

# A Dynamic Ratio-Based Model for Signalling Corporate Collapse

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## Abstract

*The recognition of behavioural elements in finance has caused major shifts in the analytic framework pertaining to ratio-based modeling of corporate collapse. The modeling approach so far has been based on the classical rational theory in behavioural economics, which assumes that the financial ratios (i.e., the predictors of collapse) are static over time. The paper argues that, in the absence of rational economic theory, a static model is flawed, and that a suitable model instead is one that reflects the heuristic behavioural framework, which is what characterises behavioural attributes of company directors and in turn influences the accounting numbers used in calculating the financial ratios. This calls for a dynamic model: dynamic in the sense that it does not rely on a coherent assortment of financial ratios for signaling corporate collapse over multiple time periods.*

*This paper provides empirical evidence, using a data set of Australian publicly listed companies, to demonstrate that a dynamic model consistently outperforms its static counterpart in signaling the event of collapse. On average, the overall predictive power of the dynamic model is 86.83% compared to an average overall predictive power of 69.35% for the static model.*

## Keywords

**Corporate Collapse**  
**Bankruptcy Prediction**  
**Behavioural Finance**  
**Classical Rational Theory**  
**Heuristic Behavioural Theory**  
**Financial Ratios**  
**Multiple Discriminant Analysis**

## Introduction

The recent emergence in the recognition of behavioural elements, has caused major shifts in the analytic framework of finance (Barber and Odean, 2000; Benartzi and Thaler, 2001; De Bondt and Thaler, 1985; Genesove and Mayer, 2001; Rabin, 2002; Shiller, 2000; Shleifer, 2000). This is particularly true when it comes to ratio-based modelling of corporate collapse (Hossari and Rahman, 2004).

The modelling approach so far has been based on the classical *rational theory* in behavioural economics (Bernoulli, 1954). The implications are that the financial ratios, which are the predictors of collapse, are assumed to be *static* over time. In other words, it is assumed that the same financial ratios are capable of signalling corporate collapse over multiple time periods. This explains why studies that tried to pre-empt the event over multiple periods, used the same model. It also explains why the pool of financial ratios, from which the predictors are selected, was chosen based on the popularity of its constituents in preceding studies. Let us refer to such a model as a *static* model.

In principle, if the classical rational theory holds, then one would expect studies that attempt to model corporate collapse to rely on a coherent assortment of predictors. However, a review of the literature has indicated that this is not the case (Hossari and Rahman, 2004; Hossari and Rahman, 2005). The justification could be that the accounting numbers used in calculating the financial ratios are influenced by heuristic behavioural attributes of company directors. Such an observation conforms to the behavioural theory put forward in Kahneman (2003), which challenged the dominant classical rational approach introduced in Bernoulli (1954).

This paper argues that in the absence of rational economic theory a *static* model is flawed; and that a suitable model is one that reflects the heuristic behavioural framework put forward in Kahneman (2003). Specifically, the paper argues for a *dynamic* model: dynamic in the sense that it does not

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rely on a coherent assortment of financial ratios for signalling corporate collapse over multiple time periods.

This paper first demonstrates how a heuristic theory applies to behavioural attributes of directors of companies heading towards collapse. The discussion deals with questions such as, what would a company director be tempted to do, and what course of action seems most natural in a situation of impending collapse? Consequently, arguments are put forward for a heuristic behavioural formulation in place of a classical rational approach, which lead to a recommendation for a *dynamic* rather than a *static* model for signalling corporate collapse.

The paper next demonstrates that there exists time variant inconsistency in the set of predictors of the event of collapse. The results are based on a review of 84 studies from 1968 to 2004. The results underscore the inappropriateness of a *static* model for signalling collapse, and consequently question the suitability of the underlying rational behavioural framework.

Finally, the paper provides the empirical backing for the recommendations made in the first section. Specifically, the predictive accuracy of a *dynamic* model is compared to that of a *static* model using a data set of Australian publicly listed companies. The results indicate that a *dynamic* model consistently outperforms its *static* counterpart. The results provide the necessary empirical evidence for a heuristic behavioural theory in the context of ratio-based modelling of corporate collapse.

### **A Heuristic Framework for Ratio-Based Modelling of Corporate Collapse**

What would a company director be tempted to do, and what course of action seems most natural in a situation of impending collapse? In order to answer these questions, it is imperative to first put forward a definition of corporate collapse.

When is a corporation considered to have collapsed? Is it when it shows signs of

financial fragility or is it when the courts legally declare it to have ceased to exist? When news about the collapse of a company is announced, what comes to mind is the sudden death of an entity. However, even though the announcement of such an event is in itself sudden, the process of dying is more often gradual and could extend over many years. Along the way, signs and symptoms appear in various forms, which vary, thus giving rise to a multitude of definitions of corporate collapse. In most cases such signs and symptoms are visible in the reported financial variables captured in the financial reports, in which case the event is defined from a financial perspective. The symptoms include: negative net worth, non-payment of creditors, bond defaults, inability to pay debts, over-drawn bank accounts, omission of preferred dividends, and the like (Karels and Prakash, 1987). However, such a formulation of the event makes it difficult to identify the point at which returning to a strong financial position is impossible, and when collapse becomes imminent. In other words, it is tricky to establish the precise moment when the process of collapse begins.

The event of collapse appears to be a subjective decision in which financial fragility persists until the company or its creditors decide to file a legal action. Financial fragility is therefore a necessary, but not a sufficient condition for corporate collapse. This explains why legal criteria are essential when defining the event.

Therefore, the event of collapse could be regarded as a process with symptoms of financial fragility and that culminates legally when the courts declare a company to have ceased to exist. Thus, a narrower legal definition of corporate collapse should be the preferred choice. In other words, when modelling corporate failure, it is best to define the event as an incident that culminates in the cessation of the company. Such a definition would include companies that have appointed an administrator, filed for bankruptcy, gone into liquidation or

receivership, failed to lodge listing fees, or wound up<sup>1</sup>.

Considering such a definition of the event, what would a company director be tempted to do, and what course of action seems most natural in a situation of impending collapse? In answering these questions, one would ideally ask directors of ailing companies to explain what they would do in a similar situation. However, intuition suggests that answers to questions of this nature are unlikely to be candid. This is particularly true when company directors are allegedly guilty of misrepresenting the financial statements of their company. Whilst not all cases of corporate collapses involve misrepresentation, such activity is nevertheless a recurring theme (Aldred, 2004; Barakat, 2004; Countryman, 2004; Gumbel, 2004; Howard, 2003; Iwan and Watts, 2002; Jarmon, 2000; Johnson, 2004; Mansell, 2004; McCrann, 2002; Reinstein and Weirich, 2002; Semple, 2002; Veverka, 2004; Westfield, 2002).

It could, therefore, be argued that possible lack of truthfulness in reporting requires one to opt for an inductive conceptual framework that could elucidate the behaviour of dubious directors. Integrative concepts in psychology offer mid-level generalisations that could explain ostensibly altered phenomena (Kahneman, 2003, p. 1449). The procedure relies on intuitive judgment. At its core lies the relationship between preferences and attitudes (Kahneman et al., 1999). The ensuing model is heuristic, guided by the notions that judgments and choices are primarily made intuitively, and that intuition and perception are governed by the same precepts (Kahneman and Frederick, 2002). Accordingly, judging the behaviour of dubious directors of collapsed corporations relies extensively on analogies.

To illustrate, let us suppose that a company is in some serious financial difficulty that could very well lead to its cessation. Let us also suppose that we are dealing with a

group of predominantly dubious directors who see no moral mischief in misrepresenting the financials of the company, in order to give stakeholders the impression that the company's viability is not at stake. What would these directors be tempted to do, and what course of action seems most natural?

According to *prospect theory* (Kahneman, 2003, p. 1454), the behaviour of the directors is *reference-dependent*, i.e. 'the perceived attributes of a focal stimulus reflect the contrast between that stimulus and a context of prior and concurrent stimuli'. The focal stimulus in this case is to give stakeholders the impression that the company's viability is not at stake, which is decidedly achieved by misrepresenting its financials. The decision, as to which financials are to be misrepresented, is guided by a context of prior and concurrent stimuli; these could be based on some concurrent court ruling in relation to misrepresented financials of some other company under investigation. Therefore, the directors would be tempted to misrepresent financials other than those recently investigated, in order to give judges the false impression that all is in good order.

In addition, *reference-dependent* behaviour is *affect heuristic*. That is to say, people's decisions to act in a certain way do not necessarily conform to what logical economic preferences would suggest. This is because they are most likely guided by the emotion of the moment. Therefore, it is indispensable to understand the psychology of emotions in order to comprehend such behaviour. The implications suggest that decisions guided by the emotion of the moment are unlikely to be economically sound (Kahneman et al., 1997).

Thus, in deciding on which financial items to misrepresent, dubious directors are guided by the emotion of the moment, and not coherent economic reasoning. In other words, their collective decision is based on which items are the safest to misrepresent in order to avoid being indicted by the judges in a court of law. The necessity to paint the best financial picture for the

<sup>1</sup> A more detailed discussion of definition of failure can be found in Hossari (2006), Chapter 2.

company takes a secondary, though important role.

Furthermore, such *affect heuristic* behaviour is characterized by what Kahneman (2003, p. 1460) refers to as *narrowness*: people make choices as the need arises, whereby these choices are influenced by the immediate consequences of the decisions they make with regards to the problem they face. The prevalence of *narrowness* in decision-making is another blow in the face of the rational framework.

Therefore, prospect theory provides a lucid explanation of the underlying precepts at work when dubious directors go about misrepresenting the financials of their ailing company. Their behaviour is *reference-dependent*, *affect heuristic* and characterised by *narrowness*; all of which point against classical rational theory.

In the context of prospect theory, what are the underlying precepts at work when the judges investigate alleged misrepresentation of company financials? According to evidence reported in Kahneman (1973), when considering unreliable information, people make decisions by reverting to *base rates*: decisions they previously made in similar situations. Both statistical as well as psychological common sense support the phenomenon. The underlying statistical reasoning dictates that unreliable information must be given little weight or low probability of being valid. The psychological underpinnings hinge upon the realisation that judgements of probability are difficult. People therefore have a tendency to substitute a judgement of probability with a judgement of familiarity (a *base rate* decision). Consequently, when judges look into alleged misrepresentation of the financials of a collapsed company, they revert to a *base rate* decision: a decision they made in a similar situation. This involves investigating the integrity of financial items that they proved questionable in prior cases. Their decision to take a close look at these specific items is anchored on their initial intuitive perception.

According to prospect theory, the behavioural elements described thus far are independent of the stakes at hand: higher stakes do not improve the quality of the decision. This implies that dubious directors would not alter their behaviour if they represent a very large corporation; they would still exhibit *reference-dependent*, *affect heuristic* behaviour characterised by *narrowness*. Likewise, judges are unlikely to depart from a *base rate* decision.

The situation just described has significant implications on signalling corporate collapse, specifically with respect to models that rely on financial ratios in pre-empting the event. Ratio-based models for signalling corporate collapse detect the event using some form of a dichotomous discriminant function. Although a myriad of methodological approaches could be used in generating the model, the explicit underlying objective remains the same: to distinguish between companies that are likely to collapse and those that are not. In doing so, the model compares financial ratios for two groups of companies: collapsed and non-collapsed. The methodological procedure used selects a subset of ratios that provide the best discrimination between the two groups. Abnormalities in the ratios of collapsed companies assist in the process. Only in a rational economic framework would such abnormalities be *recurring*. However, a heuristic behavioural framework of prospect theory is in total contradiction with economic rationality. The fact that the behaviour of directors is context sensitive, and consequently heuristic, implies that recurrence of abnormalities in financial ratios is an implausible expectation. Thus, financial ratios that are good predictors of collapse at some point in time may not necessarily be so at some other time period.

Since the seminal work of Altman (1968) on multivariate ratio-based modelling of corporate collapse, researchers have been pre-occupied with finding a consistent set of financial ratios that are capable of signalling the event. Empirical studies are swarming with instances whereby a particular model that excelled at pre-empting collapse at some point in time,

failed in doing so at some other time period. Researchers blame this on a number of factors such as, sampling issues, the methodological approach used, industry classifications and macro-economic effects. Research efforts have attempted to deal with these issues. Considering the concerns regarding the refinement of the methodological approach used in deriving a corporate collapse prediction model: when a model that could successfully pre-empt collapse no longer does so, the blame would typically be targeted against the methodological approach. This explains the plethora of methodologies witnessed during the past four decades.

However, this constitutes a superficial attempt to resolving the problem. At its root, the solution does not lie in altering the methodological approach. Although there are observed benefits from methodological refinements, the problem goes deeper than that. Primarily, the problem has to do with the underlying behavioural framework. So far, researchers have –whether explicitly or otherwise- embraced a rational behavioural framework. Accordingly, they have assumed consistency in the behaviour of rational company directors. In the case of the dubious breed, this would consequently translate to constancy in their decisions regarding which financial items to misrepresent in an effort to paint a bright financial picture of their ailing company. If this is the case, then a coherent set of financial ratios should serve as good predictors of corporate collapse. However, as the next section of this paper demonstrates, the reality is far from this. One way of tackling the problem is for researchers to go about refining the methodological approach. The fact that their innovative methodologies delivered better results than the previous ones reinforced the notion that they are on the right track. What the researchers missed out on is the fact that their innovative methodologies produced models that, in most cases, relied on sets of predictors that differed from those of their predecessors.

Thus, the solution that addresses the problem at its deepest level goes beyond methodological refinements; it demands an

overhaul of the classical behavioural framework, which at its heart assumes rational constancy. The alternative is a heuristic theory. As described in Kahneman (2003, p. 1469), agents do not necessarily reason poorly in as much as they often act intuitively. In other words, the behaviour of these agents is not guided by their ability to process straightforward information, but by what they happen to perceive at a given moment.

The next section of this paper demonstrates that there exists time variant inconsistency in the set of predictors of corporate collapse. Such evidence strikes the classical behavioural framework at its heart. It provides the necessary backing for a heuristic framework for ratio-based modelling of corporate collapse.

### **A Heuristic Framework: the Evidence**

Table One lists the overall usage rates of 44 financial ratios<sup>2</sup> in the 84 publications studied pertaining to corporate collapse<sup>3</sup>. These studies were published between 1968 and 2004. The choice of the starting date refers to the start of an era marked by the seminal work of Altman (1968). The choice of the ending date corresponds to the latest year in which relevant studies are identified at the time of starting the research project for this paper. The usage rate for a particular ratio is based on the number of studies in which this ratio was a predictor of collapse. Usage rates are listed by decade for the period 1968 to 2004. For example, the first ratio listed in Table One, 'AR/Inv', was not useful in predicting collapse in the 1960s, 1970s or 2000s; however, it was useful in signaling the event in 1 study in the 1980s and also in 1 study in the 1990s. Similarly, the second ratio listed in Table One, 'C/CL', was not useful in predicting collapse in the 1960s or 2000s; however, it was useful in signaling the event in 2 studies in the 1970s, in 1 study in the 1980s and in 3 studies in the 1990s. The ratios are listed in descending alphabetical order by numerator then by denominator.

<sup>2</sup> Abbreviations are explained in Appendix 1.

<sup>3</sup> Details of the 84 studies are in Hossari, (2006).

**Table One: The Overall Usage Rates of 44 Financial Ratios across 84 Studies by Decade (1968-2004)**

Ratio	1960s	1970s	1980s	1990s	2000s	Ratio	1960s	1970s	1980s	1990s	2000s
AR/Inv.	0	0	1	1	0	Inv/WC	0	2	1	1	0
C/CL	0	2	1	3	0	LTL/TA	0	1	3	3	0
C/S	0	1	0	0	0	LTL/TE	0	1	0	0	1
C/TA	0	1	8	6	2	MVE/TL	1	1	3	4	2
CA/CL	0	6	13	16	1	NI/S	0	3	3	3	2
CA/S	0	1	2	2	0	NI/TA	0	4	11	12	5
CA/TA	0	3	8	1	1	NI/TE	0	3	4	5	2
CF/CL	0	1	2	1	0	QA/CL	0	4	9	5	2
CF/S	0	1	2	2	0	QA/S	0	1	1	1	0
CF/TA	0	2	2	4	2	QA/TA	0	1	6	0	0
CF/TL	0	4	7	3	2	RE/TA	1	1	6	10	2
CL/TA	0	2	3	4	1	S/FA	0	2	1	2	0
CL/TE	0	2	0	0	0	S/Inv	0	1	1	1	0
EBIT/I	0	1	2	3	3	S/TA	1	2	6	7	2
EBIT/S	0	0	1	1	0	S/TE	0	2	1	1	0
EBIT/TA	1	1	11	11	2	TE/LTL	0	2	0	0	1
EBIT/TE	0	0	1	1	1	TE/TA	0	2	1	4	1
EBT/TA	0	1	0	1	0	TE/TL	0	2	2	3	0
Exp/S	0	1	0	0	0	TL/TA	0	5	12	14	3
FA/TA	0	0	2	0	2	TL/TE	0	2	8	5	6
FA/TE	0	2	0	0	1	WC/S	0	3	1	1	0
Inv/S	0	1	4	4	0	WC/TA	1	2	10	9	5

The results in Table One demonstrate that there exists time variant inconsistency in the set of predictors of corporate collapse.

If there were time variant consistency in the set of predictors of collapse, then 2 observations should be evident from the results in Table One. First, there should be evidence that a particular ratio is useful in signaling collapse during each of the 5 decades. Second, if this were to be the case, there should also be evidence that the usage rate for a particular ratio is constant or near constant as we go from one decade to another. However, none of these conditions is satisfied for any of the 44 ratios listed in Table One. This is irrespective of industry-specific or country-specific factors.

If a classical behavioural framework holds, then we would expect stability in the usage rates of financial ratios when it comes to predicting corporate collapse over time. However, the results in Table One indicate that the contrary is true.

Moreover, such an observation is further emphasised by the fact that the usage rates in Table One are low for the majority of the ratios, with none having a consensus rate of over 50%.

Therefore, the diversity of the financial ratios, coupled with their predominantly low usage rates is indicative of the absence of time variant consistency in the set of predictors of corporate collapse. These results question the validity of a classical behavioural framework, which at its heart assumes rational constancy. The alternative is a heuristic theory, which was discussed in the first section of this paper.

A heuristic behavioural framework suggests time variant inconsistency in the set of predictors of corporate collapse, which is what the results in Table One indicate. Thus, reality is aligned with a heuristic rather than a rational construct.

As discussed in the first section of this paper, in the absence of a rational construct a *static* model for signaling collapse is

flawed. The alternative is a *dynamic* model: dynamic in the sense that it does not rely on a coherent assortment of financial ratios for signaling corporate collapse over multiple time periods.

The next section provides the necessary empirical evidence to demonstrate that a *dynamic* model is indeed superior to a *static* counterpart.

### **A Dynamic Ratio-Based Model for Signalling Corporate Collapse**

The corner stone of any ratio-based empirical formulation for signaling corporate collapse is the statistical model. After all, it is the model that indicates whether or not a company is on the verge of collapse. A good model is capable of signaling collapse with a high degree of accuracy. The higher the predictive accuracy, the better the model is.

Ever since the beginnings of ratio-based modelling of corporate collapse, researchers were and still are pre-occupied with new statistical techniques that generate better models for signalling the event. However, as indicated in the first section of this paper, although there are observed benefits from methodological refinements, the problem goes deeper than that. Primarily, the problem has to do with the underlying behavioural framework.

Accordingly, the preceding discussion emphasized the necessity of deriving a *dynamic* rather than a *static* model for signalling collapse. Therefore, the objective in this section is to demonstrate the empirical superiority of a *dynamic* model, regardless of the methodological approach used in deriving it. Although the methodological approach is not the focal point, it is nevertheless necessary to choose one in order to carry out the analysis.

In reviewing 84 studies on ratio-based modelling of corporate collapse between 1968 and 2004, a variety of methodological approaches were apparent in developing the models. These statistical techniques include Multiple Discriminant Analysis (MDA) Logit analysis, Neural Network analysis,

Probit analysis, ID3, Recursive Partitioning Algorithm, Rough Sets analysis, Decomposition analysis, Going Concern Advisor, Koundinya and Puri judgmental approach, Tabu Search and Mixed Logit analysis.<sup>4</sup>

However, of all these approaches, MDA was indeed the most prominent. Its prominence is evident in two ways. First, being the dominant primary approach in the early state of the literature. Second, being the dominant benchmark against which to compare new approaches during the later state of the literature when such new approaches became common. (Hossari, 2006, chapter 5)

Therefore, MDA is used in this study for deriving both the *dynamic* and *static* models. Given the widespread use of MDA in modelling corporate collapse, it suffices to merely provide a brief explanation of this statistical procedure. This is discussed next.

### **A Brief Description of Multiple Discriminant Analysis (MDA)**

MDA could be defined as a classification procedure, which assigns future events of unknown origins to categories with a relatively low error rate (Shumway, 1982, p. 1). Stated differently, the aim of MDA is to predict the assignment of a particular 'item' to a group or a category (among several possible groups/categories) on the basis of variables measured on this item (Lebart et al., 1998, p. 163).

Thus, a basic prerequisite for MDA is that a data item could be classified into two or more groups. In the context of ratio-based models for signaling corporate collapse, two groups are readily identified: the first group includes companies that have collapsed and the second group contains companies that are still a going concern. The data item is therefore a company.

The procedure involves deriving a mathematical equation that combines financial ratios in a way that successfully

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<sup>4</sup> A detailed discussion of these statistical techniques is found in Hossari, 2006, Chapter 5.

assigns a particular company to either the collapsed or non-collapsed group.

The mathematical equation is referred to as the *discriminant function*, and the financial ratios are called *discriminating variables* (Klecka, 1982). Equation 1 gives the general specification of the MDA-based model.

**Equation 1:**

$$f_{km} = u_0 + u_1X_{1km} + u_2X_{2km} + \dots + u_pX_{pkm}$$

Where:

$f_{km}$ : The value that the discriminant function generates for company 'm' in group 'k', where 'k' represents either the group of collapsed companies or the group of non-collapsed companies. ' $f_{km}$ ' is also known as the *score*.

$X_{ikm}$ : The value for the financial ratio 'i' for company 'm' in group 'k'. 'i' goes from '1' to 'p'.

$u_i$ : Coefficients associated with each financial ratio ' $X_{ikm}$ '. ' $u_0$ ' is the constant term or the intercept.

SPSS<sup>5</sup> is used to derive Equation 1 for both the *dynamic* and *static* models. A *forward* stepwise procedure is used based on Wilk's lambda with an *F*-to-enter of 3.84 and an *F*-to-remove of 2.71. These values correspond to probabilities of 0.05 and 0.10, respectively. (Dixon, 1973; Hora and Wilcox, 1982; Huberty, 1994, p. 122; Shapiro et al., 1968)

Before presenting the models, however, it is necessary to first describe the data sample.

### The Data Sample

The data sample is a critical aspect of the empirical investigation. It facilitates the derivation of the models for signalling corporate collapse, regardless of the methodological approach used. The data sample consists of both collapsed and non-

collapsed companies. Collapsed companies are discussed first, followed by their non-collapsed counterparts.

To start with, a total of 413 Australian companies that were de-listed from the Australian Stock Exchange (ASX) during the period 1989 to 2002, are identified in the 'Fin Analysis' database. 'Aspect Huntley' publishes 'Fin Analysis', which provides up to 14 years of detailed historical financial statements for all companies that are listed on the ASX. The sample period corresponds to what is available in the 'Fin Analysis' database.

As mentioned earlier in this paper, when modelling corporate failure, it is best to define the event as an incident that culminates in the cessation of the company; this led to the inclusion of only those companies that have appointed an administrator, filed for bankruptcy, gone into liquidation or receivership, failed to lodge listing fees, or wound up. As a result, 37 such companies are identified among the total of 413 that were de-listed.

Selection of the non-collapsed companies is based on criteria discussed in (Altman, 1968; Aly et al., 1992; Baldwin and Glezen, 1992; Bird and McHugh, 1977; Charitou et al., 2004; Dambolena and Shulman, 1988; Darayseh et al., 2003; Fletcher and Goss, 1993; Gentry et al., 1985; Ginoglou et al., 2002; Gombola et al., 1987; Hamer, 1983; Kim and McLeod Jr., 1999; Koh and Killough, 1990; Lau, 1987; Levitan and Knoblett, 1985; McGurr and Devaney, 1998; Meyer and Pifer, 1970; Neophytou and Molinero, 2004; Norton and Smith, 1979; Platt et al., 1994; Sharma and Mahajan, 1980; Zavgren, 1985). Primarily, each non-collapsed company is paired to a collapsed company based on industry sector and size of assets.

With respect to size of assets, a screening procedure is adopted and is summarised as follows:

- Calculate the average size of assets for each collapsed company, for all years where data is available over the sample period.

<sup>5</sup> SPSS stands for the Statistical Package for the Social Sciences. Version 11 is used to generate the results in this study.



- Calculate the average size of assets for each non-collapsed company in the same industry as the collapsed company, over the sample period.
- The non-collapsed company that has an average size of assets that is closest to that of the collapsed company under

consideration is chosen as the paired match.

Paired companies in the data sample are listed in Table Two along with their industry sectors (GICS), which are explained in Table Three.

**Table Two: Sample of Collapsed Companies and their Non-collapsed Counterparts (1989-2002)**

Collapsed Companies		Paired Non-collapsed Companies		
ASX Code	Company Name	ASX Code	Company Name	GICS
AFN	Australian Gold Fields NL	YGL	Yilgarn Gold Ltd.	15
AKL	Australian Kaolin Ltd.	WGR	Westgold Resources NL	15
ALM	Australis Media Ltd.	AHD	Amalgamated Holdings Ltd.	25
ARS	Australian Resources Ltd.	CRT	Consolidated Rutile Ltd.	15
BAE	Barron Entertainment Ltd.	BBL	Brisbane Broncos Ltd.	25
CCN	Clifford Coporation Ltd.	PFP	WC Penfold Ltd.	20
CIA	Cinema Plus Ltd.	BKR	Becker Group Ltd.	25
CTR	Centaur Mining And Exploration Ltd.	BKW	Brickworks Ltd.	15
CUD	Cudgen Rz Ltd.	DOM	Dominion Mining Ltd.	15
CXR	Coplex Resources NL	SPP	Southern Pacific Petroleum NL	10
DHB	Dream Haven Bedding and Furniture Ltd.	LDN	Linden & Conway Ltd.	25
DHU	Denehurst Ltd.	ANM	Australian Magnesium Corporation Ltd.	15
ECT	Ectec Ltd.	LDW	Ludowici Ltd.	20
EEL	Earth Essence International Ltd.	PSG	Palm Springs Ltd.	30
EIS	Eisa Ltd.	EZY	Easy Call International Ltd.	50
FHL	Formida Holdings Ltd.	IVK	Investika Ltd.	45
GWF	Golden West Refining Corporation Ltd.	VII	Vietnam Industrial Investments Ltd.	15
HSL	Harris Scarfe Holdings Ltd.	HAM	Hamilton Island Ltd.	25
INC	International Contract Manufacturing Ltd.	FUT	Future Corporation Australia Ltd.	50
ITM	Itemus Inc.	PMM	Portman Ltd.	15
JEN	Jennings Group Ltd.	MCP	McPherson's Ltd.	20
KPL	Kinetic Power Ltd.	RPM	Roma Petroleum NL	10
LIB	Liberty One Ltd.	KYC	Keycorp Ltd.	45
MHS	Man Po Holdings Ltd.	ATP	Atlas Pacific Ltd.	25
MKP	Markwell Pacific Ltd.	EBG	Eumundi Brewing Group Ltd.	30
NFR	Nonferral Recyclers Ltd.	PEM	Perilya Ltd.	15
NMW	Normans Wines Ltd.	TSS	Tassal Ltd.	30
NTL	National Textiles Ltd.	PDR	Port Douglas Reef Resorts Ltd.	25
NWL	New Tel Ltd.	BBB	B Digital Ltd.	50
ONE	One Tel Ltd.	HTA	Hutchison Telecommunications Ltd.	50
POW	Power Pacific Ltd.	TAN	Tandou Ltd.	30
PTL	Phoenix Technology Corporation Ltd.	STH	Strarch International Ltd.	20
PTX	Pacific Matrix Ltd.	IXL	IXLA Ltd.	45
SAT	Satellite Group Ltd.	ARP	ARB Corporation Ltd.	25
SCG	Smart Communications Group Ltd.	PNH	Pineapplehead Ltd.	45
SFO	Seafood Online.com Ltd.	MSF	Maryborough Sugar Factory Ltd.	30
WSK	Woolstock Australia Ltd.	SBC	Southern Cross Broadcasting Ltd.	25

**Table Three: Industry Sectors and their Corresponding GICS Codes**

Sector	GICS Code
Energy	10
Materials	15
Industrials	20
Consumer Discretionary	25
Consumer Staples	30
Health Care	35
Information Technology	45
Telecommunication Services	50
Utilities	55

Source: (Understanding GICS, 2002)

Having identified the sample of companies, the next logical step is to describe the variables, that is, the financial ratios that are used in deriving both the *static* and *dynamic* MDA-based corporate collapse prediction models.

The ratios are primarily selected based on their technical merit (Altman, 1968; Bernstein, 1989; Casey and Bartczak, 1985; Edmister, 1972; Foster, 1986; Fraser and Ormiston, 2001; Gentry et al., 1985; Gibson, 1989; Gordon, 1971; Gupta, 1969; Lev, 1974; McKenzie, 1998; Routledge and Gadenne, 2000; Stickney, 1990; Wright, 1996). Accordingly, a total of 44 financial ratios are identified as potential predictors of collapse.

Financial statement values are collected for each company in the sample. Financial ratios are then calculated from these statement values. This process is repeated for each collapsed company and its non-collapsed counterpart, up to 5 reporting periods prior to collapse, depending on data availability. Such a choice is based upon reviewing the 84 studies mentioned earlier, where a number of observations were noticeable. First, the predictive power of the prediction models deteriorates as one moves further back from the year in which collapse occurred. Second, the models are

incapable of signaling collapse when used beyond 5-years prior to the event. Thus, a reporting period that is too long is irrelevant in that it may not yet contain information that detects financial fragility. On the other hand, a reporting period that is too short is useless in that it may be too late for purposes of signaling collapse. Therefore, it seems that the optimal reporting period is 5 years.

However, not all 44 ratios could be successfully computed. The reasons are twofold:

- There were instances where particular financial statement items were missing from the financial statements of some companies.
- There were instances where the calculation of particular ratios necessitated division by zero.

Where either problem is encountered, the problematic ratios are removed from the 44 ratios across the entire data set. The decision to remove the problematic ratios, rather than replace them by their averages across the sample, could be afforded here due to the large pool of ratios to begin with. Moreover, and in the interest of avoiding a reduction in the number of companies in the sample, it is deemed more suitable to remove a ratio rather than delete the pairs of companies whose ratios failed the screening test.

The above screening process generated 28 ratios that made it through. These ratios are: NI/TA<sup>6</sup>, CA/CL, TL/TA, WC/TA, EBIT/TA, CF/TL, TL/TE, RE/TA, S/TA, C/TA, CA/TA, QA/CL, CF/TA, NI/TE, TE/TA, QA/TA, TE/TL, C/CL, EBIT/TE, FA/TA, FA/TE, LTL/TA, CF/CL, CL/TA, CL/TE, Inv/WC, LTL/TE and S/TE.

Having described the data set of companies and financial ratios, the corporate collapse prediction models can now be derived. Derivation of the *static* model is attempted first, followed by the *dynamic* model. Not all 28 ratios make it into the final prediction

<sup>6</sup> Abbreviations are explained in Appendix 1.

models. As discussed earlier, a particular ratio-based model for signaling corporate collapse uses, on average, 2 financial ratios as predictor variables. The models derived herein rely on anything from 1 to 9 financial ratios as predictors of collapse. On average, the number of ratios in these models is about 4, which is not far from the typical average of 2.

**The Static Model**

Based on the classical rational theory in behavioural economics discussed earlier, the assumption is that the same financial ratios are capable of signaling corporate collapse over multiple time periods. Therefore, the same model is used to signal collapse for each year in the sample period. Although collapsed companies are identified from 1994 to 2002, the useful period is from 1996 to 2001: useful in the sense that there are enough collapsed companies during each year to enable deriving a *dynamic* model for each of these years later on.

Therefore, the *static* model presented in Equation 2 is derived from data collected for the period 1996 to 2001, inclusive.

**Equation 2:**

$$f_{km} = -1.472 + 1.885TL/TA + 1.626WC/TA - 1.069EBIT/TA + 2.648CA/TA - 3.146QA/TA + 0.197CL/TE$$

Where:

$f_{km}$  : The *score*; that is, the value that the model generates for company ‘*m*’ in group ‘*k*’, where ‘*k*’ represents either the group of collapsed companies or the group of non-collapsed companies.

According to Equation 2, a *score* is generated for each company in the sample. This is done in the following manner:

1. Multiply the value of the ratio ‘*TL/TA*’ by the coefficient ‘1.885’.
2. Multiply the value of the ratio ‘*WC/TA*’ by the coefficient ‘1.626’.
3. Multiply the value of the ratio ‘*EBIT/TA*’ by the coefficient ‘-1.069’.

4. Multiply the value of the ratio ‘*CA/TA*’ by the coefficient ‘2.648’.
5. Multiply the value of the ratio ‘*QA/TA*’ by the coefficient ‘-3.146’.
6. Multiply the value of the ratio ‘*CL/TE*’ by the coefficient ‘0.197’.
7. Add all the answers in steps 1 to 6.
8. Add the constant ‘-1.472’ to the result in step 7.

The *score* determines whether a company should be classified as collapsed or non-collapsed. The score could be any number. The decision to classify a company as collapsed or non-collapsed is made based on comparing its *score* to some value (the cut-off score). (Klecka, 1982, p. 49) recommends using the naïve approach for coming up with the cut-off score, which is calculated as one half the sum of the *scores* for the two group *centroids*. Each group of companies denotes a *subspace*, the center of which is called the *centroid*. (Klecka, 1982, p. 49)

**The Accuracy of the Static Model**

Having defined the *static* model, the next step is to ascertain its predictive power using the naïve approach just described. Table Four portrays the accuracy of Equation 2 in signaling corporate collapse. The results are for 1996. A company status of ‘1’ represents the event of collapse and ‘0’ of non-collapse.

**Table Four: The Accuracy of the MDA-Based Static Model in Signalling Corporate Collapse (1996)**

Actual Company Status	Predicted Group Membership		Total
	0	1	
0	10 (90.9%)	1 (9.1%)	11
1	5 (45.5%)	6 (54.5%)	11

The results in Table Four reveal the following information:

**Column 2, row 2:** out of the total of 11 non-collapsed companies, the model correctly classified 10; this corresponds to a prediction accuracy of 90.9%.

**Column 3, row 2:** out of the total of 11 non-collapsed companies, the model erroneously classified 1. This means that the model classified 1 company (9.1%) as collapsed when in reality it did not collapse. Classifying a non-collapsed company as collapsed is referred to as a Type II error. This implies that the probability of committing a Type II error is 9.1%.

**Column 3, row 3:** out of the total of 11 collapsed companies, the model correctly classified 6; this corresponds to a prediction accuracy of 54.5%.

**Column 2, row 3:** out of the total of 11 collapsed companies, the model erroneously classified 5. This means that the model classified 5 companies (45.5%) as non-collapsed when in reality they collapsed. Classifying a collapsed company as non-collapsed is referred to as a Type I error. This implies that the probability of committing a Type I error is 45.5%.

These results indicate a very high incident of committing a Type I error, despite the fact that 72.7%<sup>7</sup> of companies are correctly classified. The majority of the 84 studies mentioned earlier indicated that a high occurrence of Type I error is undesirable. This is because the erroneous classification of a collapsed company as non-collapsed is a costly mistake, whereas the erroneous classification of a non-collapsed company as collapsed is not. It is expected that the occurrence of Type I error would be reduced by using a *dynamic* model. Before considering the latter, Table Five provides the results based on the *static* model for the remaining period from 1997 to 2001.

The results in Table Five are interpreted in the same manner as those in Table Four. The summary statistics in Table Six allow for commenting on the overall predictive power of the *static* model as well as the occurrence of Type I error across the entire sample period from 1996 to 2001.

<sup>7</sup> This is calculated as  $[(90.9\% + 54.5\%)/2]$ , which is the average of the probabilities of correctly classified companies in both the collapsed and non-collapsed groups.

On average, the overall predictive power of the *static* model is 69.35% and the overall occurrence of Type I error is 42.7%. The best overall predictive power stands at 90.9% and the worst at 43.3%; these correspond to a best occurrence of Type I error of 18.2% and a worst of 70.0%. How do these results compare to those using a *dynamic* corporate collapse prediction model? This question is answered in what follows.

### The *Dynamic* Model

The first section of this paper demonstrated how a heuristic theory applies to behavioural attributes of directors of companies heading towards collapse. Furthermore, it argued that in the absence of rational economic theory a *static* model for signalling corporate collapse is flawed. A suitable model is one that reflects a heuristic behavioural framework; specifically, it is a *dynamic* model: dynamic in the sense that it does not rely on a coherent assortment of financial ratios for signalling the event of collapse over multiple time periods.

Therefore, a *dynamic* model requires a separate formulation for each year in the sample period 1996 to 2001. Each formulation relies on an independent set of financial ratios to serve as predictors of collapse. The *dynamic* model in its time-variant forms is presented in Equations 3 to 8. These equations are based on the general MDA formulation that was defined in Equation 1 earlier in this paper.

In deriving an MDA-based model for signalling corporate collapse, the objective is to determine an optimal combination of financial ratios as predictors of collapse.

MDA uses two types of *stepwise procedures* for selecting a combination of financial ratios. These are *forward* and *backward stepwise procedures*. Regardless of which procedure is used, the objectives are twofold. First, financial ratios that are poor predictors of collapse must be eliminated. Second, redundant financial ratios must be eliminated.

**Table Five: The Accuracy of the MDA-Based Static Model in Signalling Corporate Collapse (1997 to 2001)**

Period	Actual Company Status	Predicted Group Membership		Total
		0	1	
1997	0	19 (79.2%)	5 (20.8%)	24
	1	11 (45.8%)	13 (54.2%)	24
1998	0	17 (56.7%)	13 (43.3%)	30
	1	21 (70.0%)	9 (30.0%)	30
1999	0	11 (78.6%)	3 (21.4%)	14
	1	6 (42.9%)	8 (57.1%)	14
2000	0	54 (83.1%)	11 (16.9%)	65
	1	22 (33.8%)	43 (66.2%)	65
2001	0	11 (100%)	0 (0%)	11
	1	2 (18.2%)	9 (81.8%)	11

**Table Six: Summary of the Overall Performance and Occurrence of Type I Error for the MDA-Based Static Corporate Collapse Prediction Model (1996 to 2001)**

Period	Predictive Power of the Static Model	
	Overall	Type I Error
1996	72.7%	45.5%
1997	66.7%	45.8%
1998	43.3%	70.0%
1999	67.9%	42.9%
2000	74.6%	33.8%
2001	90.9%	18.2%

The elimination of unnecessary financial ratios has statistical backing of a theoretical nature, which suggests that, the fewer the ratios the better. (Hora and Wilcox, 1982)

A *forward* stepwise procedure attains these two objectives by starting with a financial ratio that provides the highest level of prediction on its own. The procedure then tests the predictive ability of the model based on two financial ratios: the one that was already selected and a second one. If the overall predictive power of the model increases, then this ratio is retained; otherwise, it is discarded. The process continues until all variables are exhausted.

A *backward* stepwise procedure, on the other hand, starts with all available financial ratios. The procedure then removes one ratio and tests the overall predictive power of the model. If it improves, then the ratio is discarded; otherwise, it is retained. Another ratio is then removed and the overall predictive power of the model is tested. If it improves, then the ratio is discarded; otherwise, it is retained. The process continues until all ratios are exhausted.

A *forward* stepwise procedure is used here. This is the default in SPSS.

Ideally, one would try all possible combinations of the financial ratios whether the stepwise procedure is forward or backward. However, this is not practical even with the most sophisticated statistical software packages that are available (Huberty, 1994, p. 122). An all-possible subset approach is certainly possible, although feasibility of such an approach might be questioned in some situations. For ‘*p*’ financial ratios, a total of ‘ $2^p - 1$ ’ possible subsets (combinations) would be assessed. In the context of the model derived here, a total of 28 ratios are considered. This amounts to  $2^{28} - 1$ , or approximately 268,435,455 subsets (possible combinations). Therefore, what the available statistical packages do instead is determine the most efficient rather than the best combination of the financial ratios.

In order to do this, a number of strategies are available at the disposal of the researcher. These are Wilk's lambda (Shapiro et al., 1968), Mahalanobis  $D^2$  (Mahalanobis, 1963), Rao's  $V$  (Rao, 1952), the between-groups  $F$  (Klecka, 1982) and the between-groups residual variance  $R$  (Dixon, 1973).

For the purposes of this study, Wilk's lambda is the most suitable. This is because it takes into consideration two criteria. These are the overall between-groups difference and the overall within-groups cohesiveness (Huberty, 1994). In the context of this study, this means that the discrimination between collapsed and non-collapsed companies is optimized; moreover, the consistency in classifying a collapsed company as collapsed and a surviving company as non-collapsed is also optimized. These criteria make Wilk's lambda a desirable strategy for this study.

In a forward stepwise procedure, every time a financial ratio is added to the corporate collapse prediction model, Wilk's lambda is calculated. If Wilk's lambda becomes smaller, this indicates that the new ratio contributed towards the overall predictive power of the model.

However, by how much should Wilk's lambda change in order to warrant the adding of a variable? There is a need for a benchmark against which to ascertain whether or not the change in Wilk's lambda is of material significance. This benchmark is called the *tolerance* (Huberty, 1994).

The tolerance is determined with reference to a partial  $F$ -statistic. Two  $F$ -statistics are relevant: an  $F$ -to-enter and an  $F$ -to-remove. The  $F$ -to-enter is a test of the increase in the power of the model after adding a predictor variable (financial ratio). Similarly, the  $F$ -to-remove is a test of the increase in the power of the model after removing a predictor variable (financial ratio). (Dixon, 1973)

The researcher sets the  $F$ -to-enter and the  $F$ -to-remove. The default values are 3.84 for  $F$ -to-enter and 2.71 for  $F$ -to-remove.

These values correspond to probabilities of 0.05 and 0.10, respectively. (Huberty, 1994) Accordingly, these are the values used when deriving the corporate collapse prediction models presented in Equations 3 to 8. It is worth noting that the coefficients presented in Equations 3 to 8 are ex-post.

**Equation 3: The Dynamic MDA-Based Model for 1996**

$$f_{km} = -0.112 + 0.894S/TA - 0.080QA/CL + 10.572CF/TA + 1.341Inv/WC + 0.246S/TE$$

**Equation 4: The Dynamic MDA-Based Model for 1997**

$$f_{km} = -0.701 + 1.029TL/TA$$

**Equation 5: The Dynamic MDA-Based Model for 1998**

$$f_{km} = -1.3030 + 5.809QA/TA - 0.134C/CL$$

**Equation 6: The Dynamic MDA-Based Model for 1999**

$$f_{km} = -4.415 + 7.857C/TA + 3.629FA/TE$$

**Equation 7: The Dynamic MDA-Based Model for 2000**

$$f_{km} = -1.561 - 2.134NI/TA + 1.014TL/TE + 0.289RE/TA + 4.234CA/TA + 0.023C/CL - 0.488FA/TE + 2.226LTL/TA - 3.45CMS/TA - 0.846CL/TE$$

**Equation 8: The Dynamic MDA-Based Model for 2001**

$$f_{km} = -3.730 - 7.502EBIT/TA - 2.117S/TA + 10.268FA/TA + 8.502CMS/TA$$

Where:

$f_{km}$  : The *score*; that is, the value that the model generates for company 'm' in group 'k', where 'k' represents either the group of collapsed companies or the group of non-collapsed companies.

The *scores* in Equations 3 to 8 are generated and interpreted in the same manner as in Equation 2; this includes using the naïve approach for coming up with the cut-off score.

**The Accuracy of the *Dynamic* Model**

The results in Table Seven portray the accuracy of Equations 3 to 8 in signaling corporate collapse. These results correspond to each year in the sample period 1996 to 2001. Table Seven is structured similar to Tables Four and Five

in order to allow for direct comparisons to be made between the results generated by the *static* model and those generated by the *dynamic* model. Therefore, the results in Table Seven are interpreted in the same manner as those in Tables Four and Five.

**Table Seven: The Accuracy of the MDA-Based *Dynamic* Model in Signalling Corporate Collapse (1996 to 2001)**

Period	Actual Company Status	Predicted Group Membership		Total
		0	1	
1996	0	11 (100%)	0 (0%)	11
	1	0 (0%)	11 (100%)	11
1997	0	24 (100%)	0 (0%)	24
	1	14 (58.3%)	10 (41.7%)	24
1998	0	21 (70.0%)	9 (30.0%)	30
	1	4 (13.3%)	26 (86.7%)	30
1999	0	13 (92.9%)	1 (7.1%)	14
	1	3 (21.4%)	11 (78.6%)	14
2000	0	59 (90.8%)	6 (9.2%)	65
	1	12 (18.5.8%)	53 (81.5%)	65
2001	0	11 (100%)	0 (0%)	11
	1	0 (0%)	11 (100%)	11

**Table Eight: Summary of the Overall Performance and Occurrence of Type I Error for the MDA-Based *Dynamic* Corporate Collapse Prediction Model (1996 to 2001)**

Period	Predictive Power of the <i>Dynamic</i> Model	
	Overall	Type I Error
1996	100%	0%
1997	70.8%	58.3%
1998	78.3%	13.3%
1999	85.7%	21.4%
2000	86.2%	18.5%
2001	100%	0%

The summary statistics in Table Eight allow for commenting on the overall predictive power of the *dynamic* model as well as the occurrence of Type I error across the entire sample period from 1996 to 2001.

On average, the overall predictive power of the *dynamic* model is 86.83% and the overall occurrence of Type I error is 18.58%. These results compare to an average overall predictive power of 69.35% and an average overall occurrence of Type I error of 42.7% for the *static* model.

The best overall predictive power for the *dynamic* model stands at 100% and the worst at 70.8%; these correspond to a best occurrence of Type I error of 0% and a worst of 58.3%. These results compare to a best overall predictive power of 90.9% and a worst of 43.3% for the *static* model, which correspond to a best occurrence of Type I error of 18.2% and a worst of 70.0%.

Table Nine provides a direct comparison of the overall predictive power and the occurrence of Type I error for both the *static* and *dynamic* models for each year during the entire sample period 1996 to 2001.

The results in Table Nine demonstrate that the *dynamic* model consistently

outperforms its *static* counterpart.

**Table Nine: Summary of the Overall Predictive Power and Occurrence of Type I Error for both the *Static* and *Dynamic* MDA-Based Models (1996 to 2001)**

Period	Predictive Power of the <i>Static</i> Model		Predictive Power of the <i>Dynamic</i> Model	
	Overall	Type I Error	Overall	Type I Error
1996	72.7%	45.5%	100%	0%
1997	66.7%	45.8%	70.8%	58.3%
1998	43.3%	70.0%	78.3%	13.3%
1999	67.9%	42.9%	85.7%	21.4%
2000	74.6%	33.8%	86.2%	18.5%
2001	90.9%	18.2%	100%	0%

This observation is true not only for the overall predictive power of the model, but also as far as the occurrence of Type I error is concerned.

The results in Table Nine provide the necessary empirical evidence for a heuristic behavioural theory in the context of ratio-based modelling of corporate collapse.

**Conclusion**

The recognition of behavioural elements in Finance, which has emerged only recently, has caused major shifts in the analytic framework. This is particularly true when it comes to ratio-based modelling of corporate collapse.

In that regard, the approach so far has been based on the classical rational theory in behavioural economics (Bernoulli, 1954). The implications are that the financial ratios, which are the predictors of collapse, are assumed to be *static* over time. In other words, it is assumed that the same financial ratios are capable of signalling corporate collapse over multiple time periods. This explains why studies that tried to pre-empt

the event over multiple periods, used the same model. This study refers to such a model as a *static* model. This paper

demonstrated that there exists time variant inconsistency in the set of predictors of the event of collapse. The results are based on a review of 44 financial ratios in 84 studies from 1968 to 2004. A usage rate was calculated for each ratio, based on the number of studies in which this ratio was a predictor of collapse. The majority of the ratios analysed had very low usage rates. The results demonstrated that there exists time variant inconsistency in the set of predictors of corporate collapse. This is particularly true when considered in light of the fact that a specific study uses, on average, 2 financial ratios in the final prediction model. Such results underscore the inappropriateness of a *static* model for signalling collapse, and consequently question the suitability of the underlying rational behavioural framework. The justification could be that the accounting numbers used in calculating the financial ratios are influenced by heuristic behavioural attributes of company directors. Such an observation conforms to the behavioural theory put forward in Kahneman (2003), which challenged the dominant classical rational approach introduced in Bernoulli (1954).

In the absence of rational economic theory, a *static* model is flawed. A suitable model is one that reflects the heuristic behavioural framework put forward in Kahneman



(2003) and discussed in the first section of this paper. Specifically, the model is a *dynamic* one: dynamic in the sense that it does not rely on a coherent assortment of financial ratios for signalling corporate collapse over multiple time periods. Section 3 of this paper provided the empirical backing for such a recommendation. Specifically, the predictive accuracy of a *dynamic* model was compared to that of a *static* model using a data set of Australian publicly listed companies. The results indicated that a *dynamic* model consistently outperformed its *static* counterpart for each year during the entire sample period 1996 to 2001. On average, the overall predictive power of the *dynamic* model was 86.83% and the overall occurrence of Type I error was 18.58%. These results compare to an average overall predictive power of 69.35% and an average overall occurrence of Type I error of 42.7% for the *static* model. Such empirical evidence provided the necessary backing for a heuristic behavioural theory in the context of ratio-based modelling of corporate collapse.

### Implications

The implication from this study could affect stakeholders in companies, regulatory bodies as well as the economy in general.

Arguably, the incident of collapse would mostly affect stakeholders in a company. These include shareholders, management, creditors, employees, suppliers and customers. All such stakeholders could incur considerable financial losses when companies collapse. Shareholders, for instance, may stand to lose most because they are the last group to receive compensation for their shareholdings upon the collapse of their company. It is an established reality that when companies liquidate their assets upon collapse, senior creditors are payed-off first, followed by junior creditors, followed by suppliers and employees –including management– and finally shareholders. In trying to be as graphic as possible in describing the consequences of collapse on stakeholders in a company, Hosking (2004, p. 23) said that they fleece the shareholders, defraud the customers and screw the workforce. To illustrate what fleecing the shareholders

might translate into, Arpe (2004) estimated that the recent collapse of Parmalat in Europe defrauded stakeholders of more than USD13 billion.

In addition to affecting stakeholders in companies, corporate collapse could also have implications for regulatory bodies. As a matter of fact, Reinstein and Weirich (2002) described the failure of Enron in the USA as something that would send shock waves with far-reaching consequences to the legal and regulatory environment of financial reporting, which were expected to give rise to serious re-valuations of accounting standards-setting and auditing practice. Regulatory bodies such as the Australian Securities and Investments Commission (ASIC), the Securities and Exchange Commission (SEC) in the USA and the Accounting and Auditing Standards Board (AASB) in most developed countries, require truthful disclosure of financial statement information by all publicly listed companies. This is to enable these regulatory bodies to adequately monitor the financial health of these companies and re-assess reporting requirements, if need be. However, when financially distressed companies collapse before being detected by regulatory bodies, this raises questions about either the truth in reporting by these companies, or the adequacy of models used by regulatory bodies to signal impending corporate collapse, or the adequacy of the reporting standards. Regardless of which one of these scenarios was prevalent, studies like this one would be most helpful in providing regulatory bodies with a superior tool for either unravelling financial fraud, or signalling impending corporate collapse before it happens, or revise reporting standards; all of which would allow for taking corrective measures.

The implications of corporate collapse do not stop with stakeholders and regulatory bodies; they may also be felt economy-wide. Considering for example the recent collapse of HIH in Australia, Veysey (2003) described the downfall of HIH as Australia's largest corporate failure. Moreover, according to Sarre et al. (2001), the downfall of HIH left a shortfall of AUD4 billion. However, this shortfall was

later revised upwards to AUD5.3 billion, by Howard (2003). Similarly, according to Edmondson and Cohn (2004) the recent collapse of Parmalat in Europe left a shortfall of USD16.2 billion. Likewise, in an attempt to put a dollar figure to what the collapse of Enron cost the U.S. economy, Reinstein and Weirich (2002) estimated the total value lost at USD63.1 billion. Such staggering amounts are larger than the Gross Domestic Products (GDPs) of many developing nations.

Having demonstrated what implications corporate collapse could have on stakeholders in companies, on regulatory bodies and on economies in general; the benefits that could be derived from this study could be re-affirmed.

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## Appendix 1

The abbreviations used in Table One are representative of the following 44 financial ratios:

CA/CL: Current Assets / Current Liabilities;  
 TL/TA: Total Liabilities / Total Assets;  
 NI/TA: Profit / Total Assets;  
 WC/TA: Working Capital / Total Assets;  
 EBIT/TA: Earnings Before Interest and Taxes / Total Assets;  
 TL/TE: Total Liabilities / Total Equity;  
 QA/CL: Quick Assets / Current Liabilities;  
 RE/TA: Retained Earnings / Total Assets;  
 S/TA: Sales / Total Assets;  
 C/TA: Cash / Total Assets;  
 CF/TL: Cash Flow / Total Liabilities;  
 NI/TE: Profit / Total Equity;  
 CA/TA: Current Assets / Total Assets;  
 MVE/TL: Market Value of Equity / Total Liabilities;  
 NI/S: Profit / Sales;  
 CF/TA: Cash Flow / Total Assets;  
 CL/TA: Current Liabilities / Total Assets;  
 EBIT/I: Earnings Before Interest and Taxes / Interest;  
 CA/S: Current Assets / Sales;  
 Inv/S: Inventory / Sales;  
 TE/TA: Total Equity / Total Assets;  
 LTL/TA: Long-Term Liabilities / Total Assets;  
 QA/TA: Quick Assets / Total Assets;  
 TE/TL: Total Equity / Total Liabilities;  
 WC/S: Working Capital / Sales;  
 C/CL: Cash / Current Liabilities;  
 QA/S: Quick Assets / Sales;  
 S/FA: Sales / Fixed Assets;  
 CF/CL: Cash Flow / Current Liabilities;  
 CF/S: Cash Flow / Sales;  
 FA/TA: Fixed Assets / Total Assets;  
 Inv/WC: Inventory / Working Capital;  
 S/TE: Sales / Total Equity;  
 C/S: Cash / Sales;  
 EBIT/S: Earnings Before Interest and Taxes / Sales;  
 EBIT/TE: Earnings Before Interest and Taxes / Total Equity;  
 FA/TE: Fixed Assets / Total Equity; S/Inv: Sales / Inventory;  
 TE/LTL: Total Equity / Long-Term Liabilities;  
 AR/Inv: Accounts Receivable / Inventory;  
 CL/TE: Current Liabilities / Total Equity;

EBT/TA: Earnings Before Taxes / Total Assets;

Exp/S: Expenses / Sales;

LTL/TE: Long-Term Liabilities / Total Equity.

*Please note that the financial ratios presented in Table One are broadly defined. For example, the financial ratio "QA/TA" may include 'Inventory' as a 'Quick Asset' when used in a particular study, but may ignore it when adopted by a different empirical examiner. However, this will not deter from an accurate analysis.*