# Small Business Failure and External Risk Factors

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ABSTRACT. Unlike much of the previous literature, which has generally focused on internal risk factors, this study seeks to explore the impact of macro-economic factors on small business mortality. The results suggest that economic factors appear to be associated with between 30% and 50% of small business failures, depending on the definition of failure used. As expected, failure rates were positively associated with interest rates (where failure was defined as *bankruptcy*) and the rate of unemployment (where failure was defined as *discontinuance of ownership*). However, somewhat unexpectedly, failure rates were found to be positively associated with lagged employment rates (where failure was defined as *to prevent further losses*) and with current and lagged retail sales (where failure was defined as either: *failed to "make a go of it"; discontinuance of ownership*; or *discontinuance of business*). This indicates that a strengthening economy may provide the trigger for an increase in voluntary business exits as individual proprietors seek to maximize the returns available to them on both their financial and human capital.

## 1. Introduction

When starting a small business, owners accept three categories of risk that together ultimately determine the success or otherwise of their business. Firstly, there is the risk associated with the economy in which that business is located. This will be referred to as *economy* based risk. Secondly, there is the risk associated with the industry in which that business is operating. This will be referred to as *industry* based risk. Thirdly, there is the risk unique to the business itself. This will be referred to as *firm* based risk. To a large extent there is little individual business owners can do to influence the economy in which they operate and Fredland and Morris (1976, p. 9) noted that during "cyclical downturns the marginal firm is more likely to fail".

If the underlying causes of small business failure are predominantly internal (endogenous) then government policy would be best directed at the level of the firm; for example by providing training and education programs and support agencies. If the underlying causes of failure are predominantly external (exogenous) then government policy would be best directed at changing the economic environment within which small business operates (Fredland and Morris, 1976).

Given the relative importance of external causes of failure it is surprising that they have been "given scant attention in the literature" (Berryman, 1983, p. 54). Understanding the factors that affect small business performance "would enable public policymakers and small business advisors to better serve the small business sector" (Gaskill and Van Auken, 1993, p. 18).

This paper has two primary objectives. Firstly, to model the relationship between small business failure rates and the aggregate levels of internal and external risk to determine the relative importance of each of these sources of risk to small business mortality. Secondly, and unlike much of the previous literature which has generally focused on internal risk factors, this study aims to explore the impact of various key macro-economic variables on small business failure rates.

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## 2. Causes of small business failure

Many studies have examined the perceived causes of small business failure.[1] These studies have generally been based on the opinions of one or more of the following three groups: failed owner/managers (Fredland and Morris, 1976; Hall and Young, 1991; Hall, 1992; Gaskill and Van Auken, 1993); non-failed owner/managers (Fredland and Morris, 1976; Peterson et al., 1983); or third parties such as liquidators or official receivers (Hall, 1992).

The two primary causes of small business failure appear to be a lack of appropriate management skills and inadequate capital (both at start-up and on a continuing basis). A number of studies also referred to the impact of exogenous factors, such as high interest rates (Peterson et al., 1983; Hall and Young, 1991).

The motivation for studies on the causes of failure is best described by Abdelsamad and Kindling (1978, p. 24) who stated that "Although failures cannot be completely avoided in a free enterprise system, the failure rate could be reduced if some of its causes are recognized and preventive action is taken".

A contrary view is expressed by Fredland and Morris (1976, p. 8) who argued that the causes of failure cannot be isolated and that "any attempt to do so is, at bottom, a futile exercise". However, they suggested that

> The issue of causation is clarified somewhat by classifying causes as endogenous (internal to the firm and presumably within its control) and exogenous (external to the firm and beyond its control). Such a classification has the merit of providing a somewhat better policy handle since if causes are endogenous, appropriate policy "helps firms help themselves"; if exogenous, appropriate policy may seek to change the economic environment (p. 8).

Previous evidence suggests that, although endogenous factors were the main cause of failure, exogenous factors had a significant effect in approximately one third of small business failures (see, for example, Peterson et al. (1983)). More recently Birley and Niktari (1995) reported that the economy ranked third as the primary cause of failure for 486 independent owner-managed businesses as described by their accountant or bank manager.

In discussing some of the research issues and problems associated with failure prediction Shailer (1989) suggested that in future research, it would be necessary to resolve what circumstances constitute failure and to pay more attention to external variables, such as interest rates and various other economic indicators. Keasey and Watson (1991, p. 15) also made the comment that "there may be a need to develop specific models for different types of firm failure" that is for different users.

## 3. Systematic and unsystematic risk

Modern finance theory suggests that there is a relationship between expected return and risk. Other things being equal, the higher the risk the higher the expected returns. However, it is important to understand how risk is assessed in this context. Only systematic (economy based) risk is rewarded, on average. Unsystematic (firm and industry based) risk is not rewarded because there are diversification strategies[2] available to limit this source of risk.[3]

A key determinant of risk is variability in earnings. Therefore, factors affecting a business's profitability, in particular the variability in profitability, will also affect the perceived risk associated with that business. DiPietro and Sawhney (1977, p. 4) argued that

> There are two important factors which jointly determine the failure rate of businesses in the economy. The first is internal – the effectiveness of management, and the second is external – the general economic environment.

Industry based risk does not neatly fall into either grouping; it is unsystematic but not under the control of an individual firm and, therefore, not endogenous (internal). Figure 1 depicts these various types of business risk.

Evidence from the U.S., reported by Sharpe (1981), suggested that systematic (economy based) risk represented approximately 25% of the total

<table>
<tr><td>Firm</td><td>Industry</td><td>Economy</td></tr>
<tr><td colspan="2">Unsystematic</td><td>Systematic</td></tr>
<tr><td>Endogenous</td><td colspan="2">Exogenous</td></tr>
</table>

Figure 1. Types of business risk.

risk associated with listed companies. Foster (1986, p. 199) reported that on average, in the U.S., exogenous factors (industry and economy) explained about 43% of the variation in business net income. However, the relationship varied substantially across industry sectors. In the retail sector, for example, exogenous factors only explained about 26% of the variation in business net income. Of this 26%, industry factors (17%) were almost twice as important as economy factors (9%).

Investors can limit the effects of unsystematic risk by investing across many firms and industries. Risk associated with the health of the economy, on the other hand, is generally regarded as non-diversifiable (systematic). Irrespective of how many businesses investors spread their investments across, their portfolios will still be affected by changes in the fortunes of the economy in which those businesses are located.[4]

Similarly, large businesses can (and many do) take steps to minimize unsystematic risk by diversifying their business operations. It should be noted that the purpose of diversification is not to increase returns (for a given level of investment), but rather to minimize the fluctuations (variability) in those returns and, thereby, to reduce risk. Ballantine et al. (1993, p. 98) found that "Profit variations for small firms is much greater than for large firms, indicating the substantial uncertainties facing the managers of small firms".

For smaller businesses there is less opportunity to reduce unrewarded risk (and, therefore, the probability of failure) through a process of diversification. Small businesses, almost by definition, are reliant on a small pool of management expertise (Hall, 1992), a major factor in the success/failure of a business. In addition, for most small business owners the majority of their wealth is linked (either directly or indirectly) to their business and, therefore, they do not have the opportunity to reduce their risk exposure by diversifying their investments. As noted by Hall (1992, p. 240) "The degree of diversification . . . will be likely to increase with size of company. As it increases there will be a concomitant reduction in risk of failure".

## 4. Definitions of small business failure

Because there are no formal reporting requirements for the majority of small businesses, it is difficult, if not impossible, to obtain sufficient reliable information to measure their performance in an economic sense, i.e. rate of return on capital. Most studies have, therefore, relied on some recorded event as a surrogate measure of failure.

A review of the literature reveals five basic measures of failure that have been used previously. The two most commonly used definitions of failure have been the *discontinuance of ownership* of the business (Churchill, 1952; Ganguly, 1985; Williams, 1993) and the *discontinuance of the business* itself (Bates and Nucci, 1989; Dekimpe and Morrison, 1991).

Fredland and Morris (1976, p. 7) argued that business discontinuance is a proxy for failure, as discontinuance suggests that resources have been shifted to more profitable opportunities. This seems to be an extremely broad definition of failure and would include as failed: businesses that are sold because the owner wishes to retire for age or health reasons; businesses that are sold for a profit; and businesses that are sold because the owner merely wishes to move on to another venture. As noted by Churchill (1952, p. 13) the sale or liquidation of a business does not necessarily imply failure because many businesses are given up due to illness or retirement or because of alternative opportunities.

The definition of failure *discontinuance of business* has primarily been used by researchers looking at entry and exit rates, particularly in manufacturing. However, this definition has two potentially significant limitations. Firstly, it excludes, as failed, any business that was sold to new owners irrespective of the reason for the sale (i.e. even if the business was bankrupt). Secondly, in many service industries a business may have to cease when the key operator retires or moves on.[5] To label this situation as a failure may be inappropriate.

A third definition of failure that is often found in the literature is *bankruptcy* (Massel, 1978; Hall and Young, 1991). While this is a very objective measure it appears to be a very narrow definition of failure and may exclude many businesses that would commonly be regarded as having failed. For example, businesses that are barely breaking even, providing neither a reasonable income for the owner, nor a fair return to the investor, could be regarded as "failing" businesses (Land, 1975, p. 1), but would not be included in this definition because they have not been placed into bankruptcy. Even if these businesses were closed they would not be considered to have failed under this definition.

Ulmer and Nielsen (1947, p. 11) defined as failures, those firms that were disposed of (sold or liquidated) with losses to prevent further losses. Losses in this context include the owner's capital and, therefore, a business could be regarded as having failed even though there may have been no loss to creditors. This definition of failure does not appear to have been used by researchers.

Finally, Cochran (1981, p. 52) suggested that "failure should mean inability to 'make a go of it', whether losses entail one's own capital or someone else's, or indeed, any capital". This definition is wider than that suggested by Ulmer and Nielsen as it would, presumably, include as failed any businesses that were not earning an adequate return (or were not meeting other owner objectives). The main difficulty with this definition is that most studies have relied on business closure, or sale, to trigger the classification of the business as either failed or non-failed. However, some businesses may continue operating even though they would be classified as having failed under this definition. In addition, an adequate return is hard to define: many small business proprietors may be willing to accept low financial returns as the cost of independence.

While this definition of failure appears to be the most relevant (particularly for owners or potential owners; advisers to small business; and policy makers) it is clearly the most subjective. It would generally have to rely on the opinion of someone associated with the business and, therefore, any results could be difficult to verify. However, the use of consistent judges (such as property managers) who are independent of the businesses concerned, may permit comparison between groups or types of business. This definition has had limited use by researchers (Gaskill and Van Auken, 1993).

Generally, the definition of failure used has, to a large extent, depended on the nature of the data available. Further discussion of these definitions and the justifications advanced for their adoption is provided in Watson and Everett (1993). While this paper will focus on failure defined as *failed to "make a go of it"*, because it would seem to be the most appropriate and least extreme definition, summary results will also be presented for each of the four other definitions of failure referred to above.

## 5. Data set

A major difficulty in studying small business is the lack of a reliable data source. Bannock and Doran (1980, p. 123) noted that "Perhaps the most important gap in British Statistics, and indeed in virtually all other countries, is in statistics on new enterprise formation (births) and failures (deaths)". Once a small business has ceased operating, information concerning the business becomes difficult to obtain. Typically most of the information resides with the owner as there is no systematic reporting of information on small businesses in the same way as is provided for larger concerns and particularly for listed companies.[6]

For purposes of this study a small business is defined along the lines proposed by the Wiltshire Committee (1971, p. 7) which defined a small business as "A business in which one or two persons are required to make all the critical management decisions: finance, accounting, personnel, purchasing, processing or servicing, marketing, selling, without the aid of internal specialists and with specific knowledge in only one or two functional areas". The definition used is also in line with more recent definitions proposed by Ang (1991, p. 3) and by Osteryoung and Newman (1993, p. 227).

This study uses data provided by managed shopping centers. Managed shopping centers normally keep on file information concerning their current, and past, small business tenants. This allows center managers to provide an unbiased and consistent opinion on the primary reason for a business being sold or ceasing to operate. However, it must be acknowledged that individual managers may disagree on the primary cause of a discontinuance, and the center manager's opinion may be different from that of the small business owner. To reduce this potential problem, center managers were provided with a set of instructions that had been developed with the help of center managers involved in a pilot study. In addition, center managers were encouraged to provide as much information as possible in cases where there was some doubt about the appropriate failure classification; and they were also encouraged to contact the researchers in difficult cases. The classifications by center managers were based on information which was objective as well as subjective, including monthly reports on file; goodwill payments; monthly sales figures (in some centers, particularly in recent years, rent was tied to sales); discussions with current tenants; and their own observations. To the extent that the classification was subjective, it was based on the informed opinion of the center manager.

Although the data has its limitations it was seen as a possible way around the problem of accessing suitable longitudinal data of the type required for this study. One important limitation of the data is that it does not include a cross section of all small businesses; it is comprised almost exclusively of retail and service establishments. This limitation is mitigated by the fact that over 71% of Australian small businesses are in the retail or services sector.[7] It should also be noted that any findings should only be related to retail and service businesses located within a managed shopping center environment.[8]

The data were collected using an instrument that had been pre-tested and then used for a pilot study prior to commencing the main study.[9] After completion of the pilot study in the researchers' home state (Western Australia) the Building Owners and Managers Association of Australia (BOAMA) were contacted to gain support for the project at the national level. In support of the project BOAMA contacted all their members providing them with details of the project and requesting members to contact the researchers directly if they wished to take part. The target group, therefore, was the population of managed shopping centers in Australia.

We were not provided with BOAMA's mailing list and, therefore, cannot report a response rate as such. However, we do know that the study included: (i) 13 (36%) of the 36 largest Shopping Centers in Australia, spread fairly uniformly across each state; and (ii) 19 (95%) of the 20 shopping centers owned/managed by Westfields (the largest owner/manager of shopping centers in Australia – they controlled 11 of the 36 largest centers in Australia at the time of the study).[10] We are unable to report a response rate for the smaller managed shopping centers.

The final questionnaire was administered nationally to shopping center managers and the resulting data set contained 5,196 small business start-ups over the period 1961–90 in 51 managed shopping centers across Australia. It is worth noting that 42% of the start-ups and 47% of the continuing businesses were located within the 13 largest centers referred to above.

Of the 5,196 start-ups approximately 50% (2,543) were sold or liquidated over the period of this study. Table I summarizes the reasons given for these sales or closures.

Cases where the reason for the sale or closure of a business was classified as "other" were examined individually to determine whether they should be treated as failed (under the *failed to "make a go of it"* definition of failure) or non-failed. Those businesses that were deemed to have failed were classified as "Other – failed". Those businesses that were considered not to have failed were classified as "Other – not failed".[11]

In Table II the reasons for sale or closure have been grouped under the various definitions of failure discussed previously. Note that in Table II the first four definitions of failure are subsets of each other. For example, *disposed of to prevent further losses* includes all businesses that went

TABLE I
Reason for sale or closure

| Reason for sale or closure | Number | Percent |
|---|---|---|
| Bankruptcy | 179 | 3.4% |
| To avoid further losses | 415 | 8.0% |
| Did not make 'a go of it' | 267 | 5.1% |
| Retirement or ill health | 126 | 2.4% |
| To realise a profit | 916 | 17.6% |
| Unknown | 329 | 6.3% |
| Other – not failed | 277 | 5.3% |
| Other – failed | 34 | 0.7% |
| Total sale or closures | 2543 | 48.9% |
| Continuing businesses | 2653 | 51.1% |
| Total start-ups | 5196 | 100.0% |

TABLE II
Reason for sale or closure grouped by failure definition

| Reason for sale or closure | Definitions of failure | | | | | |
|---|---|---|---|---|---|---|
| | Bankruptcy | To prevent further losses | Failed to make a 'go of it' | Discont. of ownership | Discont. of business | |
| 1. Bankruptcy | 179 | 179 | 179 | 179 | 114 | 64% |
| 2. To prevent further losses | | 415 | 415 | 415 | 270 | 65% |
| 3. Did not make a 'go of it' | | | 267 | 267 | 162 | 61% |
| 4. Retirement or ill health | | | | 126 | 37 | 29% |
| 5. To realise a profit | | | | 916 | 152 | 17% |
| 6. Unknown | | | 166 | 329 | 166 | 50% |
| 7. Other – not failed | | | | 277 | 78 | 28% |
| 8. Other – failed | | | 34 | 34 | 23 | 68% |
| Totals | 179 | 594 | 1061 | **2543** | 1002 | |
| | 7% | 23% | 42% | 100% | 39% | |

*bankrupt*. This does not apply to the last definition, *discontinuance of business*.

Some difficulty arises in the treatment of cases where the reason for sale or closure was unknown. From Table II there appears to be a strong relationship between discontinuance of business and the other measure of failure. Reasons 1, 2, 3 and 8 all had business closure rates over 60%. Conversely reasons 4, 5 and 7 all had business closure rates of less than 30%. In the absence of any other information it seems reasonable to classify as failed (*failed to "make a go of it"*) those businesses where the reason for discontinuance is unknown and the business is liquidated. This resulted in approximately 50% of unknown cases being classified as failed under the definition of *failed to "make a go of it"*. The direction of any bias caused by this treatment is unknown and is acknowledged as a weakness in the study.

To check the validity of the data, tests were carried out to compare failure rates across the various states and by owner/managers. Although there were some significant variations in the failure rates across both states and owner/managers, in the main, these could be explained by differences in the economic growth across states and by the fact that some of the centers reporting below average failure rates were newly established (less than two years old). As shall be seen later, failure rates peak at about year 3.

There remained one center with a significantly below average failure rate for which no appropriate explanation could be found. A close examination of the data for this center did not reveal any obvious errors that may have caused the unusually low failure rates. Removing this center from the data set did not affect the overall failure rates reported and, therefore, because there was no obvious reason to remove this center, it has been retained in the study. Five centers for which some data had initially been received were eventually excluded because we were unable to satisfactory resolve questions of missing data for these centers.

## 6. Modeling small business failure rates

To aid in modeling the relationships between small business failure rates and both systematic and unsystematic risk factors, the data set was split into six monthly intervals. The data were organized as a set of events, each event being the experience for one business over a six-month period. This experience was classified as an event "1", if the business failed according to the definition being used. The event was classified "0" if the business survived the six-month period or ceased for reasons not associated with failure (for example, if the owners retired and closed their business this would not be deemed a failure except where failure is defined as discontinuance).

### 6.1. *Data distribution across time*

The number of events considered ranged from 46,840 (where *bankruptcy* was the event of interest) to 48,083 (where *discontinuance of ownership* was the event of interest). Where *failed to "make a go of it"* was the event of interest there was a total of 48,697 events observed over the 60 half-year time periods of the study. However, from Figure 2 it can be seen that most (47,082) of these observations related to the half-year time periods 1974–90. The same was true for the other four definitions of failure. For this reason, and because some of the macro-economic variables needed to analyze systematic risk were only available from 1974 onwards, the analysis in this paper has been restricted to the half-year time periods from June 1974 to December 1990 (34 half-year time periods).

### 6.2. *Use of logistic regression*

Logistic regression was used to examine how the probability of failure was related to both systematic and unsystematic risk factors.[12] Logistic regression finds the maximum likelihood model relating the log odds of an event to the explanatory variables.[13]

The logistic model is expressed in terms of the log of the odds of an event, as follows:

$$Z_i \equiv \ln\left[\frac{P_i}{1 - P_i}\right] = \sum b_j X_{ij}. \tag{1}$$

Where $P_i \equiv$ Probability that event $i$ is a failure;
$b_j \equiv$ Coefficients estimated from the data, $j = 0 \ldots p$; and
$X_{ij} \equiv$ Independent variables, $i = 1 \ldots p$.

But equivalently, the logistic equation can be written in terms of odds rather than log odds as follows:

$$\frac{P_i}{1 - P_i} = e^{z_i}. \tag{2}$$

As the probability of an event gets small:[14]

$$\frac{P_i}{1 - P_i} \to P_i$$

$$\therefore\ P_i \approx e^{z_i}. \tag{3}$$

Since $P_i$ is small in this study, Equation 3 will be used to examine the relationship between failure and both systematic and unsystematic risk factors.

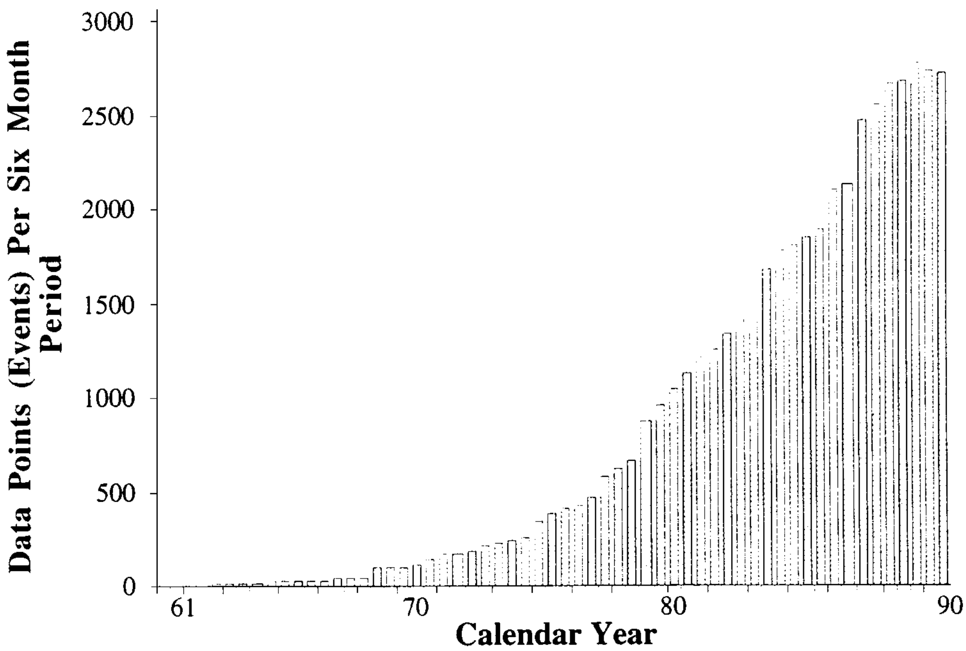


Figure 2. Data distribution across time where failure is defined as failed to "make a go of it".

### 6.3. *Systematic and unsystematic risk variables*

As the data set did not contain any variables that could be used to model unsystematic risk, it was necessary to use a proxy. Jovanovic (1982) argued that younger firms are more likely to fail because they face greater variability in their cost functions while they learn about their industry and management capabilities. It seems that once a business has survived the first few years its chances of failing are significantly reduced. This proposition has been supported by numerous studies on the relationship between age of business and failure rates (see, for example: Bates and Nucci (1989); and Evans (1987)).

Previous studies have also reported that years of education of the owner and amount of capital invested at start-up are significantly negatively related to small business failure rates (see, for example: Bates (1990); Bruderl et al. (1992); and Holtz-Eakin (1994)). More recently, however, Cressy (1996a) found that: once human capital is controlled for financial capital has no impact on firm survival; and the most important human capital item was proprietor age.

Therefore, age of business could be considered a reasonable proxy for the aggregate level of unsystematic (endogenous) risk factors; and in particular for management experience. On this basis, age was included as a variable in the model. Failure to include a full range of endogenous variables (both human and financial) may bias our results and this limitation is acknowledged as a weakness in the study. While the lack of data on specific unsystematic risk factors is unfortunate, these factors have been the subject of many previous studies. Also, the focus in this study is on the relative impact of systematic and unsystematic risk and, more particularly, the effect of specific macro-economic variables on small business mortality. This is an area that seems to have been largely overlooked by previous researchers.

Time period (half-years) was initially introduced as a proxy variable in the model to test for the presence of systematic risk factors. These factors could be expected to vary across time as the economy goes through cycles. Using these two proxies, age and time period, allow us to estimate the relative importance of systematic and unsystematic risk on small business mortality.[15] Having found evidence of systematic risk, various macro-economic variables were then introduced to replace time period in the model. This allowed us to examine the relative importance of each of these economic variables.

### 6.4. *Model development*

Therefore, assuming that the effect of age and time period are not interactive,[16] the model (from Equation 3) is:

$$P_i \approx e^{z_i} \tag{4}$$

Where $z_i \equiv b_0 + b_1 A_i + b_2 T_k$
$A_i \equiv$ Age of business in event $i$; and
$T_k \equiv$ Time period in which event $i$ occurs.

In Equation 4 failure is assumed to be a linear function of both age and time period. However, results of previous research suggests that the relationship between failure and either age or time (period) is not linear. Therefore, two options were considered for further developing the model to provide a better fit to the data. Firstly, age could be treated as a categorical variable with up to a maximum of 29 categories (the age of the longest surviving business in the sample).[17] Alternatively, a similar result can be obtained by modeling age as a polynomial and successively introducing higher order polynomial terms (for example, age, age$^2$, age$^3$, and so on) until there is no significant improvement in the model. The same process can also be applied to time period. Treating age and time period as either categorical or polynomial variables requires equation 4 to be expanded. For example, if age and time period are treated as polynomials then equation 4 is expanded as follows:

$$P_i \approx e^{z_i} \tag{5}$$

Where $z_i \equiv b_0 + (\mathrm{b}_{11} A_i + b_{12} A_i^2 + \ldots + b_{1n} A_i^n) + (b_{21} T_k + b_{22} T_k^2 + \ldots + b_{2m} T_k^m)$
$n \equiv$ Number of age polynomials
$m \equiv$ Number of time period polynomials

If age and time period were treated as categorical variables there would be 29 separate age variables and 33 separate time period variables in the model. If, however, we treat age and time period as polynomial variables we can add successively higher order variables until there is no further worthwhile improvement in the model.[18] This process of model selection will be demonstrated below.

## 6.5. *Model selection*

An advantage of treating age and time period as polynomial variables is that it allows a hierarchical approach to be taken in selecting an optimum model. That is, we can compare the reduction in Chi Square achieved with the loss of degrees of freedom as we move from less to more complicated models. The significance of each step can be judged in terms of whether the reduction in Chi Square is significant for the number of degrees of freedom sacrificed. The various model outcomes are depicted in Table III and the method used to select the optimum model is discussed below. The top panel of Table III shows the results of modeling age and time period as both categorical and polynomial variables; where failure is defined as *failed to "make a go of it"*. The lower panel of Table III provides the minimum change in the Chi Square value that would represent a significant (<1%) difference (improvement), for a number of different levels of degrees of freedom.

TABLE III

Differences in chi square (and degrees of freedom) between various logistic regression models and a saturated model for businesses that failed to 'make A go of it'

| Based model (constant ($b_0$) only) | | | Time period (Polynomial) $T^1$ | $T^2$ | $T^3$ | $T^4$ | $T^5$ | $T^6$ | $T^7$ | . . . | Time period categorical (33 categories) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **276** | 245 | 242 | 239 | 230 | 227 | 212 | 211 | . . . | 188 |
| | | (62) | (61) | (60) | (59) | (58) | (57) | (56) | (55) | . . . | (29) |
| | $A^1$ | **248** | 207 | 204 | 201 | 193 | 191 | 175 | 175 | . . . | 152 |
| | | (61) | (60) | (59) | (58) | (57) | (56) | (55) | (54) | . . . | (28) |
| | $A^2$ | **232** | 192 | 189 | 186 | 177 | 174 | 158 | 158 | . . . | 136 |
| | | (60) | (59) | (58) | (57) | (56) | (55) | (54) | (53) | . . . | (27) |
| | $A^3$ | **203** | 163 | 161 | 157 | 146 | 143 | 128 | 128 | . . . | 106 |
| | | (59) | (58) | (57) | (56) | (55) | (54) | (53) | (52) | . . . | (26) |
| Age | $A^4$ | **178** | 139 | 137 | 134 | 120 | 117 | 103 | 103 | . . . | 80 |
| (Polynomial) | | (58) | (57) | (56) | (55) | (54) | (53) | (52) | (51) | . . . | (25) |
| | $A^5$ | **156** | 117 | 115 | 113 | 98 | 95 | 82 | 82 | . . . | 59 |
| | | (57) | (56) | (55) | (54) | (53) | (52) | (51) | (50) | . . . | (24) |
| | $A^6$ | **133** | **96** | **93** | **91** | **77** | **75** | $\boxed{\mathbf{62}}$ | 62 | . . . | 38 |
| | | (56) | (55) | (54) | (53) | (52) | (51) | $\boxed{(50)}$ | (49) | . . . | (23) |
| | $A^7$ | 127 | 91 | 88 | 86 | 72 | 70 | 58 | 58 | . . . | 34 |
| | | (55) | (54) | (53) | (52) | (51) | (50) | (49) | (48) | . . . | (22) |
| | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . |
| | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . | . . . |
| Age categorical | | 91 | 55 | 52 | 50 | 38 | 36 | 24 | 24 | . . . | Saturated |
| (29 categories) | | (33) | (32) | (31) | (30) | (29) | (28) | (27) | (26) | . . . | Model |

Minimum improvement in Chi Square necessary, for a given sacrifice in df, to represent a significant (<1%) improvement in a model.

| | | | | | | |
|---|---|---|---|---|---|---|
| – Chi square improvement | 7 | 15 | 23 | 38 | 51 | 80 |
| – Sacrifice in df | 1 | 5 | 10 | 20 | 30 | 50 |

Results for the other definitions of failure were essentially the same and, therefore, the detailed results for those definitions are not reproduced in the paper.

*The optimum model*

The optimum model is found by moving from the base model (in the top left-hand corner of Table III) toward the saturated model (bottom right-hand corner) by successively selecting models that give a significant Chi Square improvement relative to the change in degrees of freedom (df). There are a number of different hierarchical paths that could be followed that would ultimately result in a similar, if not the same, optimum model. One such pathway has been highlighted in bold in Table III. Starting with the base model we can move down to the model immediately below, which includes age to the first power. This model provides a Chi Square improvement of 28 (276-248) with a sacrifice of 1 df, which is highly significant. Similarly we can move further down this path to the next model, which includes age to the first and second power. Again this model represents a significant improvement over the previous model; it has a Chi Square improvement of 16 (248-232) at a sacrifice of only 1 df.

Following the same process we can move down to the model that includes age to the power 6. Adding further age variables does not significantly improve the model. For instance, the model with age to the power 7 gives a Chi Square improvement of 6 (133-127) which, for a sacrifice of 1 df, is not significant. Similarly, there were no other models vertically below that provided a significant improvement in Chi Square. However, by moving to the right and including time period to the power 1 in the model, further significant improvement is possible. This model provides a Chi Square improvement of 37 (133-96) for a sacrifice of 1 df. Moving further to the right we find that adding time period to either the second or third power does not significantly improve the model. However, when time period to the fourth power is included (along with time period to the second and third power) the improvement in Chi Square of 19 (96-77) is significant relative to the 3 df sacrificed. Similarly by adding time period to the fifth and sixth powers a Chi Square improvement of 15 (77-62) is achieved at a sacrifice of 2 df, which is clearly significant. This final model has been highlighted with a box around it and can be considered the optimum model. There is no other model closer to the saturated model which offers a significant improvement in Chi Square relative to the additional degrees of freedom sacrificed. For instance, the model to the right provides no additional improvement in Chi Square and the model immediately below improves the Chi Square by 4 which, for a sacrifice of 1 df, is not significant.

The optimum model achieves an improvement in Chi Square, from the base model, of 214 (276-62) with a sacrifice of 12 (62-50) degrees of freedom, which is highly significant. To achieve the remaining possible improvement in Chi Square (62), by moving to the saturated model, would require a sacrifice of 50 degrees of freedom which is clearly not significant at the 1% level.

Of the 214 improvement in Chi Square for the optimum model, age (unsystematic risk) contributed 143 (276-133) or 67% and time period (systematic risk) contributed a further 71 (133-62) or 33%.[19] Interestingly, this figure of 33% is the same as that reported by Peterson et al. (1983) as being the proportion of exogenous causes of small business failure. For the other definitions of failure the contribution of systematic risk was as follows: *bankruptcy* 34%;[20] *to prevent further losses* 44%; *discontinuance of ownership* 28%; and *discontinuance of business* 46%. This provides some indication of the relative importance of the systematic and unsystematic risk factors; both are clearly important. It appears that systematic factors are associated with between 30% and 50% of small business failures; while unsystematic factors appear to be associated with between 50% and 70% of small business failures.

### 6.6. *Results for optimum model*

Table IV shows the coefficients for the optimum logistic model of failure against age and time period where failure is defined as *failed to "make a go of it"*. Coefficients for the optimum logistic models under each of the other definitions of failure indicated a similar pattern and are, therefore, not reported. No significant interactive effects were found in any of the final models.[21]

Although $Age^2$ and $Period^1$ were not significant

TABLE IV
Coefficients for logistic regression model of failure (*failed to "make a go of it"*) against polynomial functions of age and time period

| Variable | $b$ | S.E. of $b$ | df | Sig |
|---|---|---|---|---|
| $Age^1$ | $-0.2227 \times 10^{-0}$ | $0.0277 \times 10^{-0}$ | 1 | <<0.1% |
| $Age^2$ | $-0.0146 \times 10^{-1}$ | $0.0827 \times 10^{-1}$ | 1 | n.s. |
| $Age^3$ | $1.3089 \times 10^{-2}$ | $0.1568 \times 10^{-2}$ | 1 | <<0.1% |
| $Age^4$ | $-2.1496 \times 10^{-3}$ | $0.3726 \times 10^{-3}$ | 1 | <<0.1% |
| $Age^5$ | $1.2239 \times 10^{-4}$ | $0.2743 \times 10^{-4}$ | 1 | <<0.1% |
| $Age^6$ | $-0.2307 \times 10^{-5}$ | $0.0624 \times 10^{-5}$ | 1 | <0.1% |
| $Period^1$ | $-0.0042 \times 10^{-0}$ | $0.0186 \times 10^{-0}$ | 1 | n.s. |
| $Period^2$ | $0.0963 \times 10^{-1}$ | $0.0276 \times 10^{-1}$ | 1 | <0.1% |
| $Period^3$ | $0.1316 \times 10^{-2}$ | $0.0494 \times 10^{-2}$ | 1 | <1% |
| $Period^4$ | $-0.0634 \times 10^{-3}$ | $0.0229 \times 10^{-3}$ | 1 | <1% |
| $Period^5$ | $-0.1270 \times 10^{-4}$ | $0.0343 \times 10^{-4}$ | 1 | <0.1% |
| $Period^6$ | $-0.0385 \times 10^{-5}$ | $0.0117 \times 10^{-5}$ | 1 | <1% |
| Constant | $-3.7438$ | 0.0729 | 1 | <<0.1% |

in the final model, they were initially significant until the higher order polynomial terms were introduced into the model. Also the significance of the later Age and Period variables (and of the overall goodness of fit of the final model) is dependent on the inclusion of both $Age^2$ and $Period^1$.

Where failure is defined as *failed to "make a go of it"* we can then produce a graphical representation of the final model depicting the probability of failure as a function of age (for a typical time period; where typical is defined as being averaged over all periods) using equation 5 as follows:

$$\text{Prob } (event) = e^z$$

Where (from Table IV)

$$z = -3.7438 - 0.227Age^1 - (0.0146 \times 10^{-1})Age^2 + (1.3089 \times 10^{-2})Age^3 - (2.1496 \times 10^{-3})Age^4 + (1.2239 \times 10^{-4})Age^5 - (0.2307 \times 10^{-5})Age^6$$

The results for all models (i.e. for the five definitions of failure) are depicted in Figure 3.

Prior to running the optimum models both the age and period variables were standardized to a mean of zero. Figure 3, therefore, represents the probability of failure as a function of age for a typical time period.[22] Figure 3 shows that the probability of failure reached a peak for businesses aged around 2–3 years. This result may partially

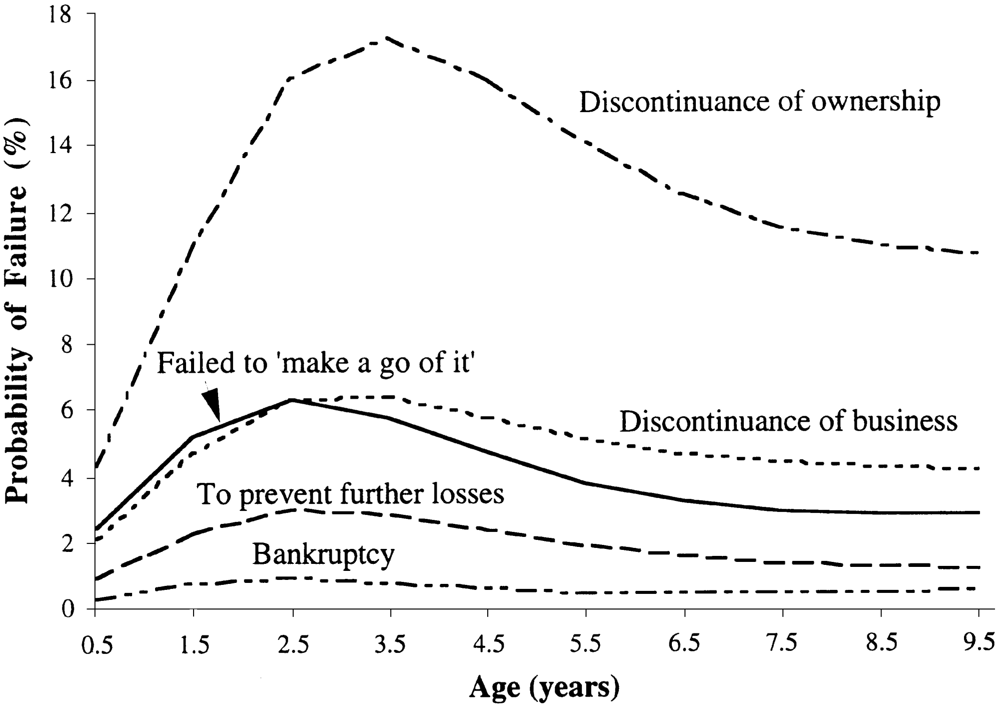


Figure 3. Probability of failure as a function of age, for an average time period.

be explained by the fact that most leases were for periods of between three and five years. The lease renewal process is often the trigger for poorly performing businesses to be sold or to cease operations. This inverted **U** shaped curve can also be explained by the fact that "Mortality rates are low immediately after starting a business because organizations can survive on initial resources, increase to a maximum, and decline afterwards" (Bruderl et al., 1992, p. 234). This mortality process has been labeled the "liability of adolescence" in contrast to "liability of newness" which depicts monotonically declining failure rates (Bruderl and Schussler, 1990). It should be noted that Cressy (1996c) and Ganguly (1985) also reported failure rate distributions conforming to a bell-shape.

Similarly, Figure 4 plots the probability of failure against time period, for a business of average age (in this case a business aged between 4–5 years) as follows:

$$\text{Prob}(\textit{event}) = e^{z}$$

Where (from Table IV)

$$\begin{aligned} z = {} & -3.7438 - 0.0042\textit{Period}^{1} + \\ & (0.0963 \times 10^{-1})\textit{Period}^{2} + \\ & (0.1316 \times 10^{-2})\textit{Period}^{3} - \\ & (0.0634 \times 10^{-3})\textit{Period}^{4} - \\ & (0.127 \times 10^{-4})\textit{Period}^{5} - \\ & (0.0385 \times 10^{-5})\textit{Period}^{6} \end{aligned}$$

Figure 4 depicts the probability of failure as generally increasing over the period of the study, with a peak shortly after the stock market crash in 1987.

### 6.7. *Introducing macro-economic variables*

Time period, as a proxy for systematic risk variables, was highly significant in the model. Therefore, the next step was to identify various macro-economic variables that could replace time period as an independent variable in the model. DiPietro and Sawhney (1977, p. 9) argued that "A shift in the total revenue or the total cost curve

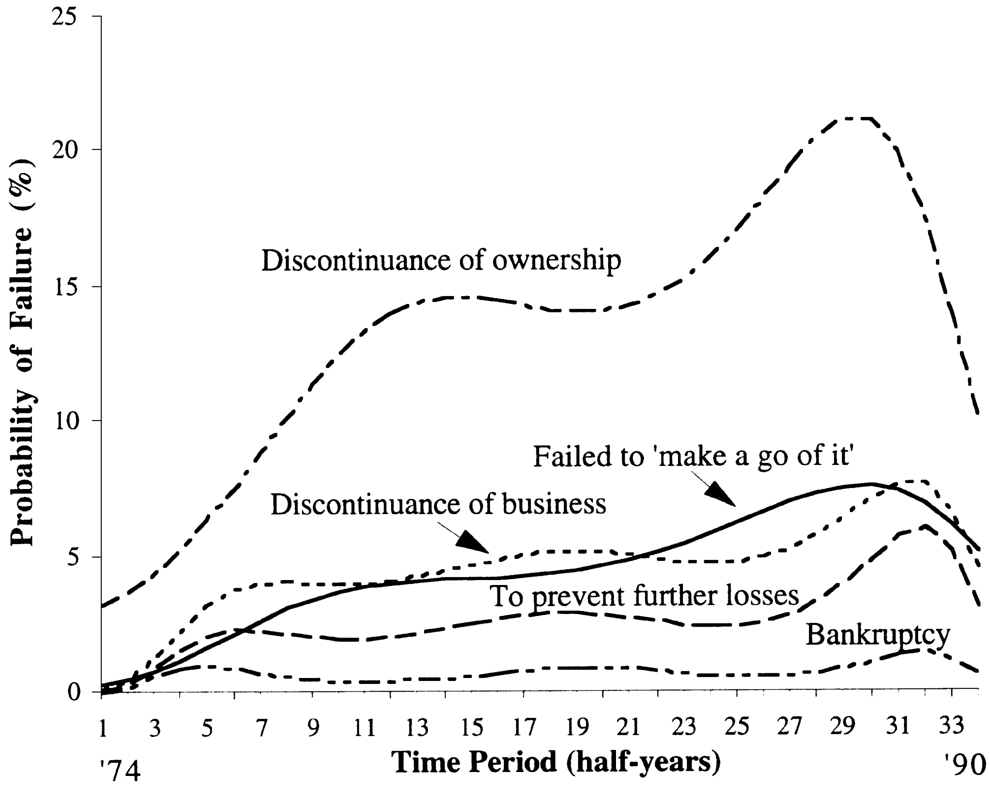


Figure 4. Probability of failure as a function of time period, for an average aged business.

will effect the probability of a firm failing for any given level of managerial competence". They further argued that

> Aggregate demand variables should be negatively related to firm failures. This is because an increase in aggregate demand will increase the total revenue curves for most firms in the economy and thus decrease the incidence of failure (DiPietro and Sawhney, 1977, p. 9).

Millington (1994) found that long-term interest rates, unemployment, and inflation were the economic variables that had the greatest impact on business failures. Data, as shown in Table V, were collected for these three key economic variables together with three additional variables (Australian business bankruptcies; employment rates; and retail sales) often referred to in the financial press in discussions about the state of the Australian economy. These variables were selected as likely to be related to the probability of failure for small businesses in managed shopping centers, for the following reasons:

1. *Consumer Price Index* (*CPI*). High rates of inflation may indicate problems in the economy. In addition, employee wages (a significant expense for most businesses) were linked to the rate of inflation over much of the period of this study. Further, Wadhwani (1986, p. 120) argued that "in the absence of index-linked loans, higher inflation implies higher liquidation rates". Millington (1994) reported this variable as being significantly related to business failure rates. For these reasons, a positive association is expected between the CPI and the probability of business failure.
2. *Trading bank interest rates*. "Most small businesses carry relatively heavy loads of short-term debt and are likely to be particularly sensitive to changes in the cost of carrying that debt" (Hall, 1986, p. 150). This may be particularly so for businesses located in managed shopping centers, where the entry costs are likely to be higher than for alternate locations. Also, in times of high interest rates consumers discretionary income is reduced. Hall and Young (1991) noted that directors, in providing reasons for the failure of their businesses, rated high interest rates as ranking eighth in importance. Peterson, Kozmetsky, and Ridgway (1983) reported that high interest rates, regulation, taxes and the economy were seen by one third of respondents to be responsible for small business failures. Wadhwani (1986) found interest rates to be positively correlated with the number of liquidations. Hudson (1989) reported a significant positive relationship between interest rates and business failure. Therefore, it is reasonable to predict a positive association between interest rates and the probability of failure.
3. *Unemployment*. High levels of unemployment may be indicative of a troubled economy with reduced consumer spending and, therefore, a reduction in business revenue. Hudson (1989) reported a significant positive relationship between unemployment rates and business failure. Following the arguments of DiPietro and Sawhney (1977) and the findings of Hudson (1989) this variable is expected to be positively related to business failure rates.
4. *Australian business bankruptcies*. The level of Australian business bankruptcies could be considered indicative of the overall health of the economy. Hall (1986, p. 89) in a similar vein to DiPietro and Sawhney (1977) argued that "government policy variables that affect the level of economic activity are also likely to affect the level of business income and, therefore, of business failures". In a growing healthy economy business revenue should be increased and, therefore, business bankruptcies should be reduced. For this reason, a positive association is expected between the level of Australian business bankruptcies and the probability of failure for businesses in this study. Note that business bankruptcies have been deflated by population because no reliable information exists on the number of operating businesses.[23]
5. *Employment*. Millington (1994), reported that total civilian labor force had some effect in explaining failure rates although the relationship was not as strong as that for unemployment rates. Strong employment growth generally indicates a strong economy with increased consumer spending and, therefore, an increase in business revenue. Following the arguments of DiPietro and Sawhney (1977) this variable is expected to be negatively related to failure.

TABLE V
Selected macro-economic variables 1974–90

| Calandar Year | Half | Australian business bankruptcies | Employed | Number of persons ('000) unemployed | Population | CPI | Trading bank int rates p.a. | $m retail sales |
|---|---|---|---|---|---|---|---|---|
| 74 | 1 | 619 | 5951 | 103 | 13723 | 24 | 9.5 | 1563 |
| 74 | 2 | 739 | 5918 | 124 | 13832 | 26 | 11.5 | 1669 |
| 75 | 1 | 767 | 5787 | 206 | 13893 | 28 | 11.5 | 1808 |
| 75 | 2 | 745 | 5852 | 288 | 13969 | 30 | 11.5 | 1980 |
| 76 | 1 | 745 | 5961 | 282 | 14033 | 32 | 10.5 | 2018 |
| 76 | 2 | 716 | 5982 | 276 | 14110 | 35 | 10.5 | 2133 |
| 77 | 1 | 786 | 5973 | 315 | 14192 | 36 | 10.5 | 2261 |
| 77 | 2 | 964 | 6024 | 354 | 14282 | 38 | 10.5 | 2332 |
| 78 | 1 | 1082 | 6031 | 393 | 14359 | 39 | 10.5 | 2483 |
| 78 | 2 | 1151 | 6125 | 445 | 14431 | 41 | 10.5 | 2634 |
| 79 | 1 | 1290 | 6096 | 393 | 14516 | 42 | 10.5 | 2682 |
| 79 | 2 | 1561 | 6257 | 431 | 14603 | 45 | 10.5 | 2874 |
| 80 | 1 | 1597 | 6270 | 409 | 14695 | 47 | 10.5 | 3123 |
| 80 | 2 | 1383 | 6427 | 436 | 14807 | 49 | 12.5 | 3321 |
| 81 | 1 | 1346 | 6414 | 354 | 14923 | 51 | 12.5 | 3487 |
| 81 | 2 | 1435 | 6507 | 438 | 15054 | 54 | 14.3 | 3702 |
| 82 | 1 | 1422 | 6414 | 452 | 15184 | 57 | 16.0 | 3903 |
| 82 | 2 | 1329 | 6370 | 677 | 15289 | 60 | 15.5 | 3997 |
| 83 | 1 | 1300 | 6267 | 693 | 15394 | 63 | 15.8 | 4208 |
| 83 | 2 | 1359 | 6456 | 690 | 15484 | 66 | 12.4 | 4369 |
| 84 | 1 | 1266 | 6499 | 632 | 15579 | 65 | 14.8 | 4455 |
| 84 | 2 | 984 | 6636 | 627 | 15677 | 67 | 13.8 | 4693 |
| 85 | 1 | 895 | 6659 | 608 | 15788 | 79 | 17.3 | 4956 |
| 85 | 2 | 925 | 6911 | 591 | 15901 | 73 | 20.6 | 5269 |
| 86 | 1 | 995 | 7008 | 564 | 16018 | 76 | 17.4 | 5451 |
| 86 | 2 | 1202 | 7117 | 656 | 16134 | 80 | 18.3 | 5654 |
| 87 | 1 | 1244 | 7129 | 603 | 16254 | 83 | 16.1 | 5769 |
| 87 | 2 | 1148 | 7331 | 621 | 16384 | 86 | 13.8 | 6129 |
| 88 | 1 | 1111 | 7378 | 569 | 16518 | 89 | 15.0 | 6368 |
| 88 | 2 | 1035 | 7623 | 563 | 16672 | 92 | 16.5 | 6619 |
| 89 | 1 | 1121 | 7721 | 477 | 16803 | 95 | 19.8 | 7013 |
| 89 | 2 | 1346 | 7942 | 502 | 16921 | 99 | 20.5 | 7265 |
| 90 | 1 | 1602 | 7910 | 542 | 17045 | 103 | 18.5 | 7401 |
| 90 | 2 | 1949 | 7941 | 705 | 17169 | 106 | 15.6 | 7394 |

Source: 1. The number of Australian business bankruptcies was taken from Annual Reports by the Attorney-General of the Bankruptcy Act, Canberra.

2. The remaining macro-economic variables were taken from ABS (Australian Bureau of Statistics) AUSSTATS Database provided by dX ONLINE, EconData Pty Ltd, Armadale, Victoria.
   - (a) The Australian population and the number of employed and unemployed persons represent the figures at the end of each half-year period.
   - (b) The CPI (consumer price index) was taken at the end of each half year for all groups and was the weighted average of the eight capital cities.
   - (c) Interest rates were calculated as half the average of the March and June quarters for the first half-year and as half the average of the September and December quarters for the second half-year. They represent the average yearly rates in effect in each period.
   - (d) Retail sales represent the level of sales in each half-year period.

6. *Retail sales*. Given that managed shopping centers rely heavily on retail sales for their prosperity, it is reasonable to predict that growth in retail sales (and, therefore, in business revenue) will be negatively related to failure. Also, at the firm level, Cressy (1996c) reported that higher average sales in the past reduced the probability of failure in the future.

Because many of these variables are highly correlated, it may be that they provide alternative explanations for failure. In building a logistic model, fitting failure rates to these independent explanatory variables, we may find that introducing one independent variable gives a model which is not significantly improved by introducing a second independent variable, even though the second independent variable on its own would have provided a significant model. The independent variables included in a model are those which are the most significant in explaining failure. The fact that a variable is left out of a model does not necessarily mean that it does not significantly relate to the probability of failure, but rather that it adds no further significant explanation after the inclusion of the variables already in the model.

The following variables were deflated by population, prior to their inclusion in the model: Australian business bankruptcies; employed and unemployed persons; and retail sales. In addition, for each of the macro-economic variables, variables representing a lag of one half-year period and growth (% change) between the current and the previous half-year period, were also examined.[24]

### 6.8. *Discussion of results for macro-economic variables*

The coefficients for the final models are reported in Table VI. Retail sales is the only macro-economic (systematic) variable to feature in more than one model (*failed to "make a go of it"*; *discontinuance of ownership*; and *discontinuance of business*). This is not surprising given the nature of the sample; predominantly retailers.

When *bankruptcy* is used as the definition of failure, interest rates is the only significant systematic variable in the model. Again this is not surprising, given that many of the businesses in the sample would probably have required significant borrowings to locate within a managed shopping center. For these businesses, interest rates would significantly affect operating costs and, therefore, their chances of survival. When businesses with substantial borrowings do fail, they have a high probability of entering, or being placed, into bankruptcy. The positive association between interest rates and bankruptcy supports the findings by Hall (1986) and Wadhwani (1986). Also Cressy (1996b) reported that failure (defined as closing a business bank account) was a direct function of interest rate margins.

Bankruptcy was the only definition of failure where the relationship with an economic variable was clear cut and as expected. For the remaining definitions of failure the direction of the association, between failure and the economic variables concerned, was generally not as predicted. The results for these other definitions of failure are discussed below. The findings suggest that some of the macro-economic variables found to be significant in this study can not be viewed as causing failure; but rather they seem to provide the trigger for small business owners to take the opportunity to sell or close their businesses.

For businesses that are sold (or cease) *to prevent further losses*, the employment rate lagged one period is the only significant systematic variable in the model. The direction of the association (positive) is of some interest. It appears that the probability of failure increases with increases in the lagged employment rate. This suggests that many marginal small business operators may have decided to move out of business and into employment when the opportunity to do so improved. It may be that a significant number of small business owners remain in marginal businesses until the opportunity to exit is improved because the alternative might be unemployment.

A similar conclusion can be drawn from the results for the remaining three definitions of failure. In each case current period retail sales (per head of population) is significantly positively related to failure. This again suggests that marginal businesses delay their exit to a time when economic factors have improved, thereby maximizing both the opportunity to sell their business, and the price for which the business could be sold.[25] An alternative explanation is that when economic factors improve shopping centers increase their rents, and this in turn forces marginal businesses to be sold or to cease operating. However, rent is often tied to retail sales over the period of the lease term, and can only be reviewed as part of the lease renewal process.

Note that the negative sign for retail sales lagged one period only arises when both retail

TABLE VI
Coefficients (and significance levels) for optimal logistic regression models of failure against age and various economic variables

| Variables | Definitions of failure | | | | |
|---|---|---|---|---|---|
| | Bankruptcy | To prevent further losses | Failed to "make a go of it" | Discont. of ownership | Discont. of business |
| Age[1] | $-0.259 \times 10^{-0}$ (<0.1%) | $-0.217 \times 10^{-0}$ (<<0.1%) | $-0.229 \times 10^{-0}$ (<<0.1%) | $-0.117 \times 10^{-0}$ (<<0.1%) | $-0.116 \times 10^{-0}$ (<<0.1%) |
| Age[2] | $0.356 \times 10^{-1}$ (n.s.) | $-0.137 \times 10^{-1}$ (n.s.) | $0.001 \times 10^{-1}$ (n.s.) | $-0.227 \times 10^{-1}$ (<0.1%) | $-0.085 \times 10^{-1}$ (n.s.) |
| Age[3] | $1.641 \times 10^{-2}$ (<0.1%) | $1.357 \times 10^{-2}$ (<<0.1%) | $1.329 \times 10^{-2}$ (<<0.1%) | $1.275 \times 10^{-2}$ (<<0.1%) | $1.059 \times 10^{-2}$ (<<0.1%) |
| Age[4] | $-3.942 \times 10^{-3}$ (<0.1%) | $-2.050 \times 10^{-3}$ (<<0.1%) | $-2.205 \times 10^{-3}$ (<<0.1%) | $-1.788 \times 10^{-3}$ (<<0.1%) | $-1.959 \times 10^{-3}$ (<<0.1%) |
| Age[5] | $2.492 \times 10^{-4}$ (<0.1%) | $1.135 \times 10^{-4}$ (<1%) | $1.259 \times 10^{-4}$ (<<0.1%) | $0.972 \times 10^{-4}$ (<<0.1%) | $1.322 \times 10^{-4}$ (<0.1%) |
| Age[6] | $-0.481 \times 10^{-5}$ (<1%) | $-0.210 \times 10^{-5}$ (<1%) | $-0.238 \times 10^{-5}$ (<0.1%) | $-0.182 \times 10^{-5}$ (<0.1%) | $-0.299 \times 10^{-5}$ (<1%) |
| Interest rates | 0.0949 (<0.1%) | | | | |
| Employment (lagged) | | 0.1658 (<<0.1%) | | | |
| Retail sales | | | 0.0164 (<1%) | 0.027 (<<0.1%) | 0.0228 (<<0.1%) |
| Retail sales (lagged) | | | –0.0143 (<1%) | –0.0258 (<<0.1%) | –0.0199 (<1%) |
| Unemployment (lagged) | | | | 0.1175 (<1%) | |
| Constant | –7.0586 (<0.1%) | –11.3452 (<<0.1%) | –4.5047 (<<0.1%) | –3.363 (<<0.1%) | –4.7859 (<<0.1%) |

sales and retail sales lagged are included in the model. Individually, both variables are positively related to failure. However, when both variables are included, the sign for retail sales lagged one period becomes negative as the model seeks to find the best fit to the failure data. This can be interpreted as follows: for a given level of current sales, if past sales have been poor there is a greater chance of failure in the current period. This indicates that while poor past sales are positively related to failure (and, therefore, may be seen as the cause of failure) good current sales appear to be the trigger for marginal businesses to exit.

When failure is defined as the sale or closure of a business for any reason (*discontinuance of ownership*) the rate of unemployment lagged one period also enters the model as a significant explanatory variable. The unemployment rate, lagged one period, is positively associated with the rate of failure. This relationship could result from either, or both, of the following factors. Firstly, a high unemployment rate may indicate problems in the economy, which in turn increases the probability of business failure. Secondly, a high unemployment rate may result in an increase in the demand for self employment and, therefore, greater opportunities to sell both marginal and successful businesses. Further research is needed to clarify this issue.

Table VII reports the differences in the improvement in Chi Square between the saturated model, for each definition of failure, and the final

TABLE VII
Differences in the improvement in chi square between the optimum models and the saturated models for the various definitions of failure

| Difference from saturated model | Definitions of failure | | | | |
|---|---|---|---|---|---|
| | Bankruptcy | To prevent further losses | Failed to "make a go of it" | Discont. of ownership | Discont. of business |
| – Chi square | 64 | 94 | 80 | 121 | 70 |
| – df | 55 | 54 | 53 | 52 | 53 |
| – Sig | (n.s.) | (<1%) | (n.s.) | (<1%) | (n.s.) |
| Pseudo $R^2$ for final models | 0.05 | 0.12 | 0.17 | 0.29 | 0.17 |

models reported in Table VI. For three of the failure definitions (*bankruptcy*; *failed to "make a go of it"*; and *discontinuance of business*) the potential improvement in the model Chi Square of moving to the saturated model was not significant. For the remaining two definitions of failure (*to prevent further losses* and *discontinuance of ownership*) there was potential for a significant improvement in the model Chi Square by moving to the saturated models. This suggests that, for these latter two definitions of failure, there were additional economic variables (not used in this study) that could have been introduced to significantly improve the models. However, for the remaining three definitions of failure, the economic variables used in this study satisfactorily explained the impact of systematic factors on the rate of small business failure in managed shopping centers.

Researchers using regression analysis are often interested in the $R^2$ value. $R^2$ gives the proportion of the variance in the dependent variable "explained" by the independent variables. There is no statistic in logistic regression with a comparable interpretation. However, Aldrich and Nelson (1984, p. 57) propose a pseudo $R^2$ which they define as:

$$\text{pseudo } R^2 = c/(N + c)$$

Where $c \equiv$ –2 times the log of the likelihood ratio;[26] and
$N \equiv$ total sample size.

Pseudo $R^2$ for each of the final models are given at the bottom of Table VII. The pseudo $R^2$ varies from a low of 0.05 for the model using *bankruptcy* to define failure to a high of 0.29 for the model where failure is defined as *discontinuance of ownership*.

Although it would be of considerable interest to compare the systematic and unsystematic risk levels for small businesses located within shopping centers and those located outside shopping centers, the data necessary to do this are not available.

## 7. Conclusions

Throughout this paper we have noted a number of limitations concerning the data used for this study. Given the limitations of the data base, it is particularly important that the conclusions we reach should be seen as relevant only to retailers and service enterprises located within a managed shopping center environment.

Our findings show that failure rates for small businesses located in managed shopping centers vary significantly with both age and time (period); indicating the presence of significant levels of both unsystematic and systematic risk. On average, systematic factors appeared to be associated with about 30% to 50% of small business failures, depending on the definition of failure used. Systematic risk appeared primarily related to retail sales; trading bank interest rates; and both employment and unemployment rates. Not unexpectedly, failure was positively associated with interest rates (where failure was defined as *bankruptcy*) and the rate of unemployment (where failure was defined as *discontinuance of ownership*). However, failure was also positively associated with lagged employment rates (where failure was defined as *to prevent further losses*) and with current and lagged retail sales (where failure was defined as: *failed to "make a go of it"*; *discontinuance of ownership*; or *discontinuance of business*).

These results suggest that many businesses are sold, or cease, voluntarily and their proprietors are able to time their exits to best take advantage of prevailing economic conditions. Thus, depending on the definition of failure adopted, a positive economic outlook may be associated with an increase in the rate of small business failure. Policy decisions made in the absence of a sound understanding of how various economic variables are likely to impact small business failure rates (under various definitions of failure) may be suspect. Further, without a clear understanding of the relationship between key economic indicators and the various definitions of failure, accurate evaluations of policies and programs designed to help small business are problematic.

The paper makes a number of significant contributions to the literature. Firstly, it provides an indication of the relative importance of systematic and unsystematic risk to the rate of small business failure. While these sources of risk are discussed by many authors there is little evidence available in the literature on their relative impact on small business failure rates. Secondly, this paper provides a detailed examination of the relative importance to the rate of small business failure of specific economic variables. Again, with the exception of Millington (1994), there is little in the literature on this issue. Finally, this paper examines the effect of these various economic factors on small business failure using a number of different definitions of failure. It seems that the definition of failure adopted not only affects the rate of failure reported but will also influence the likely impact of various economic factors.

Given the importance of both systematic and unsystematic risk factors government policy needs to be directed at both the individual firm and the economy, if the overall rate of small business failure is to be reduced. At the level of the firm Government support may include: the provision of training and education programs; counseling services; and support agencies. As far as the economic environment is concerned it appears that interest rates and unemployment levels are the key determinants in what might be considered forced failures. Other key economic indicators, such as retail sales and employment levels, were positively associated with failure. This indicates that in a strong economy there may well be an increase in voluntary business exits as individual proprietors seek to maximize the returns available to them on both their financial and human capital.

## Notes

[1] Excellent discussions and reviews of the literature on the causes of small business failure are provided by: Berryman (1983) and McMahon et al. (1993).

[2] For further discussion of the use of diversification techniques to reduce unsystematic risk refer to the pioneering work of Markowitz (1952) or, more recently, Alexander and Sharpe (1989).

[3] Ballantine et al. (1993, p. 88) noted that "It is a familiar axiom of finance, of course, that risks and returns are positively related". However they failed to distinguished between unsystematic and systematic risk.

[4] The risks associated with the economy of a particular country can be reduced, or possibly even eliminated, by investing in businesses in many countries. International diversification, however, adds further elements of risk, for example, foreign exchange risk. Further discussion of this topic is provided in Watson and Dickinson (1981).

[5] More generally, Ang (1992) noted that "Small businesses can terminate due to the departure or demise of a single individual or the dissolution of a partnership."

[6] Indeed, the Australian Government has recently made available $7.25 million over 5 years primarily to develop a database for small and medium firms which will be available for use by researchers. The rationale for this project was that "there has been a lack of official data to support research"(Bureau of Industry Economics, 1995, p. 3).

[7] From Small Business in Australia (1993, p. 6).

[8] We have been unable to determine what percentage of small retail and service enterprises are located within managed shopping centers in Australia.

[9] A copy of the final instrument and accompanying instructions can be obtained from the authors.

[10] The one missing center for Westfields was a newly acquired center for which Westfields did not have access to the past data needed for the study.

[11] Many of the businesses classified as "other – not failed" had closed because the shopping centers in which they were located were undergoing major extensions which necessitated closure of these businesses for an extended prior to time. In these circumstances some proprietors decided to either relocate elsewhere, or to close down altogether.

[12] Both multiple regression analysis and discriminant analysis were considered for use in developing a model to predict failure. "However, these techniques pose difficulties when the dependent variable can have only two values – an event occurring or not occurring" (SPSS, 1990, p. 45). In this

circumstance it is unreasonable to assume that the distribution of errors is normal as required for regression analysis. Also, in multiple regression, the predicted values cannot be interpreted as probabilities, because they are not constrained to fall in the range 0 to 1. In addition, the logistic regression model requires "far fewer assumptions than discriminant analysis; and even when the assumptions required for discriminant analysis are satisfied, logistic regression still performs well" (SPSS, 1990, p. 45).

[13] In linear regression, model parameters are usually estimated using the method of least squares. Regression coefficients with the smallest sums of squared distances between the observed and the predicted values of the independent variable are selected for model inclusion. "In logistic regression the model parameters are estimated using the maximum-likelihood method. That is, the coefficients that make our observed results most 'likely' are selected" (SPSS, 1990, p. 47).

[14] For example, if the probability of an event was 0.05, then: 0.05/(1 – 0.05) = 0.0526 = 0.05.

[15] The distinction between endogenous (unsystematic) and exogenous (systematic) risk factors is not necessarily clear cut. For example, Cressy (1996b) noted that bank margins (over the base interest rate) varied according to certain endogenous factors; such as the age of the owner. In this case the base interest rate could be considered exogenous but the margin added by the bank is affected by endogenous factors (although outside the control of the firm).

[16] There is no reason to believe that the effects of age and period should be interactive. Never the less, the final models were tested for interactive effects; none were found.

[17] This is equivalent to having 29 separate variables for age, with a 0 or 1 classification for each.

[18] Including 29 age or 33 period polynomials would be equivalent to treating age and period as categorical variables.

[19] If we look at the improvement in the optimum model provided first by period and then by age the result is 64 (276-212) and 150 (212-62) for period and age respectively. The slightly different result is caused by not having a properly controlled experimental design (with each period having the same number of similar aged firms). That is, the data set is not orthogonal. However, the fact that the results are similar suggests that the problem is not severe.

[20] Lane and Scharry (1991, p. 96) reported that, on average, the age effect was one and one-half times as large as the macro-economic effect on business failure (bankruptcy). In this study the age effect appears to be almost twice as large as the macro-economic effects.

[21] To test for interactive effects the following composite variables were added to the models: $Age^1$ times $Period^1$; $Age^1$ times $Period^2$; $Age^2$ times $Period^1$; and $Age^2$ times $Period^2$. Adding these variables did not significantly improve any of the models.

[22] Controlling for the effects of age on period and period on age in this way, minimizes the problems associated with not having a properly controlled experimental design (with each period having the same number of similar aged firms).

[23] Australian business bankruptcies would include any bankruptcies from the managed shopping centers included in this study and, therefore, the relationship between this variable and the failure rates found in this study will be overstated.

[24] Where models included a lagged or growth variable the data set had to be reduced by a further half-year period.

[25] Also, DiPietro and Sawhney (1977, p. 9) argued that "expectations of improved economic conditions will lead to fewer failures as firms will be willing to sustain current losses if they believe total revenues and profits are to rise in the near future".

[26] The likelihood ratio is equal to the value of the likelihood function if all coefficients except the intercept are 0, divided by the value of the likelihood function for the final model as fitted.

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