TWO COMMON STEPS IN FIRMS' FAILING PATH

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Abstract

This paper aims to identify two steps which are common to the path of all failing firms and result from their financial statements. Their identification support the explanation of business failure (in both fraud and no-tort cases) as encouraged by authoritative literature (Cybinski, 2001; Parker, 2012).
The analysis has been conducted through all the fraud cases (and the matched not-tort cases) mentioned by WebBRD. It has been developed through different phases: content analysis for the identification and categorization of micro-failures, a deep analysis of time variable and the implementation of survival analysis for the failing path explanation.
This paper shows that, during the failing path, firms encounter two "steps" (i.e. micro-failures and macro-failures) that make the process neither atypical nor sudden at the same time. After the identification of the relevant micro-failures, a survival analysis has been implemented to demonstrate that fraud lets firms earn time in the path to macro-failure, but its disclosure makes firms fall down macro-failure very fast.
This paper sight to encourage business failure explanation and fraud deterrence: fraud lets firms earn time and hope more to avoid macro-failure, but, after the disclosure moment, fraud firms fall down macro-failure faster than not-tort firms. The results suggest that only after a such explanation of business failure, its prediction can be properly conducted.
This paper examines in an original way failure as a path and emphasizes relations between time dimension, failure stages and accounting information**.

Keywords: Business Failure, Financial Statements, Fraud, Macro-failure, Micro-failure, Survival Analysis

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***The author would like to thank the McCombs School of Business (at the University of Texas at Austin) for providing data and precious support. Valuable comments were also gathered at the International Accounting Conference "Accounting Renaissance: Arising from the Crisis and Looking to the Future" (Venice, 4-5 November 2011), at the 15th Annual Conference "Financial Reporting And Business Communication Research" (Bristol, 2011) and at the "Emerging International Summer School Accounting Research" (Forlì, 2011) where the paper was presented.*

1 Introduction

Business failure has traditionally been considered a sudden and atypical event the analysis and prediction of which are very difficult to manage. In fact, business failures continue to happen in spite of the high number of prediction models. The most commonly used techniques of prediction are characterized by different degrees of accuracy and practicality and can be divided into two categories: statistical and machine learning methods (Lin and McClean, 2001). They aim to find a way to early detection of corporate financial distress. Consequently, most of the literature about failure attempts to create substantial agreement over the most suitable methodology for predicting business failure (Aziz and Dar, 2006).

However, a smaller number of researchers have emphasized the importance of the time dimension for failure, which should be considered a process. Moreover, the part of the literature that has sought to gain deeper insight into the failure process of a company is mostly qualitative, related to the managerial-organizational field. This study attempts to fill the gap: it examines failure as a path and emphasizes relations between the time dimension, failure stages and accounting numbers.

This paper examines failure as a path: it identifies two "common steps" (micro-failures and macro-failures) thanks to information gathered through failing firms' financial statements. Such failure stages make the process neither atypical nor sudden at the same time. The temporal dimension is of great importance and must be considered: time makes failure a sequence of steps instead of a single-still event. So, it allows failing firms to act and react and it lets failure be different from final bankruptcy.

This paper is organized as follows. In the following section, there is an overview of the literature. This is followed by a description of the sample and of the methodology applied. Then, the findings are discussed and some suggestions for further research are provided.

2 Prior and related research

The prior research that is related to the topic of this paper is dated because it refers especially to the definition of failure. This has been traditionally considered an atypical and sudden event that characterizes the end of the life cycle of firms.

It is atypical (Sharma and Mahajan, 1980) because it presents particular features according to the internal factors and external environment of the failing firms (Nelson 1991). In fact, the prediction of failure has required the consideration of the firm's size (Edmister, 1972; Beaver, 1968), age (Altman, 1968; Thornhill and Amit, 2003; Yuji, 2000), ownership structure (Mata and Portugal, 1994), industry (Beaver, 1968; Platt and Platt, 1991), market (e.g. monetary policy and investors' expectations), country (Gilbert et al., 1990). The interaction between internal and external factors, which characterizes and causes corporate failure, has been widely analyzed (Argenti, 1976; Sharma and Mahajan, 1980; Thornhill and Amit, 2003).

It seems sudden (Sharma and Mahajan, 1980) because many financial scandals are discovered only when substantial losses have already affected creditors and stockholders. Thus, the need to provide ample warning to the interested parties has long represented the main reason for seeking good methods of prediction. These should predict potential business failures as early as possible to reduce losses (Deakin, 1972). On the other hand, the inability to predict is not the only cause of a sudden announcement; this can be also due to the unwillingness to disclose (Asare, 1990). In both cases the event is suddenly announced (Hossari, 2007), but, as shown in this paper, it is the result of a gradual process that may extend over years.

The consideration of failure as an event has been a constant from the beginning of the failure literature. Beaver (1968) defines failure as a business defaulting on interest payments on its debt, overdrawing its bank account, or declaring bankruptcy. Along the same lines, Blum (1974) defines failure as "entrance into a bankruptcy proceeding or an explicit agreement with creditors which reduced the debts of the company". Other similar definitions speak about the cessation of operations by a business concern because of involvement in court procedures or voluntary actions which will result in loss to creditors (Sharma and Mahajan, 1980). Progressively, researchers have seized the importance of time as one of the main dimensions: Ismael et al. (1980) suggest that the stability of financial ratios over time considerably improves the ability of the discriminant function to predict failure. Moreover, other dated literature contributions (Argenti 1976; Laitinen, 1991) consider alternative types of failure processes according to the behaviour of different financial ratios: capturing the important dimensions or factors, which affect the financial ratios of failing firms, makes it possible to identify different failure processes. However , some literature might not appreciate the identification of alternative failure processes in a sample of failed firms: a common uniform concept of failure reduces uncertainty and the risk of inaccuracy in failure prediction models. Only more recent literature contributions have definitely taken the time variable into account (Hill, 1996; Ooghe and De Prijcker, 2008). Bankruptcy is only a single and potential event at the end of a path of financial distress that is considered a series of events that reflect various stages of corporate adversity (Turetsky, 2001). These works emphasize the interdependence between internal and external factors during the failure path; but other literature contributions underline the difficulty in the development of a cause-effect relationship between attributes that may cause or be related to bankruptcy (Mckee 2000): relevant attributes can be difficult to identify and measure also because they may occur in one or more time periods prior to bankruptcy.

Starting from these considerations, the remainder of this paper addresses the definition and analysis of the failure process in order to identify only two steps that can be considered common to the path of all failing firms. The aim is to explain rather than predict: as highlighted by Cybinski (2001), researchers should be concerned with the explanation of how firms transform from surviving or even successful ones into failed ones. According to this author (i.e. Cybinski, 2001), understanding enterprise failure presents an enormous theoretical challenge that, at the moment, has largely gone unanswered because the studies have merely produced instruments for discriminating failed from prosperous firms: failure is not a well-defined dichotomous variable because there is a also a “grey” area (i.e. the area of overlap or indecisive area) that should be reduced to a minimum.

This contribution (i.e. Cybinski, 2001) analyzes failure as a methodological problem in order to find a proper statistical model, but its considerations represent the correct premise of the present work because they try to emphasize the relationship between time dimension, failure stages and accounting information. The present paper aims to consider both this stream of research and that (Humphrey, 2008) which questions the relevance of quantitative modelling studies (to auditors, auditees, professional accounting associations and corporate regulatory authorities) both before and after the lesson of famous corporate scandals (e.g. Enron and WorldCom). In fact, the need for detailed qualitative contextual research on these crashes has been highlighted by authoritative literature (Lee, 2004; Humphrey, 2005; Parker, 2005): “the qualitative agenda has much to offer in unpacking these processes of accounting, auditing and accountability, and in addition translating qualitative management accounting issues and research designs into the financial accounting and auditing arenas." (Parker, 2012)

3 Hypotheses

The traditional stream of literature makes failure appear an instantaneous occurrence. This erroneous conviction can be due to a univocal definition of failure, which is usually considered the last stage of the life cycle of firms; but, with this meaning, it represents just one type of discontinuance which coincides with macro-failure. A firm definitely fails after a process which evolves over a period of time.

Hypothesis 1 – The path to failure is characterized by one or more micro-failures and by one macro-failure which are all mentioned in the financial statements. So, failure is not both atypical and sudden at the same time.

The traditional definition of business failure can be compared to the concept of macro-failure. This step of the failure path is defined in the paper as the last stage of a firm's life cycle: it represents an important type of discontinuance that, most of the time, requires a defensive reaction (i.e. a radical change) in the firm that wants to survive. It occurs after a process which evolves over a period of time.

Hypothesis 1b – Macro-failure does not occur suddenly.

After the definition of macro-failure, another concept of failure should be considered: it refers to the previous stage of not meeting some set objectives. Before arriving at macro-failure, firms encounter micro-failures that must be analyzed with attention as valuable signals as their identification surely gives more time to firms and stakeholders for a proper evaluation and resolution of the problem. "*If it is possible to recognize failing companies in advance then appropriate action to reverse the process can be taken before it is too late*" (Taffler, 1982). For this reason, a deep analysis of the concept of micro-failure must be made.

Hypothesis 1a – Micro-failures are not atypical.

As said before, a micro-failure represents the stage of not meeting some set objectives. Consequently, the analysis of micro-failures starts from the identification of a firm's (or its stakeholders) actions (or inactions) and the consequent missed objectives. According to this consideration, micro-failures could incorrectly be compared with causes of failure: the difference between them is the same as that between causes and effects. If a micro-failure occurs, a failure cause has already happened and a set business objective has become unattainable. A categorization of micro-failures will be presented in Section V, but the (Table 1) shows some examples to give an insight into the difference between micro-failures and business failure causes.

Table 1. Examples of micro-failures and difference with business failure causes

BUSINESS FAILURE CAUSES	MICRO-FAILURES
Product problems (timing, design, distribution/selling,….)	Customers' criticism
	Negative economic-financial trends (primarily resulting from a decrease in revenues)
Assuming debt too early	Excessive indebtedness and difficulty in obtaining new financing

All micro-failures must be taken into consideration because they represent missed objectives and they will impact on profit (because of variations in sales and expenses) and liquidity (because of variations in debt and cash flow). For this reason, as explained by the literature, great attention should be paid to different types of signals: economic-financial ratios and items; managerial events (e.g. the resignations of managers and/or auditors); other events (e.g. risky contentious procedures). Inside the set of micro-failures which characterizes a failing firm, there is a micro-failure that is especially relevant because it does influence the path to failure: as explained by the second hypothesis, after a relevant micro-failure has emerged, a firm must make a drastic choice: i.e. to reveal or not to reveal its negative consequences. So, relevant micro-failure (X_{MiF}) represents the most reliable signal that a business failure process has started. It is a common step in all business failure paths: in no-tort cases, it represents the disclosure date, i.e. the moment in which the failure spiral starts turning. In fraud cases, it is the last micro-failure to be properly represented in financial statements. If a firm decides to manipulate accounting information after a micro-failure, it will gain time (i.e. there is an increase in the amount of time between micro-failure and macro-failure thanks to earnings management), but, when discovered, it will be worse off (i.e. the time between the disclosure of bad news and macro-failure will be shorter in manipulation cases than in the true and fair view cases).

Hypothesis 2 – Fraud lets firms gain time in the path to macro-failure.

Hypothesis 2a – After relevant micro-failure, no-tort firms go toward macro-failure faster than fraud firms.

Hypothesis 2b – After the disclosure of the missed objectives, fraud firms fall into macro-failure faster than no-tort firms.

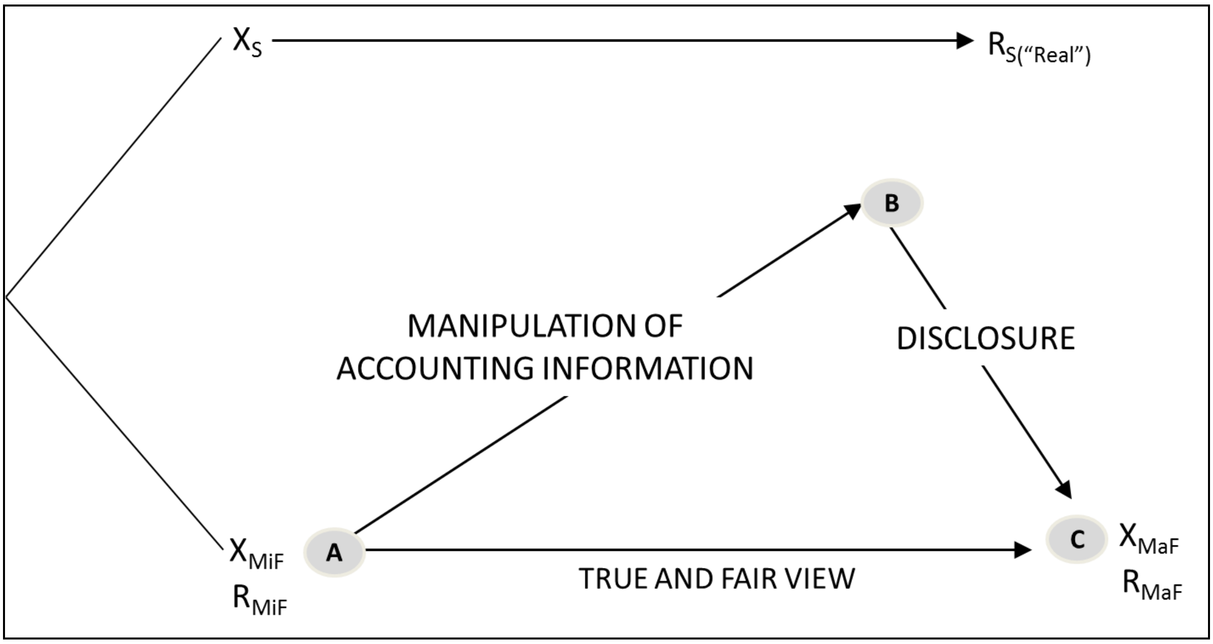
In order to give insight into the second hypothesis meaning, its application to the considered sample, which will be described in the next section, can be figured out through a graph (Figure 1). The symbols in the graph require some explanation:

- X_s represents a firm's successful state. This finds correct representation in financial reports (R_s) because firms want to show their good staying.

- X_{MiF} represents a common step in the business failure process. It is the most reliable signal that a business failure process has started and, in fraud cases, the last micro-failure that finds correct representation in financial reports (R_{MiF}).

- X_{MaF} represents the firm's macro-failure which is correctly represented in financial reports (RMaF) because firms do not have alternatives in this final step of the failure process.

Figure 1. Firms' Failing Path



So, the paper focuses on three failure stages: A (for both fraud and no-tort cases) where failing firms encounter the relevant micro-failure; B (only for fraud cases) where firms disclose the fraud; C (for both fraud and no-tort cases) where failing firms fall into macro-failure. As emphasized in the conclusion of the paper, there may be failing firms which commit fraud and become again successful cases without having to disclose the use of improper accounting methods; these are very difficult to identify. Only a progressive deepening of the subject (inside the history of failing firms, their minor events and their stakeholders' actions) may help such identification: this paper represents an initial contribution for such investigation and for a new explanation of business failure.

4 Sample

The construction of the sample requires the use of several instruments and the progressive filtration of data through different steps which are described below.

The WebBRD **(**Bankruptcy Research Database) contains data on all large, public company bankruptcy cases filed in the United States Bankruptcy Courts from October 1, 1979 to the present day. This dataset made it possible to consider all the large, public company bankruptcy cases filed through March 1, 2010. These 882 cases have been distinguished according to the U.S. Standard Industrial Classification (SIC) system, which represents a way of identifying the primary business of a company. Division H (Finance, insurance, and real estate) has not been considered in the construction of the sample because of specific regulations: 120 cases have been deleted because they belong to division H. These remaining cases can be separately analyzed thanks to the distinction in subsets proposed by WebBRD: the two subsets considered in this paper, have been labeled fraud cases and no-tort cases.

There are 31 fraud cases mentioned by WebBRD and acting in a division different from the H. For each of them a deeper analysis has been made thanks to forms 10-k and other sources of financial data. These have been collected through two databases, i.e. Mergent's database and Accounting Research Manager (ARM). The second database has been used for six fraud cases mentioned by WebBRD whose financial data are not available on Mergent's database. Successively, each case history and information was confirmed by Factiva, a global information resource, and thanks to information gathered from LexisNexis Academic.

In order to investigate the path to macro-failure in both the mentioned directions (true-fair view and manipulation of accounting information as explained in Section III), a benchmark was selected for each fraud case: the choice inside the 762 bankrupt companies listed by WebBRD is based on two conditions such as the year of filing for bankruptcy, the SIC code and/or the description of business (Table 2). These are the same criteria used in Mergent's database for the identification of competitors. So, company details (such as business description, history and subsidiaries), annual reports and other financial data were analyzed also for the benchmarks.

Table 2. The sample: fraud cases mentioned by WebBRD and matched no-tort cases

	ALL FRAUD CASES MENTIONED BY WebBRD	SIC CODE	YEAR OF FILING:	BENCHMARKS (SELECTION OF COMPETITORS)
1	Adelphia Business Solutions, Inc.	48	2002	ITC DeltaCom, Inc.
2	Adelphia Communications Corp.	48	2002	IMPSAT Fiber Networks, Inc.
3	American Banknote Corporation	27	1999	MediaNews Group Inc.
4	American Tissue, Inc.	26	2001	American Pad & Paper Company
5	Anicom, Inc.	50	2001	Inacom Corp.
6	Aurora Foods Inc.	20	2003	Interstate Bakeries Corporation
7	Bicoastal Corporation	38	1989	Tracor Holdings Inc.
8	Bonneville Pacific Corporation	16	1991	Morrison Knudsen Corp.
9	Boston Chicken, Inc.	58	1998	Flagstar Companies Inc.
10	CareMatrix Corp.	83	2000	Sun HealthCare Group, Inc.
11	Complete Management, Inc.	87	1999	ProMedCo Management Company
12	Enron Corp.	51	2001	KCS Energy, Inc.
13	Fine Host Corporation	58	1999	Planet Hollywood International Inc.
14	Footstar Inc.	56	2004	Jacobson Stores, Inc.
15	Global Crossing Ltd.	48	2002	Global TeleSystems, Inc.
~~16~~	~~Hunt International Resources Corp.~~*	~~20~~	~~1985~~	~~Imperial Sugar Company~~
17	Impath Inc.	80	2003	aaiPharma Inc.
18	Leslie Fay Companies, Inc.	23	1993	Plaid Clothing Group Inc.
19	MCSI Inc.	50	2003	CHS Electronics, Inc.
20	MiniScribe Corp.	35	1990	Daisy Systems Corp.
21	MobileMedia Communications, Inc.	48	1997	Geotek Communications, Inc.
22	OCA, Inc.	80	2006	Mediq, Inc.
23	Peregrine Systems, Inc.	73	2002	USInterNetworking, Inc.
24	Philip Services Corp. (1999)	49	1999	Waste Systems International, Inc.
25	Seitel Inc.	13	2003	Forcenergy, Inc.
26	Seven Seas Petroleum, Inc.	13	2002	Coho Energy, Inc. (2002)
27	Smartalk Teleservices, Inc.	73	1999	GST Telecommunications, Inc.
28	Sunbeam Corporation	36	2001	Sun Television and Appliances, Inc.
29	Technical Equities Corp.	34	1986	Ladish Co. Inc.
30	Washington Group International, Inc.	15	2001	WCI Communities, Inc.
31	Worldcom, Inc.	48	2002	XO Communications, Inc.

* The impossibility of data collection has implied the not consideration of one fraud case: Hunt International Resources Corp. filled for bankruptcy in 1985 and precise financial data about it cannot be gathered anymore.

5 Method of analysis

The sample analysis was developed through different phases: content analysis for the identification and categorization of micro-failures, a deep analysis of time variable and the implementation of survival analysis.

According to the definition of micro-failure given in Section III and thanks to the triangulation of methods and information described in Section IV, micro-failures have been identified for each sampled firm. As emphasized above, micro-failures are different from failure causes, but, in order to show that they are not atypical, micro-failures can be categorized by considering the traditional causes clusters. So, the first step of the analysis identifies the categories of business failure causes traditionally considered by the literature (Argenti 1976; Altman 1983) such as product/market, financial, managerial/key employee, cultural/social and accidental problems. The second step of this analysis implies micro-failure identification (and categorization according to the mentioned "traditional categories") thanks to a method concerning the content of accounting narratives (Jones and Shoemaker, 1994). This process is based on the general principles of content analysis, which represents a well-established method in the social sciences. Details and discussions about such method are provided by Boyatzis (1998), Holsti (1969), Krippendorff (1980) and Weber (1985). FASB (2001) has also emphasized the usefulness of such methodology in the disclosure of critical factors and other information used by companies to manage their operations.

Content analysis implies the classification of text units into predetermined categories. For valid inferences to be drawn, the classification procedure must be reliable and valid: different people should code the text and produce similar results about what the study aims to represent. The classification procedure can vary from qualitative methods to quantitative ones that permit statistical analysis. In fact, content analysis can be of different types: computer-aided or human-coded. The second one has the advantage of enabling the quantitative assessment of achieved reliability. The present study involves a mixture of computer and manual analysis. Computer analysis is used principally to collect the frequency data. Manual analysis has been implemented for the semantic coding and analysis of the data: it was necessary to identify not only words, but also their context and attributions. Although extremely labour intensive, this method results in a more sensitive and subjective approach. A degree of subjectivity in any analysis of narrative information is inevitable as even computer-based approaches involving systematic counts of keywords require an element of judgment and interpretation.

The coding procedure comprised two stages: the identification of the micro-failures and their categorization. In order to guarantee reliability of the present analysis a pilot test on a few annual reports was carried out. At least three coders were used. Table 3 was constructed starting from the traditional literature on business failure causes (as explained in the first step of the analysis) and employed by all the coders. Discrepancies were re-analyzed and the differences resolved (Milne and Adler, 1999). This method serves several purposes: for each sampled case the content analysis, applied to forms 10-k and other sources of financial data described in Section IV, has made it possible to identify micro-failures, the relevant micro-failure (according to the definition given in Section III) and the date when it happened (Table 4).

Table 3. Micro-failures types listed according to the traditional failure causes clusters

A. PRODUCT/MARKET PROBLEMS
A1. Competition and/or competitors with significantly greater financial resources than the company
A2. Customers' criticism because of goods quality (either too expensive or too low-quality)
A3. Depressed industry and market downturn
A4. New and stricter industry regulations
A5. Seasonal business
B. FINANCIAL PROBLEMS
B1. Excessive costs and/or additional and not essential expenses
B2. Excessive indebtedness and difficulty in obtaining new financing
B3. Investors' nervousness, bad relationship with the venture capitalists and/or creditors' pressure
B4. Negative economic-financial trends (primarily resulting from a decrease in revenues)
B5. Relationship of strong financial dependence with another subject (suppliers, customers, …)
B6. Unprofitable affairs (e.g. acquisition of unprofitable divisions)
C. MANAGERIAL/KEY EMPLOYEE PROBLEMS
C1. Conflicts of interests
C2. Core business abandonment and diversification into other industries
C3. Excessive anxiety to keep up with increasingly large competitors
C4. Important decision without obtaining board approval
C5. Legal, apparently correct but improper (e.g. deficit analytical) accountancy
C6. Poor management and disengaged board
C7. Principal's problems with justice for affairs different from the firm
C8. Private benefits (withdrawals, bonuses and compensation policy)
C9. Too aggressive growth and expansion strategy (i.e. a such rapid growth through mergers or other operations was no sustainable in the long run)
C10. Too ambitious objectives and anxiety to hit "must make" numbers (i.e. earnings targets)
C11. Wrong operations (because of riskiness or other reasons)

Table 3. Micro-failures types listed according to the traditional failure causes clusters (continuation)

D. CULTURAL/SOCIAL FACTORS
D1. Corruption
D2. Discriminating problems
D3. Powerful enemies
E. ACCIDENTAL FACTORS
E1. Calamities

Table 4. Relevant micro-failures: type and date for each sampled firm

Fraud cases	Date	Type	Matched not-tort cases	Date	Type
Adelphia Business Solutions, Inc.	01/01/1999	C9	ITC DeltaCom, Inc.	30/03/2000	B5
Adelphia Communications Corp.	01/10/1999	C9	IMPSAT Fiber Networks, Inc.	30/07/2001	A3
American Banknote Corporation	14/07/1998	C9	MediaNews Group Inc.	31/12/2007	A3
American Tissue, Inc.	30/09/1999	C9	American Pad & Paper Company	30/06/1998	B5
Anicom, Inc.	24/02/1998	C9	Inacom Corp.	09/10/1998	B6
Aurora Foods Inc.	01/01/1998	C10	Interstate Bakeries Corporation	15/11/2003	B4
Bicoastal Corporation	30/06/1986	C2	Tracor Holdings Inc.	01/10/1989	C6
Bonneville Pacific Corporation	31/07/1986	C8	Morrison Knudsen Corp.	20/10/1994	C6
Boston Chicken, Inc.	04/08/1992	C9	Flagstar Companies, Inc.	15/08/1994	D3
CareMatrix Corp.	28/04/1998	B2	Sun HealthCare Group, Inc.	01/07/1998	A4
Complete Management, Inc.	01/05/1996	C9	ProMedCo Management Company	30/06/2000	B4
Enron Corp.	01/03/1997	C5	KCS Energy, Inc.	01/01/1998	B4
Fine Host Corporation	01/01/1994	C9	Planet Hollywood International, Inc.	19/04/1996	C9
Footstar Inc.	01/01/1997	B6	Jacobson Stores, Inc.	31/05/1997	B4
Global Crossing Ltd.	01/01/1998	B6	Global TeleSystems, Inc.	04/03/1999	B2
Impath Inc.	24/02/2000	C4	aaiPharma Inc.	13/02/2004	B4
Leslie Fay Companies, Inc.	01/01/1990	A2	Plaid Clothing Group Inc.	19/11/1994	B4
MCSI Inc.	30/06/2000	C9	CHS Electronics, Inc.	10/03/1999	C5
MiniScribe Corp.	01/01/1986	C10	Daisy Systems Corp.	30/09/1989	B6
MobileMedia Comm., Inc.	29/06/1995	C6	Geotek Communications, Inc.	26/11/1997	C2
OCA, Inc.	30/09/1998	B3	Mediq, Inc.	29/05/1998	B6
Peregrine Systems, Inc.	01/04/1999	C10	USInterNetworking, Inc.	01/09/2000	B6
Philip Services Corp. (1999)	26/02/1996	C8	Waste Systems International, Inc.	03/08/1999	B2
Seitel Inc.	05/05/2000	C8	Forcenergy Inc	30/06/1997	B2
Seven Seas Petroleum, Inc.	17/05/2001	B4	Coho Energy, Inc. (2002)	30/06/2001	B2
Smartalk Teleservices, Inc.	01/01/1997	C9	GST Telecommunications, Inc.	28/10/1998	B2
Sunbeam Corporation	30/09/1996	C10	Sun Television and Appliances, Inc.	07/01/1997	B1
Technical Equities Corp.	01/01/1983	C2	Ladish Co. Inc.	30/09/1991	B4
Washington Group Intern., Inc.	28/09/1999	B6	WCI Communities, Inc.	30/09/2006	B2
Worldcom, Inc.	01/01/1999	C10	XO Communications, Inc.	16/06/2000	B2

6 Results

6.1 Hypothesis 1a analysis: micro-failures are not atypical

A descriptive analysis of the results, gathered from the content analysis, has been implemented in Stata. The frequency of the relevant micro-failures categories is summarized in the following table (Table 5); moreover, the frequency can be considered separately according to the type of failing firms (i.e. fraud or no-tort, Figure 2). The accidental factors (i.e. category E) have no influence at all on firms' relevant micro-failures. Moreover, neither categories A (product/market problems) and D (cultural/social factors) have much influence. Overall (Table 6), the five most frequent relevant micro-failure types are the following:

• over-aggressive growth and expansion strategy (i.e. such rapid growth through mergers or other operations was not sustainable in the long run); this has been labeled C9;

• excessive indebtedness and difficulty in obtaining new financing; this has been labeled B2;

• negative economic-financial trends (primarily resulting from a decrease in revenues); this has been labeled B4;

• unprofitable affairs (e.g. acquisition of unprofitable divisions); this has been labeled B6;

• over-ambitious objectives and anxiety to hit "must make" numbers (i.e. earnings targets); this has been labeled C10.

Table 5. Frequency of relevant micro-failures categories in both fraud and not-tort cases

CAT_RelMicrof	Freq.	Percent	Cum.
A	4	6.67	6.67
B	27	45.00	51.67
C	28	46.67	98.33
D	1	1.67	100.00
Total	60	100.00	

Figure 2 Frequency of relevant micro-failures categories in both fraud and not-tort cases

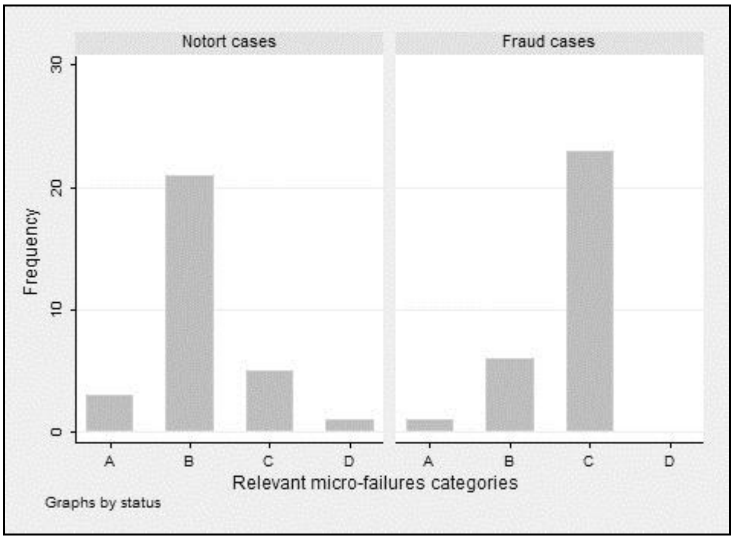


Table 6. Frequency of relevant micro-failures types in both fraud and not-tort cases

CAT&N RelMicrof	Freq.	Percent	Cum.
A2	1	1.67	1.67
A3	2	3.33	5.00
A4	1	1.67	6.67
B1	1	1.67	8.33
B2	8	13.33	21.67
B3	1	1.67	23.33
B4	8	13.33	36.67
B5	2	3.33	40.00
B6	7	11.67	51.67
C10	5	8.33	60.00
C2	3	5.00	65.00
C4	1	1.67	66.67
C5	2	3.33	70.00
C6	3	5.00	75.00
C8	3	5.00	80.00
C9	11	18.33	98.33
D3	1	1.67	100.00
Total	60	100.00	

There is a strict differentiation inside these micro-failures types according to the firms' status (fraud and no-tort): in no-tort cases financial micro-failures outnumber managerial problems and vice versa in fraud cases. More specifically, while in no-tort cases financial micro-failures (B2 and B4) outnumber all the others, in fraud cases the managerial relevant micro-failure type labeled C9 is the prevalent one.

6.2 Hypothesis 1b analysis: macro-failure does not occur suddenly

In order to analyze this hypothesis, the *time* variable has been introduced: it represents the time interval between the relevant micro-failure date (*d1*) and macro-failure date (*d3*). So, this variable is not calculated from the beginning of the business path, but from its relevant micro-failure, which is the most reliable signal of failure as emphasized in Section II. Table 7 shows a first descriptive statistical analysis of the *time* variable. The path towards failure of the sampled firms ranges from 215 days (the minimum value) to 2722 days (the maximum value). The first distinction in the distribution of the *time* variable between no-tort and fraud cases can be read in the following tables (Tables 8-9): the minimum and the maximum values of the *time* variable are lower for no-tort cases. Moreover, the range between these last two values is shorter for no-tort cases: firms which have committed fraud are more distributed over time and their path towards macro-failure lasts longer. These considerations will be further investigated in the following analysis.

Table 7. Descriptive statistical analysis of the time variable

Variable	Obs	Mean	Std. Dev.	Min	Max
time	60	945.4333	566.2778	215	2722

Table 8. Descriptive statistical analysis of the time variable in fraud cases

. sum time if id<=30

Variable	Obs	Mean	Std. Dev.	Min	Max
time	30	1273.6	566.7232	512	2722

Table 9. Descriptive statistical analysis of the time variable in not-tort cases

. sum time if id>30

Variable	Obs	Mean	Std. Dev.	Min	Max
time	30	617.2667	329.2562	215	1690

6.3 Hypothesis 2 analysis: fraud lets firms gain time in the path to macro-failure

Survival analysis includes several related techniques that focus on time until an event of interest occurs. In this paper, the time until macro-failure represents the "survival time" (Table 10). The median survival time is 753 days, considering all the 60 firms. Moreover, there are 60 failures out of 56726 firm-days, thus giving an incidence rate of 0.00106. If this incidence rate (i.e. the hazard function) could be assumed to be constant, it would be estimated as 0.00106 per day, which corresponds to 0.39 per year.

Table 10. The survival time

failure _d: status
analysis time _t: time

	time at risk	incidence rate	no. of subjects	Survival time 25%	50%	75%
total	56726	.0010577	60	527	753	1219

Overall, this function estimates about a 25% chance of falling into macro-failure within 527 days after the relevant micro-failure, 50% within 753 days and 75% within 1219 days. Summary statistics on survival time are more significant if considered separately for each group (Table 11): overall, 25% of sampled firms took at least 527 days from relevant micro-failure to fall into macro-failure, but this differs considerably between fraud and no-tort cases (at least 391 days in no-tort cases and 926 in fraud cases). The median survival time in fraud cases is estimated to be 1182 days and 559 in no-tort cases.

The previous conclusion, which has been reached by considering the *time* variable, is reversed by introducing the *time2* variable (Table 12): this represents the period of time between the disclosure date (*d2*) and macro-failure date (*d3*). In this second case, the median survival time is equal to 312 days. If the incidence rate (i.e. the hazard function) could be assumed to be constant, it would be estimated as 0.0025 per day, which corresponds to 0.91 per year. Overall, 25% of sampled firms took at least 99 days from disclosure moment to fall into macro-failure, but this differs considerably (more than before with the *time* variable) between fraud and no-tort cases (at least 391 days in no-tort cases and 53 in fraud cases). This function estimates for fraud firms about a 25% chance of falling into macro-failure within 53 days after the disclosure moment and 75% within 215 days. This function (Table 13) estimates for no-tort firms about a 25% chance of falling into macro-failure within 391 days after the disclosure moment and 75% within 748 days. So, even though overall the path towards macro-failure lasts longer for fraud cases, after the disclosure moment firms that have committed fraud fall into macro-failure more rapidly than no-tort firms. This result can be confirmed by the Kaplan-Meier method (Table 14), which estimates the survivor function. Its estimator of surviving beyond time t is the product of survival probabilities in t and the preceding periods. The cumulative hazard function from the Kaplan-Meier method can be obtained by using the relationship between the survivor and hazard functions, but there are problems in small samples with this approach. It could be more appropriate to use the formula for the Nelson-Aalen estimator (Table 15). These results can be intuitively understood through a graph: graphing the Kaplan-Meier estimator of surviving S(t) against t produces a Kaplan-Meier survivor curve for each case (i.e. fraud and no-tort, Figures 3-4).

Table 11. The survival time in not-tort and fraud cases

failure _d: **status**
analysis time _t: **time**

fraud	time at risk	incidence rate	no. of subjects	Survival time 25%	50%	75%
0	18518	.00162	30	391	559	748
1	38208	.0007852	30	926	1182	1488
total	56726	.0010577	60	527	753	1219

Table 12. The disclosure-to-macrofailure time

failure _d: **status**
analysis time _t: **time2**

	time at risk	incidence rate	no. of subjects	Survival time 25%	50%	75%
total	23164	.0025471	59	99	312	614

Table 13. The disclosure-to-macrofailure time in not-tort and fraud cases

failure _d: **status**
analysis time _t: **time2**

fraud	time at risk	incidence rate	no. of subjects	Survival time 25%	50%	75%
0	18518	.00162	30	391	559	748
1	4646	.0062419	29	53	99	215
total	23164	.0025471	59	99	312	614

Table 14. Kaplan-Meier estimator for the time variable

failure _d: **status**
analysis time _t: **time**

fraud		Survivor Function 0	1
time	215	0.9667	1.0000
	528	0.5333	0.9333
	841	0.1667	0.7667
	1154	0.0667	0.5667
	1467	0.0333	0.2667
	1780	.	0.1667
	2093	.	0.1000
	2406	.	0.0667
	2719	.	0.0333
	3032	.	.

Table 15. Nelson-Aalen estimator for the time variable

failure _d: **status**
analysis time _t: **time**

fraud		Nelson-Aalen Cum. Haz. 0	1
time	215	0.0333	0.0000
	528	0.6143	0.0678
	841	1.7117	0.2607
	1154	2.4950	0.5554
	1467	2.9950	1.2771
	1780	.	1.7117
	2093	.	2.1617
	2406	.	2.4950
	2719	.	2.9950
	3032	.	.

Figure 3. Kaplan-Meier estimator for the time variable

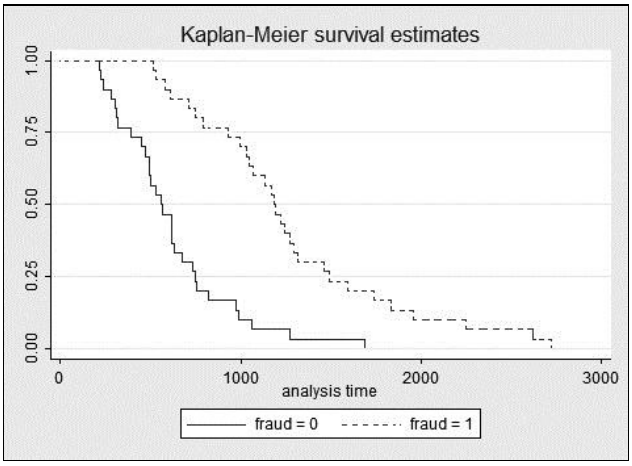
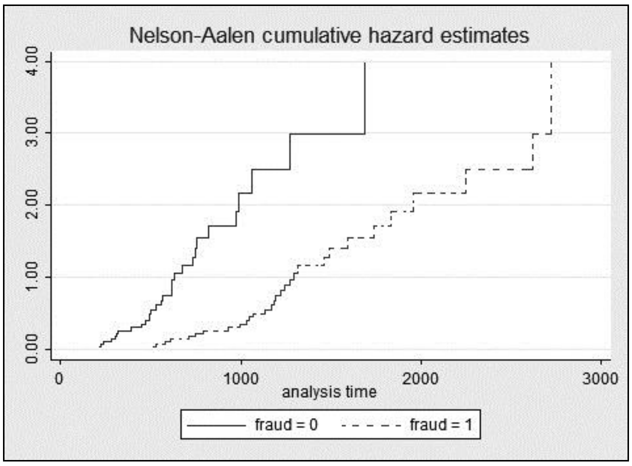


Figure 4. Nelson-Aalen estimator for the time variable



After the relevant micro-failure, macro-failure occurs more quickly in no-tort cases (i.e. fraud equals zero): the path towards macro-failure lasts longer in fraud cases (i.e. fraud equals one).

The same analysis (Tables 16-17) can be implemented for *time2* variable. After the disclosure moment, macro-failure occurs more quickly in fraud cases (i.e. fraud equals one, Figures 5-6): the interval of time between the disclosure moment and the macro-failure date lasts more in no-tort (i.e. fraud equals zero).

Table 16. Kaplan-Meier estimator for the time2 variable

failure _d: **status**
analysis time _t: **time2**

		Survivor Function	
fraud		0	1
time	6	1.0000	0.9655
	216	0.9667	0.2414
	426	0.7333	0.0690
	636	0.3333	0.0345
	846	0.1667	.
	1056	0.1000	.
	1266	0.0667	.
	1476	0.0333	.
	1686	0.0333	.
	1896	.	.

Table 17. Nelson-Aalen estimator for the time2 variable

failure _d: **status**
analysis time _t: **time2**

		Nelson-Aalen Cum. Haz.	
fraud		0	1
time	6	0.0000	0.0345
	216	0.0333	1.3666
	426	0.3042	2.4595
	636	1.0660	2.9595
	846	1.7117	.
	1056	2.1617	.
	1266	2.4950	.
	1476	2.9950	.
	1686	2.9950	.
	1896	.	.

Figure 5. Kaplan-Meier estimator for the time2 variable

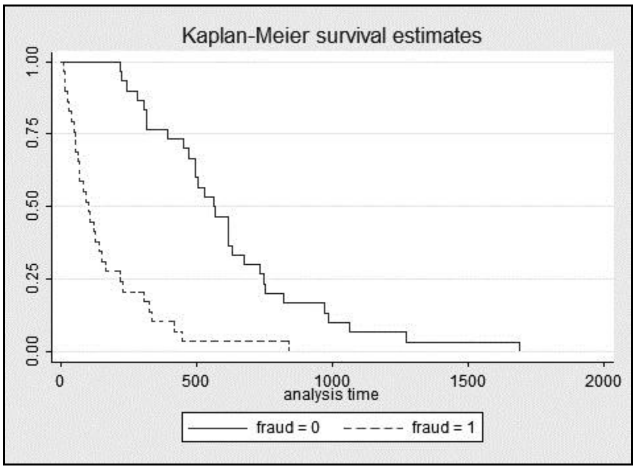
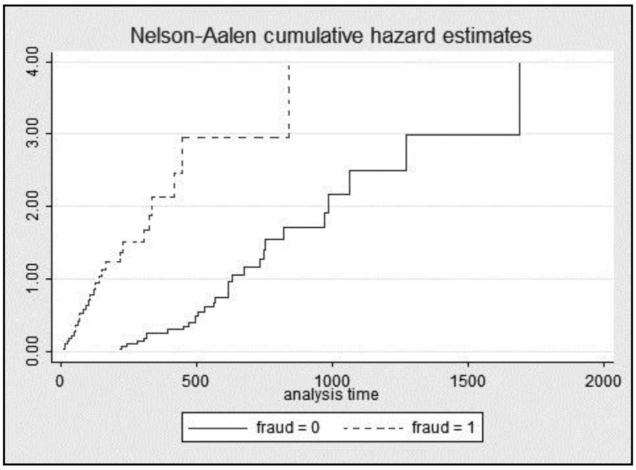


Figure 6. Nelson-Aalen estimator for the time2 variable



7 Main conclusion and suggestions for future research

Essentially, this paper has sought to encourage a new explanation of business failure through the identification of two different steps in the failing path: the first, i.e. micro-failure, is not atypical and the second, i.e. macro-failure, does not occur suddenly. Their consideration will help scholars in the explanation of also fraud happening: fraud allows firms to gain time and hope to avoid macro-failure, but, after the disclosure moment, fraud firms fall into macro-failure faster than no-tort firms.

The results suggest that only after such an explanation of business failure can its prediction be properly conducted: in the near future, the author aims to utilize the existing methods of prediction in the light of the developed explanation to predict macro-failure when the relevant micro-failure is disclosed. In addition, other suggestions for future research regard two sampled cases which have been emphasized at the end of the survival analysis through an analysis of the deviance residuals: it will be interesting to go into greater depth through a specific accounting history analysis. Moreover, the author would like to overcome some limitations of the present paper through future work: this contribution regards only American fraud and no-tort cases whose activities differ from the finance, insurance and real estate division. The implemented analysis does not consider the possibility that failing firms may commit fraud and become once again successful cases without having to disclose such improper accounting methods. These cases are very difficult to identify. Only deeper investigation of the subject (inside the history of failing firms, their minor events and their stakeholders' actions) may help such identification: this paper represents an initial contribution to this type of approach and towards a new explanation of business failure.

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