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Default risk and equity returns: Australian evidence

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ABSTRACT

We test whether default risk is related to equity returns using the Fama and MacBeth [Fama, E.F., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.] regression framework. The proxy we use for default risk is the default probability obtained from option-based models. Our findings show that default probability is negatively related to returns. While we find that size and book-to-market are related to default risk, the ability of these variables to explain cross-sectional variation in returns is not because they are proxying default risk. Further, our evidence suggests that the negative relationship between default probability and returns is not due to a leverage, volatility or momentum effect.

1. Introduction

The seminal work of Fama and French (1992) identified firm size and the ratio of book equity to market equity as the two variables that have the greatest ability to explain cross-sectional variation in returns. This led to the construction of the Fama and French (1993) model, where two mimicking portfolios are created, SMB and HML, to capture respectively, the return premium that small firms receive over large firms, and the return premium that high book-to-market firms receive over low book-to-market firms. One of the unresolved issues with the Fama–French model is what type of risk, if any, are captured by SMB and HML? Fama and French (1992, 1996) contend that book-to-market (B/M) is a measure of relative distress. They reason that the difference between market leverage and book leverage is a measure of relative distress and since B/M is, by definition, the difference between market leverage and book leverage, then B/M can be interpreted as a measure of relative distress. Chan and Chen (1991) find that firms with high leverage and cashflow problems, that is relatively distressed firms, seem to drive the size effect. In addition, Chan et al. (1985) show that the size effect is to some extent explained by a default factor, defined as the difference

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between high-grade and low-grade bond returns. Hence, there is evidence to suggest that the size and B/M effects occur because they are proxying default (distress) risk.

These findings raise a number of interesting research questions and lead to a number of testable hypotheses, which we explore in the current paper. First, if default risk is related to equity returns, and there is a positive risk-return relation, then there should be a positive relationship between default risk and subsequent realised returns. Second, if size and B/M are proxies for default risk, then there should be a negative relationship between size and default risk and a positive relationship between B/M and default risk.[1] Third, if size and B/M are proxying default risk, then there should be a negative (positive) relationship between size (B/M) and subsequent realised returns. Fourth, if size and B/M's ability to explain cross-sectional variation in returns occurs because they are proxying default risk, then in the presence of a superior proxy for default risk, size and B/M should lose their ability to explain cross-sectional variation in returns.

Based on these hypotheses, the key to the current study is identifying a reliable measure of default risk. In Gharghori et al. (2006b), default probabilities obtained from option-based models are identified as reliable measures of default risk. Hence, our proxy for default risk is the probability of default (DP) obtained from option-based models. The nature of the research questions we pose requires a cross-sectional analysis. Following the standard methodology, we employ the Fama and MacBeth (1973) regression approach where ex-ante measures of size, B/M, market beta and DP are regressed against subsequent realised returns for each firm in the cross-section.[2] The significance of each variable is inferred by analysing the time-series of regression coefficients on each variable.

There have been two US studies that have analysed the relationship between default risk, size and B/M, and their subsequent relationship with returns: Dichev (1998) and Vassalou and Xing (2004). The current study is one of the first to test the robustness of this finding outside the US and the first to look at this issue in Australia. One of our motivations for doing so is Lo and MacKinlay (1990) who state that empirical findings need to be examined out-of-sample to ensure that any conclusions reached are not a product of data snooping. The Australian market provides an ideal setting for assessing the external validity of the US findings. One of the reasons for this is that the Australian market has a much different structure to the US market. In particular, there is a heavy concentration of resource companies in Australia and these companies are inherently riskier than industrial firms. Additionally, although the Australian market is much smaller than the US market, it is still one of the largest equity markets in the world. The Australian stock market was ranked eighth on the basis of market capitalisation at the end of 2005 and is the largest in the Asia-Pacific region outside Japan.[3]

The other main reason why Australia is an ideal research setting is that the size and B/M effects are much stronger in Australia than they are in the US. Halliwell et al. (1999), Gaunt (2004), Chan and Faff (2005), and Gharghori et al. (2006a, 2007) have all shown that the size and B/M premiums are considerable in Australia. The premiums observed in these papers are much larger than those observed by Fama and French (1992, 1993) in the US. Hence, if the significance of size and B/M occurs because they are proxying default risk, then this is much more likely to be observed in a market such as Australia where the premiums are sizeable.

The primary aims of our paper are to identify whether DP, our proxy for default risk, is significant in explaining cross-sectional variation in returns and whether the relationship between default risk and returns is consistent with a risk-based explanation, that is, whether the relationship is positive. In addition, we wish to identify whether and if so, to what extent size and B/M are proxying for default risk.

Up to this point, our planned analysis is similar to Dichev (1998) and to the cross-sectional component of the Vassalou and Xing (2004) study. A major limitation of these studies is that they implicitly assume that their respective proxies for default risk are perfect. In contrast to these papers, we push our analysis further by decomposing our default risk proxy, DP, into its three components: leverage, volatility and past returns. The decomposition of our default risk proxy into its components will facilitate our attempt to

[1] With regard to size, smaller firms generally have more volatile cashflows and less capacity to raise external finance and one would expect that their risk of default is higher than that of larger firms. For B/M, high B/M firms are perceived by the market to have minimal growth prospects and one would expect that their risk of default is higher than that of low B/M firms.

[2] As expected returns are not observable, we use subsequent realised returns as our proxy for expected returns in the empirical analysis.

[3] The capitalisation of domestic companies listed on the ASX was $1. 1 trillion as of 31 December 2005. Source: Morgan Stanley Capital International (MSCI) World Index.

identify the actual cause of any observed relationship between DP and returns. The advantage of our proposed extended analysis is that it will allow us to draw stronger conclusions on any relationship observed between default risk and returns. By extension, we will also be able to draw stronger conclusions on whether size and B/M are proxying for default risk.

The paper proceeds as follows. Section 2 presents a brief literature review. Section 3 describes the methodology employed and discusses the data. Section 4 outlines the results and finally, Section 5 summarises and concludes.

2. Literature review

2.1. Default risk and returns

The seminal paper on the relationship between default risk and returns is Dichev (1998), who used accounting-based models to measure default risk. He finds that the relationship between default risk and returns is negative and significant in isolation and after controlling for size and B/M.[4] The observed negative relationship is inconsistent with a risk-based explanation for default.

Vassalou and Xing (2004) use the Merton (1974) model to infer default probabilities and measure default risk. Their preliminary analysis shows that their measure is successful in capturing default risk. The returns analysis they perform shows that the size and B/M effects are default effects, as both exist only in segments of the market with high default risk. They also find that there is a positive relationship between their default measure and returns. Further, their returns analysis shows that the default effect is concentrated in small and high B/M firms.

For their formal analysis, Vassalou and Xing (2004) use a variety of techniques, including Fama–MacBeth regressions and augmenting the Fama–French model with a default risk factor. Based on the findings of these tests, Vassalou and Xing (2004, abstract, p. 831) conclude that 'the Fama–French factors contain some default-related information, but this is not the main reason that the Fama–French model can explain the cross-section of equity returns.' Vassalou and Xing (2004) conduct three Fama–MacBeth regressions. In two of the regressions, the coefficient on DP is negative and significant and in the third regression, it is insignificant. These findings are inconsistent with a risk-based explanation for default. However, Vassalou and Xing (2004) conclude that default risk is systematic. This conclusion is predicated on the positive and significant factor premium observed on their default factor in their systems analysis of a default augmented Capital Asset Pricing Model (CAPM) and a default augmented Fama–French model.

The research method employed in the current paper to assess the default risk hypothesis involves a returns analysis and a Fama–MacBeth regression analysis. Gharghori et al. (2007) analyse whether the significance of the Fama–French factors occurs because they are proxying default risk. To do so, they construct a mimicking portfolio that captures the difference in returns between a portfolio of high and low default risk stocks. Similar to Vassalou and Xing (2004), they augment the CAPM and the Fama–French model with their default factor and perform system regressions on the asset pricing models. Their findings show that the Fama–French factors are not proxying default risk. Moreover, the realised and estimated factor premium on their default factor is negative, which suggests that default risk is not systematic. The major limitation of the Gharghori et al. (2007) study is that it does not formally establish the relationship between default risk and returns. Thus, a key aim of the current paper is to provide such an analysis. It is important to note that the analysis in the current paper is not a test of whether default risk is priced. To examine whether default risk is systematic, asset pricing tests that include a default risk factor need to be performed. This has already been undertaken in Australia by Gharghori et al. (2007).

2.2. Measuring default risk

The two US papers discussed above used starkly contrasting proxies to measure default risk. Dichev (1998) used accounting-based models, namely Altman's *Z*-score and Ohlson's *O*-score to measure default

[4] Dichev (1998) finds that for both his default risk proxies, Altman's (1968) *Z*-score and Ohlson's (1980) *O*-score, the relationship between default risk and returns is negative.

risk whereas Vassalou and Xing (2004) used the Merton model to measure default risk. Hillegeist et al. (2004) contrasted the ability of accounting-based models and the Merton model in capturing default risk and found that the Merton model was superior.

To the best of our knowledge, there is only one paper using Australian data that has measured the default risk of a broad cross-section of firms — Gharghori et al. (2006b). Similar to Hillegeist et al. (2004), they contrasted accounting-based and option-based models and found that option-based models were vastly superior in measuring default risk. The two option-based models employed were the Merton model and the Barrier model.[5]

The Merton (1974) model states that equity can be viewed as a European call option on the firm's assets. Thus, the market value of equity (V_E) is given by the Black and Scholes (1973) equation for a call option — a function of the market value of assets (V_A); the book value of liabilities (X) maturing at time T; the risk-free rate (r); and the standard deviation of V_A (σ_A). The observable inputs into the Black–Scholes equation are V_E, X and r, and T is set to one year. Following Vassalou and Xing (2004), Gharghori et al. (2006b) solve for V_A and σ_A, by using an iterative procedure. A firm's default probability (DP), i.e. the probability that $V_A(T)<X$, is given by:

$$\mathrm{DP} = 1 - N\left(\frac{ln(V_A/X) + \left(\mu - {}^1\!/_2\,\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right) \tag{1}$$

where μ is the estimated growth rate in the market value of assets.[6]

To assess the ability of their default measure to capture default risk, Gharghori et al. (2006b) employed Moody's Accuracy Ratio (AR). The AR measures a model's ability to correctly rank defaulted and non-defaulted firms. A perfect model would have an AR of 100% whereas a model with no discriminating ability would have an AR of 0%. Gharghori et al. (2006b) show that the AR for the DPs obtained from the Merton (Barrier) model is 72.5% (70.8%). This finding suggests that their default measure is very successful in capturing default risk.[7] Gharghori et al. (2006b) also used logistic regression to assess their default measure. In these regressions, the dichotomous dependent variable was set to unity if a firm defaults in the following year and zero otherwise. They found that the coefficient on DP in the logistic regressions (using both models) was highly significant. Moreover, DP remained significant when other variables such as leverage, volatility and size were introduced into the regression model. Thus, the findings of the logistic regressions reinforced those of the AR analysis, which led Gharghori et al. (2006b) to conclude that DPs obtained from option-based models were excellent proxies for default risk.

3. Methodology and data

3.1. Variable measurement

The complete list of variables used in our cross-sectional analysis is: (a) default probability; (b) size; (c) B/M; (d) market beta; (e) leverage; (f) volatility; and (g) past returns. A brief description of each now follows.

Gharghori et al. (2006b) demonstrated a clear superiority of option-based approaches over accounting-based approaches as measures of default risk. In addition, it was also identified that the performance of the two option-based models employed, the Merton (1974) model and the Barrier model, was quite similar. As such, we choose the DPs from the option-based approaches as our proxy for default risk. However, one issue with the DPs from the Merton model is that approximately 10% of the Merton DPs are zero. If Merton DPs were used in this study, then approximately 10% of the sample would have no cross-sectional variation in DP. On the other hand, one issue with the Barrier model DPs is that they are too high (particularly in comparison to the DPs from the Merton model). We therefore take a simple average of the DPs from the

5 Brockman and Turtle (2003) advocate the use of the Barrier model. They contend that a Barrier option, specifically, a down-and-out call option, should be used to model equity and infer default probabilities.

6 Gharghori et al. (2006b) also employed the Barrier model to estimate DPs using the methodology pioneered by Brockman and Turtle (2003).

7 Moreover, the ARs calculated by Gharghori et al. (2006b) compare very favourably with Vassalou and Xing (2004) who observe an AR of 58%.

Merton and Barrier models and use this DP as our proxy for default risk.[8] For the regression analysis, we employ the natural logarithm of DP.[9]

Size is measured by a firm's market capitalisation. For the regression analysis, consistent with Fama and French (1992), we take the natural log of size.

B/M is the ratio of book equity to market equity, where book equity is net tangible assets and market equity is market capitalisation.[10] Approximately 5% of our firm-month sample has negative book equity and, hence, negative B/M values. Vassalou and Xing (2004) exclude firms with negative book equity but Dichev (1998) does not. As Dichev (1998) includes firms with negative B/M values, this precludes him from taking the natural log of B/M, which is the common route followed (see Fama and French, 1992) in a cross-sectional study. If default risk is related to equity returns, it is likely to be driven by firms with high DPs. As firms with negative B/M ratios generally have high DPs, it is important to retain these firms in our sample to ensure that the 'true' relationship between DP and returns is established and, hence, to maximise external validity. However, the relationship between B/M and default risk (as shown in Gharghori et al., 2006b) is non-linear — it is dependent on whether B/M is positive or negative. Specifically, for positive (negative) B/M values, the relationship with default risk is positive (negative). If B/M is a proxy for default risk, and there is a positive default risk-return relation, then we expect to observe a positive (negative) relationship between positive (negative) B/M values and returns.

To account for the expected non-linear relationship, we use two interactive dummy variables, one for positive and one for negative B/M. Hence, our interaction term for positive (negative) B/M includes the positive (negative) B/M values and zeros in place of the negative (positive) B/M observations. Consistent with Fama and French (1992), we take the log of B/M. For negative B/M values, we take the log of the absolute value. Therefore, if B/M is a proxy for default risk and a positive relationship exists between default risk and returns, we expect a positive regression coefficient on both interaction terms for B/M.[11]

Market beta is estimated using the instrumental variable approach of Fama and French (1992). Specifically, we closely follow Chan and Faff (2003) who adapt the methodology to suit the Australian context and data constraints. Each month, pre-ranking betas are estimated for each firm using returns from the previous 48 months for firms that have a minimum of 24 valid monthly returns during this period. A Dimson (1979) adjustment using one lead and one lag is employed to estimate the pre-ranking betas. Then, firms are sorted into sextiles based on market capitalisation each month. Within each of the size sextiles, firms are further sorted into sextiles based on pre-ranking betas. Portfolio returns are calculated for each of the 36 size-beta sorted portfolios using individual firm returns from the sorting month. Next, portfolio betas are estimated using the time-series of returns from June 1995 to December 2003. Finally, the 36 portfolio betas are assigned to each of the firms in the respective portfolios in a given month. This process controls for the measurement error inherent in using individual beta estimates for each firm by using the portfolio beta as an instrumental variable.

Market leverage is the ratio of total liabilities to market equity. To remain consistent with Fama and French (1992), we take the natural log of leverage in the regression analysis. Volatility is the annualised standard deviation of market equity, which is estimated using daily data over the past year. Momentum is proxied by past six-month returns, which is the cumulative return over the past 5 months with a one-month lag.

Returns are realised monthly returns measured 1 month after size, B/M and leverage are measured. DP and volatility are measured over the past 12 months and market beta is measured over the past 48 months.

[8] The advantage of taking the simple average of the DPs from both models is that it allows us to simultaneously account for the 10% of Merton DPs that are zero and for the (relatively) high DPs from the Barrier model. See Gharghori et al. (2006b) for a discussion of the estimated DPs from the Merton and Barrier models.

[9] Preliminary tests indicate that natural logs are a good functional form for capturing default effects in returns. Three different transformations were applied to DP in an effort to identify the best functional form; these were a natural log transformation, an inverse normal transformation, and an inverse logistic transformation. Our unreported results indicate that the inferences made in this analysis are invariant to the transformation applied. The log transformation was chosen to remain consistent with the transformations on the other variables.

[10] Net tangible assets is equal to Total Shareholders Equity less Intangible Assets.

[11] The advantage of employing interaction terms for positive and negative B/M values is that it allows for asymmetry in the relationship between B/M and returns.

Hence, unlike Fama and French (1992), who measure the independent variables in their analysis on an annual basis, we measure our independent variables on a monthly basis.[12]

3.2. Data

Monthly share price data and market capitalisations are obtained from the CRIF database. Accounting data are obtained from Aspect Huntley. We require Net Tangible Assets for B/M and Total Liabilities for leverage. Daily share price data and market capitalisations, which are used to calculate the DPs and volatility, are obtained from SIRCA.[13] The test period is June 1995 to December 2003. As we use 48 months of prior data to calculate beta and 1 month of subsequent data to calculate next month's returns, the CRIF dataset spans June 1991 to January 2004. As one year of prior data is required to calculate the DPs and volatility, the SIRCA dataset spans July 1994 to December 2003. The average number of firms (per month) in our sample is 781 and the total number of firm-month observations is 80,456.[14]

3.3. Fama–MacBeth regressions

The regression analysis involves Fama–MacBeth regressions of subsequent realised returns on DP and a number of other variables. To simplify the exposition, consider a regression of returns on DP. In each month, from June 1995 to December 2003, we run cross-sectional regressions of next month's returns on DP and a constant. To estimate the time-series average of the cross-sectional slope coefficients we employ Weighted Least Squares (WLS).[15] The significance and sign of the average slope estimate allows us to draw inferences on the relationship between DP and returns.

The first regression is of returns on DP, size and B/M. The purpose of this regression is to test the claim that size and B/M's ability to explain cross-sectional variation in returns occurs because they are proxying default risk. If this claim is true, then a superior proxy for default risk, in our case DP, will subsume the power of size and B/M to explain cross-sectional variation in returns. Moreover, the implications for the regression analysis, if this claim is true, are that the coefficient on DP will be significantly positive and the coefficients on size and B/M will be insignificant. If this claim is false, then size and B/M will remain significant when regressed with DP.[16] The second regression is on DP, size, B/M and beta. The purpose of this regression is to ascertain whether the findings in the first regression are robust to the inclusion of beta.

The third regression is on DP, leverage, volatility and past six-month returns. Leverage, volatility and past returns are very similar to the three firm-specific inputs into the Merton (and Barrier) model: leverage, asset volatility and asset growth rate. As such, one can argue that the DPs from the Merton model are a function of these three variables. The motivation for this regression is to identify whether DP subsumes the power of these variables (of which it is a function) to explain cross-sectional variation in returns or whether these three variables subsume the power of DP to explain returns. The fourth regression is on all seven variables. The purpose of this regression is to identify which of these variables are jointly significant in explaining cross-sectional variation in returns.

3.4. Predicted relationship between DP, the other variables and returns

All of the variables used in this study, with the possible exception of market beta, have an expected relationship with DP. Positive B/M ratios, leverage and volatility are predicted to have a positive

[12] The advantage of measuring our independent variables on a monthly basis is that it allows us to draw stronger conclusions on the relationship between our independent variables and returns.

[13] Two criteria had to be met for a DP from the option-based models to be calculated. First, a firm must have traded in the month that the DP is calculated and it must have traded at least 50 times in the past year. Second, accounting data must be available so that market leverage can be calculated. After this filtering process was employed, DPs were calculated for an average of 856 firms per month. For a more detailed description of the data required to calculate the DPs, see Gharghori et al. (2006b).

[14] In June 1995 (the first month of the sample period), there are 535 firms. In December 2003 (the final month of the sample period), there are 971 firms.

[15] Each slope coefficient is weighted by the inverse of its cross-sectional standard error. The advantage of this regression technique is that it places more importance on slope estimates that are more precisely estimated in the cross-section.

[16] These predictions assume that size (B/M) has a negative (positive) relationship with returns. If there is no relationship observed, then our inference is that size and B/M are not proxying default risk.

relationship with DP. Size, negative B/M and past returns are predicted to have a negative relationship with DP. One justification for the predicted relationship between DP and the other variables is that they can all (except for beta) be considered proxies for default risk.[17] Specifically, B/M is, by construction, highly correlated with leverage. Leverage, which is the key component of DP, has a positive relationship with DP. Hence, positive (negative) B/M ratios should be positively (negatively) related to DP. For size, smaller firms generally have more volatile cashflows and less capacity to raise external finance and, hence, one expects that smaller firms will have a higher DP. DP's relationship with leverage, volatility and past returns is even clearer. All three variables are very similar to the firm-specific inputs into the Merton (and Barrier) model. Hence, by construction, DP will increase as leverage and volatility increase, and as past returns decrease.

If default risk is positively related to equity returns and all variables (except for beta) to some extent proxy default risk, then all variables (except for beta) will have a predicted relationship with returns based on default risk. Assuming a positive default risk-return relation, the predicted relationship between the variables and returns is as follows. As DP, positive B/M, leverage, and volatility increase, that is, as default risk increases, returns should increase. As size, negative B/M, and past returns increase, that is as default risk decreases, returns should decrease.

Some of the predicted relationships between returns and the variables used in this study, outlined above, are consistent with prior empirical research. Fama and French (1992) show that size is negatively related to returns and that (positive) B/M and market leverage are positively related to returns. Hence, the results for size, B/M and leverage are consistent with a default risk explanation. However, prior empirical research has shown that the relationship between returns and past returns is inconsistent with a default risk explanation. Jegadeesh and Titman (1993) document the existence of return momentum, the short-term continuation of trends in stock returns that suggests a positive relationship between past returns and (future) returns. Hence, with regard to past returns, either our findings will be consistent with a default risk explanation or they will be consistent with prior research. Research that uses direct proxies to measure default risk leads to conflicting conclusions. Dichev (1998) finds a negative relationship between default risk and returns. However, his analysis employs accounting-based measures of default that Hillegeist et al. (2004) show are inferior. In contrast, the majority of the techniques that Vassalou and Xing (2004) employ suggest a positive relationship between default risk and returns.[18] Further, Vassalou and Xing (2004) use an option-based default measure that Hillegeist et al. (2004) and Gharghori et al. (2006b) show to be superior.[19]

There are two conflicting arguments on the relationship between beta and default risk. According to the CAPM of Sharpe (1964), Lintner (1965) and Black (1972), systematic risk, as measured by beta, is the sole determinant of expected returns. If default risk is not systematic and can be diversified away, then there should be no relationship between beta and default risk. Conversely, if default risk is systematic, then it may be related to beta. Fama and French (1996) propose a human capital argument to explain why default risk could be systematic. They argue that if default risk is correlated across firms, then investors with specialised human capital in distressed firms will optimally avoid holding stocks in all distressed firms, as a negative shock to a distressed firm is more likely to lead to a negative shock to the value of human capital. This could induce a risk-premium in the expected return of all distressed stocks. Fama and French (1996) argue that default risk is orthogonal to systematic risk and that this is why SMB and HML should be included in their three-factor model. Therefore, their argument suggests that there should be no relationship between beta and default risk. Conversely, one could argue that default risk is non-

[17] The Accuracy Ratios (ARs) calculated and the logistic regressions performed in Gharghori et al. (2006b) show that all of the variables used in this analysis (except beta) explain some component of default risk. The ARs for the variables in descending order are: DP-Merton 72.5%, leverage 61.2%, B/M 53.6%, volatility 36.8%, and size 28.7%. The AR for asset growth rate, which is closely related to past returns, is 38.5%. Beta was not included in Gharghori et al.'s (2006b) analysis. The AR analysis indicates that DP is the best proxy for default risk. However, the AR analysis also shows that each of the variables (except beta) explains some component of default risk.

[18] The Fama–MacBeth regressions that Vassalou and Xing (2004) report show a negative relationship between default risk and returns.

[19] We are unaware of any published research (using the cross-sectional Fama–MacBeth framework) that investigates whether volatility is priced in equity returns.

Table 1
Summary statistics on all seven variables for decile portfolios formed using DP rankings.

		DP	Size	B/M	Beta	Vol	Lev	Past Rets
Low	1	0.04	754	0.382	0.739	54.6	0.173	28.9
	2	0.25	618	0.524	0.741	57.1	0.234	15.0
	3	0.74	611	0.602	0.757	60.6	0.299	9.5
	4	1.63	553	0.667	0.771	63.2	0.359	3.7
	5	3.19	598	0.715	0.779	66.2	0.442	0.5
	6	5.90	623	0.773	0.778	68.4	0.567	−2.8
	7	10.64	570	0.841	0.779	71.7	0.689	−6.2
	8	19.07	378	0.937	0.780	77.6	0.897	−11.4
	9	34.49	220	1.055	0.785	88.9	1.313	−16.6
High	10	68.05	82	2.530	0.790	116.1	7.001	−32.2

This table presents summary statistics on the seven independent variables in the analysis. Each month, from June 1995 to December 2003, firms are sorted into ten portfolios based on their DP ranking. The equally-weighted average of all seven variables is calculated for the ten portfolios. The values presented in the table are the time-series average of the monthly portfolios. DP, Vol and Past Rets are reported as percentages and Size is reported in millions of dollars.

diversifiable but is a component of systematic risk. In this instance, we would expect a positive relationship between beta and default risk.

4. Results

4.1. Preliminaries

To analyse the relationship between DP and the other seven variables, we place firms into deciles, based on their DP ranking, in each month of our sample. Each month, we calculate the equally-weighted average of all seven variables (including DP) for the ten portfolios. Table 1 shows the time-series average of the portfolios for each of the variables.

It is clear from Table 1 that the relationship between DP and the other variables is consistent with the predictions in Section 3.4. For B/M, volatility and leverage, there is a monotonic increase in these variables as DP increases. For past six-month returns, there is a monotonic decrease in past returns as DP increases.

Table 2
Correlation matrix for the transformed variables.

	DP	Size	B/M+	B/M−	Beta	Vol	Lev
Panel A: full sample							
Size	−0.344						
B/M+	0.369	−0.209					
B/M−	−0.030	−0.050	−0.093				
Beta	0.074	−0.160	−0.063	0.000 [a]			
Vol	0.312	−0.628	0.027	−0.013 [a]	0.243		
Lev	0.501	0.182	0.268	−0.059	−0.156	−0.228	
Past Rets	−0.441	0.190	−0.228	−0.008 [a]	−0.039	−0.122	−0.115
Panel B: negative B/M sample							
Size	−0.626						
B/M+	–	–					
B/M−	0.357	−0.283	–				
Beta	0.129	−0.122	–	0.092			
Vol	0.602	−0.723	–	0.277	0.219		
Lev	0.521	−0.236	–	0.579	0.042	0.209	
Past Rets	−0.397	0.240	–	−0.165	−0.059	−0.211	−0.188

This table reports the time-series average of monthly cross-sectional correlations between all seven variables, covering the period June 1995 to December 2003. The variables used to construct the matrix are the transformed variables used for the regression analysis. Panel A presents the correlations for the entire sample. Panel B presents the correlations for cases where B/M is negative.

[a] Indicates *not* significant at the 5% level.

Table 3
Returns on decile portfolios formed using rankings on each of the seven variables.

		DP	Size	B/M	Beta	Vol	Lev	Past Rets
Low	1	0.69	2.63	−0.85	1.29	1.05	−1.24	−1.71
	2	0.31	−0.79	−0.74	0.42	0.93	−0.86	−1.21
	3	−0.10	−1.40	−0.57	0.57	0.81	0.04	−0.76
	4	−0.01	−1.35	−0.25	0.56	0.54	−0.25	−0.18
	5	0.05	−0.75	−0.16	−0.42	0.03	0.19	0.13
	6	0.16	−0.32	0.26	−0.57	−0.46	0.33	0.45
	7	0.06	0.03	0.10	−0.31	−0.58	0.29	0.73
	8	−0.83	0.40	0.15	0.19	−1.03	0.55	0.72
	9	−0.70	0.38	0.80	−1.66	−0.70	0.11	0.97
High	10	−0.35	0.51	0.87	−0.76	−1.20	0.23	0.20
Hi − lo	10 − 1	−1.03	−2.12	1.71*	−2.04*	−2.25	1.47*	1.91
		(−1.31)	(−1.60)	(3.53)	(−3.75)	(−1.76)	(2.18)	(1.89)
	B/M−			−0.27				

This table reports monthly returns on decile portfolios formed using rankings on each of the seven variables. Each month, from June 1995 to December 2003, the equally-weighted (next month) return is calculated for each portfolio. The returns reported in the table are the time-series average of the monthly portfolio returns. The 10 − 1 portfolio is the difference in returns between the highest decile (10) and the lowest decile (1). The *t*-statistic for this portfolio is reported in parentheses directly below the return and is calculated from Newey and West (1987) standard errors. *Indicates significant at the 5% level. For B/M, positive B/M values are sorted into ten portfolios and negative B/M values are placed into a separate portfolio whose return is reported at the bottom of the table.

There is a clear decrease in size as DP increases but the relationship is not monotonic. With beta, there is a weak upward trend in beta as DP increases.

To further investigate the relationship between all seven variables, we produce a correlation matrix. The variables used to produce the correlations, unlike those used in Table 1, are the transformed variables used for the regression analysis. Specifically, DP, size, leverage, B/M+ and B/M− are the natural logs of the underlying raw variables. The correlation matrix for the variables is produced each month. Panel A of Table 2 presents the time-series average of the monthly correlations.

The correlation between DP and the other independent variables is consistent with Table 1 and with our predictions. DP is positively correlated with positive B/M (36.9%), volatility (31.2%) and leverage (50.1%), and negatively correlated with size (−34.4%) and past returns (−44.1%). There is a weak positive correlation between DP and beta (7.4%). DP's correlation with the three variables of which it is a function are all sizeable and as expected, the highest correlation is with leverage (which is the key component of DP). However, the correlation between DP and both size and positive B/M is quite high as well.[20]

To analyse the relationship between (next month's) returns and the seven variables chosen for this study, we place firms into deciles, based on separate rankings on each of the seven variables, in each month of our sample. Each month, we calculate the equally-weighted average return for the decile portfolios formed by ranking on each of the seven variables. Table 3 shows the time-series average of returns for the decile portfolios formed by ranking on each of the variables, in turn.[21]

There is a general downward trend in returns as DP increases. This is inconsistent with a risk-based explanation for DP. However, the difference in returns between decile 10 (high DP firms) and decile 1 (low DP firms) although negative is not statistically significant. The size effect is non-linear. Specifically, if the smallest size decile is excluded, then there is a positive relationship between size and returns. However, the smallest size decile has the largest monthly return (2.63%) of all 71 portfolios formed. For positive B/M, there is an almost monotonic increase in returns as B/M increases and the difference in returns between decile 10 and decile 1 is statistically significant, which is consistent with a risk-based explanation for B/M.

[20] In Panel A, the correlation between negative B/M and all the other variables is relatively low. This is to be expected as only 5% of the sample has negative B/M values. Panel B shows the correlation matrix for cases where B/M is negative. The correlations between the negative B/M term and the other variables are much higher and they are comparable (in magnitude) with the correlations between the other variables (excluding negative B/M) in Panel A.

[21] For B/M, we place positive B/M firms into ten portfolios based on their B/M rankings and negative B/M firms into a separate 11th portfolio.

For beta, there is a negative relationship with returns and the difference in returns for the extreme portfolios is significant. There is a positive relationship between leverage and returns, which is consistent with a risk-based explanation, but the relationship is not as strong as the relationship between B/M and returns. Nevertheless, the difference in returns between the high and low portfolios is significantly positive. The relationship between past returns and (next month's) returns indicates the existence of momentum as there is an almost monotonic increase in returns as past returns increase. Finally, there is an almost monotonic decrease in returns as volatility increases. However, for both past returns and volatility, the difference in returns between the high and low portfolios although large in magnitude is not significant at the 5% level.

The negative relationship between volatility and returns, and the positive relationship between past returns and (next month's) returns are the likely causes of the negative relationship between DP and returns. Recall that the relationship between leverage and returns is positive. The positive correlation between leverage and DP, and the positive relationship between leverage and returns indicate that the relationship between DP and returns should be positive. However, leverage is not the only variable of which DP is a function, DP is also a function of volatility and past returns. Hence, the positive correlation between volatility and DP, and the negative relationship between volatility and returns indicate that the negative relationship between DP and returns is in part due to volatility. Similarly, the negative correlation between past returns and DP, and the positive relationship between past returns and (next month's) returns suggest that the existence of momentum is in part responsible for the negative relationship between DP and returns.

One of the main aims of this paper is to test whether size and B/M are proxying default risk. In order to achieve this aim, it is important to establish the relationship between DP and both size and B/M, and their subsequent relationship with returns. By dual sorting on size and DP (and B/M and DP), one can more clearly establish the relationship of both variables with returns. In order to analyse the size effect after controlling for DP, the following set of portfolios are produced. Each month, firms are sorted into quintiles based on their DP. The firms in each of these quintiles are then further sorted into five quintiles based on size resulting in 25 portfolios being produced. The equally-weighted returns on each of the 25 portfolios are calculated and Panel A of Table 4 shows the time-series average of the monthly returns on these 25 portfolios. Panel A of Table 4 allows us to analyse the effect of size on returns after controlling for DP. Counterpart results are produced in Panels B, C and D to analyse respectively, the default effect after controlling for size, the B/M effect after controlling for DP, and the default effect after controlling for B/M.[22]

Panel A shows that the size effect is to some extent conditional on DP. The monthly return on small minus big firms increases from −1.38% for the lowest DP quintile to 4.7% for the highest DP quintile. In addition, for medium to high DP firms, quintiles 3, 4 and 5, the difference in returns between small and big firms are 0.94% pm, 1.46% pm and 4.7% pm, respectively. For low DP firms, quintiles 1 and 2, the return premiums are −1.38% pm and −0.71% pm, respectively. This suggests that the routinely observed return premium on small firms only exists for medium to high DP firms whereas for low DP firms, there is a return premium for large firms. However, only the difference in returns between small and big firms for the highest DP firms (quintile 5) is statistically significant. This is an interesting finding as it indicates that the commonly observed size effect only exists in firms that have high default risk. Further, it suggests that the size effect is, in part, related to default risk.

Panel B shows that the default effect is conditional on size. For the smallest size quintile, the return on the high minus low DP quintile is 1.92% pm and is statistically significant. For all other size quintiles, the returns on the high minus low DP quintiles are negative and the return differential is significant for quintiles 3 to 5 (returns range from −0.93% pm for quintile 2 to −2.54% pm for quintile 4). Hence, our findings indicate that default risk is rewarded with higher returns but only for small firms. Medium and large firms, on the other hand, have a negative relationship between DP and returns. In Australia, on average approximately 0.5% of firms default each year. Gharghori et al. (2006b) show that there is a strong negative relationship between firm size and subsequent default. Thus, it is not surprising that default risk is only rewarded with higher returns in small firms as it is generally smaller firms that default and only a

[22] Panels C and D were produced using all B/M values and only positive B/M values. As the findings were qualitatively similar, we only report the results using all B/M values.

Table 4
Returns on dual sorted portfolios formed using DP and size (B/M) rankings.

Panel A: Size effect controlled by DP

		Small				Big	Sm − bg	
		1	2	3	4	5		
Low DP	1	−0.46	−0.06	0.61	1.38	0.92	−1.38	(−1.60)
	2	−0.32	−0.86	0.04	0.48	0.38	−0.71	(−0.71)
	3	1.17	−0.75	−0.52	0.41	0.23	0.94	(0.79)
	4	1.09	−1.06	−0.95	−0.63	−0.36	1.46	(1.35)
High DP	5	3.40	−0.81	−1.94	−1.72	−1.30	4.70*	(4.64)
Whole		0.91	−1.36	−0.56	0.22	0.45	0.47	(0.46)

Panel B: Default effect controlled by size

		Low DP				High DP	Hi − lo	
		1	2	3	4	5		
Small	1	−0.45	1.43	1.23	0.76	1.48	1.92*	(2.44)
	2	−1.13	−1.03	−1.15	−1.34	−2.06	−0.93	(−1.38)
	3	−0.04	−0.13	−0.25	−0.64	−1.71	−1.67*	(−2.63)
	4	1.21	0.72	0.21	0.32	−1.33	−2.54*	(−4.09)
Big	5	1.29	0.98	0.27	0.24	−0.50	−1.79*	(−3.30)
Whole		0.49	−0.05	0.11	−0.38	−0.49	−0.98	(−1.42)

Panel C: B/M effect controlled by DP

		Low B/M				High B/M	Hi − lo	
		1	2	3	4	5		
Low DP	1	0.05	0.33	0.82	0.58	0.67	0.62	(1.04)
	2	−0.73	−0.76	−0.05	0.33	0.99	1.71*	(3.15)
	3	−0.75	−0.50	0.15	0.17	1.38	2.13*	(4.29)
	4	−1.85	−1.16	−0.35	0.42	1.07	2.92*	(5.33)
High DP	5	−1.11	−0.93	−0.89	−0.48	1.01	2.12*	(2.90)
Whole		−0.74	−0.52	−0.03	0.13	0.83	1.57*	(3.86)

Panel D: Default effect controlled by B/M

		Low DP				High DP	Hi − lo	
		1	2	3	4	5		
Low B/M	1	0.28	−0.63	−0.54	−1.47	−1.27	−1.55	(−1.71)
	2	0.94	−0.31	−0.75	−0.91	−1.43	−2.37*	(−3.19)
	3	0.76	0.12	0.16	−0.48	−0.68	−1.43*	(−2.04)
	4	0.57	0.25	0.17	0.41	−0.66	−1.23	(−1.42)
High B/M	5	1.20	1.59	1.04	−0.05	0.51	−0.69	(−0.79)
Whole		0.49	−0.05	0.11	−0.38	−0.49	−0.98	(−1.42)

This table reports monthly returns for dual sorted portfolios formed using DP and size (B/M) rankings. In Panel A, each month, from June 1995 to December 2003, firms are sorted into five portfolios based on their DP. Within each portfolio, firms are then sorted into five portfolios based on their market capitalisation (size). The equally-weighted (next month) return is calculated for each of the 25 portfolios. The returns reported in the table are the time-series average of the monthly portfolio returns. The small − big (sm − bg) portfolio is the difference in returns between the smallest size quintile (1) and the largest size quintile (5). The *t*-statistic for this portfolio is reported in parentheses to the right of the portfolio return and is calculated from Newey and West (1987) standard errors. Panels B, C and D are produced in the same way. In Panel B, firms are first sorted by size and then by DP. In Panel C (D), firms are first sorted by DP (B/M) and then by B/M (DP). *Indicates significant at the 5% level.

small proportion of firms actually default each year. In aggregate, our analysis suggests that default risk is not rewarded with higher returns. However, we find that amongst the smallest firms, whose likelihood of defaulting is highest, there is a default premium. Thus, the default effect is related to firm size.

In Panel C, the return difference between high and low B/M firms increases from 0.62% pm for quintile 1 (low DP) to 2.92% for quintile 4 and falls slightly to 2.12% pm for quintile 5 (high DP). The return differential is significant for quintiles 2 to 4. Thus, the B/M effect becomes stronger as DP increases indicating that the magnitude of the B/M effect is conditional on DP. In Panel D, there is an upward trend in the return differential between high and low DP quintiles as B/M increases. This suggests that the magnitude of the

Table 5
Fama–MacBeth regressions of returns on the group of variables specified.

	Const	DP	Size	B/M+	B/M−	Beta	Lev	Vol	Past Rets
DP, Size, B/M	−0.0261	−0.0025*	0.0009	0.0073*	0.0028*				
	(−1.01)	(−4.64)	(0.71)	(6.59)	(2.58)				
DP, Size, B/M, Beta	0.0061	−0.0024*	0.0004	0.0066*	0.0024*	−0.0269*			
	(0.26)	(−4.59)	(0.33)	(6.20)	(2.24)	(−5.11)			
DP, Lev, Vol, Past Rets	0.0090*	−0.0012*					0.0031*	−0.0124*	0.0139*
	(2.47)	(−2.42)					(3.34)	(−2.77)	(3.26)
All	0.0872*	−0.0024*	−0.0035*	0.0049*	0.0025*	−0.0180*	0.0034*	−0.0171*	0.0158*
	(5.89)	(−5.95)	(−4.69)	(5.86)	(2.49)	(−4.24)	(4.14)	(−4.41)	(3.78)

This table reports average Fama–MacBeth regression estimates using individual firm data for all months of our sample period — June 1995 to December 2003. In each month, a cross-sectional regression is estimated using OLS adjusted for White's (1980) heteroskedasticity-consistent covariance matrix, wherein next month's return is regressed on the group of variables specified. The values reported in the table are the average time-series slope estimates, which are obtained using Weighted Least Squares. The monthly slope estimates are weighted by the inverse of their standard error thereby giving more importance to slope estimates that are more precisely estimated. The associated *t*-statistics are reported in parentheses directly under the relevant mean estimate. *Indicates significant at the 5% level.

default effect is conditional on B/M. Specifically, the returns on high minus low DP quintiles are negative and become less negative from quintile 2 (−2.37% pm) to quintile 5 (−0.69% pm). The return difference is significant for quintiles 2 and 3.

4.2. Fama–MacBeth regressions

To gain an initial perspective, we ran simple Fama–MacBeth regressions on each of the seven variables against returns. Unreported findings show that the average coefficient estimates are significantly negative for DP, beta and volatility and significantly positive for B/M, leverage and past returns. The average coefficient estimate on size is insignificant but this is not surprising as the returns analysis in Table 3 shows that the size effect is non-linear. Thus, the Fama–MacBeth regressions for each variable in isolation are consistent with the returns analysis and show that there is a negative relationship between returns and DP, beta and volatility and a positive relationship between returns and B/M, leverage and past returns.

Table 5 presents the output for the four Fama–MacBeth regressions foreshadowed earlier. The first is a regression of returns on DP, size and B/M. The coefficient on DP is negative, the coefficient on both B/M interaction terms are positive and size is insignificant. If default risk is rewarded with higher returns, and size and B/M are proxying default risk, then we should observe significantly positive coefficients on size and B/M when these variables are regressed against returns in isolation. Our unreported findings show that this is the case with B/M but not with size. This suggests that size is not proxying default risk. If the component of returns that B/M explains is due to default risk, then in the presence of a superior proxy for default risk, DP, B/M should lose its ability to explain cross-sectional variation in returns. Hence, B/M should go from being significant when regressed in isolation to insignificant when regressed in a multiple variable model with DP. This has not occurred, as B/M remains significant when regressed with DP. Therefore, our results suggest that B/M is not proxying default risk. To assess the robustness of these findings, we re-ran the regression and included beta. The significance and sign on the coefficient estimates for DP, size and B/M have not changed and the coefficient estimate on beta is significantly negative.[23] Thus, our inference on the relationship between default risk and returns and whether size and B/M are proxying default risk is robust to the inclusion of market beta.

The third regression is on DP, leverage, volatility and past returns. The coefficient estimates are significantly negative for DP and volatility and significantly positive for leverage and past returns. Thus, the relationships observed are consistent with the returns analysis and with the simple Fama–MacBeth regressions (i.e. each variable in isolation). In the preliminary analysis, it was identified that the negative relationship between DP and returns could be due to a volatility or momentum effect. Although the coefficient on DP is smaller in magnitude and the *t*-statistic is lower compared to the earlier regressions,

[23] All Fama–MacBeth regressions that include beta were re-run using individual beta estimates as opposed to the portfolio betas assigned to each firm. The results are robust to the use of individual betas.

the coefficient on DP remains significantly negative when regressed with both volatility and past returns. Thus, we cannot conclude that the DP effect is driven by a volatility or momentum effect.

The final regression includes all variables — notably, in each case we find a significant role in explaining returns. DP, size, beta and volatility all have negative coefficients whereas both B/M variables, leverage and past returns have positive coefficients. The sign of the coefficients on the variables (with the exception of size, which was insignificant when regressed in isolation) is consistent with the findings of the returns analysis and the regressions of each variable in isolation. Thus, the relationships between each variable and returns reported earlier (except for size) are robust to the inclusion of the other variables. The inference on size is that after controlling for the other six variables, there is a negative relation between size and returns.

5. Summary and conclusions

Fama and French (1992, 1996) contend that size and B/M's ability to explain cross-sectional variation in equity returns occurs because they are proxying default risk. The primary aim of the current paper is to test this contention. However, prior to testing whether size and B/M are proxying for default risk, we must first establish whether default risk is related to equity returns. Hence, our complementary aim is to examine the relationship between default risk and returns. The default risk proxy we employ for this study is the default probability derived from two option-based models, the Merton (1974) model and the Barrier model (Brockman and Turtle, 2003). There are two stages of testing we perform to assess the default risk hypothesis of Fama and French (1992, 1996). The first is a returns analysis of characteristic sorted portfolios. The second is Fama–MacBeth regressions of returns on the variables chosen for this study. The combined import of our analysis leads to two key findings: (1) default risk is negatively related to returns; and (2) size and B/M are not proxying for default risk. However, while we find that size is not proxying default risk, we do document some interesting interrelationships between these two variables. First, we show that the commonly observed size effect only exists in firms with high default risk. Second, although we find in aggregate that default risk is negatively related to stock returns, we also show that for small firms, there is a default premium.

To further investigate the observed negative relationship between default risk and returns, we decompose our default risk proxy, default probability, into its three components: leverage, volatility and past returns. Our initial correlation and returns analysis suggests that the negative relationship between default probability and returns could be, in part, due to a volatility or momentum effect. However, the Fama–MacBeth regression analysis does not confirm this contention — none of the underlying components seems to be driving the negative returns–default risk relationship.

The findings on the relation between default risk and returns and whether size and B/M are proxying default risk are consistent with a counterpart Australian study by Gharghori et al. (2007) and are broadly consistent with a US study by Dichev (1998). However, the conclusions drawn on this issue in Australia are inconsistent with those of Vassalou and Xing's (2004) research in the US, particularly with regard to the relationship between default risk and returns and the systematic nature of default risk. As such, further research is warranted in different markets to obtain more evidence on the default risk hypothesis.

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