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Macroeconomic Instability and Business Exit: Determinants of Failures and Acquisitions of UK Firms

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We study the impact of the macroeconomic environment on business exit in a world where acquisition and bankruptcy are co-determined. We estimate competing risk hazard regression models using data on UK quoted firms spanning a 38-year period that witnessed several business cycles. We find that the processes determining bankruptcies and acquisitions depend on the macroeconomic environment. In particular, macroeconomic instability has opposing effects on bankruptcy hazard and acquisition hazard, raising the former and lowering the latter. While bankruptcy hazard is counter-cyclical and acquisition hazard pro-cyclical, the US business cycle is a better predictor than the UK cycle itself.

Introduction

Firm exits, through bankruptcy or acquisition, are extreme outcomes in the continuous process of corporate restructuring. Exits are held to be cyclical in nature, with bankruptcies associated with economic downturns and acquisitions with recoveries. However, neither the impact of macroeconomic instability on the propensity to exit nor the way in which bankruptcy and acquisition interrelate as competing hazards to the survival of the firm has received much attention in the literature. Analysis at the firm level has tended to focus either on bankruptcy or on acquisition, and along the way exit is determined by the characteristics of the firm and its industry. Analysis of the influence of the macroeconomic environment has tended to focus on the impact of aggregate shocks on aggregate amounts of firm formation and dissolution.

We investigate the impact of macroeconomic conditions on firm failure and acquisition using a framework in which these are related processes, and where changes in the macroeconomic environment may interact with relevant firm and industry features in amplifying or attenuating exit hazards. We investigate these two issues using data on all listed UK companies over an extended period—1965 to 2002—spanning several business cycles. We use a competing-risks model to consider explicitly the joint determination of the probability of an operating firm being acquired and of it going bankrupt, where these mutually exclusive processes compete with each other to restrict the survival of the firm. Unlike discrete outcome models, hazard models explicitly incorporate the timing of alternative outcomes; this is important when the objective is to identify the influence of macroeconomic conditions on business failure. We use a rich set of firm-level covariates along with industry and macro variables that might affect the likelihood of the firm being acquired, or going bankrupt.

The next section reviews the literature. Section II presents an economic framework for the joint determination of bankruptcy and acquisition decisions. The data are described in Section III. Section IV discusses hazard regression models of bankruptcy and acquisition in a competing risks framework. Section V presents the results of the estimated hazard regression models, and our conclusions are in Section VI.

I. LITERATURE[1]

The extant literature on firm exit is reviewed in Siegfried and Evans (1994) and Caves (1998). The role of firm-specific factors, age and size in particular in determining firm failure are central in theoretical models of the firm life-cycle, including passive learning (Jovanovic 1982; Hopenhayn 1992) and active learning (Ericson and Pakes 1995; Pakes and Ericson 1998) formulations. Exit rates are predicted to decline with firm age, owing to firm-level learning. In the credit scoring literature, financial ratios including leverage, cash flow and profitability, join firm age, size and industry as determinants of failure, with binary response models providing the basis for probability scores of company failure (Taffler 1982; Cuthbertson and Hudson 1996; Lennox 1999).

Several studies have noted that firm entry and exit rates are highly correlated, though the nature of the relationship between the two differ across industries, as well as over the ascending and descending stages of the business cycle. Empirical macro studies that relate the macroeconomic environment to business performance in the UK note that movements in the aggregate failure rate of business establishments coincide with changes in macroeconomic performance (Hudson 1986; Department of Trade and Industry 1989; Robson 1996). Exit rates rise during the downturn, and both growth rates and exits vary with size and financial stability ('life cycle hypothesis'), as well as nominal and real shocks.

The economic cycle (characterized by macroeconomic variables such as interest rate, unemployment rate and retail sales growth rate) affect profitability (Geroski and Machin 1993; Machin and Van Reenen 1993; Geroski *et al.* 1997) and gearing, and thereby influence company failures (Everett and Watson 1998). There is evidence of differential impact of changes in the macroeconomic environment on different segments of the cross-section of quoted companies (Higson *et al.* 2002, 2004). In an examination of the effect of changes in interest rates on insolvency, Young (1995) found companies vulnerable to unanticipated changes in real interest rates.

Caves (1998), reviewing the sizeable literature on firm exit, concludes: 'these studies . . . control for macroeconomic conditions in various ways and degrees, but they leave the impression that . . . hazard rates are rather insensitive to the observed variation in the macro environment' (p. 1958). A notable exception is Goudie and Meeks (1991), who simulate financial statements of UK firms, contingent on macroeconomic developments, and observe significant asymmetric and nonlinear impact of the exchange rate upon failure rates. Through retrospective analysis of macro shocks, they argue that, for a significant minority among the major failed corporations, the shock determined their collapse.

Theoretical work on acquisition has emphasized choices made by firms between making acquisitions or becoming targets, depending on firm-level features and the overall environment. Jovanovic and Rousseau (2002) focus on the role of Tobin's Q in acquisition investments of firms. In Shleifer and Vishny (2003) firms make acquisitions or become targets, to benefit from temporary mis-valuation of stock prices.

The large body of empirical work on acquisitions is based mainly on aggregates, and falls into two branches. The first aims at understanding time-series patterns in aggregate acquisition activity, and finds evidence of acquisition waves and stochastic trends. The second, the acquisition–macro branch, seeks explanation of acquisition wave patterns in terms of economy-wide macroeconomic and financial variables that display similar cyclical patterns. Evidence suggests that acquisition activity is positively related to aggregate share price levels (recently, Benzing 1991, 1993; Clarke and Ioannidis 1996).

For other economy-wide measures, different periods and data-sets present conflicting results.

Although bankruptcy and acquisition have each generated large bodies of literature, there has been relatively little analysis of these processes within a unified framework. Peel and Wilson (1989) argued that the acquisition of a distressed firm should be modelled as a distinct alternative to corporate failure. Schary (1991) provided a theoretical basis for considering acquisitions and bankruptcies as alternative routes to exit, pointing out that, while bankruptcies and acquisitions are both forms of exit, they will have different economic causes: while failing firms may avoid bankruptcy by being acquired, there are other economic motives and modalities for acquisitions. Models that address issues that are closest to our interests include Cooley and Quadrini (2006), who present a general equilibrium model of firm reactions to financial drivers, and show how financial factors affect firm survival through the internal finance channel. Delli Gatti *et al.* (2001) develop a theoretical model linking the macroeconomic environment, financial fragility and the entry and exit of firms. Corres and Ioannides (1996) allows for three kinds of exits: bankruptcy; endogenous exits, when the current value of expected profit stream falls below a threshold (voluntary liquidation); and exogenous exits, caused by macroeconomic shocks.

The empirical study closest to ours is Wheelock and Wilson (2000), who identify characteristics that make individual US banks more likely to fail or be acquired. They use bank-specific information to estimate competing-risks hazard regression models for failure and acquisition. Recent empirical work on UK industry by Disney *et al.* (2003) examines the UK establishment (ARD) database for the period 1986–91 and estimate a hazard model of new firm survival. About two-thirds of new entrants are observed to exit within five years; approximately half these are takeovers by other companies under the same ownership groups. They note that exit and entry rates correlate strongly, both across time and within industries. Exit rates decline with age, indicating the importance of learning.

II. An Economic Framework of Competing Exit Risks

This section presents an economic framework for analysing the manner in which the competing risks of bankruptcy and acquisition are influenced by macroeconomic conditions—specifically, macroeconomic instability. Our formulation is in the spirit of Jovanovic and Rousseau (2001, 2002).

At any time t, each firm i, is at some risk of exit through bankruptcy or by being acquired. Figure 1 gives a schematic representation of the way macroeconomic conditions affect exit risks. On one side are firms that exit as a result of financial distress (through bankruptcy or through being acquired), or choose to exit even though they are not distressed. Adverse macroeconomic conditions increase the pool of firms in financial distress. On the other side are investor firms who are in the market for acquisitions. Any firm that is not distressed will be characterized by some optimal level of investment I_{it}, conditional on the level and stability of the macroeconomy. This optimal investment, which maximizes the expected present value of the firms' future cash flows, will comprise both investment in new capital, X, and acquired capital, Y. The balance between X and Y will depend on the relative prices of acquired and new capital, as well as on the fixed and adjustment costs of acquisitions.

Let the ith firm's state of technology (or efficiency) at time t be denoted by z_{it} and its capital by K_{it}. Firms operate under an AK type production function[2] which takes the

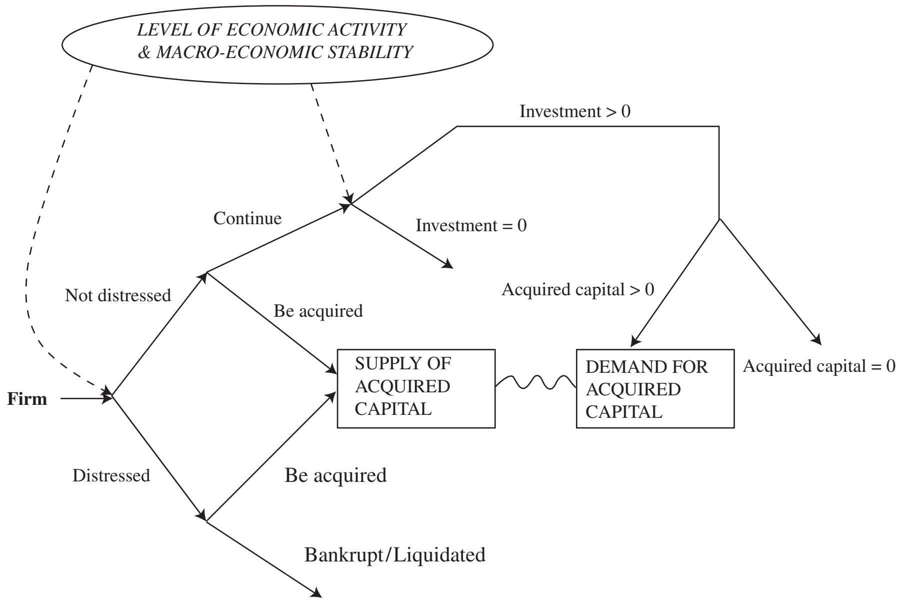

FIGURE 1. Levels of activity and stability.

form $f(z)K$. Here $f(z)$ is akin to the output–capital ratio and depends on firm efficiency: $\partial f(z)/\partial z > 0$. We assume that the dynamics in z and the economy wide macro-environment variable of interest u (denoting instability) are each governed by Markov transition processes; z and u are each assumed to be positively autocorrelated, and independent of each other. Hence z and u are jointly Markov, i.e.

$$Pr[z_{i,t+1} \leqslant z', u_{t+1} \leqslant u' | z_{it} = z, u_t = u] = F(z', u'|z, u).$$

Profits can then be written as $[f(z) - C(x,y) - x - qy - g(u)]K$, where x and y are the (per unit capital) investments in new and acquired capital respectively ($i = x + y$), $C(x,y)$ is the (per unit capital) adjustment cost of investment, and $g(u)$ is the firm-specific impact of macro environment on profits; $g(u)$ is increasing and convex in u, and $g(0) = 0$. The price of new capital is normalized to unity, and q denotes the price of acquired capital ($q < 1$). Then the market value of the firm per unit of capital under the optimal investment plan is

$$Q(z, u) = \max\nolimits_{x \geqslant 0, y \geqslant 0}[f(z) - C(x, y) - x - qy - g(u) + (1 - \delta + x + y)Q'(z, u)],$$

where

$$Q'(z, u) = \frac{1}{1 + r}\max[q, Q(z', u')\mathrm{d}F(z', u'|z, u)]$$

is the expected present value of capital in the next period, given the firm's z and the economy's u today, and δ is the rate of depreciation. Since z and u are independent and positively autocorrelated, $Q(z,u)$ is increasing in z and decreasing in u. Denote by $z_e(u)$ the level of z at which the firm is indifferent between exiting and staying in business, given macroeconomic conditions, and by $z^*(u)$, the level of technology at which the firm is indifferent between staying out of the acquisitions market or entering it.[3]

In a period of economic stability, when demand is more predictable, the incidence of financial distress will be lower. The smaller pool of distressed firms may also face a

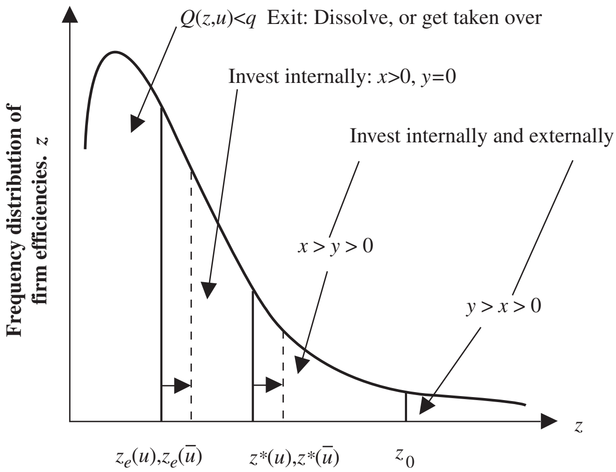

FIGURE 2. The four regions of z.

Source: From Jovanovic and Rousseau (2002); modified.

larger number of potential acquirers whose investment policies are encouraged by macroeconomic stability. Thus, firms that are on the verge of bankruptcy will have a higher probability of being rescued, and the observed bankruptcy rates can be expected to be lower. Further, in such periods the hazard of acquisitions will be higher, even though there are fewer distressed firms that are candidates for acquisition. With the boost to investment in more stable periods, the market for acquisitions may tighten, driving up the market price of acquired assets. This can be expected to induce a larger number of non-distressed firms to enter the pool of potential acquirees. These would be firms who find the offers from potential acquirers to be higher than their own continuation values (Jovanovic and Rousseau 2001).

The implications of changes in u for firm exits and acquisitions can be understood with reference to a plot of the four regions of z (Jovanovic and Rousseau 2002). Let $\overline{u} > u$; then $z_e(\overline{u}) > z_e(u)$ and $z^*(\overline{u}) > z^*(u)$ (Figure 2). In a period with higher u, a larger number of firms decide to exit, and fewer firms decide to acquire. Hence a larger number of firms are likely to go bankrupt during such periods.

Overall, in a period of economic stability, the propensity for bankruptcy will be lower, and the propensity for acquisitions will be higher. A testable implication of the model is that the impacts of macroeconomic instability on the likelihood of bankruptcy and acquisition are of opposite signs.

III. DATA

The evaluation of the impact of macroeconomic fluctuations on business exits requires data running over several business cycles. We use a database of firms quoted in the UK, constructed by combining the Cambridge-DTI, DATASTREAM and EXSTAT databases of firm accounts. The combined firm-level accounting data provides an unbalanced panel of about 4100 UK listed companies over the period 1965–2002. There were 206 instances of bankruptcy and 1858 acquisitions among 48,046 firm years over the

38-year period.[4] In terms of hazard model analysis, the data are right-censored and left-truncated.[5]

We use the term 'bankruptcy' to denote the event of compulsory liquidation. We use the term 'acquisition' to denote the event of business combination, which may take the form of a merger, an acquisition or a takeover. Interchangeable use of these words is standard in this literature.[6]

(a) Measures of macroeconomic conditions

We use the following empirical proxies for macroeconomic conditions:

- As a measure of the business cycle (BC_t), we use a quarterly Hodrick–Prescott-filtered[7] series of UK output per capita ($\lambda = 100$). Given the strong trading linkages of the UK industrial sector with the global economy, and particularly with the US economy, it is likely that the global economic environment will affect the exit decisions and outcomes for UK firms.
- We allow for the possible impact of the global economy by including a similar measure of the US business cycle.
- Real interest rates are measured as the yield on 20-year sovereign bonds, less the annual rate of inflation.
- The average annual real effective exchange rate is used to measure the exchange rate environment. Goudie and Meeks (1991) have found that a stronger pound sterling raises the propensity of firms to go bankrupt.

Figures 3 and 4 plot the annual incidence of bankruptcies and acquisitions, as well as the business cycle indicator for the year. Incidence is measured as the ratio of the number of companies that went bankrupt (and the number that were acquired) during the year to the total number of listed companies. Quoted firm bankruptcies were particularly high during years when the economy turned down after a peak, and were lower during upturns in the business cycle. The growth rates in firm registration hint at a plausible

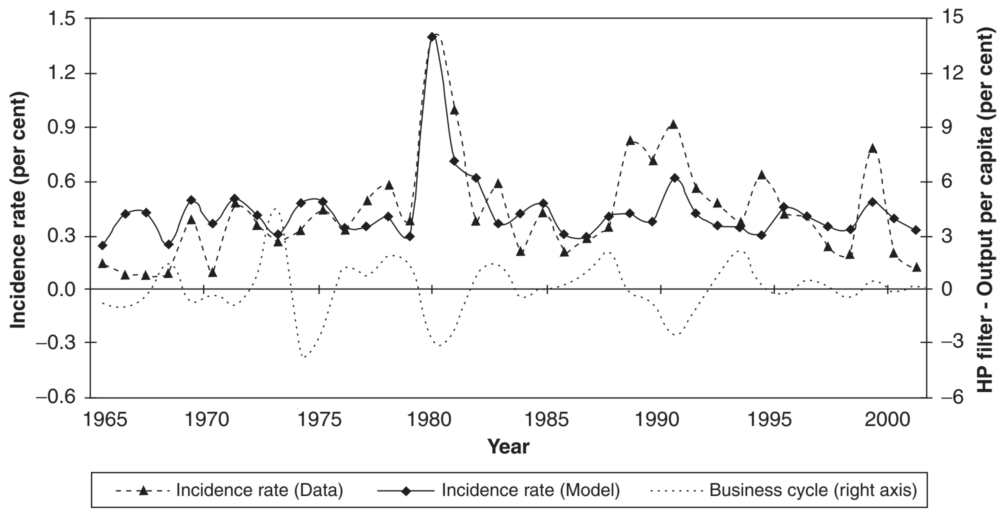

FIGURE 3. Business cycle and bankruptcy incidence (actual data and predictions).

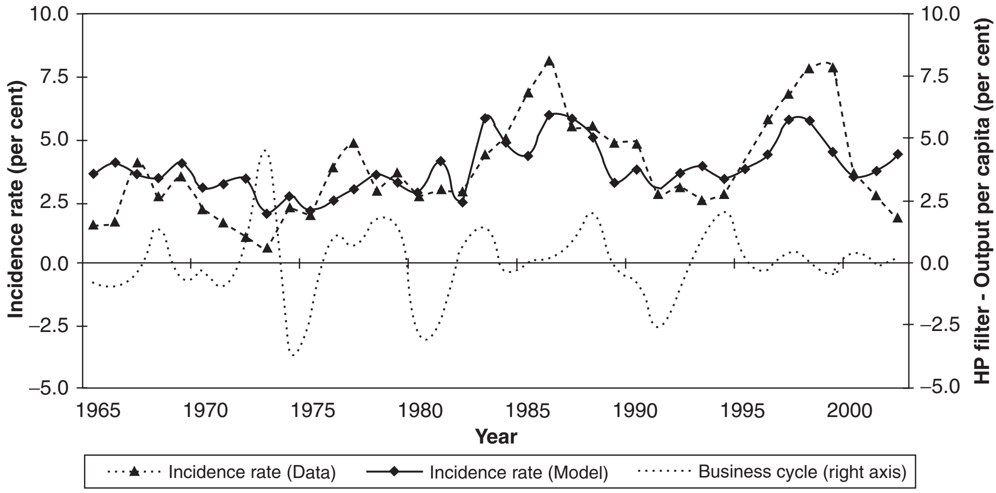

FIGURE 4. Business cycle and acquisition incidence (actual data and predictions).

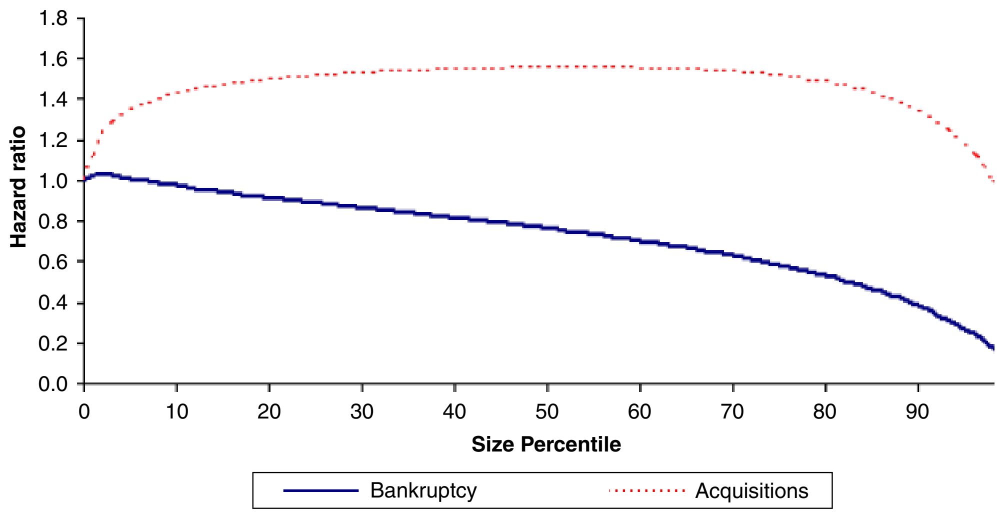

FIGURE 5. Hazard ratio v. size percentiles.

mechanism for this: entries are pro-cyclical, and it is possible that the larger number of entries during the upturn of the business cycle forces some firms out of business when the economy turns down.

Figure 5 indicates that acquisitions were procyclical. Research on aggregate mergers and acquisitions activity has found aggregate market capitalization to be a determinant of acquisition demand. Similarly, earlier research on firm exits have found explanatory power in other measures of aggregate economic activity. We experimented with several other measures, such as Tobin's q, industrial production, stance of monetary policy and capacity utilization, and found the substantive conclusions of our estimated models to be robust to variable selection. Thus, our final choice of macroeconomic variables has been guided by availability of consistent data over the 38-year period, as well as by statistical variable selection methods.

(b) Measures of macroeconomic stability

Figures 3 and 4 also suggest that, even for mature (quoted) firms, the incidence of bankruptcy and acquisition varies substantially over time. While a part of the aggregate movement may be explained by the business cycle, macroeconomic stability may also have a role to play. It has been argued that the impact of uncertainty on business performance is essentially asymmetric. For example, in economies with credit constraints, credit imperfections generate a transmission mechanism through which a small, temporary shock can generate large, persistent domestic balance sheet effects. This feature has motivated financial accelerator-type models (Bernanke *et al.* 1996), including the borrowing constraint in Kiyotaki and Moore (1997), costly state verification in Bernanke and Gertler (1989) and sudden stops in Calvo (2000). The amplification effect can explain why a small fundamental problem can evolve into a large-scale deterioration of economic performance. The credit constraint, interacting with aggregate economic activity over the business cycle, can generates asymmetric effects in response to unexpected productivity shocks.[8] There is related empirical work on mechanisms that create asymmetric volatility responses (Engle and Ng 1993).

Traditional measures of instability, for example those based on standard deviations, are not able to capture these asymmetric effects. We use signed gradients in monthly measures of macroeconomic indicators to identify sharp variations. We use the following measures of macroeconomic instability:

- To measure exchange rate instability, we use year-on-year variations in the exchange rate.
- Price instability is measured by the largest month-to-month rate of variation of the retail price index within the calendar year.
- Instability in long-term interest rate is measured by the largest month-to-month rate of variation, within the calendar year, of yield rates on 20-year sovereign bonds.

(c) Firm-level and industry-level characteristics

We include a number of variables characterizing the firm and its financial performance, and controls for unobserved heterogeneity at the industry level.

- Firm size is measured as the logarithm of fixed capital in real terms, incremented by unity.
- Profitability is measured by the ratio of cash flow to one-year-lagged total assets.
- We use current ratio, i.e. the ratio of current assets to current liabilities, as a measure of liquidity.
- Debt sustainability is measured using interest cover, i.e. the ratio of interest expenses to profits before interest and tax.
- We measure the firm's financial structure in terms of its gearing ratio, which is the ratio of debt to the sum of debt and equity.

We experimented extensively with alternative firm-level measures, but the substantive conclusions from our models were robust to choice of variables. In addition to the usual ratios, we estimated our model using lagged average sales growth over the past three and five years as a proxy for demand conditions. Again, conclusions were robust, though the sample sizes were substantially reduced.

Descriptive statistics are given in Table 1. The sample characteristics display significant variability, both across firms and over the 38-year period.

TABLE 1
SAMPLE CHARACTERISTICS OF THE EXPLANATORY VARIABLES[a]

Variables	N	Mean	Std dev.	Min.	Max.
Industry dummies					
Food/Breweries	48,094	0.054	—	—	—
Chemicals/Pharmaceuticals	48,094	0.059	—	—	—
Metals	48,094	0.012	—	—	—
Engineering	48,094	0.101	—	—	—
Electricals/Electronics	48,094	0.054	—	—	—
Textiles	48,094	0.083	—	—	—
Paper/Packaging	48,094	0.056	—	—	—
Construction	48,094	0.098	—	—	—
Media/Publishing	48,094	0.052	—	—	—
ICT	48,094	0.040	—	—	—
Trading/Superstores	48,094	0.109	—	—	—
Firm × year level					
Size: ln (rl. fixed capl. + 1)	48,094	4.768	1.91	0	13.5
Cash flow to capital	48,094	0.160	1.99	− 388.6	9.14
Current ratio	48,094	5.936	13.47	0.00	67.63
Interest cover	48,094	0.00	1.00	− 136.5	0.896
Gearing	48,094	0.00	1.00	− 42.29	147.7
Macro conditions					
UK business cycle	38	− 0.027	1.02	− 2.39	2.97
Long-term real interest rate	38	2.559	3.31	− 9.82	6.45
£–$ exchange rate	38	− 0.184	1.00	− 2.58	2.75
US business cycle	38	0.025	1.02	− 2.46	1.99
Macro instability					
Increase in exchange rate	38	0.014	0.99	− 1.94	1.56
Volatility—RPI inflation	38	0.002	1.02	− 2.40	2.90
Volatility long-term interest rate	38	0.007	1.03	− 2.60	3.31

[a]Some variables have been normalized or rescaled to facilitate interpretation of the model estimates. These include firm-level covariates interest cover and gearing, and macroeconomic variables representing UK and US business cycles, exchange rates and all measures of macroeconomic instability.

IV. ECONOMETRIC METHODOLOGY

There are a few empirical studies on firm exits based on discrete outcome or scoring models such as probit or logit,[9] but the larger part of the literature has relied on hazard regression models for inference. In our context, there are two advantages to the use of hazard models.

First, these models explicitly incorporate the timing of alternative outcomes, and therefore adequately account for sample selection arising from censoring. For example, the likelihood contribution for a firm that went bankrupt in 1980 would incorporate not only the information that the firm went bankrupt, and was not acquired in 1980, but also the fact that it neither went bankrupt nor was acquired in any of the previous years of its existence.

Second, hazard regression models can be used explicitly to segregate the age aspect of the propensity to survive (or exit) from the effect of other covariates. At the same time, this framework allows the effect of age on the hazard to be completely flexible, and the effect of other covariates to possibly vary with age of the firm. This is important in disentangling the influence of macroeconomic conditions on business exit from the influence of firm-specific and industry factors, as well as for understanding the role of learning in mature firms.

The model places the risks of bankruptcy and acquisitions in a unified framework. Each firm is conceived as being concurrently under risk of bankruptcy and acquisition during each year of its life. In other words, bankruptcy and acquisitions are mutually exclusive outcomes, influenced by their own determinants, competing to restrict the survival of an operating firm.

In a hazard model framework, this data-generating process can be parametrized using a competing risk model where inference is based on the cause-specific intensity (hazard) rates $\lambda_h(t;\theta)$, defined as

$$(1) \qquad \lambda_h(t;\theta) = \lim_{\varepsilon \to 0} \frac{1}{\varepsilon} P[T < t + \varepsilon; H = h | t \geqslant t; \theta],$$

where $h = 1, \ldots, k$ are the k competing causes of failure, and $\lambda_h(0;\theta) = 0$; $h = 1, \ldots, k$. The Cox proportional hazards (PH) model provides a convenient description of the regression relationship between the cause-specific hazard rates (equation (1)) corresponding to the competing causes of failure, and various explanatory variables (covariates) describing the firm's endowments ($\underline{x}_{i,t}$), the macroeconomic environment ($\underline{m}_t$) and macroeconomic instability ($\underline{u}_t$), given the age of the firm ($a_{i,t}$). The model postulates that the logarithm of the cause-specific hazard function is a linear function of the covariates:

$$(2) \qquad \lambda_h(a_{i,t}, \underline{z}_{i,t}; \underline{\theta}_h) = \lambda_{0h}(a_{i,t}) \exp\left[\underline{\theta_h}' \cdot \underline{z}_{i,t}\right],$$

where $\lambda_{0h}(\cdot)$ is the baseline hazard function corresponding to the hth cause of failure (in the present case h takes two values: bankruptcy or acquisition) at age $a_{i,t}$; $\underline{z}$ is the vector of covariates (comprising $\underline{x}_{i,t}$, $\underline{m}_t$ and $\underline{u}_t$); and $\underline{\theta}_h$ are the vectors of coefficients corresponding to the hth cause of failure.

The parameters of the model are (a) the two baseline hazard functions, $\lambda_{0h}(\cdot)$, corresponding to the two competing causes of failure, and (b) the distinct vectors of covariate effects ($\underline{\theta}_h$) for the two causes. In the following subsections we consider estimation in the simple case when proportionality holds, and explain some additional features of our estimation procedure. These include discussion of

1. the assumption of conditional independence of the two competing exit routes required for estimation;
2. violation of the PH assumption and modelling nonproportionality through age-varying covariate effects;
3. the effect of left truncation on the estimates.

Further checks on the robustness of our model estimates are discussed in the Appendix.

(a) Estimation under PH assumption

The assumption of proportional hazards is often violated in application and is sometimes contested by relevant theory. Respecting this, we allow covariate effects to vary with the age of the firm. This is a significant generalization of the PH model. We begin our discussion with fixed covariate effects, and extend it to the estimation of age-varying regression parameters.

Estimation of a Cox PH model in a multivariate duration model setting is discussed in Wei *et al.* (1989) and Spiekerman and Lin (1998); their model is similar to our regression model for cause-specific hazard rates (equation (2)). Inference is based on '*quasi-partial likelihood*' estimating equations with a working assumption of independence (Spiekerman and Lin 1998). In our competing-risks setting, this stipulates that censoring by the competing risks must be independent of the age of the firm at exit, conditional on the observed covariates $\underline{z}$.[10] In essence, this requires the selection of covariates such that, after conditioning on them, the competing exit processes are independent of each other. We discuss this conditional independence assumption in more detail in the following subsection.

Following Spiekerman and Lin (1998), we express the log-'quasi-partial likelihood' of $\underline{\theta_h}$, under the independence assumption, as

$$(3)\qquad l(\underline{\theta_h}) = \sum_{i=1}^{n}\sum_{h=1}^{k}\int_0^{\tau}\left[\underline{\theta_h}'\,.\,\underline{z}_{iu} - \ln\left(\sum_{j=1}^{n} Y_{jh}(u).\exp\left(\underline{\theta_h}'\,.\,\underline{z}_{ju}\right)\right)\right]\mathrm{d}N_{ih}(u),$$

where $N_{ih}(u)$ denotes the counting process for exits corresponding to the hth competing risk, and $Y_{jh}(u)$ denotes the corresponding at-risk indicator function (see Andersen *et al.* 1993). The above expression is the same as the partial likelihood for a stratified Cox model with two independent strata and independent observations in each strata.

Thus, the estimates of covariate effects, $\widehat{\underline{\theta_h}}$, are the ones that maximize the above log-'quasi-partial likelihood' (equation (3)):

$$\widehat{\underline{\theta_h}} = \arg_{\underline{\theta_h}} \max l(\theta_h),$$

and the estimates of the baseline cumulative hazard functions, i.e.

$$\Lambda_{0h}(t) = \int_0^t \lambda_{0h}(u)\,\mathrm{d}u,$$

are the corresponding Aalen–Breslow type estimators:

$$\widehat{\Lambda}_{0h}(t;\widehat{\underline{\theta_h}}) = \int_0^t \frac{\sum_{i=1}^{n}\mathrm{d}N_{ih}(u)}{\sum_{i=1}^{n} Y_{ih}(u).\exp\left(\widehat{\underline{\theta_h}}'.\,\underline{z}_{iu}\right)}.$$

There are several points to note regarding the estimation method. First, the above quasi-partial likelihood (equation (3)) is valid under certain forms of unobserved heterogeneity. Specifically, estimation based on this quasi-partial likelihood accounts for unobserved heterogeneity arising from a common scalar index of unobserved regressors for the two competing risks (Spiekerman and Lin 1998).[11]

Second, estimation of the model is straightforward. It can be seen from the form of the quasi-partial likelihood that estimating this model is equivalent to estimating two separate univariate Cox regression models corresponding to the two causes of failure—acquisitions and bankruptcies. This implies that the model can be simply estimated by maximizing the usual stratified partial likelihood function (Cox 1972). In other words, the estimation of the competing risks model involves estimation of two separate Cox PH models, one for exits resulting from bankruptcy and the other one for acquisitions. In each case we treat exits arising from the other cause as censored cases. However, unlike the univariate hazard regression model, the interpretation of our parameter estimates will relate to the cause-specific hazard functions rather than to the hazard functions themselves.

Third, the data allow us to observe the year a firm is listed and the year of its exit. Since age is recorded only in years, the duration data are continuous, but are observed in an interval censored manner. There is also considerable variation in the ages of the firms included in the sample. For example, the oldest exit resulting from bankruptcy is observed at an age of 113 years post-listing, while for acquisitions the oldest observed case is 186 years. Given the wide range in age, we estimate the model in a continuous-duration framework using Cox partial likelihood estimates of the regression models (Cox 1972), and thereby ignore the interval censored nature of observed data. It is, however, necessary to specify a method for handling ties in the ages of firms at exit while computing the partial likelihood (see Kalbfleisch and Prentice 2002). We use the Peto–Breslow approximation (Breslow 1974) to adjust for ties in computing the log quasi-partial likelihood and the Martingale residuals.

(b) Independence of exits arising from competing causes

As in the case of univariate Cox regression models, the inference procedure presented above is valid only under the assumption that censoring is independent of exit conditional on covariates included in the model. In the competing-risks model, exits are censored by competing causes of failure, and hence we have to make this assumption explicitly. Such independence can be achieved by including all regressors in both the models.[12]

Consider, for example, the regression model for the cause-specific hazard of exits resulting from bankruptcy. Under the competing-risks data-generating process, some exits arising from bankruptcy will be censored by acquisitions. Similarly, exits because of acquisitions are not unconditionally independent of bankruptcy exits. Therefore, in order to infer on exits resulting from bankruptcy, the process by which firms get censored (i.e. get excluded from the chance of going bankrupt by exit through acquisitions, or any other reason) must also be modelled along with the exit process. This requires that we include all covariates affecting the competing exit process (acquisitions) in the model for bankruptcy. We assume that, conditional on the covariates, bankruptcy exits are independent of exits arising from acquisitions, and vice versa.[13]

Thus, when we consider the hazard regression model for bankruptcy, we include all the factors affecting acquisition hazard, and assume that other forms of censoring are either independent or (at least) dependent on the same covariates. We deal in a similar way with the regression model for exit caused by acquisitions.

(c) Age-varying covariate effects

It is well known that the Cox PH model substantially restricts interdependence between the explanatory variables and duration. Proportional hazards imply that the coefficients of the hazard function regressors are restricted to constancy over time—an assumption that is frequently violated in empirical application.[14] An appealing solution to such violation of proportionality is to allow the covariate to have different effects on the hazard according to the age of the firm. Several estimators have been proposed in the literature that allow for such time-varying coefficients in the Cox regression model. We use the histogram-sieve estimators of Murphy and Sen (1991), which are intuitive and permit practical and useful inference.

This method involves dividing the duration scale into several intervals, and including the continuous covariate interacting with indicator functions corresponding to each of the intervals as covariates in a modified Cox PH model. Since we expect a non-constant covariate effect, we would ideally like to have a large number of intervals to capture this feature. An alternative would be to use kernel-based methods to estimate the covariate effect continuously over duration (see Bhattacharjee 2004). We divide the range in which the ages of firms fall into four intervals; the choice of the number of intervals and the cut-off ages was determined by considerations of parsimony and the requirement that each interval should include sufficient number of exits (of each competing type) and a balanced number of firm-years (observations).[15]

Our chosen four intervals are age 0–4 years, age 5–15 years, age 16–25 years and age >25 years, post-listing. Each of these four intervals has a reasonable incidence from the total sample, covering 7569 (16%), 13,474 (28%), 11,817 (25%) and 15,234 (32%) company years, respectively.[16]

Finding covariates that have non-proportional effects is an important step in the implementation of the above methodology. We use two statistical tests to find covariates that may have age-varying effects on the cause-specific hazard of either exit. The first is a test for the proportionality assumption based on Martingale residuals (Grambsch and Therneau 1994), and the second is a test that the effect of a given covariate does not vary with the age of the firm (Bhattacharjee and Das 2002). Both tests lead to a very similar selection of covariates. Our empirical results demonstrate that several covariates have age-varying covariate effects, and that there is segmentation of the duration scale in characterizing effectively the way the impact of a covariate varies over the life of the firm, post-listing.

(d) Left truncation and robustness of estimates

In addition to right-censoring (by dependent competing risks), our duration data are truncated to the left, in that they pertain only to the period after 1965. For a given firm, the age at left truncation is given by $L = 1965 - B$, where B is the listing-year of the firm. The Cox partial likelihood estimates based on a modified definition of risk sets (delayed entry) are valid if truncation and exits are independent either unconditionally, or at least after conditioning on the included covariates. While there is no simple way to test such conditional independence, the impact of dependence on estimates can be examined by stratifying the sample with respect to age at truncation. We evaluate the robustness of our results to dependent truncation by estimating the age at exit models conditioned on different ranges of the age at left truncation, and examining the sensitivity of model estimates. We also estimate the models for subsamples of the data based on different starting years. We truncate the sample at 1970 (instead of 1965), and estimate the models for bankruptcy and acquisitions for this subsample.

The Insolvency Act of 1986 is likely to have had a mitigating effect on corporate failures (Cuthbertson and Hudson 1996; Liu 2004).[17] In order to examine whether this has a significant effect on our results, we also estimate the model for bankruptcy for the period from 1986 onwards.

In addition to evaluating left truncation, we check the robustness of our estimates in other ways. First, we estimate comparable logit models for exits resulting from bankruptcy and acquisition and compare the results with our hazard model estimates. Second, we compute jackknife estimates of the model to evaluate the robustness of our parameter estimates and their standard errors.

Results of these robustness tests and the check for impact of the Insolvency Act 1986 are presented in the Appendix. It is evident that our hazard regression models for bankruptcies and acquisitions are robust. We do find evidence of the effect of the Insolvency Act 1986, but the conclusions from our estimates for the period since 1965 are upheld.[18] Bhattacharjee *et al.* (2003) have found similar evidence of the impact of Chapter 11 legislation on bankruptcies and acquisitions in the United States.

V. Results

The maximum partial likelihood model estimates of the two models, for bankruptcies and for acquisitions, are reported in Table 2. The reported estimates are hazard ratios, which are exponentials of the estimates of the Cox PH model regression coefficients. These estimates are interpreted as the factor by which the hazard would be increased if there were a one-unit increase in the covariate under consideration, other things equal. Hence, if the hazard ratio is unity the covariate has no effect, while if it is 2 a one-unit rise in the covariate will double the hazard of exit.

The reported *z*-scores are based on robust standard error estimates proposed by Lin and Wei (1989). These are obtained using a sandwich estimator, where clustering by year is adjusted for by summing the score residuals within each year before applying the sandwich estimator. The fit of models is judged using a Wald chi-square test, and the validity of the proportionality assumption by the tests proposed in Grambsch and Therneau (1994) and Bhattacharjee and Das (2002). These tests help us identify two regressors with age-varying covariate effects. The effect of these covariates (our measures of instability in exchange rates and inflation) are allowed to vary over the age of the firm using the histogram sieve estimator (Murphy and Sen 1991). Our checks for sensitivity of the estimates indicates that the estimated models are quite robust (see Appendix).

(a) Firm and industry-specific factors

Industry matters significantly for either form of exit. Textiles and construction companies are more likely to go bankrupt but less likely to be acquired. While firms in the paper/packaging business are more likely to be acquired, firms in the engineering and ICT industries have a lower acquisition propensity. The broad division appears to fall along the traditional/modern divide.

Firm-specific characteristics have impacts suggested in the literature. The rates of bankruptcy and acquisition decline sharply with size in the higher size-ranges. Figure 5 shows the estimated hazard ratios against size-percentiles after conditioning on other covariates. There is a sharp decline of bankruptcy hazard with size. The figure supports the stylized fact from the acquisition literature that quoted firms in the middle range of the size distribution are considerably more likely to be acquired.

Firms with higher interest cover have a low exit hazard from both bankruptcy and acquisitions. While a higher gearing enhances the risk of bankruptcy, cash-rich firms and

TABLE 2
MODEL ESTIMATES

Variables	Bankruptcy	Acquisitions
Industry dummies		
(Base = all others)	1.00	1.00
Food/Breweries	0.8349(− 0.4)	1.1755(1.7)$^{+}$
Chemicals/Pharmaceuticals	0.5888(− 1.3)	1.1079(1.1)
Metals	0.4341(− 0.8)	1.0671(0.4)
Engineering	1.2342(0.9)	0.7521(− 3.4)**
Electricals/Electronics	0.9073(− 0.3)	1.1333(1.4)
Textiles	2.0297(3.3)**	0.8283(− 2.1)*
Paper/Packaging	0.9958(− 0.0)	1.2053(2.2)*
Construction	1.4754(1.7)$^{+}$	0.7650(− 3.1)**
ICT	0.4191(− 1.7)$^{+}$	0.4400(− 5.2)**
Trading/Superstores	0.9224(− 0.3)	0.8940(− 1.5)
Firm × year level		
Current size		
ln (real fixed capital + 1)	1.1935(1.0)	1.2390(3.8)**
Size-squared	0.9614(− 1.9)*	0.9757(− 4.5)**
Cash flow to capital	1.0086(0.1)	1.3683(8.0)**
Current ratio	1.0062(1.3)	1.0105(8.7)**
Interest cover	0.9619(− 4.8)**	0.9840(− 2.2)*
Gearing ratio	1.0258(3.3)**	0.9978(− 0.1)
Macroeconomic conditions		
UK business cycle	0.9831(− 0.2)	0.9371(− 1.6)
Long-term real interest rate	0.9855(− 0.5)	1.0225(2.1)*
£–$ exchange rate	1.0383(0.4)	1.0216(0.8)
US business cycle	0.8515(− 2.2)*	1.2298(6.2)**
Macroeconomic instability		
Year-on-year increase in £–$ exchange rate = v		
$v \times I$(age 0–4 yrs)	1.2722(1.9)*	0.8691(− 2.7)**
$v \times I$(age 5–15 yrs)	1.2407(1.3)	0.8891(− 2.6)*
$v \times I$(age 16–25 yrs)	1.0437(0.2)	1.0051(0.1)
$v \times I$(age >25 yrs)	1.0424(0.3)	0.9359(− 1.5)
Vol.–RPI inflation = x		
$x \times I$(age 0–4 yrs)	1.3044(1.2)	0.8644(− 1.8)$^{+}$
$x \times I$(age 5–15 yrs)	1.0832(0.4)	0.8326(− 2.9)**
$x \times I$(age 16–25 yrs)	0.6906(− 1.3)	0.8055(− 4.5)**
$x \times I$(age >25 yrs)	0.6933(− 1.9)$^{+}$	0.8254(− 3.0)**
Volatility–long-term interest rate	1.1886(0.9)	0.7297(− 5.8)**
No. of firms	4117	4117
No. of exits	206	1,858
Total time at risk (in firm-yrs)	48,094	48,094
Log-likelihood	− 1357.808	− 12,661.188
Wald χ^2 goodness-of-fit test	135.11	383.08
d.f./p-value	29/0.000	29/0.00
χ^2 test (PH assumption)	14.92	34.77
d.f./p-value	29/0.990	29/0.251
Only macro variables (log-lik.)	− 1399.280	− 12,780.16
LRT–joint significance of. firm/ind. var. (d.f./p-value)	16/0.000	16/0.000
Only firm/ind. variables (log-lik.)	− 1375.086	− 12,714.53
LRT–joint significance of macro variable (d.f./p-value)	13/0.002	13/0.000

Notes
z-scores in parentheses.
Parameters reported are hazard ratios (exponential of the regression coefficient estimates).
Volatility is measured as maximum monthly difference during the year, divided by the number of intervening months.
**, *and $^{+}$: significant at 1%, 5% and 10% level, respectively.

firms with higher liquidity (with higher cash flow-to-capital ratio and higher current ratio, respectively) are preferred as acquisition targets.

(b) Macroeconomic factors

We conditioned on the long-term real interest rate and the sterling–dollar exchange rate. The long-term rate has a significant impact only on acquisitions, while the exchange rate has no significant impact on either bankruptcy or acquisition. We also conditioned on measures of both the UK and the US business cycle. Only the US business cycle measure has a significant effect on bankruptcies and acquisitions; apparently the US economy is a better predictor of UK bankruptcies and acquisitions than the business cycle in the United Kingdom itself. The effect of the US business cycle on acquisitions is particularly strong, possibly reflecting the dominance of US acquirers in the international acquisition markets in the period. We interpret the strong role of the US business cycle as an indication of the importance of demand for acquired capital from the international capital market in driving merger waves. In the case of bankruptcy, the effect is likely to have been driven by demand for exports.

In comparison to general macroeconomic conditions, the impact of macroeconomic instability on business exits is more pronounced, and depends substantially on the age of the firm since listing, particularly for acqusitions.[19] Newly listed firms are more likely to go bankrupt during the years when exchange rate changes are very sharp. On the other hand, acquisition hazard for younger firms is reduced during these years.

Price instability[20] and volatility in long-term interest rates subdued acquisition activity significantly. While the effect of instability on bankruptcy hazard is not significant for the entire period under analysis, the effect is more pronounced for the recent period after the introduction of the Insolvency Act of 1986 (Appendix Table A1). Overall, our findings point to the detrimental impact of macroeconomic instability on survival.

Figure 6 plots the baseline cumulative hazard functions of bankruptcy and acquisition against the age of the firm reckoned from listing date. Note that the hazard of mergers is about four times that of bankruptcy, controlling for covariates. While the baseline hazard resulting from mergers appears to be constant over the lifetime of a firm, post-listing, the baseline hazard arising from bankruptcy decreases with age up to about 20 years post-listing, arguably reflecting a learning effect. In the literature, evidence in favour of learning models has been advanced from cohort studies of new young firms, and it is interesting to note evidence for mature firms.

Figures 2 and 4 also present the year-wise predicted incidence rates of bankruptcies and acquisitions against the observed incidence rates. The close conformity between the two is noteworthy.

VI. Conclusions

Our objective was to examine the relationship between business exits and instability associated with the macroeconomic cycle, focusing on large and mature (listed) UK companies, over a long (34-year) period. We disentangled the joint determination of probabilities of two mutually exclusive processes—firms being acquired and firms going bankrupt—by estimating a competing-risks model for the probabilities of exit in either form, in terms of firm characteristics, industry and features of the business cycle. Our model explains the observed time variation in the incidence of bankruptcy and acquisitions

FIGURE 6. Baseline cumulative hazard: bankruptcy and mergers.

quite well. The two types of exit are marked by differences in the effects of firm-level drivers, industry and macroeconomic conditions, particularly macroeconomic instability.

At the firm level, our findings corroborate earlier results; the baseline hazard arising from bankruptcy and mergers decreases with age after listing. Other factors remaining constant, larger firms and firms with higher interest cover are less likely to go bankrupt or be acquired. Firms with higher liquidity and cash-rich firms are more attractive acquisition targets, and firms with higher gearing are more likely to go bankrupt.

Our results on the impact of macroeconomic instability on exits are new, to the best of our knowledge. There are notable differences in the way in which recently listed firms and those listed some years previously respond to changes in the macroeconomic environment. Uncertainty in the form of sharp increases in inflation and sharp depreciation of the pound sterling affect freshly listed firms adversely; they are more likely to go bankrupt during unstable years. Acquisition activity is also subdued in these years. Further, there are fewer bankruptcies and more acquisitions during an economic upturn, particularly when measured by the US business cycle. The finding of contemporaneous increase in bankruptcies and decline in acquisitions, in a period of instability or low economic growth, suggests the need for further work on assessing causal relationships between the two processes.

The results reported here underscore the importance of smooth macroeconomic management for the corporate sector. In an era of globalization, they also point to the role that might be played by business cycles in other economic, regions in the determination of both forms of business exit. International comparisons, estimating similar models for other economies, would aid understanding and policy. Estimates of a similar model for the United States (Bhattacharjee *et al.* 2003) also point to an important role for bankruptcy legislation.

APPENDIX: ROBUSTNESS OF MODEL ESTIMATES

We examine the robustness of our results by comparing estimates of different models and estimates over different samples of firms (firm-years). Specifically, we employ four different tests.

First, we estimate our models for different ranges of the age at left truncation. As noted earlier, the truncation duration L may be represented as $L = 1965 - B$, where B is the listing-year of the company.[21] The truncation duration L range shows considerable variation over the cross-section of firms; the first quartile (Q1), median (Q2) and third quartile (Q3) are 0, 1 and 17 years respectively. Since $1965 - B$ is known at the time of listing and is therefore deterministic, it is likely that L is independent of the age of the firm at exit. On the other hand, if characteristics of the firms listed before 1965 are substantially different from those listed more recently, we may have some dependence between age at left truncation and exit age. We conducted a formal test of independence (Tsai 1990) of truncation duration L and the (right-censored) age at exit. This test rejects the independence hypothesis for exits resulting from bankruptcy at the 5% level, but does not reject independence for acquisitions. Despite dependent left truncation, our model for exits arising from bankruptcy would still be adequate if the two durations were independent after conditioning on covariates included in the bankruptcy model. We examine robustness by estimating separate hazard models for truncation durations up to the median and up to the third quartile of the cross-sectional distribution of L. If the coefficients are similar in signs and significance with our estimates for the full sample, we can conclude that our model estimates are

TABLE A1
SENSITIVITY OF MODEL ESTIMATES: BANKRUPTCY

Variables	Full sample	1970–2002	1986–2002	Trunc. $L \leqslant 17$	Logit model
Age dummies					
(Base = I(age 0–4 yrs))	–	–	–	–	1.00
I(age 5–15 yrs)	–	–	–	–	– 0.458*
I(age 16–25 yrs)	–	–	–	–	– 0.674**
I(age > 25 yrs)	–	–	–	–	– 0.440*
Industry dummies					
(Base = all others)	1.00	1.00	1.00	1.00	1.00
Food/Breweries	0.835	0.897	1.266	0.807	– 0.139
Chem./Pharma.	0.589	0.616	0.909	0.543	– 0.504
Metals	0.434	0.470	1.243	0.442	– 0.843
Engineering	1.234	1.189	1.492	1.148	0.229
Electrical/Electronics	0.907	0.901	1.106	0.937	– 0.075
Textiles	2.030**	2.062**	1.916*	1.960**	0.704**
Paper/Packaging	0.996	0.913	1.213	0.995	– 0.005
Construction	1.475$^+$	1.331	0.891	1.445	0.391$^+$
ICT	0.419$^+$	0.394$^+$	0.374$^+$	0.409$^+$	– 0.873$^+$
Trdg./Superstores	0.922	0.921	1.431	0.779	– 0.085
Firm × year level					
Current size					
ln(real fixed capital + 1)	1.194	1.282	1.304	1.149	0.161
Size-squared	0.961*	0.953*	0.951*	0.964$^+$	– 0.036$^+$
Cash flow to capital	1.009	1.043	0.988	1.003	0.008
Current ratio	1.006	1.005	1.003	1.006	0.006
Interest cover	0.962**	0.964**	0.969**	0.962**	– 0.045*
Gearing ratio	1.026**	1.025**	1.015$^+$	1.024**	0.025**
Macroeconomic conditions					
UK business cycle	0.983	0.883	1.079	0.994	– 0.068
Long-term real interest rate	0.985	0.996	1.006	0.995	– 0.001
£–$ exchange rate	1.038	1.004	0.951	1.025	0.111
US business cycle	0.851*	0.942*	0.532*	0.842*	– 0.215**

TABLE A1
CONTINUED

Variables	Full sample	1970–2002	1986–2002	Trunc. $L \leqslant 17$	Logit model
Macroeconomic instability					
Year-on-year increase in £–$ exchange rate = v					
$v \times I$(age 0–4 yrs)	1.272*	1.236$^+$	1.712**	1.296*	0.228$^+$
$v \times I$(age 5–15 yrs)	1.241	1.222	1.393	1.237	0.240
$v \times I$(age 16–25 yrs)	1.044	1.051	1.186	1.035	0.094
$v \times I$(age >25 yrs)	1.042	1.013	1.249	0.900	− 0.060
Volatility–RPI inflation = x					
$x \times I$(age 0–4 yrs)	1.304	1.376	3.892**	1.333	0.321
$x \times I$(age 5–15 yrs)	1.083	1.201	3.359*	1.082	0.138
$x \times I$(age 16–25 yrs)	0.691	0.823	3.367*	0.672	− 0.290
$x \times I$(age >25 yrs)	0.693$^+$	0.735	2.424	0.662	− 0.160
Vol.–long-term interest rate	1.189	1.251	1.625	1.230	0.178
Constant	–	–	–	–	− 5.138**
No. of firms	4117	3781	2878	3933	–
No. of exits	203	196	114	191	203
Total time at risk (firm-yrs)	48,094	41,690	22,059	44,796	48,094
Log-likelihood	− 1357.81	− 1288.20	− 696.80	− 1291.44	− 1258.29
Wald χ^2 goodness-of-fit test	135.11	117.92	100.93	121.40	128.61
d.f./p-value	30/0.00	30/0.00	30/0.00	30/0.00	33/0.00

Notes
Parameters reported are hazard ratios (exponential of the regression coefficient estimates).
Volatility is measured as maximum monthly difference during the year, divided by the number of intervening months.
**, * and $^+$: significant at 1%, 5% and 10% levels, respectively.

robust. The above estimates for truncation duration $L \leqslant 17$ years are presented, separately for bankruptcy and acquisitions, in Tables A1 and A2, respectively.

Second, we truncate the sample at 1970 (instead of 1965), and estimate models for this sample. These estimates are included in Tables A1 and A2. Our estimates for the full sample are robust to truncation duration, as indicated by their similarity to estimates for $L \leqslant 17$ years and for the period 1970–2002.

Third, we estimate logit models comparable with our estimated hazard models. There are some important differences between hazard models and binary response models such as the logit. Unlike the logit, hazard regression models explicitly incorporate the nature of censoring inherent in duration data, and are therefore more appropriate for our focus. Further, our hazard regression model incorporates an important role for the age of the firm in determining the hazard rate of exits, in terms of non-parametric patterns for the baseline hazard function and for age-varying covariate effects. The age effect needs to be incorporated explicitly into the logit model. To allow for comparability with hazard model estimates, we use age-dummies in logit models to allow for the effect of age to be flexible, as in our framework. Though not exactly comparable, the estimated logit models allowing for flexible effect of age since listing (presented in Tables A1 and A2) return qualitatively similar results.

Fourth, we employ a jackknife procedure, by removing one company at a time from the sample and computing estimates based on all the other companies. Since different companies return different numbers of company-years, removing different companies would involve omitting different numbers of observations from the sample. In that sense this is not a proper jackknife.[22]

TABLE A2
SENSITIVITY OF MODEL ESTIMATES: ACQUISITION

Variables	Full sample	1970–2002	Trunc. $L \leqslant 17$	Logit model
Age dummies				
(Base = I(age 0–4 yrs))	–	–	–	1.00
I(age 5–15 yrs)	–	–	–	– 0.101
I(age 16–25 yrs)	–	–	–	– 0.402**
I(age >25 yrs)	–	–	–	– 0.150*
Industry dummies				
(Base = all others)	1.00	1.00	1.00	1.00
Food/Breweries	1.176^{+}	1.198^{+}	1.207^{+}	0.155
Chemicals/Pharmceuticals	1.108	1.114	1.134	0.096
Metals	1.067	1.237	0.999	0.067
Engineering	0.752**	0.728**	0.748**	– 0.310**
Electrical/Electronics	1.133	1.137	1.104	0.138
Textiles	0.828*	0.769**	0.807*	– 0.197*
Paper/Packaging	1.205*	1.237*	1.192*	0.199*
Construction	0.765**	0.809*	0.782**	– 0.279**
ICT	0.440**	0.435**	0.451**	– 0.853**
Trdg./Superstores	0.894	0.927	0.901	– 0.119
Firm × year level				
Current size				
ln(real fixed capital + 1)	1.239**	1.261**	1.224**	0.237**
Size-squared	0.976**	0.974**	0.978**	– 0.027**
Cash flow to capital	1.368**	1.401**	1.372**	0.338**
Current ratio	1.010**	1.009**	1.010**	0.012**
Interest cover	0.984*	0.990	0.984*	– 0.021^{+}
Gearing ratio	0.998	0.996	0.998	– 0.002
Macroeconomic conditions				
UK business cycle	0.937	0.846^{+}	0.947	– 0.073
Long-term real interest rate	1.023*	1.020^{+}	1.021^{+}	0.029**
£–$ exchange rate	1.022	0.996	1.024	0.002
US business cycle	1.230**	1.400**	1.243**	0.179**
Macroeconomic instability				
Year-on year increase in £–$ exchange rate $= -v$				
$v \times I$(age 0–4 yrs)	0.869**	0.853**	0.874**	– 0.167**
$v \times I$(age 5–15 yrs)	0.889*	0.879**	0.892*	– 0.140**
$v \times I$(age 16–25 yrs)	1.005	0.958	0.999	0.045
$v \times I$(age >25 yrs)	0.936	0.918^{+}	0.923	– 0.095*
Volatility–RPI inflation $= x$				
$x \times I$(age 0–4 yrs)	0.864^{+}	0.910	0.845*	– 0.074
$x \times I$(age 5–15 yrs)	0.833**	0.890^{+}	0.812**	– 0.140*
$x \times I$(age 16–25 yrs)	0.805**	0.766**	0.710**	– 0.296**
$x \times I$(age >25 yrs)	0.825**	0.871*	0.784**	– 0.165**
Volatility–long term interest rate	0.730**	0.763**	0.711**	– 0.275**
Constant	–	–	–	– 3.673**
No. of firms	4117	3781	3933	–
No. of exits	1858	1687	1789	1858
Total time at risk (firm-yrs)	48,094	41,690	44,796	48,094
Log-likelihood	– 12,661.19	– 11,249.55	– 12,289.04	– 7679.60
Wald χ^2 goodness-of-fit test	383.08	392.27	364.37	397.89
d.f./p-value	30/0.00	30/0.00	30/0.00	33/0.00

Notes
Parameters reported are hazard ratios (exponential of the regression coefficient estimates). Volatility is measured as maximum monthly difference during the year, divided by the number of intervening months.
**, * and $^{+}$: significant at 1%, 5% and 10% levels, respectively.

The jackknife results for both the parameter estimates and their standard errors are robust across various jackknife replications.

These sensitivity investigations provide convincing evidence of the robustness of our model estimates.[23]

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NOTES

1. For a more detailed discussion and additional references, see Bhattacharjee *et al.* (2002).
2. For a full discussion of the AK production function, widely used in the growth literature, see Barro and Sala-i-Martin (2003).
3. Assuming a fixed deadweight cost of investing in acquired capital ensures existence of a threshold level z^*, above which a firm invests in acquired capital, and below which it does not (Jovanovic and Rousseau 2002).
4. A firm that has irretrievably entered the path to bankruptcy may, in a precursor phase of distress, stop publishing accounts one or two years prior to actually being declared bankrupt. From the point of view of econometrically modelling bankruptcy, it is sensible to reassign the date of 'real' bankruptcy to the year of last published accounts when the firm has been declared legally bankrupt within a two-year period. Our assignment of a bankruptcy to a particular point in time captures the date of economic bankruptcy rather than declaration of bankruptcy. We assign accounting data for each company fiscal year to the calendar year that covers the majority of the accounting year corresponding to the fiscal year.
5. The data used pertain to years since 1965 during which each company is listed in the London Stock Exchange. Hence, for each company the available data are left-truncated, and do not pertain to the entire period that it is listed.
6. It is somewhat rare for a business combination to be a 'merger of equals'. These are, in practice, effectively unobservable to the extent that even case-based contextual research struggles to identify them. 'Merger of equals' is not proxied by other apparently related constructs sometimes used in the literature, such as 'friendly/hostile' or 'equity/cash consideration'—nor is it proxied by the use of pooling (merger) rather than purchase accounting for the transaction. In our data, firm B was considered to have exited the industry if it was acquired by firm A. If, at the same time, firm A changed its name to C, we treated A as remaining in in the industry.
7. This is the two-sided filter of Hodrick and Prescott (1997).
8. While a positive shock has only a small effect, a negative shock (even if temporary) can reduce the value of collateral to a discounted liquidation value. Since the liquidated assets cannot be restored when the shock is over, the amplification effect becomes persistent.
9. Multinomial probit/logit models have been used by Corres and Ioannides (1996) for analysis of competing causes of exit for US quoted companies. They also use a hazard model in their empirical work, but do not segregate the hazard processes owing to different causes of failure. We also use a flexible logit model to check the robustness of our results; this will be discussed in further detail later in the paper.
10. Note that the competing risks model is actually identified under a weaker condition, i.e. that the two competing exit processes are '*non-informative*' about each other (Arjas and Haara 1987; Andersen *et al.* 1993). However, asymptotic results are easier to derive under independence, which we assume.
11. However, because of the possible correlation between exit events in this case, asymptotic results cannot be established using the standard counting process Martingale theory approach (Andersen *et al.* 1993). One of the main contributions of Spiekerman and Lin (1998) is to provide rigorous statistical results for this case.
12. See also Andersen *et al.* (1993).
13. In some cases there may be unobserved heterogeneity, where the dependence between the two exit types is not completely described by observed covariates. As discussed above, our inference procedures are also valid under certain types of unobserved heterogeneity.
14. Proportionality may be unreasonable from the point of view of relevant economic theory. The effect of a covariate on the hazard is sometimes expected to be increasing or decreasing in age (sometimes over the whole covariate space, and sometimes over a subregion of the covariate space). This clearly constitutes a violation of the proportionality assumption.
15. We also experimented with three and five intervals. With three intervals we sacrifice some flexibility in variation of covariate effects over duration, while for five intervals some of our estimates are less

significant because of lower sample size (number of company-years, but more importantly number of bankruptcies) in each interval.
16. The incidence in terms of number of bankruptcies is 49, 56, 51 and 50, respectively, and in terms of acquisitions 379, 555, 455 and 469, respectively.
17. We are grateful to one of the referees for suggesting the relevance of this to our analysis.
18. Further work on the impact of the Insolvency Act 1986 is planned.
19. The evidence of non-proportionality of hazards with respect to cash flow underscores the usefulness of the Murphy–Sen histogram sieve estimators for inference in such non-proportional situations.
20. Wadhwani (1986) provides an explanation for how inflation volatility can contribute to bankrupcy. Firms already in a state of financial distress can be tipped over into bankruptcy as higher inflation and higher nominal interest rates increase the service element of debt.
21. For most companies in our sample, there is no delay in entering the panel after being listed; for a small number of companies there is a one- to two-year delay.
22. An exact jackknife procedure is difficult to devise in our case because we have an unbalanced panel.
23. In addition to the above, we also estimate our model for bankruptcy separately for the recent period, to investigate the impact of the Insolvency Act 1986. These estimates, presented in Table A1, are qualitatively and numerically very similar to the estimates for the full sample. The statistical significance of the estimates for macroeconomic instability is higher, suggesting a stronger impact of instability on bankruptcies after the introduction of the new Act. Additional analysis of the impact of legislation is planned.

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