients on profitability measures indicate that despite failing firms achieving relatively higher operating profit margins, their pre-tax profit margins are smaller than those of non-failed firms, suggesting perhaps the absence of signs of economic distress. At all risk horizons, models augmented with macroeconomic indicators seem to reiterate the stylised fact that high gearing increases failure risk. Precipitating failure, relatively lower liquidity ratios are important in years one, two and four before failure.

An additional explanatory power of the added macroeconomic indicators is inferred by assessing models performance in predicting failure.

Classificatory accuracy, evaluated by applying the one year prior to failure model to the data points used in fitting the model (Panel A in Table A-8), indicates that the conditioning on the effects of the macroeconomic variables improves correct classification rates both for failed and for non-failed firms as compared to the basic financial ratio-based model constructed for the same risk horizon (Panel A in Table A-6). This improvement observed across all cutoff probability values is consistent with a decrease in the overall prediction error adjusted for the downward bias. Predictions of the holdout data points, at this risk horizon, are also characterized by lower overall error rates, ranging from 9.4 per cent to 10.4 per cent (Panel A in Table A-8).

Predictive power of the model explaining the risk of failure at the risk horizon of two years (Panel B in Table A-8) is somewhat weaker than that of the one year prior to failure model. First, we should point out the deterioration in the holdout approximation at the cutoff values of 0.1 and 0.125, as compared to the financial ratio-based model performance (Panel B in Table A-6). When the cutoff probability values of 0.1 and 0.125 are used for evaluation, the overall accuracy declines to the levels of 36.5 to 42.7 per cent, being lower than a correct prediction rate of 61.5 per cent and better, which is achieved by the basic financial ratio-based model constructed for this risk horizon.

The importance of the macroeconomic factors for explaining failure risk in the long run, is supported by definite improvements in classificatory and predictive ability of models developed for three and four years prior to failure (Table A-9). In comparison to basic models with financial ratios alone, the three years prior and four years prior to failure models, augmented with the macroeconomic indicators, demonstrate improved accuracy in categorizing observations from both the estimation sample and the holdout sample across all cutoff probability values. Notably, accuracy gains provided by the four years prior model are consistent with the adjusted for the downward bias alternative estimates of prediction error of 15.2 per cent and better. The predictive quality is supported by the accuracy assessed on holdout observations where the overall error rate of 21.9 per cent and better is observed.

4 Conclusions

The objective of this paper was to re-examine the determinants of company failure by looking directly at the contribution of the environmental, macroeconomic factors to the likelihood of failure measured at the firm level in a sample of UK large quoted industrials taken from the early 1990s. Macroeconomic indicators were incorporated into conventional cross-sectional models of failure risk. Lagged yearly, unanticipated changes in the nominal interest rate and in the real effective exchange rate are significant variables in explaining failure. We assessed both short-term and long-term effects of the shifts in the two macroeconomic indicators on the probability of insolvency by fitting logit models to pooled across several years cross-section data, at different risk horizons ranging from one to four years before failure. We assessed model adequacy and inferred the importance of the macroeconomic factors from the significance of coefficient estimates and classificatory and predictive accuracy of the models.

The pattern of significance of financial statement-based determinants assessed for the four-year period prior to failure, provided evidence on the key role of gearing, liquidity and profitability, corroborating earlier results on UK company failure (Taffler, 1982; Keasey and McGuinness, 1990; Alici, 1995), and was robust to the model augmentation with macroeconomic indicators.

Models incorporating the macroeconomic indicators exhibited lower prediction errors assessed on an out-of-sample basis. The best predicting models, augmented with the two macroeconomic variables, demonstrated stability and the adequate fit on the out-of-sample data points. In holdout tests, the overall accuracy of 90.6 per cent and better was achieved at the one-year risk horizon and of 71.9 per cent and better at the risk horizons of three and four years. The achieved accuracy compares favourably with a weaker approximation of the holdout observations by the basic models based on financial ratios alone.

The empirical relation between the probability of failure and unanticipated changes in the real exchange rate and nominal interest rate appeared stable over the four-year period before failure. Obtained empirical predictors suggested that during the 1990s recession, unanticipated increases in the real exchange rate and rises in the nominal interest rate were associated with a higher propensity of UK quoted industrial company to fail, thus indicating the links to declining liquidity, to a loss in competitiveness, and to the detriment of inflation for highly geared firms.

Appendix: Data Set Description and Model Performance Results

Table A-1: Names and Years of Entering Insolvency Regime, of UK Failed Quoted Industrials Used in the Estimation Sample

Allied Partnership Group	1992	Ketson	1990
Arley Holdings	1990	Lawtex	1991
Arnkliffe Holdings	1991	Lilley	1993
Astra Holdings	1992	Lyon & Lyon	1990
AT Trust	1990	Maxwell Comms. Corporation	1991
ATP Communications Group	1992	Miller (Stanley) Holdings	1990
Audit & General	1991	Oakwood Group	1990
Bestwood	1990	Parkfield Group	1990
C.H. Industrials	1991	Pavilion Leisure	1991
Chelsea Man	1991	Pavion International	1989
Chequers Group	1992	Peters (Michael) Group	1990
Clearmark Group	1991	Polly Peck International	1990
Colographic	1992	Reliant Group	1990
Coloroll	1990	Rockwood Holdings	1990
Conder Group	1992	Rush & Tomkins Group	1990
Crown Communications Group	1993	Sale Tilney	1992
Doctus	1991	Toothill (R.W.)	1991
Ferrari Holdings	1991	Trilion	1992
Fobel International	1991	Turriff Corporation	1991
Futura Holdings	1993	Video Store Group	1991
Gaynor Group	1991	Ward Group	1992
Goldberg (A.) & Sons	1990	West Industries	1992
Grovewood Securities	1991	Westerly	1991
Halls Homes & Gardens	1992	Willaire Group	1992
Hey & Croft Group	1992	Williams (John) Industries	1990
Huges Food Group	1991	Yellowhammer	1990
International Resort Holdings	1992		

Table A-2: Names and Years of Entering Insolvency Regime of UK Failed Quoted Industrials Used in the Holdout Sample

Automagic Holdings	1995	Ferranti International	1993
Beckenham Group	1994	Harland Simon Group	1992
Bimec Industries	1994	McLaughlin & Harvey	1993
Bullers	1995	Pentos	1995
Dunkeld	1993	Scottish Heritable Trust	1994

Table A-3: Composition of the UK Company Cross-sections for the Reporting Years 1988-94, Breakdown of Observational Units by Insolvency Status and Economic Groups (Percentages in parentheses)

	FT-SE Economic Groups											
	Mineral Extraction		General Industrials		Consumer Goods		Services		Utilities		Total	
Panel A: Estimation Sample, 1988-91												
Non-Failed	1	(0.3)	173	(54.7)	35	(11.1)	106	(33.5)	1	(0.3)	316[17]	(100)
Failed	-	-	24	(45.3)	5	(9.4)	24	(45.3)	-	-	53	(100)
Panel B: Holdout Sample, 1992-94												
Non-Failed	2	(2.3)	40	(46.5)	15	(17.4)	29	(33.7)	-	-	86	(100)
Failed	-	-	7	(70.0)	1	(10.0)	2	(20.0)	-	-	10	(100)

[17] The figure excludes double-counting as the group of non-failed firms consists of data on 368 company-years represented by 316 live companies, on which the accounts data on four consecutive years were available.

Table A-4: Means and *t*-statistics – Financial Ratio-based Variables and Cases Used in the Estimation Samples for One and Two Years Prior to Failure Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years

Financial Dimension	One Year Prior Mean (n=421) (Normalised Values)			Two Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable[18]	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Size						
Log of Total Sales (Net of Trade Discounts)	-0.330	0.094	3.70***	-0.451	0.077	4.18***
Profitability						
Return on Shareholders' Capital	0.200	-0.002	1.05	-0.414	0.043	2.65***
Return on Capital Employed	-0.526	0.069	4.61***	-0.367	0.026	2.94***
Return on Net Fixed Assets	-0.442	0.046	3.97***	-0.398	0.002	2.83***
Cumulative Profitability[19]	0.227	-0.005	1.06	-0.237	0.026	1.73*
Operating Profit Margin	-0.334	0.063	4.11***	-0.564	0.048	4.81***
Pre-tax Profit Margin	-0.443	0.078	5.07***	-0.724	0.067	5.03***
Net Profit Margin	-0.407	0.099	4.32***	-0.705	0.072	4.46***
Turnover						
Turnover / Fixed Assets	-0.090	-0.016	0.52	-0.069	-0.022	0.35
Turnover / Net Current Assets	-0.258	-0.050	2.54**	-0.018	-0.022	0.05
Stock Turnover	-0.036	-0.041	0.04	-0.103	0.050	2.16**
Debtors Turnover	-0.148	0.017	1.08	-0.075	0.010	1.10
Creditors Turnover	-0.362	0.090	3.04***	-0.320	0.059	2.73***

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

[18] See ratio definitions in the Company Accounts Definitions Manual published by DATASTREAM, Issue 5, May 1994.
[19] The cumulative profitability ratio is a variant of the measure employed in Altman, Haldeman and Narayanan (1977) and is has been calculated by dividing revenue reserves by total assets employed.

Table A-4: - *Continued*

Financial Dimension / Accounting Variable	One Year Prior Mean (n=421) (Normalised Values) Failed	Non-failed	*t*-value	Two Years Prior Mean (n=421) (Normalised Values) Failed	Non-failed	*t*-value
Gearing						
Capital Gearing	0.662	-0.035	5.49***	0.147	-0.14	0.61
Income Gearing	0.459	-0.046	1.97*	0.073	0.005	0.63
Borrowing Ratio	-0.125	-0.009	0.34	0.464	0.020	2.15**
Gross Cash-flow / Total Liabilities	-0.734	0.089	5.61***	-0.760	0.072	6.66***
Loan Capital / Equity and Reserves	0.267	0.008	0.93	0.320	0.026	1.71*
Liquidity						
Working Capital Ratio	-0.640	0.069	9.44***	-0.428	0.040	5.20***
Quick Assets Ratio	-0.552	0.048	4.25***	-0.346	0.024	2.88***
Working Capital / Assets Employed[20]	-0.180	0.021	-0.47	-0.184	0.038	2.27*
Other						
Market Value/Book Value	-0.385	-0.028	2.76***	-0.061	-0.010	0.47
Payout Ratio	-0.300	0.023	2.71***	-0.284	0.078	2.07*
Assets Index	0.125	0.031	0.47	0.125	0.017	0.35
Tax Ratio	-0.200	0.100	1.54	-0.640	0.044	2.36*

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

[20] A similar ratio was used in Altman (1968).

Table A-5: Means and *t*-statistics – Financial Ratio-based Variables and Cases Used in the Estimation Samples for Three and Four Years Prior to Failure Sample Period 1988-91, 53 Failed Companies and 368 Non-failed Company-Years

Financial Dimension	Three Years Prior Mean (n=421) (Normalised Values)			Four Years Prior Mean (n=421) (Normalised Values)		
Accounting Variable	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Size						
Log of Total Sales (Net of Trade Discounts)	-0.490	0.062	4.56***	-0.577	0.033	5.17***
Profitability						
Return on Shareholders' Capital	-0.231	0.076	1.68*	-0.235	0.040	2.38**
Return on Capital Employed	-0.179	0.028	1.41	-0.279	0.086	2.41**
Return on Net Fixed Assets	-0.133	0.044	1.40	-0.396	0.085	2.79***
Cumulative Profitability	-0.058	0.033	0.46	0.139	-0.026	0.62
Operating Profit Margin	-0.305	0.056	2.82***	-0.249	0.070	2.13**
Pre-Tax Profit Margin	-0.401	0.085	3.77***	-0.394	0.082	3.24***
Net Profit Margin	-0.345	0.077	3.35***	-0.304	0.043	2.61***
Turnover						
Turnover / Fixed Assets	0.089	-0.013	0.73	0.096	0.027	0.45
Turnover / Net Current Assets	0.346	0.007	1.90*	0.029	-0.003	0.20
Stock Turnover	0.333	-0.034	1.43	-0.012	0.057	0.39
Debtors Turnover	0.018	0.037	0.11	-0.081	0.053	0.85
Creditors Turnover	-0.103	0.022	0.61	-0.086	0.020	0.69

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A-5: - *Continued*

Financial Dimension *Accounting Variable*	Three Years Prior Mean (n=421) (Normalised Values)			Four Years Prior Mean (n=421) (Normalised Values)		
	Failed	Non-failed	*t*-value	Failed	Non-failed	*t*-value
Gearing						
Capital Gearing	0.483	-0.089	3.19***	0.576	-0.096	3.16***
Income Gearing	0.195	-0.038	2.13**	0.074	-0.017	0.60
Borrowing Ratio	-0.031	-0.043	0.11	-0.123	-0.033	0.40
Gross Cash-Flow / Total Liabilities	-0.429	0.069	3.46***	-0.520	0.128	4.30***
Loan Capital / Equity and Reserves	-0.170	-0.055	0.45	-0.195	0.010	1.61
Liquidity						
Working Capital Ratio	-0.279	0.060	2.88**	-0.314	0.104	2.36**
Quick Assets Ratio	-0.197	0.036	1.70*	-0.229	0.103	1.84
Working Capital / Assets Employed	-0.221	0.013	1.29	-0.086	0.028	0.44
Other						
Market Value/Book Value	0.297	0.003	0.97	-0.271	-0.036	1.16
Payout Ratio	-0.064	0.012	0.34	-0.286	0.029	2.17**
Assets Index	0.148	-0.027	0.59	0.077	-0.039	0.47
Tax Ratio	-0.231	-0.023	2.35**	-0.294	0.081	1.89*

*** Significant at 0.01.
** Significant at 0.05.
* Significant at 0.10.

Table A-6: Classification and Predictive Ability of Financial Ratio-Based Models, One and Two Years Prior to Failure:

1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies).

Panel A: **One Year Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	73.6	79.1	92.7	97.8	99.2	99.5
Failed	90.6	79.2	54.7	45.3	18.9	9.4
Overall	75.8	79.1	87.9	91.2	89.1	88.1
Overall Error Rate Bias Estimated by Efron's Formula	1.9	2.4	3.9	5.2	6.2	6.5
Estimate of Prediction Error	26.1	23.3	16.0	14.0	17.1	18.4
Holdout Sample						
Non-failed	73.3	77.9	90.7	96.5	96.5	96.5
Failed	100.0	100.0	60.0	40.0	30.0	30.0
Overall	76.1	80.2	87.5	90.6	89.6	89.6

Panel B: **Two Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	67.7	75.8	93.2	98.4	99.2	99.7
Failed	86.8	77.4	45.3	18.9	7.5	3.8
Overall	70.1	76	87.2	88.4	87.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	4.1	5.1	5.5	5.7
Estimate of Prediction Error	32.0	26.6	16.9	16.7	17.9	18.1
Holdout Sample						
Non-failed	59.3	65.1	88.4	96.5	98.8	100
Failed	80.0	70.0	50.0	20.0	10.0	0.0
Overall	61.5	65.6	84.4	88.5	89.6	89.6

Table A-7: Classification and Predictive Ability of Financial Ratio-Based Models, Three and Four Years Prior to Failure:

1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies).

Panel A: **Three Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	62.8	75.5	92.4	98.4	99.7	99.7
Failed	83.0	73.6	34	9.4	3.8	3.8
Overall	65.3	75.3	85	87.2	87.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	1.8	2.3	3.8	5	5.3	5.4
Estimate of Prediction Error	36.5	27.0	18.8	17.8	17.7	17.8
Holdout Sample						
Non-failed	27.9	29.1	34.9	38.4	40.7	40.7
Failed	50.0	40.0	30.0	30.0	30.0	30.0
Overall	30.2	30.2	34.4	37.5	39.6	39.6

Panel B: **Four Years Prior to Failure: Correct Classification**, Percentage						
Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample						
Non-failed	67.9	75.3	90.2	98.6	100	100
Failed	77.4	69.8	39.6	24.5	9.4	1.9
Overall	69.1	74.6	83.8	89.3	88.6	87.6
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	4.2	5.6	6.3	6.5
Estimate of Prediction Error	33.0	28.0	20.4	16.3	17.7	18.9
Holdout Sample						
Non-failed	60.5	65.1	83.7	94.2	95.3	95.3
Failed	80.0	80.0	50.0	0.0	0.0	0.0
Overall	62.5	66.7	80.2	84.4	85.4	85.4

Table A-8 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables:

One and Two Years Prior to Failure,
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

1988-91 Estimation Period
(53 Failed Companies and 368 Non-failed Company-years);
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **One Year Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Non-failed	97.6	98.6	99.2	99.5	99.5	100
Failed	94.3	94.3	92.5	90.6	84.9	83
Overall	97.1	98.1	98.3	98.3	97.6	97.9
Overall Error Rate Bias Estimated by Efron's Formula	1.1	1.2	1.4	1.7	2.1	2.3
Estimate of Prediction Error	4.0	3.1	3.1	3.4	4.5	4.4
Holdout Sample:						
Non-failed	98.8	98.8	98.8	98.8	98.8	98.8
Failed	20.0	20.0	20.0	10.0	10.0	10.0
Overall	90.6	90.6	90.6	89.6	89.6	89.6

Panel B: **Two Years Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Non-failed	73.1	79.9	95.4	98.6	99.2	99.7
Failed	75.5	73.6	56.6	39.6	17.0	9.4
Overall	73.4	79.1	90.5	91.2	88.8	88.4
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.5	3.7	4.7	5.3	5.6
Estimate of Prediction Error	28.7	23.4	13.2	13.5	16.5	17.2
Holdout Sample:						
Non-failed	29.1	38.4	68.6	93.0	97.7	98.8
Failed	100.0	80.0	50.0	50.0	10.0	0.0
Overall	36.5	42.7	66.7	88.5	88.5	88.5

Table A-9 Classification and Predictive Ability of Models Incorporating Macroeconomic Variables:

Three and Four Years Prior to Failure,
Classifications and Predictions Conditioned on Interactive Effects between Macroeconomic Variables and Failure.

1988-91 Estimation Period;
(53 Failed Companies and 368 Non-failed Company-years),
1992-94 Holdout Period
(10 Failed and 86 Non-failed Companies)

Panel A: **Three Years Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Non-failed	78.2	84.5	96.5	99.2	99.5	100.0
Failed	84.9	79.2	56.6	41.5	18.9	5.7
Overall	79.1	83.8	91.4	91.9	89.3	88.1
Overall Error Rate Bias Estimated by Efron's Formula	2.1	2.6	3.7	4.7	5.4	5.8
Estimate of Prediction Error	23.0	18.8	12.3	12.8	16.1	17.7
Holdout Sample:						
Non-failed	38.4	38.4	39.5	43	43	45.3
Failed	40.0	40	40	30	30	30
Overall	38.5	38.5	39.6	41.7	41.7	43.8

Panel B: **Four Years Prior to Failure: Correct Classification**, Percentage

Cutoff Value	**0.1**	**0.125**	**0.25**	**0.5**	**0.75**	**0.875**
Estimation Sample:						
Non-failed	87.8	92.7	96.2	100.0	100.0	100.0
Failed	83.0	83.0	77.4	67.9	52.8	41.5
Overall	87.2	91.4	93.8	96.0	94.1	92.6
Overall Error Rate Bias Estimated by Efron's Formula	2.4	2.6	3.5	4.4	5.0	5.4
Estimate of Prediction Error	15.2	11.2	9.7	8.4	10.9	12.8
Holdout Sample:						
Non-failed	80.2	80.2	81.4	81.4	83.7	83.7
Failed	60.0	60.0	60.0	60.0	60.0	60.0
Overall	78.1	78.1	79.2	79.2	81.3	81.3

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