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Why Do Companies Fail?

Rose Kenney, Gianni La Cava and
David Rodgers

RDP 2016-09

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Abstract

We explore the determinants of corporate failure in Australia using a large panel of public and private non-financial companies. A novel finding of our research is that corporate failure depends on 'structural' company-level characteristics. For instance, public companies are more likely to fail than comparable private companies; perhaps because the greater separation of ownership and control within public companies allows their managers to take greater risks.

Consistent with overseas research, we find that cyclical company-specific factors are important determinants of failure; a corporation is more likely to fail if it has low liquidity, low profitability or high leverage. Cyclical and structural company-level characteristics are the key determinants of the relative risk of a company failing, while aggregate (macroeconomic) conditions appear to be an important determinant of annual changes in the rate of corporate failure.

We quantify the potential contribution of corporate failure to financial stability risks using a 'debt-at-risk' framework. By our estimates, less than 1 per cent of aggregate corporate debt is currently at risk, with debt at risk concentrated in some very large companies. Our estimates suggest that trade credit (or business-to-business lending) is an important component of the relationship between corporate failure and financial stability.

JEL Classification Numbers: D22, E32, G33, L25

Keywords: failure; bankruptcy; business cycle; financial stability; leverage

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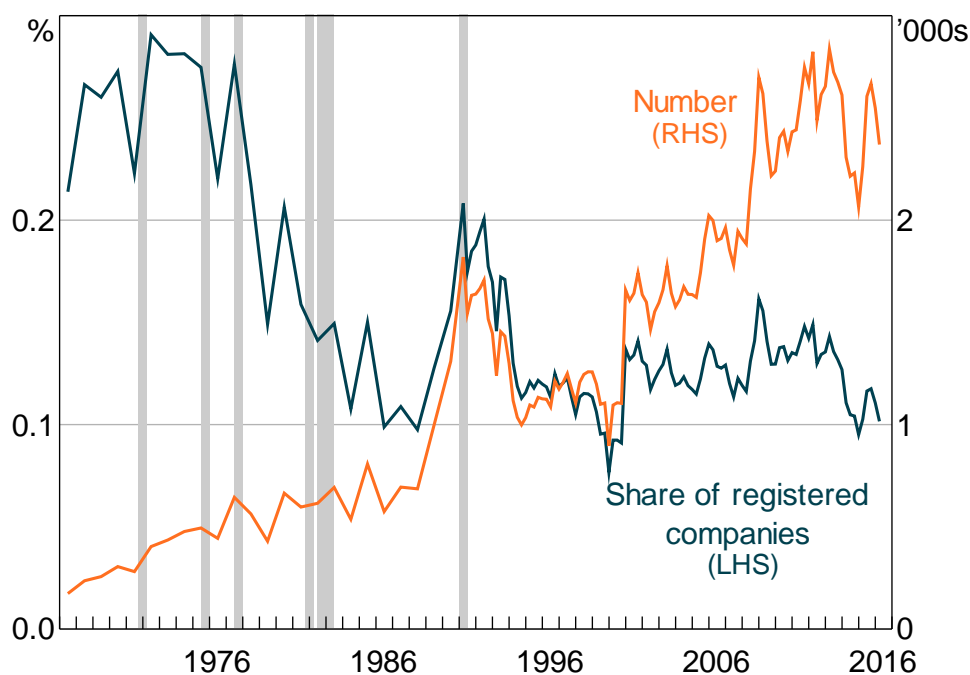
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1. Introduction

We explore the determinants of corporate failure in Australia. Our paper is motivated by two observations: corporate failure is closely linked to financial stability risks, and it is also associated with fluctuations in the business cycle. Despite these close links, there has been little research to date on why Australian companies fail.

The link between aggregate corporate failures and the business cycle is shown in Figure 1. The aggregate failure rate typically rises during economic downturns. This is most evident in the early 1990s recession. But there also seem to have been structural breaks in the level of the aggregate failure rate; for instance, the failure rate increased sharply around the start of the 2000s. This is due, at least in part, to changes in corporate insolvency law that reduced the cost of entering insolvency for companies.¹ This suggests a range of factors are important in determining corporate failure.

Figure 1: Aggregate Company Failures
Quarterly



Notes: Seasonally adjusted; data from 1967 to 1991 are estimates based on annual data for some states; shaded areas indicate periods of recession

Sources: Australian Securities and Investments Commission; Authors' calculations

¹ Several events occurred around 2000/01 which may have led to a permanent rise in the average company failure rate. These include: the introduction of employee entitlement schemes which effectively reduced the cost of companies entering insolvency; the introduction of the goods and services tax (GST), which may have increased the cost of being a registered company; and legislation introducing harsher penalties for trading while insolvent (Connolly *et al* 2015). The structural break also appears to reflect measurement issues and, in particular, an increase in the share of registered companies that are 'inactive'. We discuss this in more detail later.

Financial stability risks are closely related to failure among non-financial companies because failing companies often do not repay creditors. History shows that bank credit losses in Australia are closely tied to conditions in the non-financial corporate sector (Rodgers 2015). Non-financial companies account for a disproportionate share of bank non-performing loans; 35 per cent of outstanding non-performing assets but 23 per cent of banks' outstanding credit at the end of June 2016. More notably, non-performing loans to non-financial companies explained more than half of the total stock of non-performing loans during the global financial crisis of 2008–09.

It is important to be clear at the outset on the meaning of 'company failure'. Company failure is defined as an entry into external administration – the process by which a company's creditors take control of the company's assets to recover funds owed to them. Failure can include voluntary administration, liquidation and receivership. By this definition, a company must be indebted for it to fail.

A company failure is not the same as a company 'exit'. Fewer than 10 per cent of business exits are estimated to be due to failure (Productivity Commission 2015). Failures do not always result in companies ceasing their activities – some companies in external administration will be sold as a going concern or will satisfy their creditors and regain control from external administrators. Similarly, a company may exit the business population for reasons other than failure. For example, a company may exit voluntarily if it does not earn a sufficient return or because the owners retire.

So what causes companies to fail? A regular survey of external administrators by the Australian Securities and Investments Commission (ASIC) points to a wide range of possibilities, including: weak organisational structure, poor business strategy, technological change and economic conditions. For instance, more than 4 in 10 respondents cite 'poor strategic management' as a cause of company failure, suggesting internal 'structural' causes at the company level. But a similar share of respondents also indicate that 'cyclical' factors specific to the company, such as 'inadequate cash flow', are important. Furthermore, around 1 in 5 respondents attribute failure to 'general economic conditions', suggesting that the state of the economy might play a role over and above company-specific factors.

The challenges in identifying the causes of corporate failure are highlighted by a well-publicised Australian case – the collapse of the electronics retailer, Dick Smith Electronics. In its own company reports, Dick Smith Electronics attributed failure to cyclical factors specific to the company, namely unexpected weakness in sales and constraints on its ability to finance inventory investment. But some equity market analysts have suggested that structural company-specific factors were important too; in particular, poor corporate governance arrangements and low transparency in financial reporting (Knapp 2016).

In this paper we attempt to disentangle the relative importance of the factors that cause company failure. To do so, the causes of failure are grouped into three broad categories: 1) company-specific factors that vary with time, which we label 'cyclical' factors, such as profitability and leverage; 2) 'structural' company-specific factors that do not necessarily vary with time, such as whether the company is listed on the stock exchange or is a subsidiary of a parent company; and 3) external macroeconomic conditions, such as the state of the real economy.

Identifying the causes of company failure should help policymakers to better understand the underlying drivers of the business cycle. For instance, corporate failure could be a key channel through which weaker demand for goods and services translates into lower output and employment during a recession, particularly if there are costs involved in shifting labour and capital from failed firms to surviving firms. There is evidence that business exits amplify and propagate the effects of aggregate shocks (Clementi and Palazzo 2016). Corporate failures can also have 'ripple' effects if businesses that are suppliers to or customers of the failing companies also subsequently fail (Bams, Pisa and Wolff 2015). In the extreme, a wave of company defaults may set off a downward spiral of fire sales, falling asset prices and reduced credit supply, which exacerbates the economic downturn (Acharya, Bharath and Srinivasan 2007).

To the best of our knowledge, there has been limited research to date that examines the causes of corporate failure in Australia.² Our paper therefore makes several key contributions to the corporate failure literature.

First, we estimate the model based on a large panel of companies, including: 1) publicly listed; 2) publicly unlisted; and 3) private companies. Most existing research on corporate failure relies on samples of publicly listed companies.³ The additional cross-sectional variation means our results are more applicable to the broader population of companies than previous research; private companies typically make up 99 per cent of companies and nearly 50 per cent of both total sales and assets.

The additional cross-sectional variation also allows us to determine the relative importance of 'structural' company-specific factors, such as the type of ownership. Previous research has studied whether corporate survival is affected by the legal structure of a company and, in particular, whether it has limited liability or not (e.g. Harhoff, Stahl and Woywode 1998; Mata and Portugal 2002; Esteve-Pérez, Sanchis-Llopis and Sanchis-Llopis 2010). But, to the best of our knowledge, few studies have looked at how the risk of failure varies between private and public companies.

The broad-based nature of the company sample also allows us to better identify the underlying cyclical drivers of failure. There is extensive evidence that cyclical company-specific factors, such as profitability and leverage, are important determinants of failure (Bhattacharjee *et al* 2009; Black *et al* 2012). We examine the extent to which this is true for both public and private companies.

Second, we explore the extent to which macroeconomic conditions matter to corporate failure. There has been extensive research into the links between firm dynamics and the business cycle (see Siegfried and Evans (1994), Caves (1998), and Gil (2010) for literature reviews). And the literature points to a clear role for the business cycle in determining business exits (Gil 2010). We examine whether this is true even after controlling for changes over time in company-specific factors, such as leverage and profitability.

2 The Australian research that does exist has typically taken an accounting approach to develop credit risk models rather than focus on the links between corporate failures and the business cycle. These papers include Castagna and Matolscy (1981), Jones and Hensher (2004) and Gharghori, Chan and Faff (2006). Black *et al* (2012) focus on the factors that influence the survival of small businesses (rather than all businesses).

3 Kim (2011) estimates a survival model for financial distress based on a sample of Australian listed companies.

Third, we quantify the potential risks to financial stability via defaults on non-financial corporate debt. To do this, we combine our company-level estimates of the probability of default with balance sheet information on the outstanding stock of debt to construct estimates of 'debt at risk' (DAR) for each company in our sample. The outstanding stock of debt includes estimates of 'net trade credit' (or business-to-business lending), which makes up a significant share of debt for the average Australian company (Fitzpatrick and Lien 2013). We then use this framework to analyse both aggregate risks and the distribution of those risks.

Our key findings include:

- Structural characteristics are important determinants of failure. Public companies, and in particular listed companies, are more likely to fail than comparable private companies. This is consistent with these companies having a greater separation of ownership and control, which may encourage managers to take more risk. As far as we know, this is a novel finding in the corporate failure literature.
- Cyclical company-level characteristics are important too. Corporate failure is more likely when companies have high leverage, low liquidity and low profitability. Structural and cyclical characteristics together appear to determine the relative riskiness of companies.
- In contrast, aggregate conditions, such as the macroeconomic environment, appear to determine the annual level of the corporate failure rate.
- Debt at risk is estimated to comprise a small amount of total corporate debt (currently less than 1 per cent). However, DAR is highly concentrated among some large companies; it is possible for a company to be identified as a very low risk of default and yet have such large holdings of debt that they pose a significant risk to financial stability in aggregate.

2. Institutional Background

2.1 Failures, Exits and the Corporate Life Cycle

To gain a better understanding of the corporate life cycle we analyse data on all registered companies from ASIC and the Australian Business Register. There were 2.4 million companies registered in Australia at some point during 2015. Of these registered companies, only about 36 per cent were active companies (companies that are registered to pay GST, which we take as an indication of being economically active).⁴

It is important to recognise that estimates of average failure rates based on company-level analysis (as in this paper) will typically be higher than those based on aggregate indicators (as shown in Figure 1). This is because the company-level analysis captures only *active* companies, while the aggregate estimates are measured as the ratio of failures to *all registered* companies.

⁴ Many inactive companies are superannuation trustee companies for self-managed superannuation funds. Other inactive companies are likely to be mainly used for holding assets and providing tax and liability benefits.

Moreover, the distinction between active and registered companies is likely to matter for the trends in the corporate failure rate. This is because there has been a trend increase in the share of inactive companies in Australia. Inactive companies face minimal insolvency risk. It follows that the aggregate measure of the failure rate may understate the 'true' probability of failure over recent decades.⁵

2.2 Company Ownership Structure

As highlighted above, we evaluate the importance of ownership type as a potential determinant of failure. We identify three separate types of company ownership – publicly listed, publicly unlisted and private companies.

A public company is a company that may have an unlimited number of shareholders from which to raise capital. A listed public company is listed on a stock exchange, while an unlisted public company is not. A private company is a company whose shares may not be offered to the public for sale and which operates under legal requirements less strict than those for a public company.⁶

For the purposes of our analysis the main differences between public and private companies are:

- Public companies are more able to raise equity from the general public and should have better access to external finance than private companies.
- Public companies have more dispersed ownership and greater separation of ownership and control than private companies, and this is particularly true for publicly listed companies.
- Public companies have greater disclosure requirements than private companies – again this difference is greatest for publicly listed companies.

On the surface, it is not clear whether these factors will imply that public companies are more or less likely to fail than private companies. For example, the greater separation of ownership and control within public companies may mean that their managers are more likely to make decisions that are in their own interest rather than in the interests of the company, leading to greater risk-taking.⁷ Conversely, the greater disclosure requirements of public companies should make them more transparent, making it harder to hide problems from creditors and therefore less likely to take risk.

To develop some testable hypotheses on how company ownership structure affects failure, we need to briefly discuss the Australian corporate insolvency system.

5 This is not a problem for our company-level analysis, as it captures only active companies.

6 See La Cava and Windsor (2016) for more details.

7 Public companies may also be more likely to have diversified shareholders than private companies, which encourages them to take more risk (García-Kuhnert, Marchica and Mura 2015; Faccio, Marchica and Mura 2011).

2.3 The Australian Corporate Restructuring and Insolvency Systems

By international standards, the Australian corporate insolvency system ranks highly in its ability to resolve company failures. In 2015, Australia ranked 13 out of nearly 190 economies in resolving corporate insolvencies based on an index developed by the World Bank.⁸

It is not our goal to provide a detailed outline of the Australian corporate insolvency system; see Bickerdyke, Lattimore and Madge (2000) and the Productivity Commission (2015) for comprehensive overviews. Nor are we interested in examining how the insolvency system affects the overall probability of company failure. Instead, we want to briefly highlight some of the institutional features that can influence the costs and benefits of failure *for different types of companies*. This will allow us to develop some testable hypotheses regarding how company ownership structure affects the likelihood of failure.

Australian insolvency law is mainly governed by the *Corporations Act 2001*.⁹ Among other things, this legislation regulates companies that are in financial distress and are unable to pay their debts or other obligations. Australian insolvency law is designed to balance the competing interests of debtors, creditors and the wider community. The aims of the legislation include:

- providing an orderly and fair procedure for handling the financial affairs of insolvent companies
- ensuring a *pari passu* equal distribution of the assets among creditors
- minimising delays and costs in the resolution process
- rehabilitating financially distressed companies where viable
- engaging with stakeholders in the resolution of insolvency issues
- allowing an examination of insolvent companies, and the reasons for their failure.

Broadly speaking, the insolvency process consists of two stages. First, there is the 'restructure' stage; when there is hope of salvaging the company, several options exist to restructure the company so that it continues as a viable entity, including voluntary administration and informal workouts. Second, there is the 'wind up' stage; when a company is irretrievably insolvent and unlikely to recover, several processes can be used to wind up the company, including various forms of liquidation and receivership.¹⁰

8 The main criterion for determining the ranking is the 'recovery rate', which calculates how many cents on the dollar secured creditors recover from an insolvent company at the end of insolvency proceedings. In Australia, creditors are estimated to recover about 82 cents in the dollar compared to an OECD average of around 72 cents.

9 Under Australian law, the term 'insolvency' is usually used with reference to companies, and 'bankruptcy' is used in relation to individuals.

10 There are several steps to be taken for a business to be closed. These include finalising tax obligations, fulfilling obligations to employees and suppliers and cancelling or transferring any business registrations. The process of deregistration is complicated for companies that have complex operations or ownership structures. In particular, dealing with employee requirements under the *Fair Work Act 2009* is often complex and time consuming (Productivity Commission 2015). As a result, the process of winding up a company can often take years to complete.

More importantly for our purposes, the potential benefits and costs of the Australian insolvency system are likely to vary with the characteristics of each company, such as the ownership structure and size of the company.

For instance, at the 'restructure' stage, a company can enter into an informal workout. These workouts are private agreements between the company and its creditors, with no involvement of outside parties. This reduces the chance that the company's reputation will be affected by the stigma of entering external administration. Public companies are typically more transparent than private companies in their financial reporting. Importantly, the higher degree of transparency at public companies, and particularly publicly listed companies, may hinder the process of corporate restructure via informal workouts and hence increase the probability of failure; the requirement to keep the market informed can undermine sensitive deals and thwart attempts at restructure, leading to higher rates of insolvency, on average (Productivity Commission 2015).

The threat of insolvent trading may also encourage company directors to seek the protection of voluntary administration rather than try to restructure the company. This is because, under current insolvency laws, company directors are exposed to potential civil liability if they incur any additional debt when the company is already insolvent (or becomes insolvent because of the additional debt). For directors, the threat of personal liability can outweigh any potential benefits from attempting to continue the business. As a result, directors may claim insolvency even when the company is only experiencing temporary financial distress and, in fact, has good long-term growth prospects.

The potential personal liabilities are likely to be greater for directors with 'more visible' reputations to uphold. To the extent that the owners of public companies are more visible to the general public than that of private companies, it might be expected that public companies have a greater incentive to voluntarily choose to enter administration rather than informally restructure the company. A similar dynamic could make directors of publicly listed companies more likely to opt for external administration than directors of publicly unlisted companies.

This allows us to develop two testable hypotheses:

- **H1:** Public companies should have a higher rate of failure than comparable private companies, on average.
- **H2:** Within public companies, listed companies should have particularly high rates of failure, on average.

3. Modelling Approach

Survival analysis is our preferred approach to examine the determinants of corporate failure. We opt for survival models because of the advantages they offer over discrete choice models (e.g. probit or logit models) that are more common in the literature.

The primary advantage of survival analysis is that it parsimoniously accounts for 'time dependence'; the idea that the probability of failure is a function of company age (which we measure as the time since a company registered). If company age has a significant effect on

failure risk, survival analysis is more appropriate than discrete choice models, which often treat failure as a 'static' classification problem and do not allow failure risk to evolve over a company's life cycle.

A further advantage of survival analysis is that it explicitly accounts for our limited ability to observe company failure. Many of the companies in the sample do not fail by the end of the sample period and it is not known if (or when) they subsequently fail – the data are 'right censored'. Listed companies are not observed prior to their listing and unlisted companies are not observed before they apply for a credit report – the data are also 'left truncated'. Survival analysis controls for both of these problems.

Given that survival models are used infrequently in the corporate failure literature, the next section outlines some basics of survival analysis. The subsequent section explains our preferred approach: a discrete-time survival model. This discussion borrows heavily from Rodríguez (2010) and Gupta, Gregoriou and Healy (2015).

3.1 Basic Outline of Survival Models

Survival analysis involves estimating two key functions – the survival and hazard functions. Standard survival analysis treats time as a continuous variable, and this section proceeds on that basis.

The survival function is the probability of surviving until at least time t : in our case the probability of a company not failing between its registration and time t (inclusive). More formally, let T be a non-negative random variable denoting the time between a company registering and failing. The survival function is:

$$S(t) = 1 - F(t) = P(T > t)$$

where $F(t)$ is the cumulative distribution function of T evaluated at t . The survivor function is equal to one when t is equal to zero and approaches zero as t approaches infinity. In the context of corporate failures, this means that a company is certain to fail over a long enough time horizon.

The continuous-time hazard function, $\lambda(t)$, can be derived based on the survivor function:

$$\lambda(t) = \lim_{\Delta t \rightarrow 0} \frac{S(t) - S(t + \Delta t)}{\Delta t \cdot S(t)} = \frac{-d \ln S(t)}{dt}$$

This expression states that the hazard function is the (limiting) probability that failure occurs within a given time interval, Δt , given that the company survived to the start of that interval. The continuous-time hazard is not strictly a probability – it has units of probability over time – and is perhaps most easily thought of as an instantaneous failure *rate*. A hazard rate of zero indicates no risk of failure at that instant while a rate of infinity indicates certain failure at that moment. The hazard rate can vary over time in a non-monotonic way.

A common way to specify the hazard rate is the semi-parametric Cox proportional hazards (CPH) model (Cox 1972). This model assumes the instantaneous risk of failure is a function of 'time at risk' (company age in our case) and other risk factors (e.g. company ownership type). In this model, the hazard function for company j at time t is assumed to be:

$$\lambda_j(t|\mathbf{X}_j) = \lambda_0(t)e^{\beta\mathbf{X}_j}$$

where \mathbf{X}_j is a vector of explanatory variables for company j , β is a vector of coefficients, and the baseline hazard rate, $\lambda_0(t)$, is an unspecified function of time. The baseline hazard rate is the explicitly time-dependent part of the hazard function and corresponds to the hazard rate when all covariate values are equal to zero. The proportionality of the model stems from the multiplicative effect on the baseline hazard of (time-invariant) explanatory variables – if a particular change in an explanatory variable doubles the baseline hazard at $t = 1$, it does the same at $t = 2$ and so on. This proportionality simplifies estimation of the continuous-time model.

3.2 Discrete-time Survival Model

Company failure is experienced at an instant in continuous time, which suggests that we should use a continuous-time survival model. This would be appropriate *if* survival times were recorded in relatively fine timescales (e.g. seconds, hours or days) *and* there were no tied survival time periods (i.e. no two companies survive for exactly the same length of time).

But these conditions are violated when accounting data are used to model corporate failure. This is because financial reporting typically occurs on coarse timescales. For instance, we observe the state of unlisted companies only every year and listed companies only every six months. In this case, discrete-time models are more appropriate. In effect, we have a case of 'interval censoring'. This occurs when the event is experienced in continuous time but we only record the time interval within which the event takes place. Interval censoring leads to discrete-time data.

Discrete-time survival models explicitly account for this type of censoring. The discrete-time survival function, based on the continuous-time proportional hazard function above and representing survival to the end of the interval $[t_{m-1}, t_m]$, is:

$$S(t_m, \mathbf{X}_j) = e^{-\int_0^{t_m} \lambda_j(u|\mathbf{X}_j) du} = e^{-H_m} e^{\beta\mathbf{X}_j}$$

where $H_m = \int_0^{t_m} \lambda_0(u) du$ is known as the 'integrated baseline hazard'. The discrete-time hazard for the same interval, $h(t_m|\mathbf{X}_j)$, follows from the laws of conditional probability:

$$h(t_m|\mathbf{X}_j) = \frac{S(t_{m-1}, \mathbf{X}_j) - S(t_m, \mathbf{X}_j)}{S(t_{m-1}, \mathbf{X}_j)} = 1 - e^{\beta\mathbf{X}_j(H_{m-1} - H_m)}$$

Applying a complementary log-log transformation:

$$\ln\left(-\ln\left(1-h_j\left(t_m|\mathbf{X}_j\right)\right)\right)=\boldsymbol{\beta}\mathbf{X}_j+\varphi_m$$

where $\varphi_m = \ln(H_m - H_{m-1})$ is the log of the baseline hazard evaluated over the interval. A key step in estimating this model is to choose a baseline hazard function. We choose a parsimonious specification for our benchmark model, with the baseline hazard assumed to be a function of the natural log of company age. In unreported results, we estimate a flexible specification that includes separate dummy variables for each company age observed in the sample. This model provides results very similar to the benchmark model.

Some of the explanatory variables used in the analysis vary over time: it is straightforward to extend the above to $\mathbf{X}(t)_j$ instead of \mathbf{X}_j . The explanatory variables include 'cyclical' company characteristics, such as size, profitability and leverage. We discuss these explanatory variables in more detail later.

Macroeconomic conditions, such as the state of the business cycle, may also matter. Given the relatively coarse time dimension of our (annual) data, we choose to model the effect of all *aggregate* conditions jointly, by including time fixed effects, represented by a series of year dummies, λ_t .¹¹ The benchmark model is therefore written:

$$\ln\left(-\ln\left(1-h_j\left(t_m|\mathbf{X}(t)_j\right)\right)\right)=\varphi_m+\boldsymbol{\beta}\mathbf{X}(t)_j+\lambda_t \quad (1)$$

These time fixed effects capture the effects of macroeconomic conditions that are not captured by the variation over time in the firm-level variables. For example, variation in company-level profitability may capture some of the variation in demand growth over the sample period. This set-up works against us finding a significant independent effect of macroeconomic conditions on corporate failure. Notably, the time fixed effects also capture the effect of other aggregate conditions, such as institutional factors (e.g. changes in insolvency legislation) and the average levels of any omitted company-level variables (e.g. risk appetite).

Finally, we cluster the standard errors by company to control for unobserved shocks within a company that may be correlated over time and affect the probability of failure.

11 Models were also estimated in which macroeconomic variables were directly included. These included: 1) real GDP growth for each Australian state (to capture the state-level business cycle); 2) the difference between the interest rate on loans to large businesses and the cash rate (to proxy for aggregate credit risk); and 3) the cash rate (to capture financing conditions). There was some tentative evidence that the credit risk variable was positively correlated with the probability of failure at the company level, but, in general, the results were not very robust.

4. Data

4.1 Sample Selection

We construct our sample of companies based on two separate datasets. For both datasets we exclude companies in the financial services industry.¹² The sample period covers the years from 2000 to 2015. The combined dataset is an unbalanced panel as companies drop in and out of the sample due to factors such as failure, mergers and acquisitions.

Data on listed companies come from Morningstar. The listed company data include all domestically domiciled non-financial companies listed on the Australian Stock Exchange. These data are semiannual and cover more than 2 400 companies. The median number of observations per company is 24. Data on unlisted companies are from Dun & Bradstreet (D&B). The D&B panel is based on annual data covering more than 20 000 companies, with a median of about four observations per company.¹³

Overall, the combined dataset comprises more than 90 000 observations on over 23 000 companies. To maximise comparability between the listed and unlisted company samples we estimate the benchmark model using annual data. For more details on the composition of the sample see Table 1.

We identify failed companies in our data using publicly available information on corporate insolvency available from ASIC. These data cover all failed companies and are matched to the sample of companies in the combined dataset for which we have financial statement information.

The D&B sample of companies is based on its primary business as a credit bureau. Companies in the database are likely to be those that applied for credit, and D&B can most easily obtain financial information on relatively large companies, which are required to file their financial reports with ASIC. As a result, compared to the population of all private and unlisted public companies in Australia, the sample is biased towards larger companies, though it does still have some coverage of very small companies (those with revenue less than \$500 000).

The slant towards larger companies wanting to borrow does not necessarily undermine the motivation for our work. In fact, the direction of any possible sample selection bias is unclear. To the extent that the sampled companies are relatively large and/or have better access to credit, they may be less likely to fail than the average company in the population as a whole. On the other hand, the sampled companies may be more leveraged than the representative Australian company and therefore more vulnerable to unexpected negative shocks, and hence more likely to fail.

An additional practical challenge is that the exact date at which a company fails is typically known, but the characteristics of the company, such as the state of the balance sheet, are rarely observed

12 The determinants of failure are likely to be quite different for financial services companies. For example, a financial institution may be highly leveraged because of the nature of its business (e.g. loan provision) rather than excessive risk-taking.

13 The unlisted company financial statements are somewhat sporadic in our dataset, even for 'healthy' companies; D&B may not collect the financial statements of a company every year, but only every few years.

at the precise moment of failure. For example, in the Dick Smith case, the company released its last annual report in August 2015 and entered external administration in January 2016. There was at least a six-month period in which the conditions of the company were not transparent to investors, creditors and employees.

It is somewhat surprising how rarely this type of censoring is discussed in the corporate failure literature given its pervasiveness. To address this issue, we adopt a simple form of imputation, which is known as 'last value carried forward' (Allison 2010). Under this approach, the company at the moment of failure is assumed to have the financial characteristics that it had in its most recent financial reports. For example, Dick Smith's balance sheet for 2014/15 was known at August 2015 and this information would be carried forward to the year of failure in 2016. We allow financial data to be carried forward by at most one year. If financial data are not observed within one year of a company failing, we do not capture this failure within our sample.¹⁴

4.2 Model Variables

The benchmark model includes a range of cyclical company-level variables that are fairly standard in the literature on modelling corporate exit. We outline each variable in turn.

Age

We explicitly account for company age (measured as the natural log of the number of years since the company registered with ASIC) in the baseline hazard rate. A consistent research finding is that younger companies are more likely to fail than older companies, presumably due to 'learning-by-doing' (e.g. Jovanovic 1982).¹⁵ Because of their limited track records, start-ups typically face restricted access to external finance and are less experienced in developing business models and company strategies.

Size

We include company size (as measured by the natural logarithm of assets) as a key determinant of corporate failure. The existing overseas literature commonly finds that small companies are more likely to fail than large companies (e.g. Hunter and Isachenkova 2006; Bhattacharjee *et al* 2009).¹⁶ This is presumably because small companies are more likely to be credit constrained, given they have less capacity to raise bank finance and have limited access to non-bank finance (e.g. corporate bonds). Similarly, small companies presumably have less bargaining power with suppliers and creditors, so financing conditions may be more restrictive in terms of business-to-business lending.

14 There are only 100 failures for which we observe financial data in the same year, so 432 of our 532 failures are represented by financial data carried forward from the prior year.

15 ABS business count data indicate that about half of all start-ups typically survive to the age of 4 years.

16 ABS business count data indicate that small businesses are about three times more likely to exit than large businesses.

Profitability

Profitability is likely to be a key determinant of company failure. We measure profitability as the ratio of earnings before interest and tax to total assets. Higher earnings increase the ability of companies to service their debt payments.

Leverage

Existing research indicates that the level of indebtedness is an important driver of corporate failure (Bunn and Redwood 2003). The link between leverage and default risk is a key component of distance-to-default models (e.g. Robson 2015). Companies that are more leveraged (and hence have less equity) are more vulnerable to asset devaluations. Companies with high leverage also typically have greater debt-servicing burdens and hence are more vulnerable to negative earnings shocks.

We measure leverage in two ways. First, we construct a traditional estimate based on the reported debt-to-assets ratio of each company. This debt includes both bank debt and non-bank debt (e.g. corporate bonds). Second, we construct a more novel estimate based on the level of trade credit (or business-to-business lending) of each company. More specifically, we measure (net) trade credit as accounts payable outstanding (loans *from* other firms) less accounts receivable (loans *to* other firms) and we divide this net debt estimate by total assets. We refer to this as the 'trade credit-to-assets ratio'.

Liquidity

Liquidity is likely to be a key factor determining whether a company remains solvent or not; higher levels of liquid assets allow companies to absorb any unexpected adverse shocks to their balance sheets. We measure liquidity as the ratio of cash (and cash equivalents) to total assets.

Structural characteristics

The model also includes a set of variables that are designed to capture structural characteristics. We include a variable to capture the type of ownership (*PUBLIC*); the dummy is equal to one when the firm is a public company and is equal to zero when the firm is a private company. Separate to this, we include a dummy variable to indicate whether a public company is listed or not (*LISTED*). The benchmark model also includes industry fixed effects to capture the possibility that some industries may be inherently riskier than others (e.g. construction and mining).

Before estimation we exclude outliers in some of the company-level variables. First, we exclude observations in which assets, debt or cash are reported to be negative. Second, we exclude observations in which the company holds debt that is more than twice the value of its assets, cash

that is more than the value of total assets, and a ratio of earnings to assets that is greater than 10 in absolute terms.¹⁷

The benchmark model is estimated across the full sample of companies. In an extension, we also estimate separate specifications for the listed and unlisted company sub-samples. This allows us to see whether the determinants of failure vary with the type of ownership. Moreover, these disaggregated models provide additional flexibility in terms of variable choice. For example, the D&B database provides information on subsidiary status for unlisted companies, which is not available for listed companies in the Morningstar database. The listed company model is also estimated on semiannual data rather than annual data which provide more timely information to precisely identify the causes of failure.

4.3 Summary Statistics

Our final sample comprises over 90 000 observations on more than 23 000 companies. Over the whole sample period, 0.6 per cent of company *observations* are incidents of failure, which is an unconditional estimate of the annual failure rate. And, over the sample period, 2.3 per cent of *companies* are observed to fail (there are around four observations per company on average). Many non-failing companies are still present in the sample at the end of 2015 (are right censored), but others drop out of the sample before 2015 for a variety of reasons that are not easy to observe (e.g. mergers and acquisitions, voluntary exits and missing data).

The probability of failure varies with company ownership status. On an annual basis, the average rates are 0.75 per cent for publicly listed companies, 0.50 per cent for publicly unlisted companies, and 0.55 per cent for private companies.

The key features of our company-level variables are summarised in Table 1, which splits observations into failing and non-failing observations. In terms of cyclical variables, failing companies are more leveraged, less profitable and less liquid than surviving companies. Failing companies are also generally smaller and younger than the average in our sample.

17 We have experimented with alternative approaches to treating outliers. For example, rather than excluding outliers, we have constructed estimates based on quintiles of the distribution of leverage, profitability and liquidity. Under this approach, a company that reports a debt-to-assets ratio of 1 000 is given the same weight in the regression as a company that reports a debt-to-assets ratio of 1. These results are very similar to those presented in the benchmark model and are available upon request.

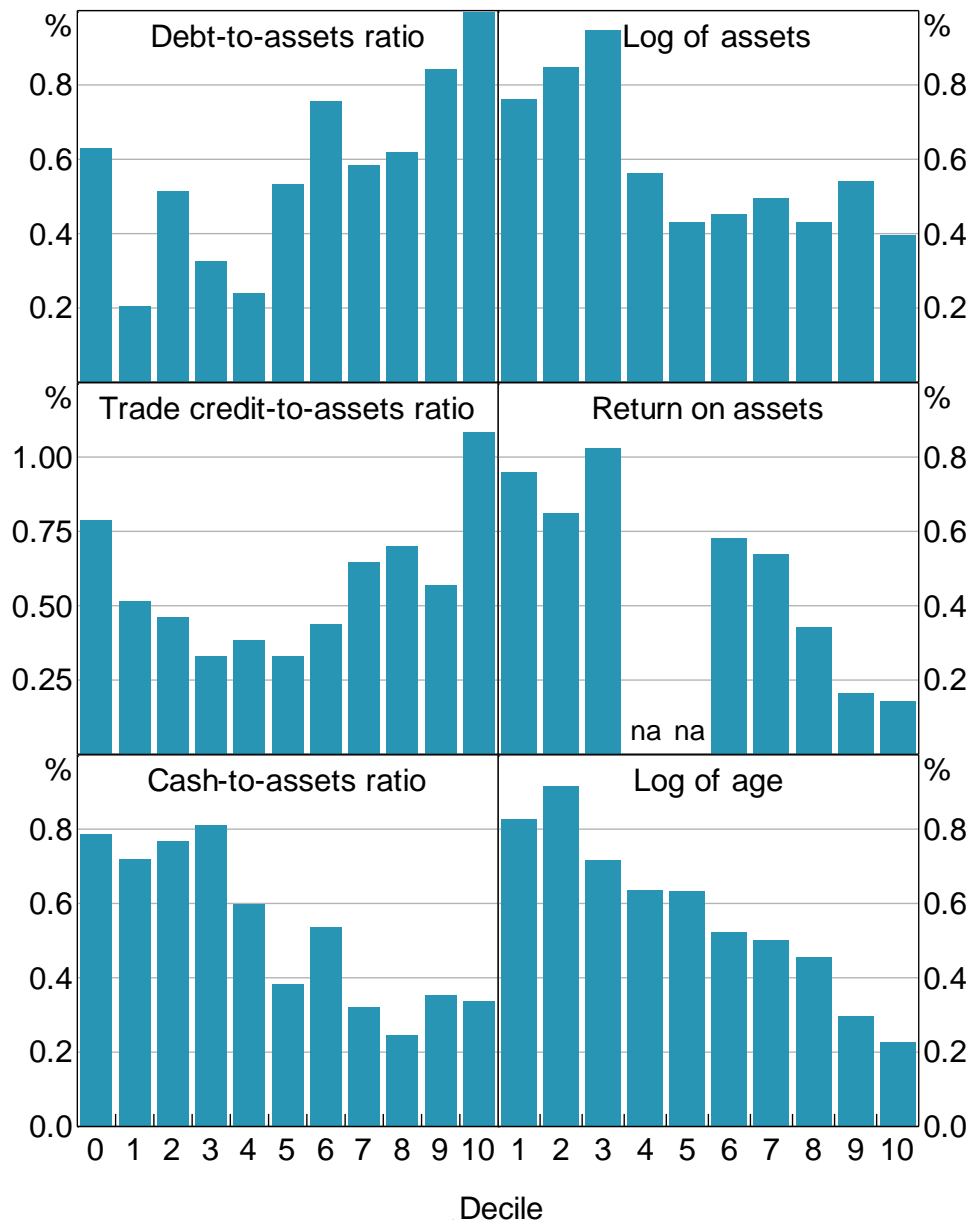
Table 1: Sample Characteristics
2000 to 2015

	Mean	Percentile			Standard deviation
		25th	Median	75th	
Failures					
Age (years)	14.2	6.0	10.0	19.0	12.5
Log of age	2.3	1.8	2.3	2.9	0.8
Assets (\$m)	82.2	1.4	5.3	30.0	349.5
Log of assets	1.9	0.4	1.7	3.4	2.3
Debt-to-assets ratio (%)	24.0	0.0	7.2	37.7	34.0
Trade credit-to-assets ratio (%)	7.0	-0.3	0.1	12.8	28.0
Cash-to-assets ratio (%)	8.3	0.0	0.8	6.3	19.1
Return on assets (%)	-9.1	-8.0	0.0	0.0	239.7
Observations	532				
Non-failures					
Age (years)	19.7	8.0	15.0	26.0	17.5
Log of age	2.6	2.1	2.7	3.3	0.9
Assets (\$m)	281.0	2.5	11.7	47.5	2 467.4
Log of assets	2.4	0.9	2.5	3.9	2.5
Debt-to-assets ratio (%)	17.2	0.0	4.1	26.7	25.4
Trade credit-to-assets ratio (%)	1.4	-5.9	0.0	6.5	24.0
Cash-to-assets ratio (%)	12.8	0.0	3.3	15.6	20.9
Return on assets (%)	104.2	0.0	0.0	219.1	338.3
Observations	90 197				
Note: Statistics shown are for the sample of companies used in estimation					

It is also interesting to examine how average failure rates vary across the distributions of some of the key variables. In Figure 2, we construct estimates of the mean failure rate across the distributions of each of the company-specific cyclical indicators, where the distributions of each indicator are divided into deciles.

For some variables, such as the debt-to-assets ratio, the net trade credit-to-assets ratio and the cash-to-assets ratio, it is helpful to separate out company-year observations that are reported to be zero. For these variables, we construct distributions only across the observations reporting non-zero values. The mean failure rates for the company-year observations with zero values are summarised as a separate column indicated by a decile of '0'.

The cross-sectional distribution of the return on assets is difficult to represent graphically in a histogram. More than a third of observations have a zero value for return on assets – these observations are all included in the third decile of this distribution. The first and second deciles of this distribution represent company-year observations with a negative return on assets, while the sixth to tenth deciles are observations with positive return on assets.

Figure 2: Mean Failure Rate by Cyclical Indicator

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

The histograms indicate that average failure rates are positively correlated with leverage and negatively correlated with size, age, profitability and liquidity. Based on these distributions, we choose a simple specification for the benchmark model and ignore potential non-linearities between the probability of failure and the company-specific cyclical factors.

5. Results

Before estimation it is useful to show how the failure rates of different companies evolve as they grow older. This is neatly summarised by Kaplan-Meier failure estimates. This method estimates the survival probability non parametrically, assuming no specific underlying function. The basic Kaplan-Meier estimate of the probability of surviving beyond time t is:

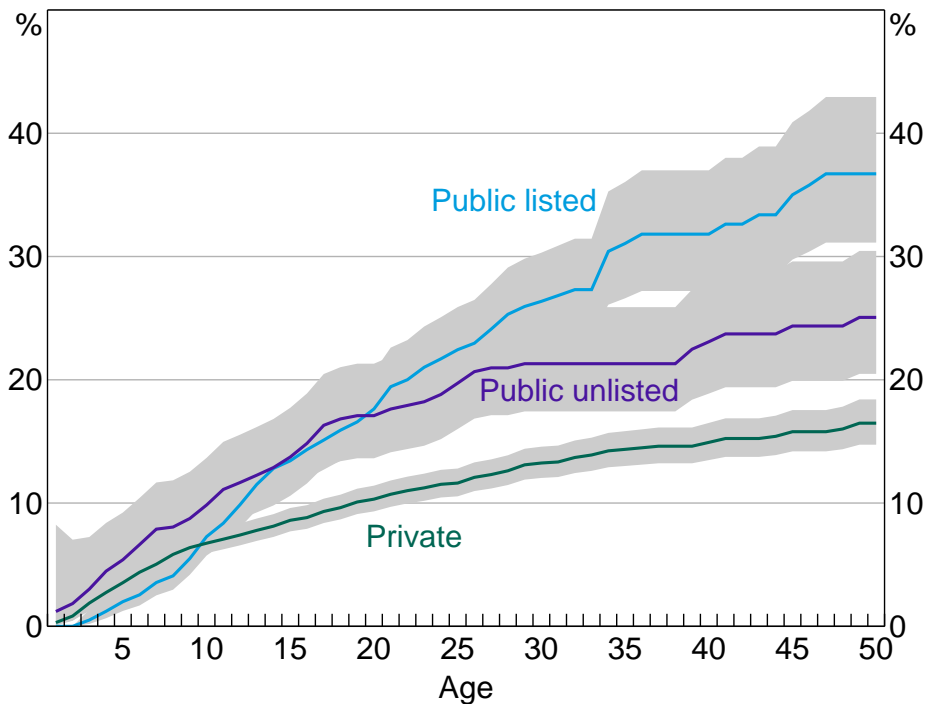
$$S(t) = \prod_{t_k | t_k < t} \left(\frac{n_k - d_k}{n_k} \right)$$

where t_k are points in time indexed by positive integers k , n_k is the number of companies eligible for failure at time t_k (taking into account right censoring) and d_k is the number of companies that fail between time t_{k-1} and t_k . The failure rate is then simply estimated as 1 minus the survival rate.

Figure 3 shows Kaplan-Meier estimates of the failure rates for publicly listed, publicly unlisted and private companies. These failure curves indicate that, controlling only for age, failure risk varies across ownership types. Across most ages, private companies are significantly less likely to fail than public companies. Within older public companies, listed companies appear to be more risky than unlisted companies. Given the age-dependent nature of this relationship, we allow the effect of ownership type to vary with age in the benchmark model.

Figure 3: Kaplan-Meier Failure Curves

Probability of failing by each age



Note: Shaded areas represent 95 per cent confidence intervals

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

The estimation results of the benchmark model are shown in Table 2. Note that the reported estimates are average marginal effects. The average marginal effect of a given covariate is the average over the sample of the marginal effect computed for each company observation at the observed values of its covariates (marginal effects in the complementary log-log model are a function of the covariates). The average marginal effects can be interpreted as the change in the probability of failure due to a change in the given covariate, provided other covariates are held constant.

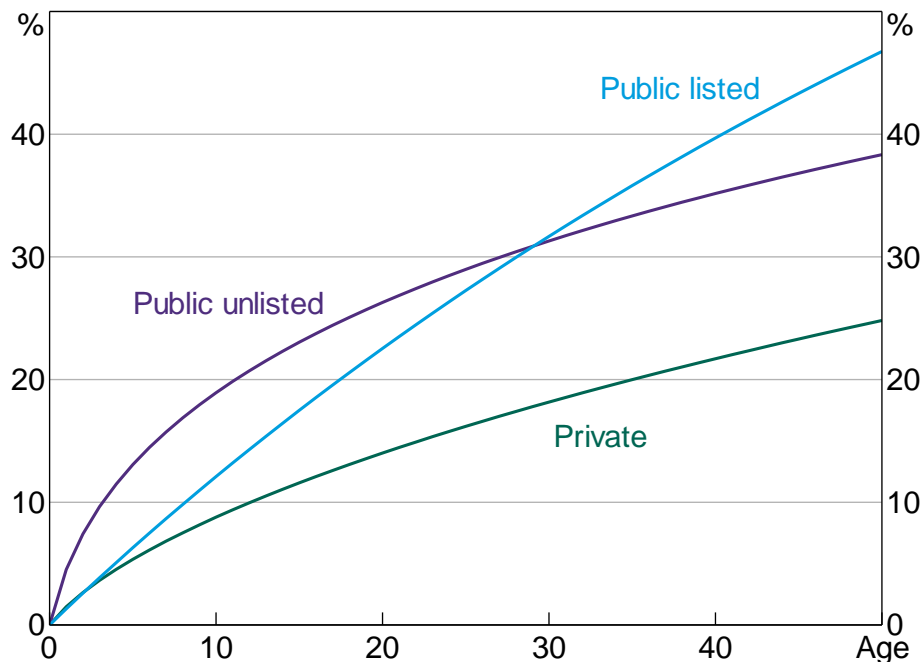
Table 2: Complementary Log-log Model Estimates of Failure

Average marginal effects on hazard rate

Structural characteristics	
Public (average over the sub-sample of unlisted companies)	0.43*** (0.01)
Listed (average over the sub-sample of public companies)	0.10 (0.48)
Cyclical characteristics	
Log of age	-0.12*** (0.00)
Log of assets	-0.12*** (0.00)
Debt-to-assets ratio	0.12*** (0.00)
Trade credit-to-assets ratio	0.11*** (0.00)
Cash-to-assets ratio	-0.19*** (0.00)
Return on assets	-0.13*** (0.00)
Time fixed effects	Yes
Industry fixed effects	Yes
Wald test (<i>p</i> -value)	0.00
Area under ROC curve	0.73
Observations	90 729
Companies	23 326
Failure observations	532
Notes:	Standard errors are calculated using the delta method; <i>p</i> -values are reported in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively; for structural characteristics, marginal effects shown are for a change from private to public company and a change from unlisted to listed company; for cyclical characteristics, marginal effect of one standard deviation change; ROC curve denotes a receiver operator characteristic curve

The results indicate that the type of ownership is important in predicting company failure. A public company is around 0.4 percentage points more likely to fail in a given year than a comparable private company. Moreover, listed companies have failure probabilities that differ from unlisted public companies, but in a way that varies over time, so is not visible in the age-invariant average marginal effect above (the full regression results in Appendix A make this clear). Figure 4 shows estimated failure functions for three companies that differ only by their structural characteristics. Private companies are less likely to fail than public companies at almost all ages. Early in their life, publicly listed companies are less likely to fail than comparable unlisted public companies, but this situation reverses and listed companies are less likely to survive beyond 30 years of age. These life-cycle patterns are consistent with the Kaplan-Meier failure curves shown in Figure 3. This indicates that the age profile of failure risk for different types of corporate ownership is not affected by controlling for cyclical and macroeconomic variables.

Figure 4: Estimated Failure Curves by Structural Characteristic
Probability of failing by each age



Note: Estimates from the benchmark model for a company with median cyclical characteristics, in the manufacturing industry, in 2011

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

The higher failure curve for public companies – the gap between the green and purple lines in Figure 4 – is consistent with the hypothesis that public companies take greater risks than private companies because of their greater separation of ownership and control or because of their more dispersed ownership structures (i.e. shareholders of public companies have less 'skin in the game'). The higher degree of transparency of public companies may also discourage company directors from attempting to restructure the company and instead push them towards insolvency during periods of stress.¹⁸ The higher failure curve for listed companies versus publicly unlisted companies at higher ages – the gap between the blue and purple lines – is also consistent with these 'agency' and 'transparency' hypotheses.

It is not clear what is driving the result that young publicly listed companies are less likely to fail than young publicly unlisted companies (the area in which the purple line is above the blue line in Figure 4). It might be that companies with better growth prospects self-select into listing at a young age. These 'superstar' companies may thus have lower failure probabilities at an early stage of life but this effect dissipates over time. In addition, there may be greater market scrutiny of young listed companies, such that it is more difficult at that stage to take risks.

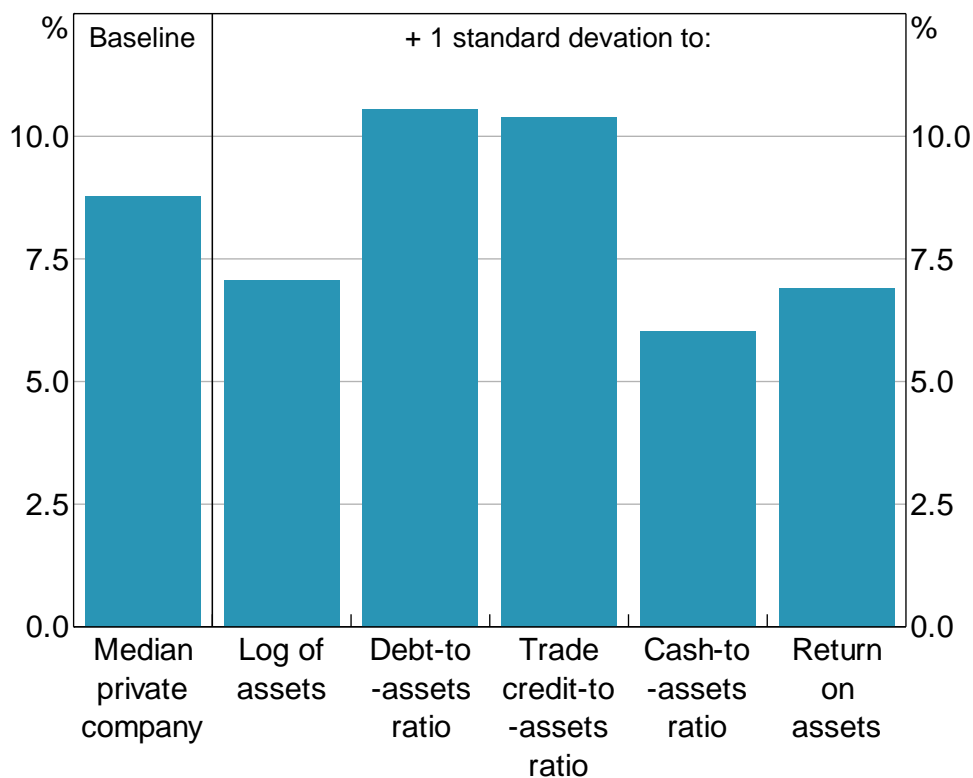
Not surprisingly, cyclical company-level characteristics are associated with the probability of failure. The signs of the marginal effects of these variables align with our hypotheses. Larger companies are less likely to fail than smaller companies, and older companies are less likely to fail than

¹⁸ It is also possible that public companies are more focused than private companies on short-term profits and, for listed companies, share price targets, which may lead them to be more myopic and adopt more aggressive growth strategies (Haldane 2011).

younger companies. A higher level of debt or trade credit relative to assets raises the probability of failure. The liquidity of a company's balance sheet also matters; more cash lowers the probability of failure, as does higher profitability.

A one standard deviation change in each of the cyclical variables is estimated to change failure probabilities by between 11 and 19 basis points. These effects appear small, but are large in the context of our unconditional failure probability of around 60 basis points. In addition, such differences in cyclical firm-level characteristics can have a 'cumulative effect' and lead to significant differences in the probability of failure when measured over a longer time horizon. For example, a one standard deviation increase in the log of total assets – equivalent to a company growing from \$12 million in assets to \$138 million – is associated with a lower failure probability of about 12 basis points in a given year. But the same increase in size would make an otherwise median private company about 1.7 *percentage points* less likely to fail over the first 10 years of its life (Figure 5).

Figure 5: Cumulative Impact of Cyclical Characteristics
Cumulative probability of failure in first 10 years after registration



Notes: Estimates from benchmark model for a private company with otherwise median cyclical characteristics, in the manufacturing industry, in 2011; changes in the baseline will affect the estimated level of the cumulative impact but will not affect the relative contribution of each of the cyclical company-level factors

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

Leverage from reported debt (bank and non-bank debt) and leverage from trade credit (business-to-business lending) have roughly equal impacts on the probability of failure. A one standard deviation increase in these measures (which is equivalent to around 25 percentage points for both measures) is associated with an increase in failure probability of around 11 basis points over a year, and 1.7 percentage points over a 10-year period.

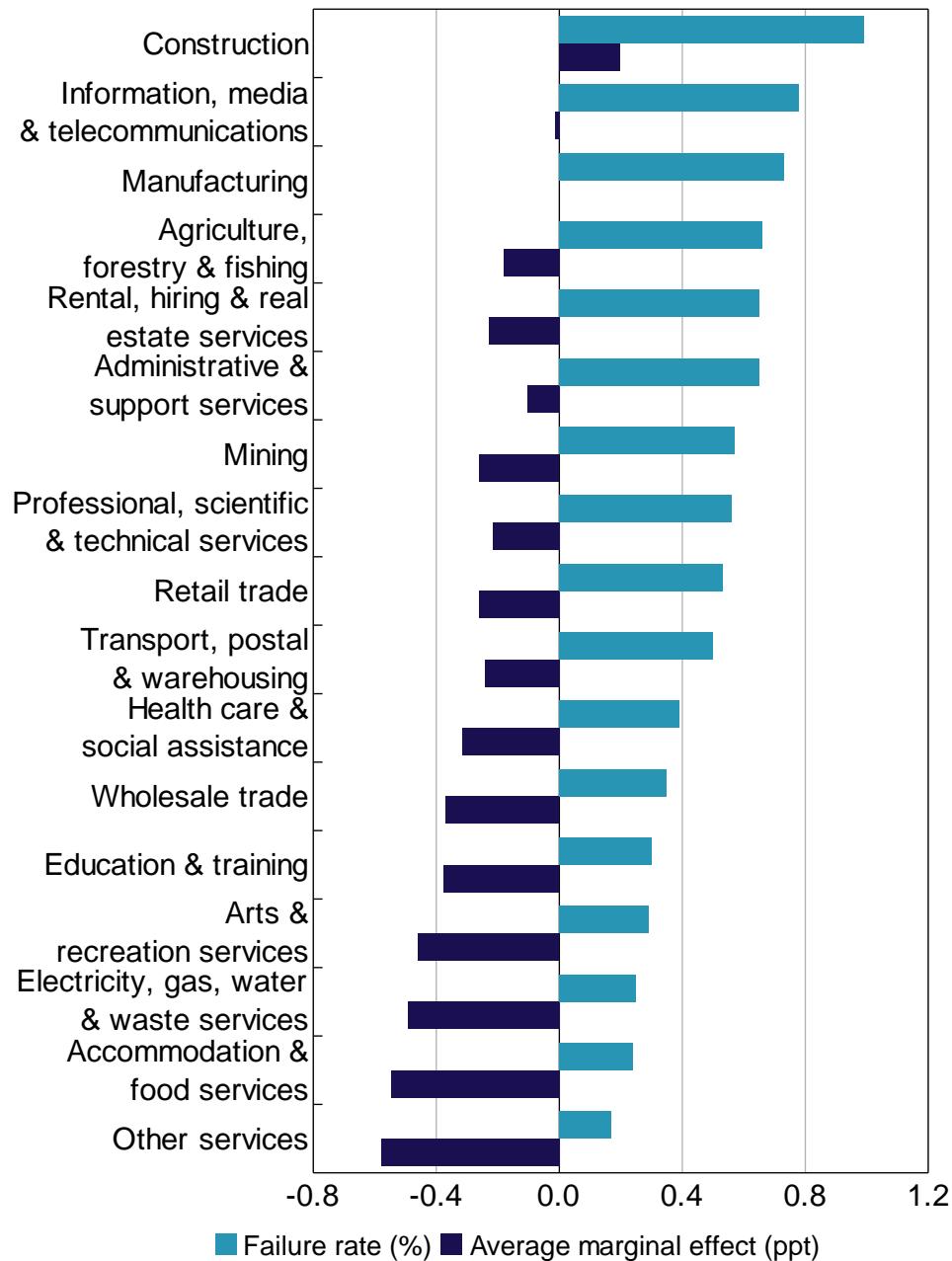
The effect of liquidity is particularly important; a one standard deviation rise in the cash-to-assets ratio lowers the probability of failure by around 19 basis points over one year, or 2.8 percentage points over the first ten years of life for the median private company. A one standard deviation increase in profitability has a smaller effect, roughly equivalent to that of company size.

The probability of failure varies a lot by industry. This is shown by the marginal effects of the industry dummies (Figure 6). The estimated average marginal effects indicate that, across all companies, construction companies are most prone to fail when controlling for other observable differences between industries. The relatively high failure rate for construction companies led to a Senate inquiry into the industry in 2015. The inquiry listed a wide range of potential causes for the high failure rate in the construction industry, including a heavy reliance on subcontracting, 'illegal phoenix activity' and even the weather (Senate Economics References Committee 2015).¹⁹

The relative ranking of industries in terms of 'failure risk' is barely affected by the inclusion of control variables (this is shown by the relative ranking of industries based on both the unconditional failure rate and the average marginal effects in Figure 6). This suggests that variation across industries in company characteristics, such as leverage and profitability, do not fully capture industry risk.

19 Illegal phoenix activity involves the intentional transfer of assets from an indebted company to a new company to avoid paying creditors, tax or employee entitlements. The directors leave the debts with the old company, often placing that company into administration or liquidation, leaving no assets to pay creditors (ASIC 2015).

Figure 6: Failure Rates by Industry
2000 to 2015



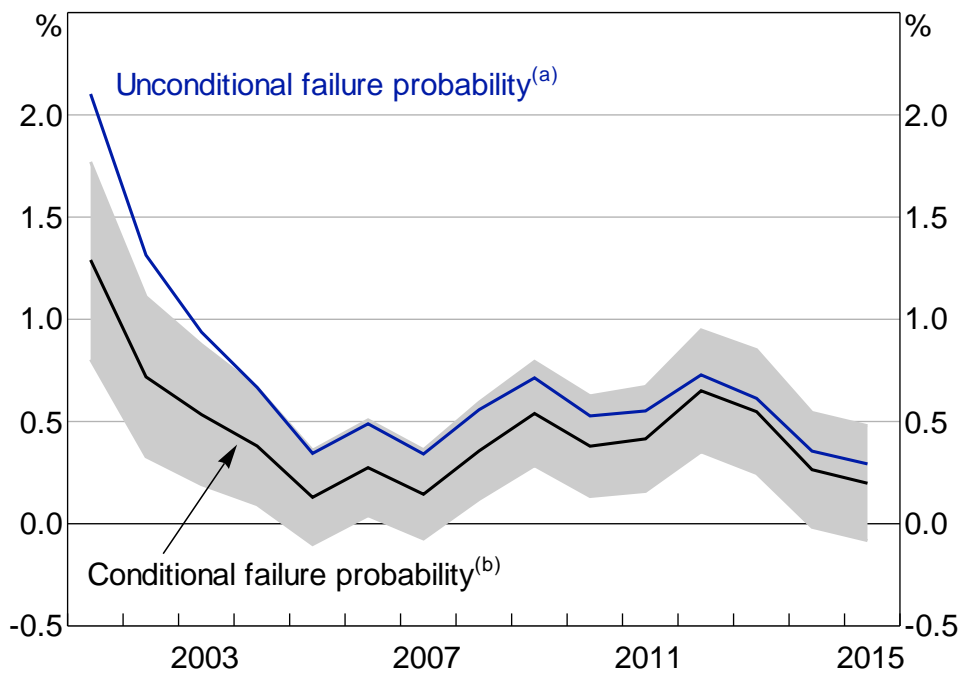
Note: Marginal effects are calculated relative to the manufacturing industry

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

We also find evidence that aggregate conditions matter for the probability of failure, even after controlling for company-level characteristics. This is shown by the estimates of the time fixed effects in the model (the 'conditional failure probability' in Figure 7). The observed pattern in the time dummies suggests they represent macroeconomic conditions. For instance, they typically spike during slowdowns, as demonstrated during the 2001 and 2008–09 periods. There is also some evidence of a spike around 2012 and 2013, suggesting that the decline in commodity prices and the fall in mining investment were associated with a relatively high rate of company failure.

A comparison of the average annual failure probabilities (the 'unconditional failure probability') and the conditional failure probabilities in Figure 7 highlights the relative contribution of the company-level characteristics in explaining failure. Changes in company-level characteristics have caused a reduction in estimated failure risk over the sample period. The portion of this improvement that occurred between 2007 and 2012 is consistent with the improvement in non-financial corporations' balance sheets over this period (RBA 2016).

Figure 7: Macroeconomic Conditions and Failure
Estimated failure probabilities from benchmark model



Notes: (a) Average predicted failure probability in each year
(b) Average marginal effect of the year dummies; 2000 is the base year; shaded area represents 95 per cent confidence intervals

Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

The statistically significant effect of the time dummies is also consistent with the importance of network effects (or 'ripples of risk') – the failure of one company during a downturn can lead to the widespread failure of related companies through, for instance, trade credit linkages.

The benchmark model has good explanatory power in that it can adequately distinguish companies that fail from those that do not. This is shown by the estimated area under the receiver operator characteristic (ROC) curve. The area under the ROC curve for a model that perfectly distinguishes failing and non-failing observations is 1. The expected area under the curve for a model that effectively guesses failure probabilities (a model with no information) is 0.5. The area under the ROC curve for the benchmark model is 0.73, which is similar to that for a market-based predictor of listed company failure (Robson 2015).²⁰ If the time dummies are removed from the model, the estimated area drops only slightly to 0.71. This indicates that structural and cyclical company-level characteristics are sufficient to *rank* companies in terms of failure risk.

²⁰ Robson also provides a more detailed explanation of the ROC curve.

6. Robustness Tests and Extensions

6.1 Alternative Models

The estimates from the benchmark model are robust to changes in the sample period, the treatment of outliers and the inclusion of company-specific random effects.²¹ In addition, we have estimated the benchmark specification using a range of models that are more standard in the literature:

1. a continuous-time survival model – the semi parametric CPH model;
2. a discrete-time survival model with a logit, rather than complementary log-log link function; and
3. logit and probit binary dependent variable models.

The key results from these models are similar to those from the benchmark model and are available on request.

6.2 Listed Versus Unlisted Companies

Next, we briefly consider whether the determinants of failure differ for listed and unlisted companies in Australia. We estimate the benchmark model for listed and unlisted companies separately. The results are shown in Table 3.

The effects of the cyclical variables on the predicted probability of failure vary somewhat when estimated separately on the listed and unlisted company sub-samples. For instance, size is more closely associated with failure among listed companies, while age seems to be more closely associated with failure for unlisted companies. More notably, the type of leverage seems to matter. Debt appears to be associated with failure only for listed companies, while trade credit matters for both types of company.

The results also suggest that, for unlisted companies, subsidiaries are significantly less likely to fail, particularly subsidiaries of foreign parents. This suggests that the liquidity and solvency of subsidiary companies are closely tied to the performance of their parent companies. To the extent that business performance is not perfectly correlated across subsidiaries within the parent company, these results are consistent with internal capital markets effectively insulating

21 The company-specific random effect captures the fact that some companies are more prone to failure because of unobserved characteristics, such as management quality, corporate governance structure and risk appetite. In survival analysis terms, some companies are more 'frail' than others. The random effects model assumes that the unobserved characteristics are not correlated with any of the observed characteristics that act as control variables. It is plausible that risk appetite is correlated with factors such as leverage, which would violate this assumption. As such, the benchmark model was preferred over the random effects model.

subsidiaries from liquidity shocks through cross-subsidisation (Becchetti and Sierra 2003; Dewaelheyns and Van Hulle 2006).²²

Table 3: Complementary Log-log Model Estimates of Failure

Average marginal effects on hazard rate

	Listed companies	Unlisted companies
Structural characteristics		
Public		0.23* (0.08)
Domestic subsidiary (not foreign subsidiary)	na	-0.19** (0.01)
Foreign subsidiary (not domestic subsidiary)	na	-0.61*** (0.00)
Cyclical characteristics		
Log of age	-0.00 (0.98)	-0.17*** (0.00)
Log of assets	-0.17** (0.03)	-0.00 (0.93)
Debt-to-assets ratio	0.41*** (0.00)	0.03 (0.25)
Trade credit-to-assets ratio	0.33* (0.08)	0.11*** (0.00)
Cash-to-assets ratio	-0.18*** (0.01)	-0.19*** (0.00)
Return on assets	-0.50*** (0.00)	-0.11*** (0.00)
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	18 150	72 578
Companies	1 755	21 661
Failure observations	137	395

Notes: Average marginal effects are calculated for each company based on the observed values of the explanatory variables for that company and averaged across companies; standard errors are calculated using the delta method; *p*-values are reported in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively; for structural characteristics, marginal effects shown are for a change from base category; for cyclical characteristics, marginal effect of one standard deviation change

22 The internal capital markets hypothesis assumes that companies are 'randomly assigned' to being subsidiaries or standalone companies. It could be the case that 'healthy' companies are more likely to be subsidiaries than unhealthy companies, particularly if they have been identified as a target for acquisition. Alternatively, 'healthy' parents with strong management skills and experience may be more likely to establish subsidiaries and the subsidiaries 'inherit' this unobserved human capital. These alternative hypotheses suggest that the link between probability of failure and subsidiary status is due to some latent characteristic of the subsidiary (or parent) rather than internal capital market funding.

6.3 Debt at Risk

We now take the benchmark model estimates and develop a simple framework to measure the potential effect of corporate failure on financial stability. In particular, we construct estimates of debt at risk (DAR) for each company in the sample and then aggregate these estimates to make inferences for the Australian economy. The DAR for each company is constructed as the estimated probability of failure multiplied by the reported stock of debt outstanding on the company's balance sheet. We aggregate the DAR estimates for each individual company at a given point in time and normalise this by the total stock of debt. The result is the share of aggregate debt that is expected to default each year. We refer to this as the DAR ratio or 'debt-weighted probability of failure':

$$DAR\,RATIO_t = \frac{DAR_t}{\sum_{j=1}^N D_{jt}} = \frac{\sum_{j=1}^N pd_{jt} D_{jt}}{\sum_{j=1}^N D_{jt}}$$

where pd_{jt} is the probability of failure estimated from the benchmark model and D_{jt} is the total stock of debt for company j in year t . We also create an alternative measure that, instead of reported (bank and non-bank) *debt*, uses each company's net *trade credit* (we call this 'trade credit at risk' (TCAR)). The share of TCAR in total trade credit is referred to as the TCAR ratio (or 'trade credit-weighted probability of failure'). We censor net trade credit at a lower bound of zero in calculating this measure, so that companies that are net trade creditors do not cancel out those that are net trade debtors.

DAR and TCAR are the amounts that creditors could expect to lose if a company fails and there is a 100 per cent loss rate. In a sense, these estimates are an upper bound on creditor losses. But the framework ignores the possibility that a corporate default can have knock-on effects to other companies.²³ The estimates might therefore also underestimate the share of aggregate corporate debt that is at risk of default to the extent that such flow-on effects are important.

By our estimates, around 0.5 per cent of total debt was 'at risk' over the sample period, with the share of debt at risk being higher for listed companies than for other companies (Table 4). On top of this, around 0.4 per cent of trade credit was at risk in aggregate. The slightly lower estimate of aggregate risk for trade credit is due to private companies being the main users of trade credit (three-quarters of aggregate trade credit is held by private companies) and private companies are generally at lower risk of failing than public companies.

23 The spillover effects are captured to some extent by the time fixed effects in the benchmark model in that the year dummies capture the average level of spillovers each year.

Table 4: Debt at Risk and Trade Credit at Risk

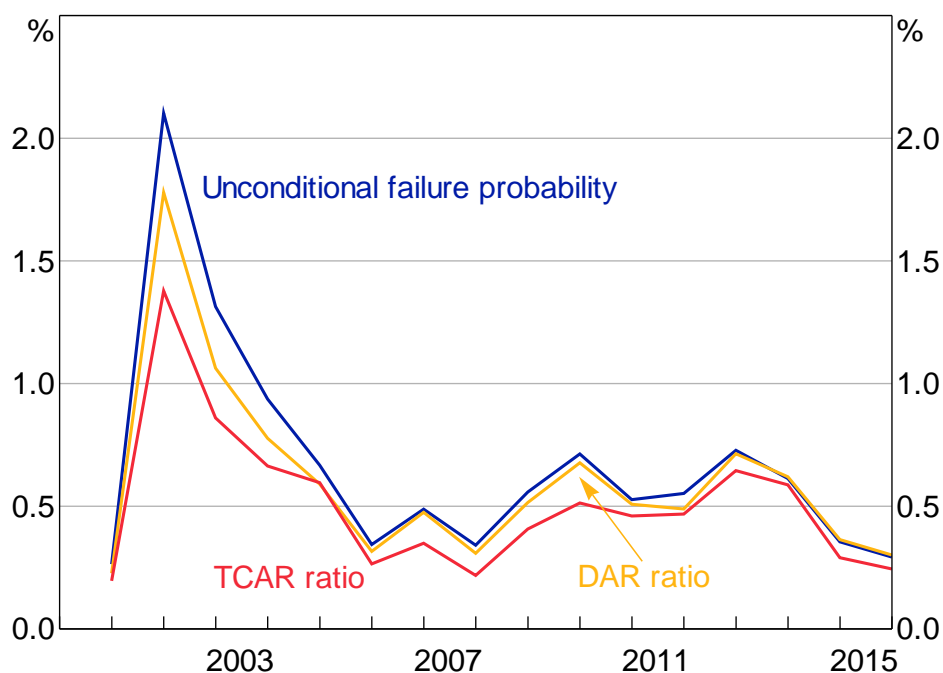
Company type	Share of DAR ratio	Share of TCAR ratio	For each company type	
			Debt as a share of aggregate company debt	Trade credit as a share of aggregate company trade credit
Public listed	0.65	0.68	46.3	11.4
Public unlisted	0.42	0.48	15.3	14.1
Private	0.43	0.38	38.4	74.5
All companies	0.53	0.43	100.0	100.0

Large companies account for a disproportionate share of debt at risk. Across all companies, more than 90 per cent of aggregate DAR is held by companies in the highest debt quintile. This is in part because our sample is skewed towards larger companies (it covers almost all listed companies, but only a small proportion of unlisted companies), but is also indicative of a large right tail in the distribution of debt at risk.

The shares of both debt and trade credit at risk have declined over recent years (Figure 8). This reflects the decline in the estimated failure probabilities, as can be seen by the close correlation with the annual estimate of the unconditional failure probability from the benchmark model. This implies that the drivers of the average failure probability – in particular, macroeconomic conditions – are also a key driver of aggregate corporate credit risk in Australia. The fact that the TCAR ratio is only slightly less cyclical than the DAR ratio suggests trade credit may play a role in propagating aggregate shocks.

Figure 8: Debt-at-risk and Trade Credit-at-risk Ratios

Estimated failure probabilities from benchmark model



Sources: Australian Securities and Investments Commission; Authors' calculations; Dun & Bradstreet; Morningstar

7. Conclusion

This paper uncovers the key determinants of the risk of failure among Australian companies.

First, structural company-specific factors matter – an apparently novel result in the corporate failure literature. For instance, public companies are much more likely to fail than private companies, on average, with listed companies being most vulnerable beyond about 30 years of corporate life. This is consistent with public companies taking more risk because of the greater separation of ownership and control, particularly later in life. Companies that are subsidiaries of foreign parents are also found to be much less likely to fail than standalone companies.

Second, cyclical company-level factors are also important. These factors include the 'usual suspects', such as high leverage and low profitability, with low liquidity playing a particularly important role. The cyclical factors that are correlated with failure are similar for both listed and unlisted companies. However, increases in leverage and decreases in size raise the probability of failure more for listed companies, while ageing reduces the probability of failure more for unlisted companies. Liquidity and profitability matter for all companies.

Third, aggregate conditions are the most important determinant of annual failure rates. Corporate failure is more likely during an economic downturn, even after controlling for changes over time in company-specific characteristics. Company-specific factors, in contrast, provide the information necessary to rank companies in terms of failure risk.

The potential contribution of corporate failure to financial stability risk is measured using a debt-at-risk framework. The estimates indicate that corporate debt at risk is low in aggregate and concentrated among large companies. Furthermore, our results highlight the importance of trade credit, both as a form of leverage that can influence the likelihood of corporate failure, and as a potential channel through which shocks may be propagated. While trade credit accounts for a smaller proportion of liabilities than debt for Australian businesses, its importance to financial stability is increased through its ability to transmit distress between businesses directly.

These results provide guidance as to the characteristics that should be monitored in financial stability surveillance of the non-financial corporate sector. Notably, most of these characteristics are already regularly monitored in the Reserve Bank's semiannual *Financial Stability Review*. It also provides a model that could be used to create debt-at-risk estimates and expected loss measures for Australian banks' lending to the business sector.

Appendix A: Regression Results

Table A1: Complementary Log-log Model Estimates of Failure

	Benchmark model	
	Estimated coefficient	Exponentiated coefficient
Structural characteristics		
Public	1.13*** (0.00)	3.09*** (0.00)
Public * log of age	-0.24* (0.08)	0.79* (0.08)
Public listed	-1.25*** (0.00)	0.29*** (0.00)
Public listed * log of age	0.57*** (0.00)	1.76*** (0.00)
Cyclical characteristics		
Log of age	-0.34*** (0.00)	0.71*** (0.00)
Log of assets	-0.09*** (0.00)	0.91*** (0.00)
Debt-to-assets ratio	0.76*** (0.00)	2.13*** (0.00)
Trade credit-to-assets ratio	0.73*** (0.00)	2.08*** (0.00)
Cash-to-assets ratio	-1.88*** (0.00)	0.15*** (0.00)
Return on assets	-0.07*** (0.00)	-0.93*** (0.00)
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Company random effects	No	No
Wald test (<i>p</i> -value)	0.00	0.00
Area under ROC curve	0.73	0.73
Observations	90 729	90 729
Companies	23 326	23 326
Failure observations	532	532

Notes: Standard errors are clustered by company; *p*-values are reported in parentheses; ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level, respectively

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