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Predicting Firm Failure: A Behavioral Finance Perspective*

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Abstract

In this article we first argue that researchers in the area of financial distress and failure cannot ignore the human/managerial/decision-making side of the business and just focus on the business' operations side; as has been the case so far for almost all the research in the area. We then discuss how psychological phenomena and principles, known as heuristics or mental shortcuts, could be utilized in building more powerful success/failure prediction models especially for small and medium sized enterprises (SMEs).

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Introduction

A Two-Element Model to Study Financial Distress and Failure

For the purposes of this writing, it is helpful to remind ourselves that all firms, public or private, large or small, are essentially made up of two related elements:

A. a human or decision-making element; as represented by the management and/or the owner-manager who makes all the business judgments and decisions; and
B. a commerce or operating element- where all the managerial decisions are executed and actual business is conducted.

Furthermore, given judgments and decisions always precede actions and operations within any corporate body, element A can be thought of as *the cause* element and element B as *the effect* element. Now, with the just stated cause and effect in mid, and further recognizing that almost all the business failure studies have mainly used financial data in their analyses, a quick review of the literature reveals that almost all the existing research have focused on the commerce side of the corporation (the effect/data side) and not on its managerial side (the cause/human side)[1]. Stated differently, the researchers' study of business failure could be compared with the practice by a group of physicians who just focus on the symptoms of a given disease and not on the cause(s) of the disease that would provide key information to prevent similar cases from happening in the future. Obviously, such an approach does not take us very far and so it is not surprising that a comprehensive review of the related literature concludes that after 35 years of academic research into bankruptcy prediction, there is "no academic consensus as to the most useful method for predicting corporate bankruptcy"[2].

To be fair, it could be argued by some that the one-sided effect-based approach as mentioned in above might still make sense for large publicly traded companies; especially when such companies are controlled by well-established business systems and processes that reduce the importance of a single person's judgment and action. In addition to the diverse range of expertise available within the modern corporation, top executives at Fortune 1000 companies can easily tap into other sophisticated talent pools for advice on key decisions by using external consultants and members of the Board of Directors, a group referred to as the "Outside View" in the behavioral finance literature[3]. Additionally, the extent of the easily available computerized financial information about public firms has made it a relatively effortless process for researchers to access and study such data using sophisticated statistical tools ranging from MDA and LOGIT and PROBIT models to even more sophisticated Artificial Intelligence (AI) and Expert Systems (ES) approaches. Moreover, by making the

[1] Studies conducted by scholars like Kahneman and Lovallo (1993), Camerer and Lovallo (1999), and Wu and Knott (2005) are among the few exceptions in this respect; as will be further discussed in this chapter.

[2] See Aziz and Dar (2006), p. 26.

[3] Theoretically, the significance of a board of directors lies in the fact that such a body can "debias" many of the top management's cognitive biases that could lead to very expensive errors in judgment, including errors leading to failure and bankruptcy. This is also an example regarding the forgotten human/managerial side in failure studies that we intend to emphasize in this chapter.

simplifying assumption that management in a public corporation acts to maximize shareholders' wealth, coupled with the market efficiency assumption, it's easy for researchers to just focus on the *effects* of the management processes, as revealed by the financial data, rather than to try to focus on management's decision making processes that *caused* the financial problems in the first place[4].

In this article we argue that researchers cannot ignore the human/managerial/decision-making (cause-based) side of the equation for any company, large or small. It is obviously wrong to do so for startups, early-stage ventures, and even pre-IPO companies because the majority of such firms rely heavily on individuals (mainly entrepreneurs) for both strategic and operational decisions. The cause-based approach, especially if coupled with what we have already learned so far about failure prediction, has the potential of further enabling us to gain better insights regarding problem areas that might lead to financial distress and failure later on. In our efforts, new theoretical and empirical breakthroughs in the field of cognitive psychology and neuroscience can help us develop effective and realistic models to help predict successes or failures for not only the small and entrepreneurial firms, but also for large publicly traded corporations. This writing first provides a quick review of the current state of the failure prediction literature relevant to the small and medium sized enterprises (SMEs). It then discusses in general terms how psychological phenomena and principles, also known as heuristics or mental shortcuts, need to be utilized in building more powerful success/failure prediction models. A summary will appear at the end.

Small Firm Failure Prediction Studies

Most small firm studies focus on loan default and credit scoring models since this is the type of classification problem facing the entities that are the usual source of data from small private firms. The earliest study performed on small firm sample data was published by Edmister (1972). Using small firm financial data from a Small Business Administration's (SBA's) guaranteed loan database and Robert Morris and Associates *Annual Statement Studies* data he constructs a number of dummy variables, some of which are designed to reflect deviations of the ratios from industry benchmarks. He then uses these variables with an MDA approach to examine the ability of his model to predict either loan repayment or loan default. His sample contains information from 42 different firms; 21 firms that repaid their loans and 21 firms that failed to repay. He examines a number of different variable construction methods including single year ratio variables as predictors, dummy variables representing the trend of changes in ratios over a three year period, and three year average ratio variables. His final model using the three year average ratio data is as follows:

$$Z = .951 - 0.423X_1 - .293X_2 - 0.482X_3 + 0.277X_4 - 0.452X_5 - 0.352X_6 - 0.924X_7$$

Where:

X_1 = 1 if annual funds flow / current liabilities ratio is < .5, or = 0 otherwise,

X_2 = 1 if equity / sales is < .07, or = 0 otherwise,

[4] We are not denying the possible roles that macro elements such as economic conditions and regulatory factors can play in a given company's failure. However, we believe our "Two Element-Model" contains the factors that are among the most relevant for explaining as why firms develop financial distress or fail.

X_3 = 1 if net working capital / sales ratio relative to the appropriate RMA benchmark ratio is < -.02 or = 0 otherwise,
X_4 = 1 if current liabilities / equity ratio relative to the appropriate SBA benchmark ratio is < .48 or = 0 otherwise,
X_5 = 1 if inventory / sales ratio relative to the appropriate RMA benchmark ratio is in an uptrend and still < .04 or = 0 otherwise,
X_6 = 1 if quick ratio relative to the appropriate RMA benchmark ratio trend is down and is < .34 or = 0 otherwise, and
X_7 = 1 if quick ratio relative to the appropriate RMA benchmark ratio trend is up or = 0 otherwise.

Edmister finds his first three variable coefficients (X_1 - X_3) are significant predictors for loan default at the .01 significance level and that the coefficients for variables X_4, X_5 and X_7 are significant at the .05 level. His final model with estimated coefficients correctly classifies 39 of 42 firms (93% accuracy).

Most of the later studies use more traditional types of financial ratios and many focus on variable sets that reflect, as closely as possible, the variables that Altman's various studies examine. Some studies, however, do examine unique predictive variables. Kallberg and Udell (2003) focus on the added value of private firm credit information available from Dun & Bradstreet Corporation (D&B) and examine whether it is of additional value to lenders when evaluating the probabilities of credit default. They use a LOGIT approach to examine 241 failed firms and 2482 non-failed firms and in addition to the standard types of financial ratios, they include the D&B "PAYDEX" score that reflects the average number of days the firm was "past due" on any trade credit obligation. They also include dummy variables representing age, negative Uniform Commercial Code filings, and the existence of secured lending agreements. Their results provide a model with predictive ability of about 89% in both the estimating sample and a hold-out sample and the results indicate the D&B variable adds significant predictive power above and beyond the variable constructed from public information.

In a series of papers, Keasey and Watson argue studies of small firm failure are usually driven by data availability rather than theory and they focus on the addition of non-financial data to the analysis and prediction of firm failure.[5] Abouzeedan and Busler (2004) develop a *Survival Index Value*® (*SIV*®) model that incorporates both financial and non-financial variables into the predictive process where the non-financial variables are chosen based on the Keasey and Watson work. They also provide a review of traditional MDA based models and a good discussion of past studies that apply MDA to SMEs. While they provide an interesting discussion of the financial versus non-financial variable issue they don't provide any comparison of the performance of their model relative to the performance of more common variable specifications and model approaches.

[5] See Keasey and Watson (1986), Keasey and Watson (1987), Keasey and Watson (1988) and Keasey and Watson (1991).

Impact of Basel II and Recent Small Firm Studies

Basel II, the recommendations on new banking regulations, were developed in the late 1990's and the final recommendations were originally published in 2004. Since then many banking regulatory authorities around the world have been adopting the new proposed regulations. One aspect of the new regulations is that banks are allowed to use internal models to assess the risk of credits they have extended to their banking clients and to use these risk assessments to calculate their risk adjusted capital requirements. This shift in the regulatory framework for banks has created a renewed interest in applying failure prediction models to SME data both in the US and in foreign countries.

Mramor and Valentincic (2002) examine private firm data from 19,627 very small private companies operating in 28 different industries in Slovenia in order to predict which firms will develop liquidity problems. The dataset contains both financial statement data and data on cash balances held by these firms in their banks and they compare the performance of PROBIT, LOGIT and MDA models on industry subsamples. Their results indicate that, in general, the PROBIT and LOGIT models perform significantly better than the MDA models.

Grunert, Norden and Weber (2004) examine SME credit data using client data obtained from four German banks using a PROBIT methodology and examine whether the inclusion of non-financial firm data improves the model's ability to forecast credit defaults. Their non-financial data include measures of management quality and market position. They find inclusion of these qualitative data variables significantly improves the model's predictive ability.

Pompe and Bilderbeek (2005) examine private firm data from annual reports filed with the Belgian National Bank using both an MDA approach and a NN approach. Their data contains of both young firms and older, established firms. They find similar predictive results with both methods of analysis. They also report that using trends in ratios failed to increase the predictive power of the models, predictive ability is weaker when analyzing younger firms, and almost every ratio examined had some predictive power.

Altman and Sabato (2007) focus on modeling credit risk for SMEs in the US market using a LOGIT approach on a sample of over 2,000 firms that have annual sales of less than $65 million. They compare their SME model to a later version of Altman's Z score model developed in Altman and Hotchkiss (2005) which they term a "generic" corporate MDA model. While the research focus is on SMEs, the data is financial data drawn from the COMPUSTAT database. While all firms have sales of less than the cutoff mentioned earlier, detailed statistics on the final sample are not given and it is hard to determine just how representative of small firms the final sample is. Their results indicate that with a log transformation of the input variables, predictive accuracy of the LOGIT model reaches 89%, which outperforms the MDA model that they also run for comparative purposes.

Wiklund, Baker and Shepherd (2008) focus on the factors related to SME firm failure in the first 7 years of operations. Using data from 37,782 incorporations filed with the Swedish government agency that regulates these firms they tracked the firm performance either to the time of failure or to the end of the 7 year period. Using a discreet time LOGIT analysis they find that greater liquidity, lower leverage, and greater profitability are extremely important determinants of early success for new firms with the importance of these factors decreasing through time, In Altman, Sabato and Wilson (2009) the authors test the model developed in Altman and Sabato (2007) on a dataset from the UK and they expand the model to include the addition of qualitative variables to the model. Qualitative data included in the analysis represent "default events" such as court filings for unpaid debts, the timeliness of the filing of financial information with the government agency collecting the data, a dummy variable for whether the financial accounts are audited, the age of the firm, and dummy variables representing whether a firm has been recently established or has existed for more than 3 years. Their results indicate that inclusion of qualitative variables improves the predictive accuracy of the models.

Vallini, Ciampi and Gordini (2009) apply MDA, LOGIT and NN approaches to data representing over 6,000 small Italian firms. The data are drawn from the CERVED database in Italy that contains data collected by local Chambers of Commerce on private firms throughout the country. While predictive accuracy of the models examined was low (in the 60% to 70% accuracy range) for the entire sample, the NN model narrowly outperformed the MDA and LOGIT approaches. When the data is partitioned by some combination of size, geographic location within Italy, and business sector, the predictive accuracy of all three methods improve but the NN predictive accuracy improves significantly more than the other approaches. For example, when partitioned by size, the NN approach provided predictive accuracy of over 71% while the MDA and LOGIT approaches only provided accuracy of 64% for the larger private firms in the sample.

Using one of the newest AI/ES approaches called Support Vector Machines (SVMs) Kim and Sohn (2010) examine both financial data and non-financial firm variables that is combined with economic variables in order to predict default rates in a sample of 4,590 Korean technology firms. The firm data examined comes from a government technology credit guarantee program and their results indicate that the SVM approach outperforms both standard neural network approaches and LOGIT models.

Existing Research on Small Business Failure

While there have been a number of studies using small private firm data in foreign countries, very little of the recent research has focused on small private firms in the U.S.. This may be partially due to the ease of access U.S. researchers have to large databases of public firm data such as CRSP and COMPUSTAT. Finding the necessary data to perform studies on small private firms is not always easy. There isn't a central data source in the U.S. for small private firm data similar to the Italian data based used by Vallini, Ciampi and Gordini (2009) or the Belgian Central Bank data used by Pompe and Bilderbeek (2005). One starting point for U.S. researchers is to look into the data sources discussed earlier in this book in the chapter written by Charles Ou. Another source of small private firm data might be large commercial banks. Researchers may be able to approach the banks and access data collected from bank's loan customers as Grunert, Norden and Weber (2004) did when they created their sample from loan data supplied by German banks. Given the banking industry's new interest in modeling the credit risk of their customers they may be more amenable to making the effort to provide researchers with data. Finally, small firm researchers need to consider incorporating the newer AI/ES modeling techniques into their research. Many studies have concluded that these newer empirical approaches are more efficient at forecasting distress and failure so they should be considered in future research.

Psychological Phenomena as Possible Predictors of Business Success or Failure

The Importance of the Human Decision

As alluded to in above, the findings from the fields of cognitive psychology and neuroscience have fundamentally changed the way we now look at how financial decisions are made. For example, an entrepreneur might assign a low risk assessment to an otherwise high-risk project if they particularly like that individual project and subsequently take on a riskier project then the potential return justifies. While the riskier project has a higher chance of failing, the entrepreneur does not see it that way mainly because of the affect heuristics. Since it is usually the human decision that makes or breaks a private company, our focus in this section shifts from the commerce/operational (*effect*) side of failure analysis to the human/managerial/decision making (*cause*) side of it.

The Role of Heuristics

Starting, financing, managing, and growing any private venture is a rather complicated decision and if the venture is launched, it will bring further uncertainty and ambiguity for the decision maker. These types of ambiguities also exist in large publicly held corporations when, for example, a CEO contemplates entering into a new market or acquires another company. It is because of such complexities and uncertainties, and the added fact that the human brain is not wired to handle very complex scenarios, that both entrepreneurs and managers resort to a limited set of mental shortcuts (or heuristics) to simplify things and move forward. While heuristics are very beneficial in such cases and can get things accomplished, their use also introduces cognitive biases into the decision process that may lead to errors in judgment.

While arguments for shifting the focus away from the commerce/operational side of failure analysis to its human/managerial side have some novelty, the idea of applying psychological factors and heuristics to economic activities such as business entry is not new. For example, Roll (1986), through a comprehensive literature review and analysis, forwarded “The Hubris Hypothesis of Corporate Takeovers”. Cooper, Woo and Dunkelberg (1988) documented the existence of overconfidence in entrepreneurs. Kahneman an Lovallo (1993) and Camerer and Lovallo (1999), respectively, suggested and directly tested the prevalence of overoptimism and overconfidence and concluded that their findings were consistent with the prediction that both phenomena would lead to excessive business entry and failure. Simon, Houghton, and Aquino (1999) tested the role that three key cognitive biases play in starting up a business. More recently, Wu and Knott (2005) discussed in detail the entrepreneur’s overconfidence relative to entry decisions. While some recent work has focused on these important issues, the failure literature lacks a comprehensive framework that allows for modeling decision process variables. This is exactly the area where we see much potential for improving our failure/success prediction models.

Building upon the literature briefly discussed above and borrowing from the findings in the field of behavioral finance and economics, it is apparent there exists a relationship between the probability of failure at any given venture and the intensity of the cognitive biases of the entrepreneur or manager behind that venture. Recognizing that "cognitive biases" is a catch-all variable that needs to be deconstructed into a subset of relevant biases that can be empirically tested, we offer a call to action for a shift in research method in future failure oriented studies. Specifically, in future business failure studies, and especially those that involve startups, SMEs, and IPO companies, primary attention should be placed on the individual decision maker responsible for the companies' well being. It is only then that we can study, and possibly "debias" the decision makers' cognitive biases that could make or break their companies. Given the limited nature of our analysis in here, the balance of the section will discuss some key psychological factors that prior research has shown can play an important role in the individual decision making process, including those that could lead to business failure[6].

The Affect Heuristic

Simply stated, the very powerful affect heuristic has been defined as a feeling state, such as "goodness or badness", when one faces an investment opportunity or a startup potential. Affect can also be viewed as a quality, such as acceptable and unacceptable, when associated with a risky business venture. Additionally, affect can be described as behavior that places heavy reliance on intuition, instinct, and gut feeling[7]. Affect heuristic is probably among the top mental short cuts employed because it has been able to explain the otherwise peculiar negative relationship between expected risk and expected return or gain in investment situations[8]. For example, a "good feeling" toward a high-risk proposition like a startup would lead to a higher perceived benefit in that startup and a lower risk perception in that venture.

New research has shown that "affective reactions to stimuli (like venture proposals) are often the very first reactions, occurring automatically and subsequently guiding information processing and judgment"[9]. Based on such findings, it follows that entrepreneurs start businesses they like (and not necessarily the ones they consider as high potential) and venture capitalists (VCs) finance ventures they find attractive (and not necessarily the ones they consider as highly profitable).

[6] This section is built upon the discussion on cognitive biases in Yazdipour (2009).
[7] For a good coverage of the latest literature on the issue see Slovak (1972, 1987), Slovic and Peters (2006), Olsen (2008) and Shefrin (2007).
[8] Normally, in investment situations investors in high risk assets require high returns. However, from what we have learned from psychology, if an individual develops a "good feeling" (positive affect) for a high-risk investment, she/he may require low return from such an investment.
[9] Finucane, Alhakami, Slovic, and Johnson (2000, p.2) note that it was Zajonc (1980) who first made this argument.

The Representative (Similarity) Heuristic

According to Tversky and Kahneman (1974), many of the probabilistic questions that people are concerned with can be characterized by, "what is the probability that object A belongs to class B" or "what is the probability that event A originates from process B?". To answer questions like these, people utilize the representative heuristics, in which probabilities are evaluated by the degree to which A resembles B. For example, when A is highly representative of B, the probability that A originates form B is judged to be high.

In such cases the representative heuristic assists in evaluating the probabilities dealing with objects or processes A and B. As an example, when A is highly representative of B, the probability that A originates from B is judged to be high. The problem is that representativeness (similarity) should not affect the judgment of probability. What should be considered in the judgment to probability is "prior probability" or "base rate." However, the latter is not the case in practice. (violation of Bayes' rule).

The key aspects of the Representativeness Heuristic:

1. The "representativeness heuristic" is a built-in feature of the brain for producing rapid probability judgments, rather than a consciously adopted procedure.
2. As humans we are not aware of substituting judgment of representativeness for judgment of probability.

The Availability or Recency Heuristic

To understand this judgment heuristic, it is important to understand that people disproportionately recall the salient events that they have observed; those that are very recent or those that individuals are emotionally involved with in the very recent past are considered more important. The more salient an event is, the more likely the probability that the event will be recalled. With the availability heuristics, people search their memories for relevant but recent information and data. The result is that this sort of bias prevents managers and entrepreneurs from considering other potential information and possible related outcomes that may not have occurred recently. For example, a San Francisco Bay Area entrepreneur may assess the risk of starting a new venture by recalling all the positive reports on successful startups that they have recently been reading about in the business section of the Silicon Valley Mercury News. The problem, however, is that not all memories are equally retrievable (or available) and this leads to error in judgment. In the above example, more recent incidences and more salient events (all positive reports on successful startups) will weigh more heavily than possible reports of failures and non-reported incidences and this will, in turn, lead to prediction biases that would distort one's judgment or estimate of a future outcome.

Anchoring and Adjustment

Anchoring refers to a tendency to anchor on, and stay around, an initial arbitrary value which may be suggested by the way a proposition is presented or by some initial computation. When forming estimates and predictions, perceptions can be influenced by such prior suggestions. In addition, people adjust away from an initial value suggested to them (the anchor) insufficiently to arrive at the true value of the subject under consideration.[10] An example would be the way an investment banker uses the Relative Valuation model (multiples method) to arrive at an IPO price; or a Venture Capitalist (VC) uses the same method to price a venture capital deal. In both cases prevailing multiples which are chosen and adjusted up or down on an arbitrary basis are used to come up with a price and this "anchored" adjustment introduces a bias. A more sensible alternative would be to look at the risks involved and the types of cash flows expected from the business and then come up with a value while ignoring anchors suggested by past experience.

From the VC's point of view, anchoring bias can be used to statistically argue that an entrepreneur may overestimate the chances of success of the business. Following Tversky and Kahneman (1973,1974) and Minniti and Levesque (2008), it follows that starting a new venture is a conjunctive event; meaning for a startup to succeed, it must succeed in all the steps that are needed for its success as a whole. For example, in order for a startup to succeed, it must first succeed in producing a working prototype, then employing the needed resources including financing to actually manufacture the product, and later to hire a marketing and sales force to bring in revenue. However from a statistical point of view, the overall probability of a conjunctive event like a startup is lower than the probability of each elementary component events if such events are independent. This means even if each of the steps are very likely, the overall probability of the venture's success as a whole is low. This leads to excessive optimism by entrepreneurs as they take the probabilities of elementary events as a reference point and adjust them up or down insufficiently to arrive at a desired overall probability for the venture as a whole.

Summary and Some Suggestions for Future Research

To summarize, research from the fields of cognitive psychology and neuroscience has shown that individuals, including entrepreneurs and corporate managers, use mental short cuts like the ones discussed above when the decisions are overly complex. While such heuristics simplify the decision making process and reduce the decision maker's anxiety level, they also introduce biases that can lead to errors in judgment. And this is exactly why we encourage failure researchers to focus their attention on the decision maker, the entrepreneur and/or the manager, in addition to the financial data. Zeroing in on the commerce (effect) side of failure, as has been the case for almost all the research up to this point, only reveals to us a half-image of the foundation of the firm under consideration. To see the whole foundation we must also consider information about the decision maker and especially her/his predisposition toward the known heuristics. The challenge then, is to develop research methodologies that satisfy such requirements that are dictated by behavioral finance while building on the empirical methodologies that have developed in the more traditional failure prediction literature. But that task is beyond the scope of this current paper and, hopefully, will be the subject of many research papers to come.

[10] See Tversky and Kahneman (1973,1974).

REFERENCES

Abouzeedan, A. and M. Busler (2004), "Typology Analysis of Performance Models of Small and Medium-Size Enterprises (SMEs)," *Journal of International Entrepreneurship 2*, pp. 155-177.

Altman, E. (1968), "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance*, *23:4*, pp. 589-609.

Altman, E. (1993), *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*, New York: Wiley.

Altman, E. (2000), "Predicting financial distress of companies: revisiting the Z-score and ZETA® models" New York University, New York.

Altman, E., R. Haldeman, and P. Narayanan, (1977), "ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations," *Journal of Banking and Finance*, pp. 29–54.

Altman and Hotchkiss (2005), *Corporate Financial Distress and Bankruptcy*, *3rd. edition*, John Wiley & Sons, New York.

Altman, E.I., and Sabato, G. (2007), "Modeling Credit Risk for SMEs: evidence from the US market," *ABACUS*, *43:3,* pp. 332-357.

Angelini, E., G. di Tollo, and A. Roli (2008), "A Neural Network Approach for Credit Risk Evaluation," *The Quarterly Review of Economics and Finance 48*, pp, 733-755.

Atiya, A. E. (2001) "Bankruptcy Prediction for Credit Risk Using Neural Networks: a survey and new results," *IEEE Transactions on Neural Networks 12:4*, pp. 929-935.

Aziz, M. Adnan and Humayon A. Dar (2006), "Predicting Corporate Bankruptcy: where we stand?" *Corporate Governance*; pp. 18-33.

Balcaen, S. and H. Ooghe (2006), "35 Years of Studies on Business Failure: an overview of the classic statistical methodologies and their related problems," *The British Accounting Review 38*, pp. 63-93.

Beaver, William H. (1966), "Financial Ratios as Predictors of Failures," *Empirical Research in Accounting: selected studies*, pp. 71-111.

Camerer, C. and D. Lovallo (1999), "Overconfidence and Excess Entry: An Experimental Approach," *American Economic Review 89:1*, pp. 306-318.

Chen, H., S.Y. Huang, and C.S. Lin (2009), "Alternative Diagnosis of Corporate Bankruptcy: A neuro fuzzy approach," *Expert Systems with Applications 36*, pp. 7710-7720.

Coats P. K. and L. F. Fant (1993), “Recognizing Financial Distress Patterns Using a Neural Network Tool,” *Financial Management 22:3*, pp. 142-155.

Cooper, A., C. Woo and W. Dunkelberg (1988), “Entrepreneurs’ Perceived Chances for Success,” *Journal of Business Venturing 3* , pp. 97-108.

Dimitras, A.I., R. Slowinski, R. Susmaga and C. Zoupounidis (1999), “Business failure prediction using rough sets,” *European Journal of Operation Research 114:2*, pp. 263-280.

Dugan, M. and Forsyth, T. (1995), “The Relationship Between Bankruptcy Model Predictions and Stock Market Perceptions of Bankruptcy,” *The Financial Review, 30,* pp. 507-528.

Edmister, R. (1972), "An Empirical Test to Financial Ratio Analysis for Small Business Failure Prediction," *The Journal of Financial and Quantitative Analysis 7*, pp. 1477-1493.

Etemadi, H., A. A. Rostamy, and H. F. Dehkordi (1990), “A Genetic Programming Model for Bankruptcy Prediction: Empirical Evidence from Iran,” *Expert Systems with Applications 36*, pp. 3199-3207.

Finucane, M.L., Alhakami, A., Slovic, P., & Johnson, S.M. (2000), “The affect heuristic in judgments of risks and benefits,” *Journal of Behavioral Decision Making 13*, pp. 1-17.

Fitzparick, P. J. (1932), “A Comparison of Ratios of Successful Industrial Enterprises with Those of Failed Firms,” *Certified Public Accountant*, pp. 598-605, 656-662, and 727-731.

Grice, J.S. and Dugan, M.T. (2003), “Re-estimation of the Zmijewski and Ohlson Bankruptcy Prediction Models,” *Advances in Accounting 20*, pp. 77-93.

Grunert, J., Norden, L. and Weber, M. (2004), “The Role of Non-Financial Factors in Internal Credit Ratings,” *Journal of Banking and Finance, 29:2*, pp. 509-531.

Kahneman, D. and Lovallo, D. (1993), “Timid choices and bold forecasts: A cognitive perspective on risk taking,” *Management Science, 39 (1)*, pp. 17-31.

Kallberg, J. G. and G. F.Udell (2003), “The Value of Private Sector Business Credit Information Sharing: The US case” *Journal of Banking and Finance 27*, pp. 449-469.

Keasey, K and R. Watson, (1986), “The Prediction of Small Company Failure: Some Behavioural Evidence for the UK”, *Accounting and Business Research 17:65*, pp. 49–57.

Keasey, K. and R.Watson, (1987), “Non-financial Symptoms and the Prediction of Small Business Failure: A Test of the Argenti Hypothesis”, *Journal of Business, Finance and Accounting 14:3*, pp. 335–354.

Keasey, K. and R.Watson, (1988), “The Non-Submission of Accounts and Small Company Financial Failure Prediction”, *Accounting and Business Research 19,* pp. 47–54.

Keasey, K. and R. Watson, (1991), “The State of the Art of Small Firm Failure Prediction: Achievements and Prognosis,” *International Small Business Journal 9:4*, pp. 11–29.

Kim, H. S. and S. Y. Sohn (2010), “Support Vector Machines for Default Prediction of SMEs Based on Technology Credit,” *European Journal of Operational Research 201*, pp. 838-846.

Kun Chang Lee, Ingoo Han and Youngsig Kwon (1996), “Hybrid neural network models for bankruptcy predictions,” *Decision Support Systems 18:1*, pp. 63-72.

Merwin, C.L. (1942) “Financing Small Corporations in Five Manufacturing Industries, 1926-1936,” (New York: National Bureau of Economic Research).

Meyer, P.A. and H. Pifer (1970). “Prediction of bank failures,” *The Journal of Finance 25*, pp. 853–868.

Minniti, M. and Levesque, M. (2008), “Recent developments in the economics of entrepreneurship,” *Journal of Business Venturing 23*, pp. 603-612.

Mramor, D. and A. Valentincic (2002), “Forecasting the Liquidity of Very Small Private Companies,” *Journal of Business Venturing 18*, pp. 745-771.

Ohlson, J.A. (1980), “Financial ratios and the probabilistic prediction of Bankruptcy,” *Journal of Accounting Research, 18:1*, pp. 109-131.

Olsen, R. A. (2008), “Perceptions of Financial Risk: Axioms and Affect,” *The Icfai University Journal of Behavioral Finance, 5:4* pp. 58-80.

Palepu, Krishna G., Erik Peek, Victor L. Bernard and Erik Peck (2007) *Business Analysis and Valuation: text and cases*, Thompson Learning, London.

Platt, H.D. and M.B. Platt (2002), “Predicting Corporate Financial Distress: reflections on choice-based sample bias,” *Journal of Economics and Finance 26*, pp. 184-199.

Pompe, P. and J. Bilderbeek (2005) “The Prediction of Bankruptcy of Small and Medium Sized Industrial Firms,” *Journal of Business Venturing 20*, pp. 847-868.

Ramaswami, M. (1987), **“**Stock Market Perception of Industrial Firm Bankruptcy,” *The Financial Review 22:2*, pp. 267-279.

Roll, R. (1986), “The Hubris Hypothesis of Corporate Takeover,” *Journal of Business, 59:2*, pp. 197-216.

Salchenberger, L., E. Cinar and N. Lash (1992),"Neural Networks: a new tool for predicting thrift failures," *Decision Sciences 23*, pp. 899-916.

Serrano-Cinca, C. (1996), "Self Organizing Neural Networks for Financial Diagnosis," *Decision Support Systems 17*, pp. 227-238.

Sheffrin, H. (2007), *Behavioral Corporate Finance: Decisions that Create Value*, McGraw Hill, Irwin.

Simon, M., S.H. Houghton, and K. Aquino (1999), "Cognitive Biases, Risk Perception, and Venture Formation: How Individuals Decide to Start Companies," *Journal of Business Venturing, 15*, pp. 113-134.

Slovic, Paul. (1972), "Psychological study of human judgment: Implications for investment decision making," *The Journal of Finance*, *27(4)*, pp. 779-799.

Slovic, Paul. (1987), "Perception of risk," *Science, 236 (4799)*, pp. 280-286.

Slovic, P. and Peters, E. (2006), "Risk Perception and Affect" *Current Directions in Psychological Science, 15:6*, pp. 322-326.

Tversky, A. and Kahneman, D. (1973), "Availability: A heuristic for judging frequency and probability," *Cognitive Psychology, 4*, pp. 207-232.

Tversky, A. and Kahneman, D. (1974), "Judgment under uncertainly: Heuristics and biases," *Science, New Series*, *185(4157)*, pp. 1124-1131.

Vallini, Ciampi and Gordini (2009), "Using Artificial Neural Networks Analysis for Small Enterprise Default Prediction Modeling: Statistical Evidence from Italian Firms" *Oxford Business and Economics Conference Program.* http://www.docstoc.com/docs/21423327/Using-Artificial-Neural-Networks-Analysis-For-Small-Enterprise/.

Varetto, Franco (1998), "Genetic algorithms applications in the analysis of insolvency risk," *Journal of Banking and Finance 22*, pp. 1421-1439.

Wiklund, J., T. Baker and D. Shepherd (2008), "The Age-Effect of Financial Indicators as Buffers Against the Liability of Newness," *Journal of Business Venturing (forthcoming)* doi:10.1016/j.jbusvent.2008.10.011.

Winakor A. and R.F. Smith (1935), "Changes In Financial Structure of Unsuccessful Industrial Companies," *Bureau of Business Research, Bulletin No. 51* Urbana: University of Illinois Press.

Wu, B. and A. M. Knott (2005), "Entrepreneurial Risk and Market Entry", Working Paper, U.S. Small Business Administration.

Yazdipour, R. (2010), (ed), Advances in Entrepreneurial Finance: With Applications from Behavioral Finance. Springer, New York.

Yazdipour, R. (2009), "What Can Venture Capitalists and Entrepreneurs Learn from Behavioral Economists?" *Strategic Change Journal, 18,* pp. 241-247.

Zajonc, R. B. (1980), "Feeling and Thinking: Preferences Need No Inferences" *American Psychologist 35*, pp. 151-175.

Zhang, Hu, Patuwo, and Indo (1999), "Artificial Neural Networks in Bankruptcy Prediction: general framework and cross-validation," *European Journal of Operational Research 116*, pp. 16-32.

Zmijewski, M.E. (1984), "Methodological Issues Related to the Estimation of Financial Distress Prediction Models," *Journal of Accounting Research: Studies on Current Econometric Issues in Accounting Research 22*, pp. 59-82.