

Effect of IFRS adoption on financial reporting quality: Evidence from bankruptcy prediction

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Structured Abstract:

Purpose: The purpose of this paper is to investigate whether IFRS-based data improve bankruptcy prediction over Australian GAAP-based data. In doing so, we focus on intangibles because conservative accounting rules for intangibles under IFRS required managers to write off substantial amounts of intangibles previously capitalized and revalued upwards under Australian GAAP (AGAAP). Our focus on intangibles is also motivated by empirical evidence that financially distressed firms are more likely to voluntarily capitalize and make upward revaluations of intangibles compared with healthy firms.

Design: We analyze a sample of 46 bankrupt firms and 46 non-bankrupt (healthy) firms using a matched-pair design over the period 1991 to 2004. We match control firms on fiscal year, size (total assets), GICS-based industry membership, and principal activities. Using Altman's (1968) model, we compare the bankruptcy prediction results between bankrupt and non-bankrupt firms for up to five years before bankruptcy. In our tests, we use financial statements as reported under AGAAP and two IFRS-based datasets. Our IFRS-based datasets are created by considering the adjustments on the AGAAP data required to implement the requirements of *IAS 38*, *IFRS 3* and *IAS 36*.

Findings: We find that, under IFRS, Altman's (1968) model consistently predicts bankruptcy for bankrupt firms more accurately than under AGAAP for all of the five years prior to bankruptcy. This greater prediction accuracy emanates from smaller values of the inputs to Altman's model due to conservative accounting rules for intangibles under IFRS. However, this greater accuracy in bankruptcy prediction comes with larger Type II errors for healthy firms. Overall, our results provide evidence that the switch from AGAAP to IFRS improves the quality of information contained in the financial statements for predicting bankruptcy.

Research limitations/implications: Small sample size may limit the generalizability of our findings.

Originality/value: Although bankruptcy prediction is one of the primary uses of accounting information, the burgeoning literature on the benefits of IFRS adoption has so far neglected the role of IFRS data in bankruptcy prediction. Thus, we document a new benefit of IFRS adoption. In this paper, we demonstrate how the restrictions on the ability to capitalize and revalue intangibles enhance the quality of information used to predict bankruptcy. These results provide evidence to international standard setters of what they can expect if their efforts to remove non-restrictive accounting practices for intangibles are abandoned.

Keywords: bankruptcy prediction, intangibles, IFRS, financial reporting quality

Article Classification: Research paper

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1. Introduction

This paper examines the effect of International Financial Reporting Standards (IFRS) on the quality of financial statements data from a bankruptcy perspective. In particular, we examine whether the changes in rules for intangibles due to the switch from Australian GAAP (AGAAP) to IFRS improve bankruptcy prediction. Key inputs to bankruptcy prediction models come from financial statements. Thus, any improvement in bankruptcy prediction when prediction models are held constant can be attributed to the accounting standards that generated the financial statements. Specifically, the rules for intangibles under IFRS appear to be more conservative and restrictive compared to those under AGAAP (more discussed in Section 2.2). For example, some forty billion dollars of intangible assets were expected to be written off from Australian balance sheets with the adoption of IFRS in Australia (Tabakoff, 1999). We are interested to know whether this greater conservatism in accounting for intangibles leads to improved bankruptcy prediction.

We use the Australian setting because Australia is one of the earliest adopters of IFRS.¹ Our motivation to investigate whether IFRS-based data improves bankruptcy prediction is twofold. First, bankruptcy prediction is one of the primary uses of accounting information (Beaver, 1966, Beaver *et al.*, 2005). Second, as of 1 October 2014, about 128 jurisdictions/countries have adopted or converged to IFRS (Deloitte IAS *Plus*, 2014), but the burgeoning literature on IFRS adoption has so far neglected the utility of IFRS-based data in predicting bankruptcy. Due to the unique and “soft” nature of intangibles (discussed in Section 2), managers of financially distressed firms tend to capitalize and revalue intangibles upward leading to overstated assets and earnings (Jones, 2011). Thus, the discretionary nature of intangibles plays a crucial role in masking and detecting bankruptcy.

A related study on intangibles using the Australian setting is Jones (2011). A fundamental difference between this study and Jones (2011) is that, we examine the effect of switching to more restrictive IFRS rules for intangibles on the quality of accounting information. Jones (2011) focuses on accounting choice and debt contracting literature to examine whether managerial opportunism is the primary motivator for voluntary capitalization of intangibles in

¹ Along with the European Union, Australia adopted IFRS on 1 January 2005.

failing firms. By contrast, we employ Altman's (1968) model to three alternative datasets to measure whether financial statements reported under IFRS are of higher quality compared to that under AGAAP. Because we hold Altman's model constant across three datasets, any improvement in bankruptcy prediction under IFRS can be attributed to the corresponding dataset.

We identified a sample of 46 firms that were delisted from the Australian Securities Exchange (ASX) over the period 1996-2004,² which represents the 'AGAAP' period. We chose this period because 1996 represents the year in which *AASB 1013 Accounting for Goodwill* was last amended, and 2004 is the final year prior to the adoption of IFRS in Australia. We matched each bankrupt firm in our sample with a control firm that did not face bankruptcy within the sample period. We adopted a four-way matching strategy. We matched control firms first by fiscal year-end, second by total assets, third by GICS-based industry classification, and finally by principal activities (sources of sales revenue). We employed both multivariate and univariate tests to address our research question.

We find that, under IFRS, Altman's (1968) model consistently predicts bankruptcy more accurately than under AGAAP for all of the five years prior to bankruptcy. Specifically, the bankruptcy prediction accuracy rate for bankrupt firms ranged from 76.9% (two years prior to bankruptcy) to 94.4% (one year prior to bankruptcy) for IFRS data compared with 72.5% to 86.1% for AGAAP data, respectively. The systematic change that occurs in the way Altman's (1968) model classifies some firms as bankrupt or non-bankrupt suggests that the absence of intangibles from balance sheets results in greater transparency and reliability of the financial reporting data. The differences in the *Z-scores* and individual ratios for both bankrupt and non-bankrupt firms support these results. Overall, our results provide evidence that the switch from AGAAP to IFRS improves the quality of information contained in the financial statements for predicting bankruptcy. Our results challenge the view of Beaver *et al.* (2012) that unrecognized intangibles impair the quality of financial statement data.

Our study makes three contributions to the literature. First, we document a new benefit of IFRS adoption. The burgeoning literature on the merits of IFRS adoption has so far neglected the role of IFRS data in bankruptcy prediction. In this paper, we demonstrate how the restrictions on

² However, our analysis runs from 1991 to 2004 because we follow each bankrupt firm up to five years prior to bankruptcy (discussed further in Section 4.6).

the ability to capitalize intangibles, especially by managers of firms facing bankruptcy, enhances the quality of information used to predict bankruptcy. Second, to the best of our knowledge, no one has tested the efficacy of the most revered bankruptcy prediction model (i.e., Altman's (1968) model) on IFRS-based data. Third, our findings provide important insight for the global debate on whether to remove discretionary capitalization of intangibles from accounting standards.

The remainder of the paper is organized as follows. Section 2 discusses the regulatory setting for this paper. The hypothesis is developed in Section 3. Section 4 discusses the research models, sample selection and data. Section 5 discusses the empirical results. Section 6 presents the summary and conclusions of the paper.

2. Background

2.1 Nature of intangibles

Intangibles differ from other financial statement items on several dimensions, including how they are acquired, their life span, liquidity, and identification. For example, unlike most assets which are acquired through market transactions, intangibles can be generated internally (e.g., goodwill). Intangibles can have indefinite (e.g., goodwill) or definite life spans (e.g., patents, copyrights). Many intangible items lack any organized liquid markets leading to unobservable price. Finally, while most intangibles can be separated from the business, goodwill cannot be separated from the business. Thus, due to their unique characteristics, accounting for intangibles has been subject to controversies.

Regulators and accounting researchers claim that managers of financially distressed firms engage in creative reporting practices for intangibles within the bounds of AGAAP to camouflage their declining poor performance (Margret, 2005, Clarke and Dean, 2001, ASIC, 1998). Moreover, prior to the switch from AGAAP to IFRS in 2005, many had expressed concerns that the application of *International Accounting Standards (IAS) 38, IFRS 3, and IAS 36* would potentially reshape ASX-listed firms' financial statements by significant amounts (Chalmers and Godfrey, 2006, Finch, 2005, Dagwell *et al.*, 2007). In particular, many believed that restricting the capitalization of intangibles and goodwill would result in many firms writing off billions of dollars of value from their balance sheets (Tabakoff, 1999, West, 2004). Others

suggested that limiting managements' choices to record intangibles as assets tends to reduce, rather than improve, the quality of the balance sheet and investors' information set (Wyatt, 2005).

2.2 Key differences between AGAAP and IFRS about intangibles

The accounting standards that mainly guided the recognition, disclosure and measurement subsequent to recognition of intangibles under AGAAP were *AASB 1013 Accounting for Goodwill*, *AASB 1011 Accounting for Research and Development*, *AASB1010 Revaluation of Non-current Assets* (replaced by *AASB 1041 Revaluation of Non-current Assets*), *AASB 1015 Acquisition of Assets*, and *AASB 1021 Depreciation*. On the other hand, the relevant accounting standards for intangibles under IFRS are *IAS 36 Impairment of Assets*, *IAS 38 Intangible Assets*, and *IFRS 3 Business Combinations*.

Key differences for intangibles between AGAAP and IFRS can be summarised under three broad categories: purchased goodwill, acquired identifiable intangible assets, and internally generated identifiable intangible assets. Under AGAAP, purchased goodwill could be amortized on a straight-line basis over a maximum period of 20 years (*AASB 1013*). In contrast, under IFRS, purchased goodwill cannot be amortized but is subject to impairment test every reporting year (*IAS 36*). For acquired identifiable intangible assets, under AGAAP, both research and development costs could be capitalized if future economic benefits could be expected beyond reasonable doubt (*AASB 1011*). On the other hand, under IFRS, research expenditures must be expensed as they are incurred (*IAS 38*) and intangible assets with indefinite useful lives are subject to annual impairment test (*IAS 38*). Under AGAAP, brands, mastheads, publishing titles, and customer lists were allowed to be capitalized if future economic benefits were expected to be recoverable beyond reasonable doubt (*AASB SAC 4*). In contrast, brands, mastheads, publishing titles and customer lists cannot be capitalized at all under IFRS. In sum, IFRS rules for intangibles are a lot more restrictive than AGAAP rules. Hence, a switch from AGAAP to IFRS will lead to a reduction in the types of intangibles that can be capitalized and the amounts at which they can be capitalized. Table 1 provides a summary of the key differences in accounting for intangibles between AGAAP and IFRS.

[INSERT TABLE 1 APPROXIMATELY HERE].

3. Prior research and hypothesis

Most bankruptcy prediction studies come from the US, and thus principally focus on US data. This has drawn criticism from others, because the US studies fail to consider discretionary accounting methods for intangibles in regulatory environments other than the US (Percy & Stokes, 1992). In the Australian context, Monem (2011) suggests that bankrupt firms are more likely to overstate assets and earnings via discretionary capitalization and upward revaluation of intangibles. Moreover, several empirical studies document that managers in failing or troubled firms engage in fraudulent financial reporting practices to conceal their distress (Schwartz, 1982, Sharma and Stevenson, 1997, Rosner, 2003, Sharma, 1999, Persons, 1995, Rezaee, 2005). Specifically, Jones (2011) finds compelling evidence of failing firm managers' propensity to voluntarily capitalize intangibles, which is significantly associated with earnings management proxies. Moreover, failing firms capitalize intangibles more aggressively than non-failing firms, particularly over the five-year period leading up to firm failure.

This paper contributes to the IFRS adoption literature by demonstrating the role of conservative accounting rules for intangibles under IFRS in predicting bankruptcy. We argue that, prior to the switch to IFRS in 2005, financially-distressed Australian firms were likely to exploit the flexibility and discretion within AGAAP to mask their real performance and financial position. In particular, the opportunity to capitalize research and development costs, capitalize and subsequently amortize purchased goodwill, and capitalize internally generated intangibles gave financially-distressed firms enormous latitude in masking their financial distress until bankruptcy became inevitable. Hence, the removal of the opportunity to capitalize research, internally generated intangible assets, subsequent revaluation of these intangibles and the requirement to undertake annual impairment testing of purchased goodwill significantly reduced managers' ability to overstate assets and overstate earnings. In sum, the real financial performance and financial position of financially-distressed firms would be revealed much sooner under IFRS than under AGAAP. In turn, bankruptcy prediction models are likely to perform much better under IFRS than under AGAAP. Thus, we hypothesize the following:

H1: The prediction of bankruptcy improves under IFRS compared to that under AGAAP.

4. Research design

4.1 Design overview

To test H1, we employ Altman's (1968) multiple discriminant analysis (MDA) model on three sets of financial statements data: a dataset based on AGAAP as reported by sample firms, and two researcher-created datasets where AGAAP data were adjusted to mimic IFRS data *as-if* IFRS rules for identifiable and unidentifiable intangibles had been applied retrospectively (discussed in Section 4.3). This permits us to compare the ability of accounting information in predicting bankruptcy using non-restrictive recognition rules for intangibles under AGAAP with the more restrictive rules under the IFRS. We test H1 firstly by showing how accurately Altman model classifies 'bankrupt', 'grey/undecided', or 'non-bankrupt' firms, secondly by testing model robustness and thirdly, by identifying the sources of improvement in bankruptcy prediction.

4.2 The model

We employ Altman's (1968) MDA model on the three datasets as described in Section 4.3 and interpret its predictive power as a measure of the quality of IFRS. We use Altman's (1968) model rather than the hazard model (Beaver *et al.*, 2012, Beaver *et al.*, 2005) or the logit model (Franzen *et al.*, 2007, Jones, 2011) because it is still the most widely used bankruptcy prediction model in the accounting literature. It has been widely recommended as an auditing analytical tool in the formation of a going concern opinion (Constable and Woodliff, 1994), and as an assessment tool of a firm's credit worthiness by lending institutions (Altman, 1968, Altman *et al.*, 1977). It has been successfully applied to many different regulatory environments (Altman, 1984) and across diverse industries, such as hospitals (Almwajeh, 2004, Jennings, 2005), service industries (Hanson, 2003) and airlines (Kroeze, 2005).

Following Altman (1968), the general form of the MDA model we estimate is as follows:

$$Z = 0.012WCTA + 0.014 RETA + 0.033 EBITTA + 0.006 MVEBVTL + 0.999STA \quad (1)$$

where WCTA is the working capital (i.e., current assets – current liabilities) scaled by total assets, RETA is the ratio of retained earnings at the end of a year scaled by total assets, EBITTA is earnings before interest and taxes scaled by total assets, MVEBVTL is the ratio of market value of equity to book value of total liabilities, and STA is the total sales revenue scaled by total assets. In Eq. (1), the dependent variable Z is the discriminant function and 0.012, 0.014, 0.033, 0.006 and 0.999 are the discriminant coefficients in Altman's (1968) original model (p. 594). The magnitude of Altman's Z -score for a firm is inversely related to its potential risk of failure because all of the ratios have positive coefficients in the equation. Logically then, higher (lower) Z -scores would be expected for the more successful firms like our sample of solvent (bankrupt) firms.

In selecting the cut-off scores for his model, Altman (1968) considered the costs of Type I and Type II errors (defined below) and prior failure probabilities. This resulted in the following classification rule: if the Z -score is greater than or equal to 2.99 the firm is classified as safe; if the Z -score is between 1.82 and 2.98, the firm falls into the grey or undecided area and is not classified; and if the Z score is below 1.81, the firm is classified as bankrupt.

4.3 Conversion of AGAAP data to IFRS data

As stated earlier, we employ Altman's (1968) MDA model on three datasets. The first dataset (S_1) represents the original financial statements data as reported by 46 bankrupt firms and 46 non-bankrupt firms using AGAAP during 1991-2004. The second dataset (S_2) involves restating the AGAAP-based dataset 'as-if' IAS 38, IFRS 3 and IAS 36 were applied retrospectively (Smith *et al.*, 2001b). Hence, total assets and operating profit are reduced by the dollar amount of total capitalized intangible assets for each year in which data are available (t_1 to t_5). This adjustment is justified based on empirical evidence that if firms are facing bankruptcy, managers aggressively capitalize these intangibles opportunistically to conceal the firms' declining poor performance (Jones, 2011). The same can be said regarding the subsequent revaluation of any existing intangible assets. Taken together, in the reported statements, total assets and operating profits were inflated to avoid detection by shareholders, creditors and lenders. Hence, all capitalized intangible assets must now be derecognized because they will fail the strict recognition and measurement criteria under IAS 38 and IFRS 3. The restatement process requires all existing identifiable and unidentifiable intangibles to be written off against

the current balances of total assets (balance sheet), current profit (income statement) and retained profit (balance sheet). Any adjustment (restatement) against profit must also consider whether there is a tax effect, and if so, adjusted accordingly.

Following Lev and Sougiannis (1996), we treat intangibles as expenses for each year in the five-year study period. These adjustments assume: (1) all capitalization of intangibles that fail to qualify for IAS 38 are expensed in the current period and, as such, are deductible for tax purposes, whereas goodwill impairments are tax exempt; (2) there is no tax effect adjustment for firms reporting a taxable loss (Constable and Woodliff, 1994). As a result of the first assumption, a deferred tax liability is recognized for financial reporting purposes (but not for tax reporting purposes) and total liabilities decrease. With regard to the second assumption, firms reporting tax losses are assigned a zero effective tax rate (ETR) to remove the ambiguity of a positive ETR resulting from situations where a taxable benefit is divided by a negative accounting income. If left unadjusted, the model would be biased in favour of identifying bankrupt firms as a result of the carry forward of tax credits.

In creating S_2 the adjustments we make to reported financial statement numbers are as follows. First, we deduct all existing intangible assets involving cash outlays and non-cash outlays (such as revaluations and capitalized intangibles that were internally generated) from total assets on the balance sheet and expense them to the income statement. Second, we assume that goodwill (such as consolidated and acquired) is assessed as irrecoverable and written down (fully impaired) to zero (Goodwin *et al.*, 2008: 96). Hence, we deduct the carrying amount of goodwill from total assets and create an expense for the same amount on the income statement. Third, we identify the accounting items used in Eq. (1) that the adjustments in assumptions (1) and (2) above create a tax effect (Goodwin *et al.*, 2008: 95, Walpole, 2008) we adjust accordingly. Finally, we adjust both retained earnings and shareholders' equity at each year-end because they both contain the same closing operating profit after tax balances from each particular reporting period.

Our third dataset (S_3) entails a slight variation of the assumptions made in S_2 . For constructing S_3 , we assume that there is no impairment of goodwill as reported in balance sheets and hence, operating profits and total assets are not adjusted for goodwill. Therefore, all adjustments are identical to those in S_2 except goodwill is not deducted from total assets.

4.4 Model accuracy

We first examine whether Altman's (1968) model classifies bankrupt firms more accurately in datasets S_2 and S_3 (that mimicked IFRS adoption) compared to that in the dataset S_1 (prepared using AGAAP). Specifically, we compare the three-way classifications ('bankrupt', 'grey/undecided', or 'non-bankrupt') in S_2 and S_3 with those in S_1 for each of the five years prior to a firm's bankruptcy. Both the bankrupt and matched non-bankrupt firm data are pooled, classified and tested for differences in these classifications. The Wilcoxon Signed Rank Test is used to test the predominant direction of any changes in the classification outcomes that may occur under IFRS (i.e., whether the changes are generally towards more bankrupt classifications than non-bankrupt classifications or vice-versa).

4.5 Model robustness

Since the coefficients in Altman's model are positive and lower *Z-scores* lead to a higher propensity to be classified as 'fail' in that model's specifications, one-tailed tests are applied for *Z-scores* related to each dataset. For each dataset, we expect that the mean-paired difference between the bankrupt firms' *Z-score* (Z_B) and non-bankrupt firms' *Z-score* (Z_{NB}) (i.e., $Z_B - Z_{NB}$) is consistently negative for the five years before failure. Our expectation is based on the notion that *Z-scores* are usually smaller for bankrupt firms than for non-bankrupt firms.

4.6 Sample selection

The failed firm sample includes three major forms of bankruptcy proceedings available under the legislative provisions of the Australian Corporations Act (ASIC, 2001): (1) voluntary administration, (2) liquidation, and (3) receivership. Distressed firms that are delisted from the ASX for not paying their annual listing fees are also included in the sample. We define a 'bankrupt' year (t_0) as the year the firm was legally pronounced bankrupt and subsequently delisted from the ASX, i.e., the first year with *no* financial statements tendered. We analyse each bankrupt firm for five years before its bankruptcy. The year 1996 represents the year in which *AASB 1013* (issued in 1987) was amended and reissued mandating all firms must amortize goodwill using the straight-line method for 20 years. The year 2004 was the last year in which firms were permitted to capitalize internally generated intangible assets (such as brand,

mastheads, and intellectual property), subsequent revaluations of such assets, and amortization of goodwill. However, the study period had to be extended to include the five-year period prior to failure for firms that failed in 1996 (t_0). This means for firms failing in 1996, 1991 is their fifth year prior to bankruptcy (t_{-5}). Thus, the sample period is the reporting period ending 30 June, 1991 to 30 June 2004, and is denoted as the ‘AGAAP’ period.

The initial sample of 668 Australian publicly delisted firms that failed between 1991 and 2004 was sourced from Huntley’s Delisted Company Database (Huntley’s Financial Services Pty. Ltd., 1999) and Investogain Australia Limited (InvestoGain Australia Limited, 2012). From this sample of 668 failed firms, a total of 140 firms were removed because they were either foreign domiciled,³ or in industries such as insurance, superannuation, banking and finance,⁴ utility, and mining.⁵ A further 462 firms were removed as a result of firms being engaged in a distressed merger and/or takeover activity, and compulsory acquisitions (Chapter 17.1–17.4 of ASX Listing Rules). Finally, 30 firms were removed because they underwent privatisation, redeemed shares, reorganisation or selective capital reductions, or had missing data.⁶ The final number of bankrupt firms used in the estimation models is 46, yielding 181 firm-year observations. Panel A of Table 2 summarizes the sample selection procedure.

In Table 2, Panel B, we report the industry distribution of the sample. As Panel B reveals, 32% of our sample firms come from industrials followed by 22% firms in the consumer discretionary sector. Other sectors that are represented in the sample are information technology (13%), consumer staples (13%), telecommunications (11%) and healthcare (7%).

³ These companies are excluded because they have to prepare statements according to the country’s accounting standards where they are domiciled e.g. USA.

⁴ These industries are excluded because they have unique accounting standards such as AASB 1023 Financial Reporting of General Insurance Activities, AASB 1032 Specific Disclosures by Financial Institutions.

⁵ Mining industries are not included because they capitalize E&E expenditure was discretionary under AASB 1022, paragraph 0.11, *Accounting for the Extractive Industries*, which was in force over the sample period *_1989–2004_*. However, AASB 1022 was silent on whether E&E expenditure should be classified in the balance sheet as intangible or tangible. Australia’s current standard on extractive industries, AASB 6, paragraph 15, *Exploration for and Evaluation of Mineral Resources*.

⁶ The term, missing data, refers to data from financially distressed firms that was unavailable, and, if excluded from the estimation sample, would lead to an under-representation bias and thus, a large error probability for misclassifying firms (Type I error) in the resulting model Cybinski, P. (2003) *Doomed Firms: An Econometric Analysis of the Path to Failure*, England, Ashgate Publishing Limited..

[INSERT TABLE 2 APPROXIMATELY HERE].

Following Altman (1968), we used a matched-pair design and selected control firms based on size (total assets), industry membership (GICS), principal activities (sources of sales revenue) and fiscal period. It is well-documented that total assets is the best size-based criterion to control for three bankruptcy-related effects, viz.:

- (1) the higher incidence of failure among smaller firms (Altman, 2001),
- (2) the higher likelihood of larger firms to engage in reporting manipulations because of the complexity of their operations and the difficulty for external users to detect such manipulations (Lobo and Zhou, 2006, Hossari *et al.*, 2007, Watts, 2006), and
- (3) distressed firms using non-restrictive capitalization of intangibles to avoid bankruptcy (Smith *et al.*, 2001a, DeAngelo and DeAngelo, 1990, Healy and Palepu, 1990).

Matching control firms on principal activities ensures that each successful non-bankrupt firm conducts similar principal activities. It also controls for corporate (*diversification*), business (*market share, firms size*) and financial (*resources*) strategies as well as cooperative inter-organizational linkages among competing firms (Sheppard, 1994). Hence, firms generating sales from similar principal activities own similar “resource-based assets” and are more likely to use similar reporting practices to account for those assets and sales. If failing firms do not mimic their competitors by ‘*sticking to their knitting*’, they could be denied access from the proper mix of resources to ensure its survival (Sheppard, 1995: 53). Moreover, bankrupt firms make capital expenditure to mimic health firms (Kedia and Philippon, 2009).

5. Results

5.1 Results of prediction accuracy tests

Table 3, Panel A shows that Altman’s (1968) model correctly classifies a higher proportion of bankrupt firms than it classifies non-bankrupt firms across all of the three datasets. More importantly, across all of the lagged years, the model consistently performs better in predicting bankrupt firms in datasets S_2 and S_3 (variants of IFRS-based data) compared with its performance in dataset S_1 (AGAAP-based data). Compared with an accuracy rate of 72.7% for bankrupt firms in S_1 , the accuracy rate in S_2 (S_3) is 81.8% (81.0%) in the year t_5 . Although the

accuracy rates drop slightly in years t_2 and t_3 for datasets S_2 and S_3 , the model performs best in the year t_1 with 91.7% accuracy in S_3 and 94.4% accuracy in S_2 . By comparison, the model has an 86.1% accuracy rate in the dataset S_1 for the year t_1 . The decline in accuracy rates across all of the three datasets in the year t_2 could be suggestive of opportunistic accounting choices to mask deteriorating performance and financial health of the bankrupt firms.

The prediction accuracy rates for the non-bankrupt (healthy) firms are very moderate. For the S_1 dataset, the accuracy rate ranges from 39.1% in year t_4 to 62.1% in year t_2 . For the dataset S_2 (S_3), the accuracy rate ranges from 34.5% (36.0%) in year t_3 (t_4) to 50.0% (56.7%) in year t_5 (t_2). Notably, in every year in the sample, Altman's (1968) model consistently classifies non-bankrupt firms correctly at a higher proportion when the dataset S_1 is used.

As reported in Table 3, Panel A, the Type II errors are much larger than the Type I errors and whenever the Type I error decreases, the Type II error increases. Thus, there is always a trade-off between Type I and Type II errors and many authors hold that a Type I error (misclassifying a bankrupt firm) is more costly than a Type II error (misclassifying a non-bankrupt firm) (see White *et al.* (1997) and Altman *et al.* (1977)). This is also consistent with evidence in the literature that large proportions of misclassification will occur if failure prediction models contain variables that are affected by creative accounting (Sharma (1999, p. 72)). The large Type II errors are signalling that the non-bankrupt firms in the sample were perhaps not very healthy financially. In fact, Altman (1968) finds that an additional sample of non-bankrupt *but financially troubled firms* gave a Type II error of 21% , up from 3% in his original sample.

The results of the Chi-square tests in Panel A (Table 3) show a significant improvement in the classification accuracy of Altman's model using IFRS dataset in t_1 ($\chi^2=13.3$; $p<0.00$) compared to that in AGAAP dataset ($\chi^2=14.2$; $p<0.00$). Similar results are obtained in the year t_2 with IFRS dataset showing better classification accuracy than that of the AGAAP dataset ($\chi^2=5.7$; $p=0.02$).

In sum, when comparing the prediction accuracy test results for the different calculation methods, we observe that the adjustments to exclude intangibles and goodwill from the five ratios have improved the model's ability to classify bankrupt firms, but these have impaired the model's ability to accurately classify healthy firms. The results obtained in this study are similar to those of Altman's (1968, p. 601) secondary sample testing. The reduction in prediction

accuracy going back in time from the bankruptcy event is understandable for the bankrupt-firms sample because failure is more remote and the indications are less clear. Altman (1968: 576), explains that when firms are four or more years from failure they usually appear as ‘healthy’ firms.

5.2 Robustness of Altman (1968) model

Table 3, Panel B, shows the results of the Wilcoxon Signed-Ranks test which tests for the significance of any changes in classifications that occur between the datasets, i.e., from S_1 to both S_2 and S_3 , and the general direction of those changes. Comparing Altman (1968) model’s classifications between IFRS-compliant data (S_2, S_3) and pre-IFRS AGAAP data (S_1) shows that less than 30% of the firm classifications had changed for each of the five years before failure. So the majority of classifications remain unchanged when using IFRS data as opposed to AGAAP data (more than 73%, depending on the prior year). But for the rest (between 6-27% of classifications), the claim that no systematic change occurs in the way that Altman’s (1968) BPM classifies firms as bankrupt, grey or non-bankrupt when using the different calculation datasets for total assets, is rejected ($p < 0.05$) for *all* prior years except t_4 , when it is marginally significant ($p_{S_2-S_1} < 0.1$). This result is based on the nonparametric Wilcoxon Signed-Ranks test on the combined dataset, both bankrupt and matched non-bankrupt firms. We can therefore conclude that systematic change indeed occurs in the way Altman’s (1968) model classifies up to a quarter of the firms when using different calculations for total assets. Moreover, excluding all ties (no change in firm classification across all of the datasets), the changes that occurred were mostly in the direction of more ‘grey’ or ‘bankrupt’ classifications for both IFRS datasets rather than vice versa, regardless of whether the firm was actually a bankrupt or non-bankrupt firm. Thus, an important finding here is that higher Type II errors and lower Type I errors occur when using IFRS data.

The classification changes were more highly significant between S_2 and S_1 than between S_3 and S_1 . This provides further evidence that the restriction of capitalized intangibles can effect a change in the Altman classifications. The classification changes were most significant in the year immediately prior to bankruptcy at t_{-1} ($p < 0.001$, one-tailed test) for both the comparison datasets. Indeed, these changes in classifications were still highly significant ($p < 0.01$) for all of the three years immediately prior to bankruptcy for the S_1 and S_2 datasets.

[INSERT TABLE 3 APPROXIMATELY HERE]

5.3 Results for Z-scores

Paired t -tests are used to examine whether the mean-paired differences in Z-scores between the bankrupt and non-bankrupt firms in Altman's model are *consistently negative* for the five years before failure. Table 3, Panel C, shows that the differences are consistently negative and statistically significant ($p < 0.1$) for S_2 and S_3 at prior years t_2 ($p_{S_2} = 0.01$; $p_{S_3} = 0.02$), t_4 ($p_{S_2 \& S_3} = 0.03$), and t_5 ($p_{S_2} = 0.04$; $p_{S_3} = 0.05$) and for S_1 , only at t_2 ($p_{S_1} = 0.03$) and t_5 ($p_{S_1} = 0.06$). In these prior years and datasets, bankrupt firm mean Z-scores are *significantly* smaller than non-bankrupt ones, allowing better discrimination between the firm groups. The results reported in Table 3, Panel C, also shows that, except for t_1 , the p -values for the Z-score differences in both S_2 and S_3 are universally smaller (more significant) than for S_1 . These results confirm that in the absence of intangibles, i.e., for S_2 and S_3 , there is greater reliability in the financial reporting data, especially in the years: t_2 , t_4 , and t_5 . The finding from *this test* adds to the compelling evidence that IFRS data is more enlightening regarding bankruptcy risk.

5.4 Sources of improvement in bankruptcy prediction

In this Section, we identify the sources of improvement in bankruptcy prediction by examining each ratio that is an input into Altman (1968) model. Table 4 reports the results of paired t -test for each of the five ratios within each dataset (S_1 , S_2 , and S_3). As Table 4 shows, in each dataset, all of the five ratios that are inputs in Altman (1968) model are smaller in bankrupt firms than in non-bankrupt firms. This is evidenced by a negative mean difference (i.e., B – NB) in each comparison. More importantly, the negative mean differences are more pronounced in S_2 and S_3 datasets as evidenced by larger t -statistics and smaller p -values. Specifically, out of the 25 cases (5 ratios x 5 lag years = 25), the ratios differ between bankrupt and non-bankrupt firms statistically in 11, 14, and 14 cases within S_1 , S_2 , and S_3 datasets, respectively.

Among the five ratios, the greatest improvement in segregating bankrupt firms from non-bankrupt ones is in EBITTA followed by RETA and WCTA. The mean differences in EBITTA are significant only in two of the five prior years within S_1 (i.e., t_1 and t_2). In contrast, they are significant in four (three) of the five prior years in S_2 (S_3) dataset. The mean differences in

RETA and WCTA are significant in two, three, and three years within S_1 , S_2 and S_3 dataset, respectively. Thus, conservative accounting rules for intangibles under IFRS reveals poorer performance in bankrupt firms more consistently than AGAAP does. It is notable that around years t_3 and t_4 , the performance differences between bankrupt and non-bankrupt firms become obscure (non-significant t -statistics). This could be indicative of income-increasing earnings management in financially troubled firms to mask their ‘true’ performance by taking advantage of the flexible rules for intangibles under AGAAP.

In sum, restrictive accounting rules for intangibles under IFRS presumably constrain poorly-performing firms from masking their ‘true’ performance via capitalization of intangibles. Thus, smaller values of the performance-based ratios (e.g., EBITTA, RETA) produce smaller Z -scores and thereby, improving the accuracy of bankruptcy prediction.

[INSERT TABLE 4 APPROXIMATELY HERE]

6. Summary and conclusion

In this paper, we investigate the effect of IFRS rules for intangibles on the performance of Altman’s (1968) bankruptcy prediction model. We choose Altman’s model because it is the most widely used and most widely cited model in bankruptcy prediction literature. We adopt a matched-pair design in the Australian setting. We analyse a sample of 46 bankrupt firms and 46 non-bankrupt firms over the period 1991-2004. When we employ the same Altman’s model to three alternative datasets (one AGAAP dataset, and two variants of IFRS datasets), we find evidence that restrictive accounting rules for intangibles under IFRS improve the quality of financial statement data by enabling better bankruptcy prediction. Because we hold the bankruptcy prediction model constant across three datasets, any improvement in bankruptcy prediction can be attributed to the corresponding dataset. In particular we find that, poorly performing firms are unable to mask their ‘true’ performance via capitalization of intangibles under IFRS. We also identify the source of improved bankruptcy prediction. Under IFRS, smaller input values into Altman’s model lead to smaller Z -scores enabling the model to classify bankrupt firms more accurately. The findings in this study support the notion that the new

conservative rules for intangibles under IFRS act to constrain managers of failing firms from using creative accounting practices for intangibles to manage total assets and reported earnings.

The increased bankruptcy prediction in IFRS setting, however, comes with a cost; a smaller Type I error is achieved with a larger Type II error. Although this situation is not ideal, in the case of bankruptcy prediction, a smaller level of Type I error might be more desirable than a smaller level of Type II error from lenders' and investors' perspective. Thus, the prediction that the overall classification accuracy of the Altman (1968) model for five years prior to failure would be significantly improved by the removal of intangibles was supported – but only for the bankrupt firms. The adjustments to exclude intangibles and goodwill from the five ratios improved the model's ability to classify bankrupt firms, but these have impaired the model's ability to accurately classify healthy firms.

The findings of this paper have implications for both national and international accounting standard setters, regulators, financial analysts, auditors, investors and various financial institutions. Introducing more conservative accounting standards is one way regulators attempt to constrain managers of firms facing insolvency from engaging in fraudulent creative accounting practices. The results of this study provide empirical support for the notion that, even in the presence of differences between bankrupt and non-bankrupt firms, the incidence with which Australian firms appear to have misstated their total assets and income by capitalizing intangibles has compromised the effectiveness of accounting-based failure indicators. Therefore, amending *AASB 1013*, *AASB 1011*, and *AASB 1018* (as per ASIC, 2001) seemingly had a 'revolving door' effect: as standard setters closed the door on certain intangible assets as a mode of creative accounting, another door leading to other identifiable and internally generated intangible assets opened, allowing these assets and incomes to be overstated.

These results provide evidence to international standard setters of what they can expect if their efforts to remove non-restrictive accounting practices for intangibles are abandoned. Excluding intangibles that fail the asset test under *IAS 38* improves the effectiveness of accounting-based BPMs, such as Altman's (1968) model, to predict failure. This finding contrasts with the claims of Australian and US academics that more flexible reporting rules for intangibles could improve the quality of balance sheets and investors' information sets (Barth *et al.*, 2001, Aboody and Lev, 1998, Easton, 1998, Chalmers *et al.*, 2008). Our results also provide some answers to Beaver's (2012) question as to whether differences in financial reporting

attributes impair the predictive ability of financial ratios for bankruptcy. Finally, the results provide national and international investors and lending institutions caution when assessing any firm with intangibles as potential investment.

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