Company accounts based modelling of business failures and the implications for financial stability

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Abstract

This paper examines the determinants of failure among individual UK public and private companies over the period from 1991 to 2001. Using information on profitability, interest cover, capital gearing, liquidity, company size, industry, whether a firm is a subsidiary and overall economic conditions, it is possible to construct estimates of the probability of failure for individual companies. These are used to calculate each company's 'debt at risk': the probability of failure multiplied by its outstanding debt. By summing the firm-level debt at risk over all companies it is possible to produce an aggregate measure of financial risk that takes account of how debt is distributed across individual companies. Aggregate debt at risk, as a percentage of total debt, has fallen from the levels reached in the early 1990s and has remained relatively stable despite the build-up in corporate debt since then.

Key words: Corporate failure, probit, financial stability.

JEL classification: C25, G33.

Summary

Corporate failure poses a threat to financial stability if firms who fail default on their debt. Although the failure of an individual firm is unlikely to have systemic implications, if a number of firms with large amounts of outstanding debt fail simultaneously there may be systemic implications. Previous work in the Bank of England, which aimed at monitoring these risks to financial stability arising from corporate failure, has been relatively qualitative. The aim of this paper is to supplement that work with a more quantitative approach. We use firm-level data to develop a model of corporate failure, which we then use to analyse both the aggregate risks and the distribution of those risks.

The early literature used balance-sheet information and a discriminate-analysis method to try and predict firm failure. More recent articles have favoured probit models, and this is the approach we take. Most of the papers in the existing literature use a relatively small number of firms or a relatively short timescale. We attempt to address this problem by using a sample of over 100,000 observations from 29,361 public and private UK non-financial firms between 1991 and 2001.

We estimate a probit model for individual company failure using firm-level balance-sheet information and aggregate data on macroeconomic conditions. We find that there is a negative relationship between profitability and corporate failure, but this relationship is non-linear, with negative profitability being associated with the largest marginal effect on the probability of failure. There is a positive association between the debt to assets ratio and the likelihood of failure, and there is an additional positive impact on the probability of failure if above-average capital gearing coincides with the firm making a loss. The probability of a firm failing is found to be negatively related to its interest cover and liquidity. If a firm is large and a subsidiary, it is less likely to fail, holding all other factors constant. Our model controls for industry: firms in the service sector are less likely to fail than those in manufacturing, primary industries and utilities. We incorporate macroeconomic effects into the model by including GDP growth and find a negative correlation between GDP growth and failure, even after controlling for all of the firm-level characteristics.

We use the firm-level probabilities of failure generated by the model and apply these to the analysis of risks to financial stability arising from the UK corporate sector. We do this by defining debt at risk: the probability of failure of an individual firm multiplied by its debt. To derive an aggregate measure of financial risk we sum debt at risk across all firms in each year. We find that this micro-based measure of financial risk performs better in predicting debt at risk of default than a macro-based approach, which involves multiplying the average probability of failure by the total stock of debt and therefore does not fully exploit the firm-level dimension of the data. Debt at risk, as a proportion of total debt, was at its highest in the early 1990s, and it has been relatively stable since 1993, although the stock of debt has risen over this period.

As well as analysing aggregate measures of debt at risk, the paper also looks at the distribution. The distribution appears heavily skewed, with debt at risk being concentrated among a small number of firms. The implication of this is that we should particularly focus on these firms in order to monitor what is happening to the aggregate measure. While debt at risk is concentrated

among a relatively small number of firms, in general these are not the firms with the highest probabilities of failure. The firms with the highest probabilities of failure tend to be small firms, which do not hold large amounts of debt in absolute terms.

1 Introduction

Corporate failure poses a threat to financial stability if firms who fail default on their debt. While the impact of an individual firm failing is likely to be limited, if a number of firms fail at the same time and if the failing firms have large amounts of outstanding debt then this poses more of a threat. If one firm fails there may be knock-on effects, because this could lead to other firms, which are reliant on receiving payment from the failed firm, subsequently failing. If the balance sheets of banks are severely affected by company failure these banks may be quicker to call in their loans to high-risk companies, and they may subsequently demonstrate increased risk aversion on loan approvals. There are potential systemic implications if the solvency of a bank is threatened by corporate failure, which could lead to a loss of confidence and runs on that bank, and ultimately a collapse.

The size of the potential risk to financial stability arising from an individual company failure depends on both the probability that the firm will fail and the amount of debt on which it could potentially default. We aim to evaluate different ways of assessing these aggregate risks to financial stability from corporate failure.

In the Financial Stability area of the Bank of England a number of different approaches are taken to monitoring the potential risks arising from the UK corporate sector. Much of the earlier work in this area was relatively qualitative. In recent times there has been a move towards supplementing this qualitative work with more quantitative assessments of the risks to financial stability.(1)

In this paper we use firm-level data to construct a model which allows us to assess the risks arising from the UK corporate sector at both individual firm and aggregate levels. The motivation for this is to analyse the risks arising from individual firms, and the overall distribution of the risks. We do this in order to assess how important it is to use a firm-level model, rather than an aggregate model of the type used by Benito, Whitley and Young (2001).

A substantial amount of work has already been done using firm-level data to analyse the determinants of company failure. In this paper we use a large data set containing both public and private companies between 1991 and 2001. This overcomes some of the limitations of previous papers that use either a relatively small number of firms or a short time period that is not long enough to allow for the incorporation of macroeconomic effects into the model.

The majority of work on firm failure has been done to analyse the determinants of failure. While we are also interested in why firms fail, we develop our model for the purpose of estimating firm-level probabilities of failure. We find general support for the results of previous studies on the determinants of company failure; the probability of failure is negatively influenced by profitability, liquidity and company size, and positively influenced by capital gearing. We also conclude that interest cover and whether a firm is a subsidiary or not are additional influences. The probability of a firm failing proves to be negatively related to improvements in

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(1) Stated by the Bank as one of its 2000-01 objectives, see *Bank of England Annual Report 2001*.

macroeconomic conditions (proxied by GDP growth), even after controlling for its firm-level characteristics.

We use the predicted probabilities of failure from our model to calibrate the risks to financial stability arising from the UK corporate sector. We construct a measure of debt at risk, that is the predicted probability of failure for an individual firm multiplied by its gross total debt. The debt at risk of a firm is a measure of the threat that it poses to financial stability.(2) Firm-level debt at risk can be summed across firms in each year to monitor the magnitude of the aggregate risks over time. We compare our measure of aggregate financial risk based on firm-level data to a more simplistic estimate that involves multiplying the average probability of failure by the total debt stock. We find that the measure which uses firm-level information performs much better in predicting how much debt is at risk of being defaulted on as a result of corporate failure.

We exploit our firm-level estimates of debt at risk to analyse the distribution and concentration of debt at risk to see where the main risks within the aggregate figures lie. Debt at risk is concentrated among a small number of firms, but these firms are not necessarily those with the highest probabilities of failure. This concentration of debt at risk suggests it is important to monitor the individual firms with the highest levels of debt at risk. The firms with the highest probabilities of failure are in general small, and therefore they do not hold large amounts of debt in absolute terms.

The structure of this paper is as follows. Section 2 reviews the literature on firm failure. Section 3 discusses the methodology, the model specification, the data and some descriptive statistics. Section 4 presents the model of company failure. Section 5 analyses the implications for financial stability arising from this model. Section 6 concludes the paper.

2 Literature

This section of the paper looks at evidence on the determinants of firm failure, on which there is a wide literature. The first branch of the literature looks at aggregate determinants of the corporate liquidations rate. Wadhwani (1986) finds that real wages, real input prices, capital gearing, the real interest rate, the nominal interest rate and measures of aggregate demand are all significant in explaining corporate liquidations. Davis (1987) uses the same model as Wadhwani, but includes the debt to GNP ratio instead of capital gearing, and finds this to be significant. Young (1995) extends Wadhwani's model and uses the gilt term structure to infer nominal interest rate expectations, and NIESR inflation forecasts to construct *ex-ante* real interest rates. He finds that the unanticipated component of the real interest rate is significant when regressed on the liquidations rate. He concludes that the higher-than-expected outturn of real interest rates was the primary cause of the large number of corporate liquidations in the early 1980s, whereas rising debt levels were responsible in the early 1990s. Vlieghe (2001) finds the real interest rate to be a

(2) This estimate of debt at risk is an estimate of the maximum losses that could occur, assuming that the bank's recovery rate is zero. In fact, the actual recovery rate will almost certainly be positive, so debt at risk is not debt which would be defaulted on in the event of failure, just debt which is 'at risk' of being defaulted on.

long-run determinant of the aggregate UK corporate liquidations rate, as well as the debt to GDP ratio, deviations of GDP from trend and real wages. This work implies that the rise in liquidations in the early 1990s was a result of a rapid rise in indebtedness at the end of the 1980s, while the subsequent fall in liquidations was due to lower real interest rates, lower real wages and the recovery of GDP.

The second strand of the literature uses firm-level data to explain why individual firms either fail or survive, and this is the area on which our paper focuses. Early multivariate firm-level studies of company failure used discriminant analysis to identify failing firms. First developed by Beaver (1966) and Altman (1968), discriminant analysis uses financial ratios derived from company accounts as predictors of potential failure. A discriminant function takes the form:

$$Z = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_j X_j \qquad \textbf{(1)}$$

The β terms represent the discriminatory coefficients and the X terms are the financial ratios known as the discriminating variables. The higher the Z-score, the more likely the company is to fail. The coefficients are generated using a sample of failed and non-failed companies. Further details on the procedure used to estimate the discriminatory coefficients can be found in Anderson (1958). There is no common consensus on which ratios should be used but most studies include at least some measure of profitability, capital gearing and liquidity.

Goudie and Meeks (1991) use a Z-score approach similar to that described above. They define failure as entering liquidation or receivership, and examine 975 firms, taken from the Cambridge/DTI databank between 1960 and 1974. They combine five discriminating variables; profitability, liquidity, cash flow and two measures of gearing, in a discriminant function, which produces a Z-score for a particular firm. They also find that an exchange rate appreciation increases the probability of failure for major companies.

Most recent papers use logit or probit models to model company failure.[(3)] Lennox (1999) compares logit and probit models with discriminant analysis. He uses a sample of 949 UK listed companies over the period 1987-94 based on data from Datastream. A firm is defined as failed if it enters liquidation, receivership or administration, and filed its final annual reports prior to failing. Lennox finds that measures of profitability and liquidity are significant with negative coefficients, and capital gearing is significant with a positive coefficient. The coefficients associated with company size and industry sector are also found to be significantly different from zero. A firm is more likely to fail if it is small or if it operates in the construction or financial services sectors. Lennox examines the role of the economic cycle, by using replies to CBI Quarterly Industrial Trends Surveys, and finds macroeconomic effects proxied in this way to be significant; an improvement in the macroeconomic environment reduces the likelihood of failure. Geroski and Gregg (1997) use a probit model and the EXSTAT database, containing both private and public firms, to examine which factors determine the likelihood of a firm failing. They do this over two time periods; an expansionary period, 1988 to 1990, and a recessionary period, 1991 to 1993, with about 2,000 firms in each sample. Geroski and Gregg define failure as a firm going into receivership or liquidation at any time within each sample, and they include only firms

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(3) This estimation methodology is described in more detail in Section 3.1.

with 500 or more employees. Geroski and Gregg take a non-linear approach to examining the impact of profitability on the probability of failure by creating dummy variables for different ranges of profit margins. They find the coefficient on the negative profit variable to be significant and positive, whereas the coefficients on the other profit dummies are not significantly different from zero. Other variables with coefficients that are statistically significantly different from zero are the debt to assets ratio, and employment, as a proxy for the size of the firm. An increase in the debt to assets ratio of a firm increases the likelihood of failure, while the greater the number of employees the less likely a firm is to fail. Geroski and Gregg find the coefficients on both the cash to liabilities ratio and turnover growth over the previous two years (1991 to 1993 model only) to be insignificant.

Bhattacharjee *et al* (2002) examine an unbalanced panel of 4,300 UK quoted companies over the period 1965 to 1998. They consider two models, one that defines failure as firms going into liquidation and one that defines failure as a firm being acquired. They report that higher cash flow and profitability reduce the probability of entering liquidation, as does an increase in the size of the firm. The business cycle (measured by a HP-filtered series of UK output per capita) only has a direct impact on the probability of liquidation for firms that have been listed within the previous five years. Increased volatility in the retail price index (a proxy for uncertainty) increases the chance of liquidation, as does being in the construction industry.

A drawback of the above papers is that although some, such as Lennox and Bhattacharjee *et al*, do consider macroeconomic effects, most lack any detailed incorporation of macroeconomic effects. Geroski and Gregg's comparison of an expansionary and a recessionary period shows that macroeconomic effects may be important, but they do not include them in a way that allows the model to be used for projecting firm-level probabilities of failure. Although there is quite an extensive literature on modelling company failure, few studies examine a large sample of both public and private firms over a long enough time period to allow for the incorporation of macroeconomic effects into the model. We hope to contribute to the literature in this area by reporting such a study.

There are alternatives to the company accounts based approach to modelling the probability of company failure. One is the Merton-type approach based on up to date market information, initiated by Black and Scholes (1973) and Merton (1974). Recent work in the Bank of England to develop an in-house Merton-type model is described in Tudela and Young (2003). The Merton model imposes assumptions about the value of a firm's underlying assets and their capital structure. Whether a firm defaults or not is determined by the market value of the firm's assets in conjunction with its liability structure. When the value of the assets falls below a certain threshold, the firm is considered to be in default.

The approach taken at the Bank in surveillance work is to use a range of models. Tudela and Young (2003) find that probabilities of default from their Merton model have more predictive power than those from a simple company accounts type model. But, there are reasons why supplementing the Merton model with a company accounts based approach may be appropriate. First, the Merton model is dependent on equity price data and can therefore only be applied to quoted companies, which account for just over 1,000 of the 1.6 million registered companies in the United Kingdom. It is important that we have a model that can also be applied to private companies. Second, although the Merton model provides a good ordinal ranking of companies on the basis of their probability of going into receivership, there is evidence that the implied probabilities of default may be limited as a cardinal indicator of risk. The company accounts based approach may yield more accurate cardinal probabilities of failure because the estimation of the model takes into account the proportion of companies that failed in the past. Third, it is difficult to explain the reasons why a probability is at a particular level in the Merton model because information is subsumed in share prices. This is easier in a company accounts based model, and this approach also permits an assessment of the effect of changes in profits, gearing, etc on probabilities of failure.

3 Methodology and data

3.1 Methodology

We use a probit approach rather than discriminant analysis, as supported by Lennox (1999).(4) The initial model we estimate is a standard maximum likelihood probit model. This model estimates the probability of company failure based on both a firm's financial characteristics in the previous year (x_{1i}), other firm-level characteristics such as size, industry, and whether the firm is a subsidiary or not (x_{2i}), and on macroeconomic effects (x_{3i}). We observe the company status variable (y), which is either failure ($y_i = 1$) or survival ($y_i = 0$), but we define the dependent variable as a latent variable y^*.

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$y_i^* = x_{1i}'\beta_1 + x_{2i}'\beta_2 + x_{3i}'\beta_3 + \varepsilon_i \qquad \text{where } \varepsilon_i \sim \mathrm{N}(0,\sigma^2) \tag{3}$$

$$y_i^* = x_i'\beta + \varepsilon_i \qquad \text{where } x_i'\beta = x_{1i}'\beta_1 + x_{2i}'\beta_2 + x_{3i}'\beta_3 \text{ and } \varepsilon_i \sim \mathrm{N}(0,\sigma^2) \tag{4}$$

The probability that a firm fails ($y_i = 1$) can therefore be written as:

$$\Pr(y_i = 1) = \Pr(y_i^* > 0) \tag{5}$$

$$\Pr(y_i = 1) = \Pr(x_i'\beta + \varepsilon_i > 0) \tag{6}$$

$$\Pr(y_i = 1) = \Pr\left(\frac{\varepsilon_i}{\sigma} > \frac{-x_i'\beta}{\sigma}\right) \tag{7}$$

Given that ε_i/σ follows a standard normal distribution (mean zero and variance of unity) and the probit distribution is symmetric the probability of failure can be evaluated using the standard normal distribution function, $\Phi(\,)$.

$$\Pr(y_i = 1) = \Pr\left(\frac{\varepsilon_i}{\sigma} < \frac{x_i'\beta}{\sigma}\right) \tag{8}$$

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(4) Lennox (1999) compares both probit and logit, and discriminant analysis models, and concludes that well specified probit and logit models can more accurately identify failing companies.

$$\Pr(y_i = 1) = \Phi\left(\frac{x_i'\beta}{\sigma}\right) \quad \textbf{(9)}$$

Having estimated our initial probit model we test for heteroscedasticity using the score test. Heteroscedasticity is a frequent phenomenon in cross-sectional micro-data. The consequences are more severe in probit models than in linear regression because the coefficients as well as the standard errors are biased in the presence of heteroscedasticity. Consequently this could lead to biased predicted probabilities. We find evidence of heteroscedasticity, and therefore estimate a heteroscedastic probit model to allow for this. To do this we adopt an exponential functional form, which is the most commonly used specification. This allows the variance to be a function of the variables who fail the score test (z_i).

$$y_i^* = x_i'\beta + \varepsilon_i \qquad \text{where } \varepsilon_i \sim \mathrm{N}(0,\ (\exp(z_i'\gamma))^2) \quad \textbf{(10)}$$

The probability of failure is then derived in the same way as above.

$$\Pr(y_i = 1) = \Phi\left(\frac{x_i'\beta}{\exp(z_i'\gamma)}\right) \quad \textbf{(11)}$$

3.2 Variable specification

The variables we use to identify which companies are most at risk can be divided into four main groups: profitability, financial ratios, firm characteristics and macroeconomic variables.

Economic theory suggests that the probability of firm failure should be negatively related to profitability. In our model we include the profit margin variable as three separate dummy variables, thus allowing us to take a non-linear approach to the effect of profitability on the probability of failure. The relevant profit margin dummy takes the value of 1 if a firm has a negative profit margin, a profit margin between 0% and 3%, or a profit margin between 3% and 6%. The reference group is firms with a profit margin of greater than or equal to 6%. These particular profit margin boundaries are selected so as to be wide enough to allow the coefficients on these variables to be significantly different from each other. The boundaries we use are the same as those used in Geroski and Gregg (1997), and they result in a relatively even distribution of firms between the four categories.

Interest cover,(5) the debt to assets ratio and the current ratio are all modelled as continuous variables. We expect that capital gearing will be positively related to the probability of failure, and interest cover and liquidity will be negatively related. We also include an interaction term, which takes the value of 1 for a firm if its profit margin is negative **and** if its debt to assets ratio is in excess of 0.35. This broadly represents firms who have above average capital gearing and are loss making.(6) It should allow us to evaluate whether the combination of negative profitability and high capital gearing raises the probability of failure by more than the effect of the two factors taken individually.

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(5) Values of interest cover in excess of the 90th percentile in each sample year are recoded to that value. Negative values of interest cover (which all result from negative profitability) are recoded to zero.
(6) Across all sample years the mean debt to assets ratio is 0.37, the median is 0.32.

The number of employees is included to test the hypothesis that small firms are more at risk of failure than large firms. We use seven industry dummies based on primary 1992 SIC codes. The reference group for the industry dummies is manufacturing, primary industries, and utilities. Primary industries and utilities are amalgamated with manufacturing because these sectors are relatively small and there are not enough failures in our data in those industries to justify including separate industry dummies. A subsidiary dummy is incorporated in the model to account for the fact that a subsidiary in trouble can be bailed out by its holding company, which should reduce the probability of failure for subsidiaries. We also include an interaction term that takes the value of 1 if a firm is a subsidiary and its profits are negative. This will allow us to assess whether or not there is any additional effect over and above the standard effect of being a subsidiary if a firm is loss making.

After controlling for all of the firm-level characteristics, if there were no additional factors influencing the probability of company failure we would expect year dummies to have coefficients insignificantly different from zero. We estimate a preliminary model including year dummies, and find the coefficients on the year dummies to be jointly significant. The pattern of the marginal effects associated with the year dummies seems to approximately follow the pattern of the economic cycle. We therefore replace the year dummies with the twelve-month GDP growth rate, using the GDP growth rate as a proxy for macroeconomic conditions.

3.3 Sample summary

The data used is company accounts data for UK registered companies taken from the Bureau van Dijk FAME database.(7) We are making the assumption that the accounting data provides an accurate picture of the financial position of each firm. By making this assumption we are ignoring any potential distortions which could be present in the data as a result of earnings management strategies or off balance sheet financing.

Financial companies are excluded from our analysis. We do not model firms with less than 100 employees because accounts become increasingly incomplete as firms get smaller. Both public and private companies are included. Our data set is a pooled cross-section covering eleven years from 1991 to 2001. We define a year as a financial year, from 1 April to 31 March in the following calendar year. We were unable to extend the data back further because of the limited number of company accounts available on FAME in earlier years. If an observation had one or more missing values for any explanatory variable used, that observation was deleted from the data set before any analysis took place. Similarly, outliners with respect to explanatory variables were removed.(8)

We define a firm as failed in a particular year if its company status (according to FAME) is in receivership, liquidation or dissolved, and its last reported accounts were in the previous year.

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(7) Bureau van Dijk FAME is a subscription database of financial information for UK and Irish companies. The FAME database is produced by Bureau van Dijk, one of Europe's leading suppliers of business information. From hereon we refer to the database only as FAME.
(8) Observations were dropped if profit margin>1, profit margin<-1, debt to assets ratio>5 or current ratio>5.

This definition includes voluntary liquidation and dissolution where there may be no risk of default, but we are unable to distinguish between voluntary and compulsory failures in our data. Companies whose last reported accounts were before the end of the sample period but who are still live were deleted from the data set. We do not consider being taken over to be a failure.

The data set we use is a pooled cross-section between 1991 and 2001. An individual firm can appear as a separate observation in each sample year. The data contains 105,687 observations, which includes 29,361 individual firms. Table A summarises the number of observations and the percentage of firms that fail in each year.

Table A: Sample summary

Year of survival/failure	Number of surviving firms	Number of failed firms	% of firms who fail	Total number of firms
1991	3,885	183	4.50	4,068
1992	6,408	205	3.10	6,613
1993	8,715	171	1.92	8,886
1994	9,189	148	1.59	9,337
1995	9,397	135	1.42	9,532
1996	10,233	122	1.18	10,355
1997	10,806	150	1.37	10,956
1998	11,180	206	1.81	11,386
1999	11,334	193	1.67	11,527
2000	11,316	223	1.93	11,539
2001	11,291	197	1.71	11,488
Total	103,754	1,933	1.83	105,687

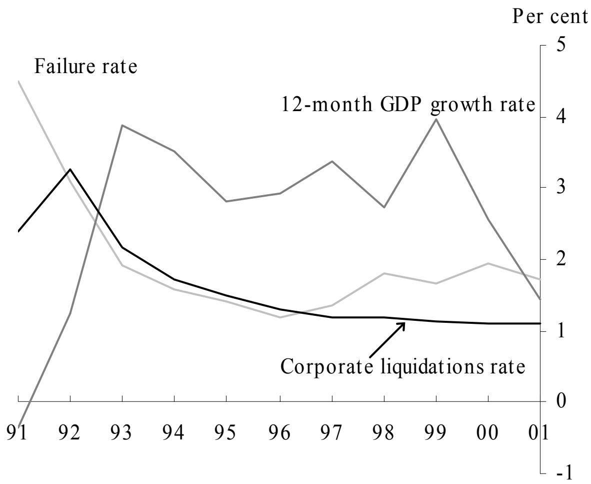
The number of observations increases in the later years in our sample, which reflects rises in the number of firms with over 100 employees and more comprehensive recording of company accounts by FAME. The proportion of companies failing was at its highest in 1991. The failure rate fell every year between 1992 and 1996, although the largest falls were in the earlier years. There was an increase in the percentage of firms who failed in the second half of the 1990s, but the failure rate has remained well below the early 1990s peak.

Chart 1 plots the failure rate by sample year along with the GDP growth rate.(9) The pattern of company failures looks broadly to fit the pattern of the economic cycle.(10) The highest failure rate coincides with the only year of negative GDP growth in our sample. Chart 1 also shows that the profile of our failure rate roughly follows that of the corporate liquidations rate. We must

(9) The measure of GDP used is GDP at constant market prices. We define the twelve-month GDP growth as the percentage growth rate from Q1 to Q1, therefore measuring the growth over Q2, Q3, Q4, and Q1. We define a year as 1 April to 31 March, so a direct comparison can be made.
(10) While our sample does not cover a full economic cycle it contains enough of the cycle for us to be able to identify some trends.

stress that there are significant differences between the two series. The corporate liquidations rate is defined as the number of insolvencies divided by the number of active companies. It includes all incorporated companies of any size, whereas our definition of failure includes only firms with 100 or more employees. Only liquidations are included in the aggregate liquidations rate measure, whereas we also define a firm that enters receivership as failing.

Chart 1: The failure rate and macroeconomic variables



Sources: Bureau van Dijk, DTI and ONS.

3.4 Descriptive statistics

All explanatory variables are taken from company accounts in the year preceding the year of survival/failure, as it is not always possible to obtain contemporaneous information for failed companies. Using data from the previous year's accounts also allows us to estimate the probability of failure in a given year without having to wait for companies to file their accounts for that year. Full definitions of all variables used can be found in the appendix. Table B summarises descriptive statistics for all explanatory variables for surviving firms and for failed firms.

Table B: Descriptive statistics – variable means[11]

	All firms (N=105687)	Surviving firms (N=103754)	Failed firms (N=1933)	Difference in mean test t statistic[12]
Profit margin	0.048	0.049	-0.018	22.17
Profit margin <0*	0.179	0.174	0.444	-23.82
Profit margin >=0 & <0.03*	0.227	0.227	0.240	-1.33**
Profit margin >=0.03 & <0.06*	0.211	0.212	0.163	5.78
Interest cover	6.961	7.046	2.401	36.29
Debt to assets ratio	0.374	0.373	0.461	-9.90
Profit margin <0 & debt to assets>0.35*	0.114	0.111	0.294	-17.65
Current ratio	1.225	1.230	0.979	22.82
Number of employees	1314	1331	369	33.66
Subsidiary*	0.620	0.627	0.236	39.99
Profit margin <0 & subsidiary*	0.122	0.123	0.109	1.88
Industry dummy: Manufacturing, Primary Industries and Utilities*	0.429	0.429	0.398	2.81**
Industry dummy: Construction*	0.060	0.059	0.094	-5.20
Industry dummy: Wholesale and Retail*	0.160	0.160	0.158	0.23**
Industry dummy: Hotels and Restaurants*	0.037	0.037	0.032	1.24
Industry dummy: Transport, Storage and Communication*	0.065	0.065	0.049	3.33
Industry dummy: Real Estate, Renting and Business Activities*	0.174	0.173	0.205	-3.47
Industry dummy: Other Services*	0.076	0.076	0.065	2.05

The descriptive statistics on the factors that influence company failure are broadly in line with our priors. Without holding other factors constant, firms which fail have a significantly lower (and negative) mean profit margin than firms who survive. The level of interest cover of firms who fail is significantly lower than that of firms who survive. Failed firms have a significantly higher mean debt to assets ratio and a significantly lower current ratio than surviving firms. The mean number of employees of firms who fail is significantly lower than the mean number of employees of firms which survive, suggesting that small firms are more likely to fail than large ones. The descriptive statistics also imply that a firm is less likely to fail if it is a subsidiary.

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[11] * Indicates that these are dummy variables, therefore the variable mean is the proportion of firms for which this variable equals one.
[12] ** Indicates that variances of the two sub-samples are assumed to be equal in the construction of the difference in the means test. Otherwise they are assumed to be unequal.

4 Results

4.1 Initial results

Our first probit model estimates the probability of company failure as a function of firm-level characteristics and year dummies.(13) In our estimation we adjust the standard errors to allow for clustering by each individual company. The adjusted standard errors we report are robust standard errors. We make this adjustment for clustering because our sample is pooled which violates the assumption that each observation is drawn independently. The adjustment we make means we now only need to assume independence across companies but not across time. We make a similar adjustment to the standard errors of the other models reported in the paper.

After controlling for all of the firm-level characteristics, if there were no additional factors influencing the probability of company failure we would expect the coefficients on year dummies to be insignificantly different from zero. However we find the coefficients on the year dummies to be jointly significant.(14) In 1991 and 1992 the coefficients are positive and significantly different from zero at the 1% level. If the year of survival/failure was 1991 rather than 2001 the probability of a firm failing was 1.6 percentage points higher (on a scale of 0 to 100), *ceteris paribus*. For 1992 the size of this marginal effect was 0.7 percentage points. The pattern of the marginal effects associated with the year dummies in this initial model approximately follows the economic cycle. This is the motivation for replacing the year dummies with the twelve-month GDP growth rate, using the GDP growth rate as a proxy for macroeconomic conditions.(15) The results of our probit estimation of the model with GDP growth and the corresponding marginal effects are reported in Table C.

The coefficients and subsequent marginal effects associated with the firm-level variables are almost identical whether we include year dummies or GDP growth. A similar interpretation can therefore be applied to both models. The log-likelihood ratios of the two models are very similar implying that including GDP growth captures the effects of the year dummies well.

Using the 5% significance level all of the coefficients on the firm-level characteristic variables are significantly different from zero in the model along with GDP growth, except for that on one industry dummy. Most are significant at the 1% level. The coefficients associated with the profit dummies are jointly significantly different from zero, and they are all significantly different from each other at the 5% significance level.(16)

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(13) The results are reported in Table E in the appendix.
(14) Test statistics and other specification tests are reported in Table G of the appendix.
(15) We use the Q1 to Q1 percentage growth rate of GDP at constant market prices.
(16) See Table G in the appendix for test statistics.

Table C: Model 2 - Probit model using GDP growth as a proxy for macroeconomic conditions

N:	105687
Log likelihood:	-8232.50
Pseudo R^2:	0.1469

	Coefficient	Standard error	T ratio	Marginal effect[17]
Profit margin <0	0.684	0.042	16.10	0.0295
Profit margin >=0 & <0.03	0.224	0.032	6.94	0.0064
Profit margin >=0.03 & <0.06	0.146	0.033	4.42	0.0040
Interest cover	-0.012	0.002	-5.42	-0.0003
Debt to assets ratio	0.159	0.032	4.99	0.0039
Profit margin <0 & debt to assets>0.35	0.107	0.042	2.52	0.0029
Current ratio	-0.231	0.025	-9.37	-0.0057
Ln (number of employees)	-0.129	0.011	-11.40	-0.0032
Subsidiary	-0.569	0.028	-20.53	-0.0173
Profit margin <0 & subsidiary	-0.365	0.047	-7.82	-0.0066
Industry dummy: Construction	0.135	0.040	3.39	0.0038
Industry dummy: Wholesale and Retail	-0.111	0.032	-3.52	-0.0025
Industry dummy: Hotels and Restaurants	-0.309	0.060	-5.15	-0.0055
Industry dummy: Transport, Storage and Communication	-0.118	0.048	-2.47	-0.0026
Industry dummy: Real Estate, Renting and Business Activities	0.001	0.028	0.03	0.0000
Industry dummy: Other Services	-0.233	0.045	-5.17	-0.0046
12-month GDP growth rate	-0.069	0.009	-7.61	-0.0017
Constant	-0.889	0.081	-10.99	-

If a firm has a negative profit margin rather than a profit margin greater than or equal to 6%, its probability of failure over the following year increases by 3 percentage points, all else held constant. This increase is 1.6 times the mean predicted probability. The magnitudes of the marginal effects on the profit variables are in line with our expectations. By far the largest marginal effect is associated with negative profits, the second largest with a 0% to 3% profit margin, and the smallest with a 3% to 6% profit margin.

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(17) The marginal effects are evaluated at the sample means for each variable. For continuous variables the slope of the probability function is calculated to measure the change in the predicted probability for an infinitesimal change in that variable. The marginal effect on the predicted probability from a one-unit change in that variable is then extrapolated out from this. For dummy variables the marginal effects are calculated as the change in the predicted probability of failure when the variable changes from zero to one, with all other variables evaluated at their sample means.

An increase in interest cover reduces the probability of failure, while increases in capital gearing (defined as the debt to assets ratio) raise it. The marginal effect associated with interest cover implies that a one-unit increase in interest cover reduces the probability of a firm failing in the next year by 0.03 percentage points, *ceteris paribus*.[18] A one-unit increase in the debt to assets ratio will raise the predicted probability of failure by 0.39 percentage points if we hold all other factors constant.

If a firm has a negative profit margin and a debt to assets ratio greater than 0.35, its probability of failure is increased by 0.29 percentage points, after controlling separately for the effect of its negative profit margin and above average debt to assets ratio. This increase is equivalent to 16% of the mean predicted probability of failure. The combination of low profitability and high gearing levels therefore leads to a higher predicted probability of failure than if the two variables were treated separately.

The more liquidity (as measured by the current ratio) a firm has the less likely it is to fail. A one-unit increase in the current ratio reduces the probability of failure in the following year by 0.57 percentage points, *ceteris paribus*. We also find that small firms are more likely to fail than large ones after controlling for all other factors. A 1% increase in the number of employees a firm has reduces that firm's probability of failure by 0.32 percentage points, holding all other factors constant.

We find that if a firm is a subsidiary its probability of failure is 1.7 percentage points lower than if it is not a subsidiary, all else held constant. If a firm is a subsidiary and has a negative profit margin, having controlled for those two characteristics separately, that firm's probability of failure is a further 0.7 percentage points lower. This suggests that if a subsidiary is in trouble it is less likely to fail, holding other factors constant, because of the possibility that its holding company will bail it out. This effect is exaggerated further if the subsidiary is loss making.

The coefficients on the service sector industry dummies except for real estate, renting and business activities are all negative and significantly different from zero. The service sector dummies are jointly significant, which implies that if a company is in the service sector rather than in manufacturing, primary industries and utilities it is less likely to fail, all other factors held constant.[19] This is a plausible result given the strength of the service sector and the weakness of manufacturing in the 1990s. If a firm is in the construction sector rather than manufacturing, primary industries and utilities its probability of failure is 0.38 percentage points higher, *ceteris paribus*.

The coefficient associated with the twelve-month growth rate of GDP is negative and significantly different from zero. A 1 percentage point increase in annual GDP growth reduces the probability of failure for a firm by 0.17 percentage points, having controlled for its firm-level characteristics. This is evidence that macroeconomic conditions influence the individual firm-level probability of failure. Macroeconomic conditions can affect the demand for firms' goods

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[18] Interest cover, the debt to assets ratio and the current ratio are all defined as ratios in the model.
[19] Test statistics reported in Table G in the appendix.

and services, but these effects should be accounted for largely by changes in their financial characteristics. The fact that GDP growth is significant having controlled for firm-level characteristics implies there is something associated with economic conditions but not individual firm-level characteristics which is influencing the probability of company failure. This could be explained by interactions between companies or by a change in the behaviour of banks. In times of recession banks may be less willing to lend and quicker to close companies down. There are two possible reasons for this. First, in times of recession banks may be under pressure to improve their own balance sheets, which would involve closing down the highest risks more rapidly. In good times there may be more scope to tolerate high risks. Second, the likelihood of a company in trouble turning itself around is lower and the subsequent recovery time would be longer in a recession. Banks would therefore be more likely to close down companies in this situation.

4.2 Heteroscedastic probit models

If a probit model is estimated in the presence of heteroscedasticity the coefficients and standard errors are biased, unlike in the standard linear regression model where only the standard errors are biased. It is therefore important for us to test for heteroscedasticity. We constructed the score test for heteroscedasticity with respect to each variable, and then estimated a heteroscedastic probit model, allowing the error variance to be a function of the variables that failed the score test at the 1% significance level. This heteroscedastic probit model for the specification including GDP growth is reported in Table F in the appendix. The same coefficients are significantly different from zero, and with the same signs in both the probit and heteroscedastic probit models. The marginal effects from the heteroscedastic probit model are relatively similar to those from the probit estimation, although on average they are smaller.

A problem with estimating heteroscedastic probit models is that a functional form for the heteroscedasticity has to be imposed. This is arbitrary and can influence the results. We choose the commonly used exponential function form.[20] There is also an issue over which significance level to use when constructing the heteroscedasticity tests. This can influence which variables are allowed to be a function of the error variance. As a consequence of these two issues, there is often a lack of robustness associated with heteroscedastic probit models.

4.3 Model evaluation

Charts 2 and 3 attempts to assess the size of the biases in the predicted probabilities arising from the presence of heteroscedasticity. Chart 2 looks at the distribution of the predicted probabilities using a probit and a heteroscedastic probit for the specification including GDP growth.[21] We can conclude from this that the distributions of predicted probabilities from the standard probit and the heteroscedastic probit are relatively similar. Chart 3 shows that there is very little difference in the mean predicted probability from the probit or from the heteroscedastic probit model in any given year.

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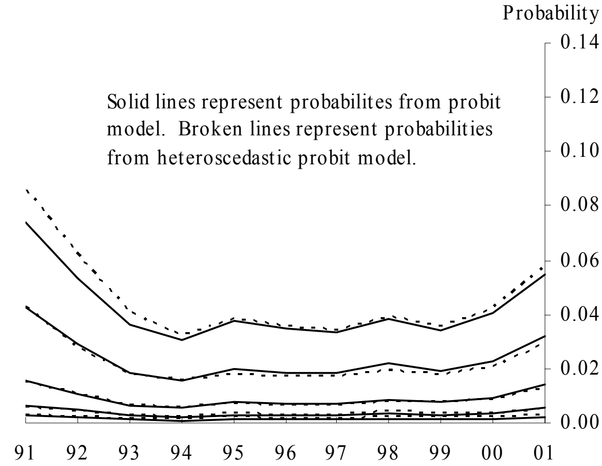
[20] See equations **(10)** and **(11)**, as discussed in Section 3.1.
[21] Any predicted probability greater than 0.25 is rounded down to 0.25 (40 predicted probabilities are rounded down out of a total of 105,687). This is to prevent unreasonably high probabilities arising from outliners in the data set.

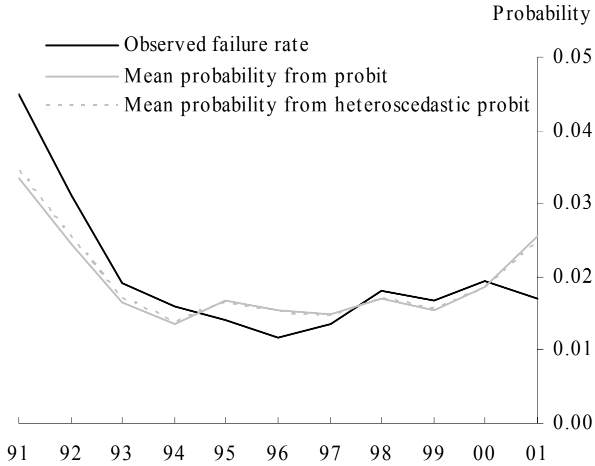
The conclusion we draw from this analysis is that heteroscedasticity is present in our data set, but the biases arising from it are relatively small. Given the lack of robustness associated with the heteroscedastic probit models and the fact that a standard probit is more straightforward to interpret, we focus on the probit results in the remainder of our analysis. Moreover, the impact of the decision to use the probit rather than the heteroscedastic probit on debt at risk and its distribution is minimal.

Chart 2: Distribution of predicted probabilities of failure[(a)]



(a) 90th, 75th, 50th, 25th and 10th percentiles shown for each distribution.

Chart 3: Mean predicted probabilities of failure

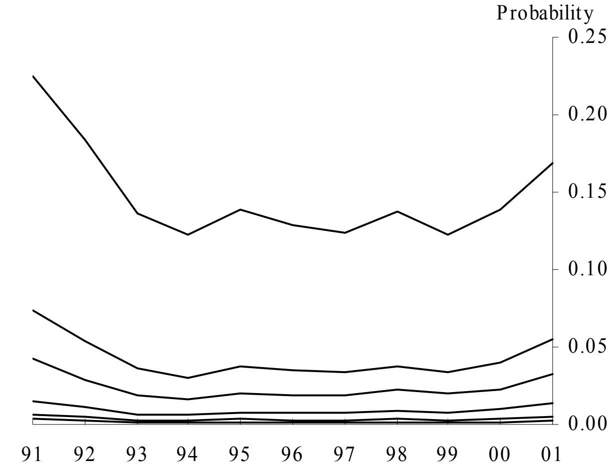


The highest mean predicted probabilities of failure are observed in 1991. Like the failure rate the mean predicted probability fell in the early 1990s and has been relatively constant since 1993, although there has been an increase since 1999. The model slightly underpredicts the failure rate in the early 1990s, and then overpredicts between 1995 and 1997 and in 2001. The model with year dummies would be a better predictor of the mean predicted probability in each year as it can pick up more than just macro effects, which are included in our preferred model via GDP growth. However, a model with year dummies is less useful than a model with GDP growth for predicting future probabilities of failure because we would have to make an assumption about the size of the year effect in the model with year dummies, whereas we can forecast GDP.

Chart 2 shows that the distribution of predicted probabilities is skewed towards the lower predicted probabilities. When the 99th percentile is included in the distribution (Chart 4) the scale of this skew becomes even more apparent. There are a large number of firms with very low predicted probabilities of failure, and only a few with high predicted probabilities. This implies that in terms of monitoring which firms are most at risk of failure we should particularly focus our attention on those at the very upper end of the distribution. The distributions are widest in the early 1990s, they have narrowed since although there has been some widening since 1999. This contrasts with Benito and Vlieghe (2000) who find evidence of widening dispersion throughout the 1990s in profitability, capital gearing and liquidity among quoted companies, which we would expect to translate to a widening in the distribution of predicted probabilities. We do not see the distribution of predicted probabilities widening because we do not find the widening in the distributions of profitability, capital gearing and liquidity on the scale that was apparent in

Benito and Vlieghe's work. This can be explained by the fact that we include large numbers of private companies in our data, whereas Benito and Vlieghe only look at quoted companies.

Chart 4: Distribution of predicted probabilities of failure[(a)]



(a) 99th, 90th, 75th, 50th, 25th and 10th percentiles shown.

Table D analyses a breakdown of the predicted probabilities from our preferred model. It shows that the mean predicted probability of firms who fail is approximately three and a half times that of firms who survive. The difference in the mean predicted probability between firms who survive and firms who fail is statistically significant.(22) The median predicted probability is approximately five times greater for firms who fail than for firms who survive.

Table D: Average predicted probabilities

	Mean predicted probability	Median predicted probability
All firms (N = 105687)	0.0183	0.0085
Surviving firms (N = 103754)	0.0175	0.0082
Failed firms (N = 1933)	0.0615	0.0396

5 Applications to financial stability

5.1 Measuring risks to financial stability

In this section of the paper we apply the model presented in the previous section to the issue of monitoring potential risks to financial stability arising from the UK corporate sector. To assess the risks we analyse debt at risk, which quantifies the size of the risk to financial stability. All of the analysis in this section is based on the results from our preferred model, reported in Table C.

(22) Difference in the means test has a t-statistic of –34.19, allowing for unequal variances.

Firm-level debt at risk is a crude measure of the expected loss on loans to each firm, reflecting both the probability of failure and the expected loss in the event of default. Our measure of debt at risk assumes a 100% loss rate, and is therefore not a measure of loss given default. It is an upper bound to the expected losses because in practice, a proportion of each loan to a failed company is likely to be recovered and banks make provisions for impaired loans. Not all of the outstanding debt of UK companies is owed to UK banks; foreign banks and corporate bond holders will also have exposures. Nonetheless, debt at risk still provides a useful approximation of risks to the UK banking sector and UK financial stability. We define firm-level debt at risk as the predicted probability of failure for a firm multiplied by its total debt (equation **(12)**).

$$DAR_i = pp_i * D_i \tag{12}$$

D_i is the total gross debt of firm i, and pp_i is its predicted probability of failure. The sum of all the firm-level estimates of debt at risk gives an aggregate micro-based measure of debt at risk (equation **(13)**).

$$DAR_{MICRO} = \sum_{i=1}^{n} pp_i D_i \tag{13}$$

The aggregate level of debt at risk can be approximated using a macro-based measure which involves multiplying the mean predicted probability by the total amount of debt held by all firms (equation **(14)**).

$$DAR_{MACRO} = \overline{pp} \sum_{i=1}^{n} D_i \tag{14}$$

The mean predicted probability of failure is $\overline{pp}$, an unweighted average of all the firm-level probabilities of failure. This is equivalent to assuming that the probabilities of failure are the same for all companies in the micro-based measure. An alternative way to think about this would be to assume that debt is evenly distributed among firms. If firms with an above average probability of failure have the same amount of debt as firms with a below average probability of failure the macro and micro-based measures should still be equivalent. In Sections 5.2 and 5.3 we compare the macro and micro-based measures and evaluate the validity of the assumptions used when calculating our macro-based measure of financial risk.

The two measures of debt at risk described so far are both *ex-ante* measures. It is also possible to measure debt at risk *ex post* ($DAR_{EX\text{-}POST}$) by summing the debt of all failed companies (equation **(15)**). This is a retrospective measure, which effectively is what debt at risk *ex ante* is trying to predict. By comparing debt at risk *ex ante* and *ex post* on an aggregate level we can assess how well our model has performed during the 1990s. D_i^F is the total debt of firm i if firm i failed.

$$DAR_{EX\text{-}POST} = \sum_{i=1}^{n} D_i^F \tag{15}$$

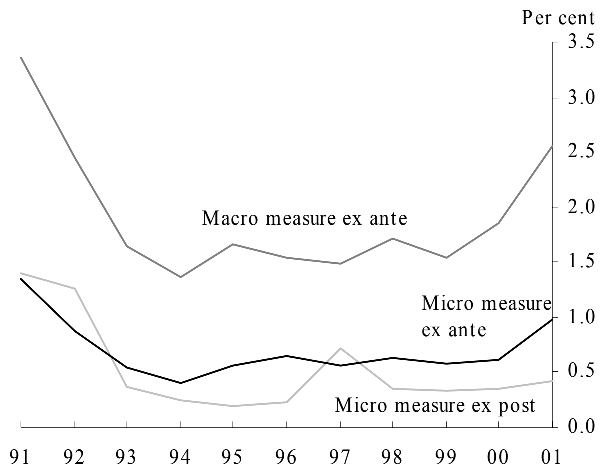
Having defined these measures of debt at risk there are different ways of representing them over time. We take two different approaches to analysing debt at risk in this paper, both of which enable us to compare aggregate debt at risk in different years, despite different numbers of firms appearing in the sample each year. First, we look at debt at risk as a proportion of total debt.

Second, we look at debt at risk scaled by the number of firms in each year (mean firm-level debt at risk) to account for variations in the total level of debt over time.

5.2 Debt at risk as a proportion of total debt

Chart 5 shows the aggregate measures of debt at risk as a percentage of total gross debt. Debt at risk *ex ante* as a proportion of total debt was at its highest in 1991 (approximately 1.3% on the micro-based measure). After falling as the economy moved out of recession, the debt at risk was relatively constant between 1993 and 2001, although there was an increase in 2001 to the highest level since 1993. A deterioration in profitability and a slowdown in GDP growth are the main explanations for the increases in these predicted probabilities of failure for 2001.(23)

Chart 5: Debt at risk as a percentage of total debt



The *ex-ante* macro measure follows a similar profile to the *ex-ante* micro measure, but at a higher level. This result contrasts with the finding of Benito, Whitley and Young (2001) who apply estimates of the effects of profitability and gearing on the probability of failure from Geroski and Gregg (1997) to a set of quoted companies and perform a similar analysis.(24) They find that the *ex-ante* micro measure exceeds the *ex-ante* macro measure throughout the 1990s. This reflects the fact that a different model and different data is used. If we apply the same parameters to our data set we find that the corresponding micro measure of *ex-ante* debt at risk is in general above the macro measure, but well above the *ex-ante* and *ex-post* micro measures from our model. We look at both public and private companies, whereas Benito, Whitley and Young (2001) only included quoted companies.(25)

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(23) The mean profit margin from 2000 company accounts (2000 accounts data is used to generate the predicted probabilities of failure for 2001) fell to 3.6% from 4.4% in 1999. Consequently the number of loss-making firms increased to 22.7% from 19.9%.
(24) These estimates are derived from a model estimated for firms with over 500 employees between 1991 and 1993.
(25) Benito, Whitley and Young (2001) have 1,000 to 1,500 public companies in their sample in each year, whereas we have up to 12,000 public and private companies per year.

It is clear from Chart 5 that our micro-based estimate of debt at risk *ex ante* comfortably outperforms the macro-based measure in terms of predicting debt at risk *ex post*. Therefore the assumption of an even distribution of debt between firms does not look to hold. The fact that the macro measure of debt at risk is always above the micro measure suggests that the macro-based measure overstates the risks to financial stability because debt is concentrated among firms with low probabilities of failure.(26) Debt at risk *ex post* was at its highest in 1991 at 1.4% of total debt. This is just above our micro-based *ex-ante* measure. There is an indication that our model may underpredict debt at risk in times of recession and overpredict in more prosperous times, although the mean error is close to zero.(27) The evidence of overprediction in the last few years of the sample suggests that banks may be getting better at restructuring companies in trouble.

5.3 Mean firm-level of debt at risk

From a risk assessment perspective it is perhaps more relevant to use a measure of debt at risk that additionally takes into account what is happening to the stock of total debt, to place the analysis as a proportion of total debt in context. Scaling aggregate debt at risk by the number of firms in the data in each year is one way to do this.

Chart 6 shows the mean level of total debt per firm between 1991 and 2001 in both nominal and real terms.(28) In the remainder of our analysis we focus on the inflation-adjusted measure of debt at risk. We do this because increases in debt at risk that arise from inflation clearly do not increase the risks to financial stability in the same way that an increase in debt at risk from deteriorating profitability would. Chart 6 shows that the mean level of debt was relatively stable until the late 1990s, since when it has grown significantly. Although debt at risk as a proportion of total debt has been relatively constant since 1993, the real level of debt at risk has been growing since the late 1990s.

Chart 7 shows the mean level of debt at risk per firm in real terms both *ex ante* and *ex post*. The most striking thing about Chart 7 is the sharp increase in mean firm-level of *ex-ante* debt at risk in 2001 to a level above that of the early 1990s. This arises because of increases in both the predicted probabilities of failure (which reflects a deterioration in the health of the corporate sector particularly with respect to profitability, and a slowdown in GDP growth) and the average level of debt of each firm. As before the model still underpredicts in the early 1990s, and overpredicts in recent years, but on average the mean error is again close to zero.

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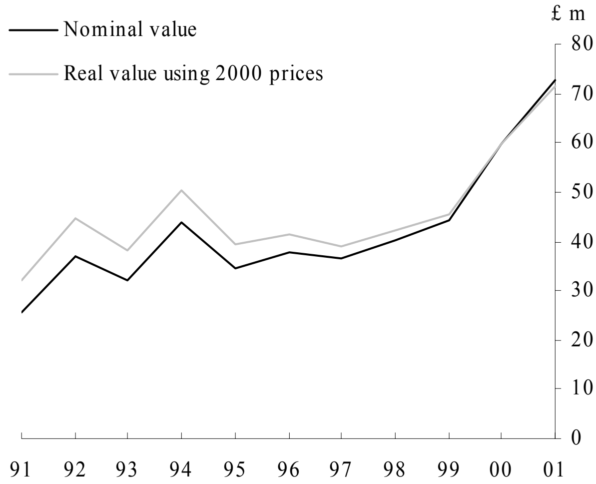
(26) See Section 5.4 for further discussion of this.
(27) Mean sample year error (debt at risk *ex post* minus micro-based debt at risk *ex ante*) is -0.1% of total debt.
(28) Inflation-adjusted data is at 2000 prices, deflated using the GDP deflator.

Chart 6: Mean level of total debt per firm[(a)]



(a) Real measure at 2000 prices, deflated using the GDP deflator.

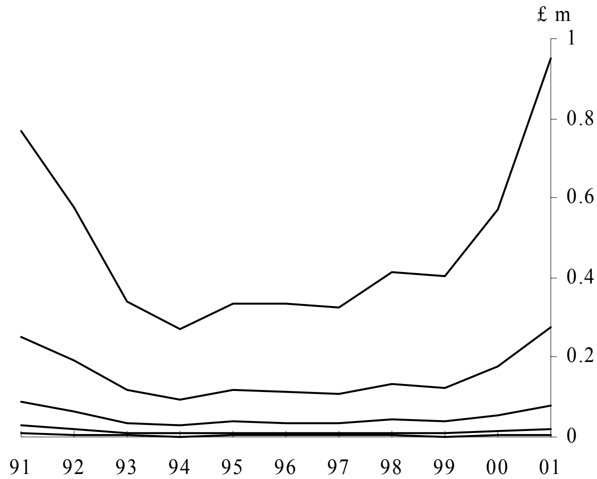
Chart 7: Mean level of debt at risk per firm[(a)]

(a) At 2000 prices, deflated using the GDP deflator.

5.4 Distribution of debt at risk

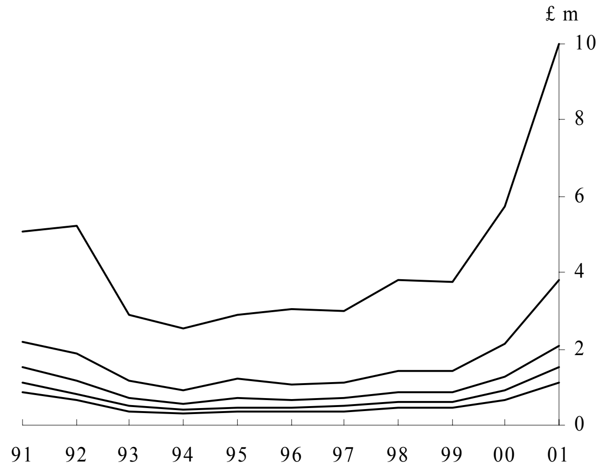
While the aggregate level of debt at risk is clearly important in monitoring risks to financial stability, it is also useful to analyse the distribution of debt at risk to see where the risks within the aggregate figures lie. Charts 8 and 9 look at the distribution of real firm-level debt at risk. The charts show that debt at risk *ex ante* is concentrated among a very small number of firms. This is well illustrated by the fact that the 99th percentile is on average nine times larger than the 90th percentile. This concentration of debt at risk provides a strong motivation for monitoring the individual firms with the highest levels of debt at risk particularly closely, as these are the firms that pose the key risk to aggregate financial stability. The individual firms with the very highest levels of debt at risk are predominantly very large companies with a lot of debt in absolute terms and a probability of failure that is in many cases above average but rarely extremely high.

Chart 8: Distribution of firm-level debt at risk[(a)(b)]



(a) 90th, 75th, 50th, 25th and 10th percentiles shown.
(b) At 2000 prices, deflated using the GDP deflator.

Chart 9: Distribution of top 10% of firm-level debt at risk[(a)(b)]



(a) 99th, 97th, 95th, 93rd and 91st percentiles shown.
(b) At 2000 prices, deflated using the GDP deflator.

As well as looking at the simple distribution of debt at risk we are also interested in whether or not debt is concentrated among the firms with the highest probabilities of failure. To analyse this we construct an index of debt at risk concentration (I), defined in equation **(16)**:

$$I = \frac{\sum_{i=1}^{n} pp_i D_i}{\overline{pp}\sum_{i=1}^{n} D_i} = \frac{DAR_{MICRO}}{DAR_{MACRO}} \quad \textbf{(16)}$$

The predicted probability of firm failure for firm i is pp_i, D_i is the gross total debt held by firm i, and $\overline{pp}$ is the unweighted mean predicted probability of failure for all firms. The index of debt at risk concentration is equivalent to the aggregate *ex-ante* micro measure divided by the macro measure. If this index is greater than 1 the implication is that debt at risk is concentrated among the highest-risk firms. This would clearly pose more of a risk to financial stability than if the index were less than 1. Any increases in the index would represent an increase in the risks. The index of concentration over time is plotted in Chart 10.

To aid our understanding of what this index of concentration means consider the following example. Assume that debt remains constant while the mean probability of failure increases by 10%, which could occur as a result of a macroeconomic slowdown. If the index of concentration of debt at risk was 2 (and remained at 2) this would imply that the micro-based measure of debt at risk (our preferred measure of financial risk) would increase by 20%. However, if the index of concentration were 0.5 (and remained at 0.5) the increase in the micro-based measure of debt at risk would be only 5%. The index of concentration of debt at risk is a measure of how concentrated debt is among high-risk firms. The larger this index the more highly concentrated debt is among high-risk firms.

Chart 10: Index of concentration of debt at risk

Chart 10 shows the index of debt at risk concentration to be relatively constant throughout the sample period at around 0.35, substantially less than unity. The relative stability of this index suggests that the macro measure of debt at risk is a reasonable approximation of changes in debt at risk, if not the level.

The implication of the concentration of debt at risk index being less than 1 is that debt is not concentrated among the highest-risk firms. As noted earlier, this result contrasts with that of Benito, Whitley and Young (2001), reflecting both their different model and the fact that their data set is confined to larger, quoted companies. The inclusion of large numbers of smaller private companies in our data set significantly changes the results. The explanation for this is that we find that firms with the very highest probabilities of failure are generally small and do not have large amounts of debt. Of the top 250 firms ranked in terms of probability of failure across all sample years only 16 have more total debt than the mean level of total debt in the relevant sample year. The mean number of employees of these 250 firms is 212, compared to 1,316 in the sample as a whole. The highest-risk firms are relatively small, and therefore they do not hold a large amount of debt in absolute terms.[29]

The conclusion from the analysis of the distribution of firm-level debt at risk is that debt at risk is concentrated among a small number of firms, but those firms are generally not the firms with the highest probabilities of failure. In terms of assessing the risks to financial stability it is clearly important to monitor the aggregate position, but it is also important to monitor the individual firms with the highest levels of debt at risk.

6 Conclusion

The motivation for this paper is to develop a model using firm-level data to quantify the risks to financial stability arising from business failures in the UK corporate sector. We want to analyse the distribution of the risks to see how the aggregate risks are determined and to find out where we should focus our attention in terms of which firms to monitor. Our main contribution to the literature is to develop a model to forecast firm-level probabilities of failure, and to show how the predicted probabilities can be used to construct an indicator of debt at risk, in order to assess risks to financial stability.

We construct a model of the probability of individual company failure using company accounts data between 1991 and 2001. Our data include both public and private firms with over 100 employees. We find that low profitability increases the probability of failure in a non-linear fashion, with especially large effects if profitability is negative. Low levels of interest cover, high capital gearing, low levels of liquidity and a small number of employees all increase the probability of failure. If firms have low profitability and high capital gearing, we find that they are more likely to fail than they would be if we consider the effects of these two factors separately. We also find that firms that are subsidiaries are less likely to fail than firms that are not, holding all other factors constant. Being in the service sector rather than in manufacturing, primary industries or utilities reduces the probability of a firm failing. We consider the impact of the macroeconomic environment on company failure and find that, even after controlling for firm-level characteristics, a firm is more likely to fail during a cyclical downturn than in an upturn.

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[29] This does not mean that their capital gearing – one of the explanatory factors in determining predicted probabilities of failure – cannot be high.

Having developed the model, we apply it to the analysis of the risks to financial stability arising from the UK corporate sector by defining a variable called debt at risk. Firm-level debt at risk measures the size of the risk posed by an individual firm. By summing firm-level debt at risk across the corporate sector we generate an aggregate measure of debt at risk. We find that this micro-based measure of financial risk performs better in predicting debt at risk of default from corporate failure than a macro-based approach, which involves multiplying the average probability of failure by the total stock of debt and therefore does not fully exploit the firm-level dimension of the data.

Aggregate debt at risk, as a proportion of total debt, was at its highest in the early 1990s, and it has been relatively stable at a modest level since 1993, although there was an increase in 2001. Throughout the 1990s the mean level of total debt per firm has been rising, particularly since 1999. Consequently the mean level of *ex-ante* debt at risk per firm has also been rising, and it exceeded the 1991 peak in 2001.

As well as analysing the aggregate risks the paper looks at the distribution of the risks. It finds that debt at risk is concentrated among a small number of firms. The implication of this is that we should closely observe the firms among which debt at risk is concentrated, in order to monitor the profile of the aggregate figure. Although debt at risk is concentrated among a few firms, we find that these firms are generally not the firms with the highest predicted probabilities of failure. The firms with the highest predicted probabilities of failure tend to be small and therefore hold relatively small amounts of debt.

One possible extension to this paper would be to analyse what the size of the threat from debt at risk to UK financial stability would mean in terms of its impact on the solvency of UK financial institutions. This would involve making assumptions about UK banks' exposure to UK firms and the recovery rate on loans. In theory, it should then be possible to calculate how much debt at risk would be required to have a material impact on banks' profitability and solvency.

Appendix

Variable definitions

All data is taken from the Bureau van Dijk FAME database. All variables are taken from the company accounts in the year preceding the year of survival/failure.

A year is defined as 1 April to 31 March.

Definition of year of failure: A firm is defined as failed in a particular year if their company status (according to FAME) is in receivership, liquidation or dissolved, and their last reported accounts were in the previous year.

$$\textbf{Profit margin} = \frac{\text{Profit before interest and taxation}}{\text{Turnover}}$$

In the models we include three dummy variables for the profit margins. These are:
Profit margin < 0
0.03 > Profit margin >= 0
0.06 > Profit margin >= 0.03
Reference category: Profit margin >=0.06

$$\textbf{Interest cover} = \frac{\text{Profit before interest and taxation}}{\text{Interest payments}}$$

$$\textbf{Debt to assets ratio} = \frac{\text{Short term debt and overdrafts} + \text{Long term debt}}{\text{Total assets}}$$

$$\textbf{Liquidity} = \frac{\text{Current assets}}{\text{Current liabilities}}$$

Subsidiary dummy: = 1 if firm is a subsidiary

Interaction dummies: (I) = 1 if profit margin < 0 and debt to assets ratio > 0.35
(II) = 1 if profit margin < 0 and firm is a subsidiary

Industry dummies: Manufacturing, Primary Industries, and Utilities (reference)
Construction
Wholesale and Retail
Hotels and Restaurants
Transport, Storage and Communication
Real Estate, Renting and Business Activities
Other Services

Year dummies: 1991 to 2000, 2001 is the reference year

Table E: Model 1 - Probit model with year dummies

N: 105687
Log likelihood: -8194.67
Pseudo R^2: 0.1508

	Coefficient	Standard error	T ratio	Marginal effect
Profit margin <0	0.698	0.042	16.48	0.0302
Profit margin >=0 & <0.03	0.235	0.032	7.27	0.0067
Profit margin >=0.03 & <0.06	0.149	0.033	4.49	0.0040
Interest cover	-0.011	0.002	-4.89	-0.0003
Debt to assets ratio	0.160	0.032	5.02	0.0039
Profit margin <0 & debt to assets>0.35	0.097	0.042	2.30	0.0026
Current ratio	-0.235	0.025	-9.46	-0.0057
Ln (number of employees)	-0.129	0.011	-11.38	-0.0031
Subsidiary	-0.569	0.028	-20.35	-0.0171
Profit margin <0 & subsidiary	-0.352	0.047	-7.52	-0.0064
Industry dummy: Construction	0.127	0.040	3.19	0.0035
Industry dummy: Wholesale and Retail	-0.111	0.032	-3.52	-0.0025
Industry dummy: Hotels and Restaurants	-0.309	0.060	-5.14	-0.0054
Industry dummy: Transport, Storage and Communication	-0.113	0.048	-2.37	-0.0025
Industry dummy: Real Estate, Renting and Business Activities	-0.012	0.028	-0.42	-0.0003
Industry dummy: Other Services	-0.226	0.045	-5.04	-0.0044
Year dummy: 1991	0.409	0.049	8.32	0.0157
Year dummy: 1992	0.235	0.046	5.11	0.0073
Year dummy: 1993	0.016	0.046	0.34	0.0004
Year dummy: 1994	0.000	0.048	-0.01	0.0000
Year dummy: 1995	-0.022	0.049	-0.46	-0.0005
Year dummy: 1996	-0.098	0.050	-1.98	-0.0022
Year dummy: 1997	-0.013	0.048	-0.27	-0.0003
Year dummy: 1998	0.113	0.045	2.52	0.0030
Year dummy: 1999	0.053	0.045	1.18	0.0014
Year dummy: 2000	0.082	0.044	1.87	0.0021
Constant	-1.128	0.084	-13.42	-

Table F: Model 3 - Heteroscedastic probit model using GDP growth as a proxy for macroeconomic conditions [30]

N: 105687
Log likelihood: -8185.22

	Coefficient	Standard error	T ratio	Marginal effect
Profit margin <0	0.529	0.068	7.77	0.0099
Profit margin >=0 & <0.03	0.204	0.043	4.73	0.0030
Profit margin >=0.03 & <0.06	0.171	0.042	4.12	0.0025
Interest cover	-0.129	0.016	-8.24	-0.0005
Debt to assets ratio	0.135	0.043	3.18	0.0018
Profit margin <0 & debt to assets>0.35	0.157	0.052	3.03	0.0023
Current ratio	-0.400	0.096	-4.17	-0.0032
Ln (number of employees)	-0.142	0.014	-10.04	-0.0019
Subsidiary	-0.633	0.134	-4.74	-0.0112
Profit margin <0 & subsidiary	-1.231	0.473	-2.60	0.0011
Industry dummy: Construction	0.190	0.048	3.95	0.0030
Industry dummy: Wholesale and Retail	-0.133	0.037	-3.58	-0.0016
Industry dummy: Hotels and Restaurants	-0.387	0.070	-5.54	-0.0037
Industry dummy: Transport, Storage and Communication	-0.148	0.057	-2.62	-0.0018
Industry dummy: Real Estate, Renting and Business Activities	-0.001	0.035	-0.02	0.0000
Industry dummy: Other Services	-0.626	0.181	-3.47	-0.0014
12-month GDP growth rate	-0.076	0.011	-7.11	-0.0010
Constant	-0.543	0.115	-4.72	-
Ln σ^2				
Interest cover	0.028	0.003	10.04	-
Current ratio	0.048	0.030	1.60	-
Subsidiary	-0.017	0.045	-0.38	-
Profit margin <0 & subsidiary	0.350	0.155	2.25	-
Industry dummy: Other Services	0.139	0.061	2.30	-

[30] Error variance is allowed to be a function of interest cover, current ratio, subsidiary, profit margin<0 and subsidiary, and industry dummy: other services. These are the variables which fail the score test for heteroscedasticity at the 1% significance level.

Table G: Specification tests

Null hypothesis	Model 1	Model 2
All coefficients jointly equal to zero	$Chi^2(26) = 2397.03$**	$Chi^2(17) = 2283.18$**
Coefficients on profit variables jointly equal to zero	$Chi^2(3) = 279.34$**	$Chi^2(3) = 266.48$**
Coefficient on <0% profit margin dummy = coefficient on 0-3% profit margin dummy	$Chi^2(1) = 140.59$**	$Chi^2(1) = 138.22$**
Coefficient on 0-3% profit margin dummy = coefficient on 3-6% profit margin dummy	$Chi^2(1) = 7.48$**	$Chi^2(1) = 6.16$*
Coefficients on industry dummies jointly equal to zero	$Chi^2(6) = 75.95$**	$Chi^2(6) = 80.94$**
Coefficients on service sector industry dummies jointly equal to zero	$Chi^2(4) = 48.95$**	$Chi^2(4) = 50.28$**
Coefficients on year dummies jointly equal to zero	$Chi^2(10) = 152.48$**	-

** Indicates the null hypothesis is rejected at the 1% significance level.

* Indicates the null hypothesis is rejected at the 5% significance level.

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