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PINPOINTING THE EARLY STAGES OF CORPORATE DECLINE

A PREDICTION MODEL FOR BUSINESS DISTRESS IN LARGE NORDIC LISTED FIRMS

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ABSTRACT

This paper attempts to analyze the multidimensional nature of corporate decline for large, publicly held firms in Denmark, Finland, Norway and Sweden to determine (i) whether early stage decline can be clearly distinguished and (ii) whether it can be predicted in advance by investors and analysts using cross-disciplinary determinants. In doing so, we attempt to standardize commonly used key terms pertaining to corporate failure, and to aggregate the various approaches used by academia, credit rating firms, and turnaround professionals to investigate firms using data from 2001 to 2011. Early stage decline is herein referred to as *business distress*, and it precedes financial distress and insolvency, which are defined as the subsequent stages of the decline progression. We find evidence supporting the notion that business distress is a distinguishable sub-stage of decline that can be objectively identified using qualitative determinants, and classified as it occurs through the use of accounting ratios related to financial gearing, covenants, profitability, and liquidity, as well as market factors, and company characteristics. We conclude that business distress can be predicted by logistic regression using various combinations of these factors up to five years prior to the occurrence of a "distress event", with an in-sample classification accuracy ranging from 72% to 78%.

KEYWORDS:
Business distress; Financial Distress; Failure prediction; Turnaround; Nordic Firms

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1. INTRODUCTION

1.1. Purpose of the study

This paper attempts to standardize a definition of "distress" based on the occurrence of one or more key developments that can have a bearing on the longevity of a company. This is done with the intent of enabling lenders, shareholders, and professionals to quickly identify companies in the early stages of decline in order to facilitate successful turnarounds - thereby minimizing the risk of bankruptcy and the subsequent losses to stakeholders. The primary purpose of the study is thereby to (1) *explore whether business distress can be objectively identified*, and (2) *evaluate whether there are factors that can explain or predict the occurrence of distress*.

The research is based on quantitative and qualitative data extracted from the Standard & Poor's Capital IQ database. The sample includes 342 firms listed on the four major Nordic stock exchanges: OMX Stockholm, OMX Helsinki, OMX Copenhagen, and OB. All firms meet the criteria to be classified as 'large' based on the new definitions of small and medium firms published by the European Commission in 2005.[1] The sample represents all sectors except the Financial and Utilities sectors, since the latter two are structured differently and are subject to distinct bankruptcy regimes (Ohlson 1980).

In the paper we will try to reconcile current business practices with the models developed in academia in order to define, identify, and predict business distress. A review of the literature shows that the definitions used vary to a great extent depending on the purpose of the study, whether the study relies on qualitative or quantitative data, and the specific research discipline. The resulting models are therefore difficult to compare across disciplines and other dimensions such as time, country, and industry. This is an attempt to aggregate cross-disciplinary factors into one model, and apply it to different industries in a distinct geographical region to explore whether the concept of business distress can be generalized across these dimensions without forfeiting the possibility of prediction. This can provide lenders, shareholders, and professionals with a tool that enables them to analyze a portfolio of companies within the region in order to

[1] Turnover greater than 50 EURm or Total assets greater than 43 EURm

quickly identify which holdings are distressed, and which are likely to become distressed given their current development.

1.2. Background

The financial crisis in Europe has led to significantly lowered interest rates, combined with the implementation of quantitative easing measures. Widespread austerity measures combined with a decrease in aggregate demand have put a strain on companies that are under pressure to remain afloat after years of gearing for growth. In the Financial Times' Special Report on business turnarounds (2012), it was found that interventions by governments and central banks throughout Europe in 2008 and 2009 managed to placate debt markets and protect many distressed firms from going bankrupt. It also found that despite the current Eurozone crisis, the default rate is approximately 3 percent, which is significantly below the long-run historical average of 4.5 percent (Moody's Global Corporate Finance 2008). In Europe, distressed debt funds as well as turnaround industry professionals are disappointed with the artificially depressed level of defaults, especially when taking into account the weak economic growth, shrinking banking sector, high unemployment levels, and lower consumer confidence – particularly in southern Europe.

The banking sector in particular is faced with a unique set of challenges as regulators step in to tighten liquidity requirements following bank bailouts in multiple Eurozone member states. The International Monetary Fund (IMF) estimates that in 2013, the supply of credit in Europe will decrease by 1.7 percent, and it is expected that the banking sector may be unable to meet the needs of European companies over the next five years. To make matters worse, the professed 'wall of refinancing' is set to occur in the time period from 2013 to 2015, in which debt issued in 2006 and 2007 will mature and need to be refinanced in a less favorable borrowing environment. In spite of these conditions, Moody's predicts that default rates in 2013 will only be slightly above pre-crisis rates. Interestingly enough, the pressures on the banking sector has resulted in a lower number of restructurings and debt defaults for the following four reasons:

1. Interest rates are low, which has allowed even heavily leveraged firms to service their debt.

2. Banks subject to tougher regulatory requirements and significant political pressure prefer to 'amend and extend' corporate loans within their portfolios rather than to push firms into insolvency and take immediate losses on the books.

3. Distressed funds are not very active in Europe, partially due to the fact that banks are unwilling to sell their debt portfolios.

4. Bankruptcy regulations in the most troubled countries, such as Greece, Cyprus, Italy, and Spain are virtually untested and lenders are therefore unwilling to pursue this path.

The overwhelming trend favors negotiation and leniency, rather than liquidation and losses. This phenomenon is echoed in the ongoing calls in many Western countries to revise bankruptcy codes, marking a clear departure from "liquidation codes" in favor of regulation that promotes business reorganizations. This is particularly true in the Nordics, where changes to bankruptcy laws were made in the mid-1990s in Finland, Norway and Sweden in a distinct move toward Chapter 11 of the U.S. Bankruptcy Code [2] (Strömberg & Thorburn 1996). There have been no bankruptcy filings or reported debt defaults among large listed firms in Denmark, Finland, Norway or Sweden from 2006 to present, which is interesting given the fact that large firms in the Nordics tend to be export-focused and thereby highly sensitive to the implications of a global crisis.

On the other hand, corporate banking in the Nordics is characterized as highly relationship-driven, and banks try to play the role of active business partners where possible. A lender takeover of a failing firm is therefore highly unlikely in this region, partially owing to the fact that Nordic banks do not have the resources necessary to step in and manage firms. As a result, the Eurozone crisis has resulted in an increased tendency for Nordic banks to pursue active debt renegotiations with their large clients. In practice, this translates into the issuance of short-term covenant waivers combined with turnaround plans to get companies back on track while avoiding the market repercussions of reported defaults. This development has resulted in default rates that are lower than what would be expected under normal conditions (Ernst & Young

[2] Ch. 11 bankruptcy keeps the firm as a going concern while financial claims are restructured. It also allows management to retain control of ongoing operations during the process.

Restructuring Forum 2012). Distressed companies may take advantage of their strong relations with banks to reduce information asymmetries and prolong the time to exit (Diamond 1984; Fama 1985; Boot 2000, all cited in Balcaen, Manigart & Ooghe 2011, p. 420). Maintaining close relationships with banks may enable firms to get debt financing at lower costs or to renegotiate the terms of current debt financing, which may facilitate recovery since loosened credit is followed by constant monitoring and rapid intervention when performance deterioration is detected.

NOTE: An important distinction should be made between reported defaults, in which failure to meet debt obligations is reported to the market, and technical defaults in which loan covenants are effectively breached but where covenant-waivers are granted to buy the company time to fulfill its obligations. Since technical defaults are unreported, it is difficult for outside stakeholders to identify whether a firm is at risk or not. We hypothesize that the rate of de facto defaults (reported and not reported) is larger than the statistics suggest. As a result, we have decided to apply a broader definition of distress in our study, with the aim of capturing companies in at-risk situations. This will enable us to more accurately analyze distressed companies during the financial crisis, and create a generalizable model that captures not only firms in default, but also the below-average performers that are legally surviving but failing from a shareholder value perspective.

1.3. Delimitations

This paper will develop a model tailored to the Nordic region – a distinct market where large firms frequently compete, source, and distribute goods across borders. Our model will incorporate variables that are specific to, and byproducts of, the respective macroeconomic, regulatory, financial, and competitive environments in which large, export-oriented, listed firms interact. This study will not evaluate or take into consideration how specific environmental factors differ between individual countries in the Nordics, nor how they differ from those of other regions. The reason for this is to minimize the level of subjectivity inherent in determining the specific macroeconomic, judicial, legislative, and commercial factors that are the relevant drivers of business distress.

Furthermore, this model will rely on ratios based on accounting data from both before and after the 2005 implementation of IFRS in the Nordics. Changes in the reported accounting data as a result of the new regulatory standards will not be considered. Finally, it is important to bear in mind that the time period from which the data is taken largely represents a distinct and extreme financial downturn, and as a result, the macroeconomic variables and fiscal measures undertaken to alleviate the crisis may render the coefficients unusable in future periods.

2. KEY CONCEPTS

In this section, we will first summarize the most commonly applied definitions of the concepts of *distress*, *decline*, *default*, and *failure* in existing qualitative and quantitative literature, and present the definitions that apply in this paper. We will then aggregate key findings and current developments in related research disciplines such as bankruptcy prediction, credit default risk, and qualitative business failure research in order to provide a holistic overview of the factors that play a role in distressed situations. Finally, we will discuss how this study attempts to address these factors and what the implications are on distress prediction for large Nordic listed firms.

2.1 Definitions used in previous literature

Depending on the scope of the research and the availability of data, different definitions of the terms *decline* and *failure* are adopted in the literature. In business life-cycle literature, the *decline* phase characterizes companies that are beginning to stagnate as markets dry up and product lines become antiquated (Miller & Friesen 1984). A *decline* phase is not bound by time; a firm can be in a *decline* phase temporarily and subsequently *recover*, or the degree of decline can worsen and approach *financial distress*, and ultimately, *failure*. *Failure* can either refer to technical failure, such as defaults and insolvency, or business failure, which is the more general notion of failing to maximize shareholder value.

Here is a brief overview for the purpose of illustrating the wide range of *failure* definitions used in the literature over time: [3]

- Altman (1971) and Ohlson (1980) exclusively associated *failure* with legal bankruptcy.

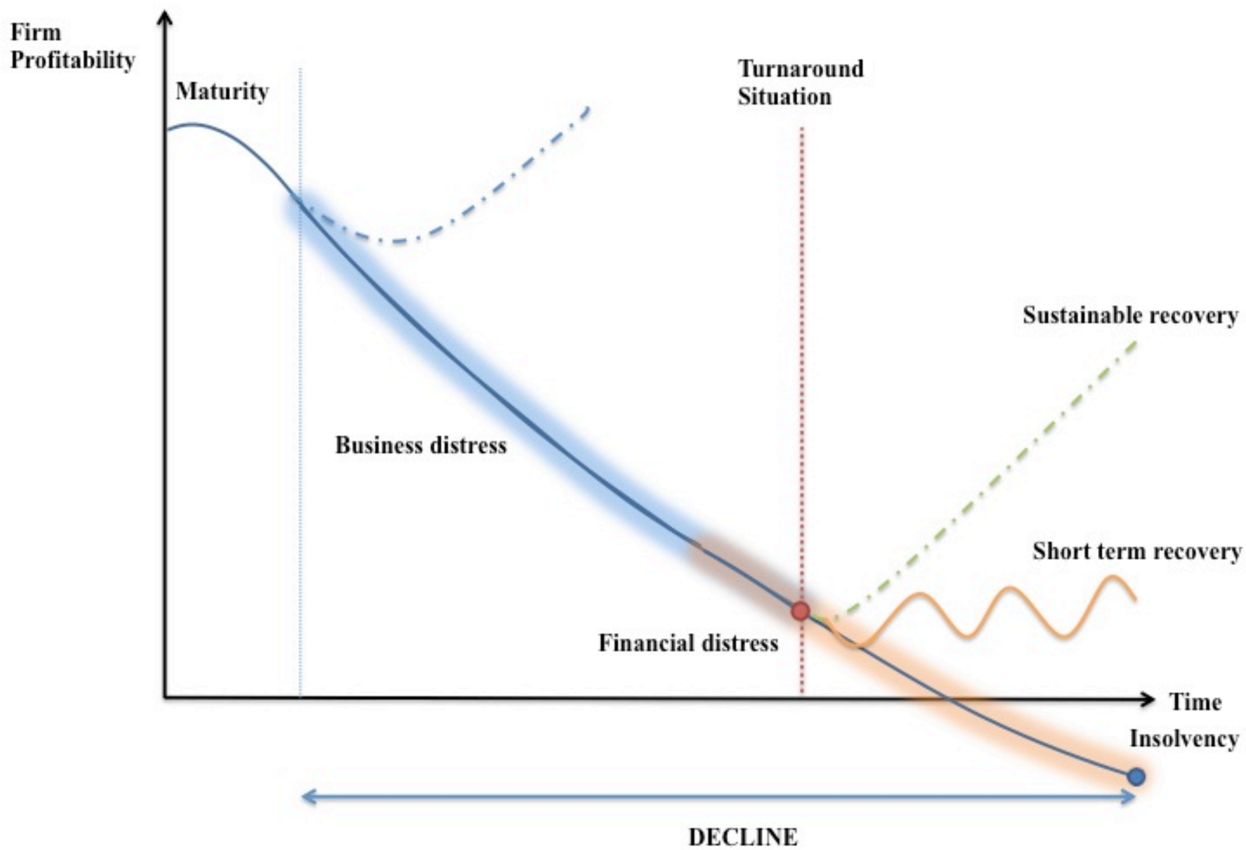
[3] For further details of previously used definitions, refer to Appendix – Table A.

- Skogsvik (1988) operationalized *failure* as the occurrence of bankruptcy filings and/or composition arrangements, voluntary shutdowns of core operating activities, and the receipt of substantial government support.
- Gilson, John & Lang (1990) broadened the scope of *failure* in order to capture situations where firms avoid bankruptcy by negotiating with creditors out of court.
- Liao (2004) (cited in Pretorious 2009, p. 9) confirmed that terms such as closures, exit, dissolution, bankruptcy, or insolvency are often used for *failure*.
- Campbell, Hilscher & Szilagyi (2008) defined *failure* as bankruptcy, financially motivated delistings, or D ratings.

Some studies do not include any definition of failure at all, relying on the reader's general understanding of the concept. The lack of a universal definition and distinction between terms related to failure results in low comparability across studies. Watson & Everett (cited in Pretorius 2009, p. 4) found that differences in sectorial failure rate reports might be due to the application of different definitions. In an effort to explicate a universal construct of failure in order to provide direction for future researchers, Pretorius (2009) distinguished between three types of definitions based on the scope of the research: decline-focused, failure-focused, and turnaround-focused. He proposed a clear distinction between *decline* and *failure*, depending on whether a *turnaround* could be deemed feasible or not. According to this methodology, a company is in a state of *decline* when performance declines over consecutive periods, and *decline* is a natural precursor in the process of *failure*. A company *fails*, on the other hand, when it "involuntarily becomes unable to attract new debt or equity funding to reverse decline; [and] consequently, cannot continue to operate under the current ownership and management" (Pretorius 2009). The most important distinction between the notions of *decline* and *failure* is that a declining firm can be turned around while a failed firm cannot. *Decline* precedes *failure*, with *failure* being the final stage in performance deterioration. This is in direct contrast to a *turnaround situation*, in which the focus is on the signs and causes of decline, and the goal is to resume normal operations (Pretorius 2009).

2.2 Key definitions used in this paper

FIGURE 1 – OVERVIEW OF KEY CONCEPTS



Since the purpose of this paper is to provide a tool that enables stakeholders to identify companies in the early stages of decline in order to facilitate successful turnarounds, we will rely on the definitions used by Slatter & Lovett (1999): A *declining* firm is often a stagnant business in a changing product-market environment, with under-utilized assets and ineffective management. It tends to be in "stable and mature industries with a competitive advantage that exists for largely historical reasons" (Slatter & Lovett 1999, pp. 1-2). A *turnaround situation* refers to firms "whose financial performance indicates that the firm will fail in the foreseeable future unless short-term corrective action is taken" (Slatter & Lovett 1999, p. 1). *Short-term recovery* refers to "firms which survive but never make an adequate return on capital employed, or survive only in the short term and then become insolvent". *Sustainable recovery* "involves achieving a viable and defensible business strategy, supported by an adequate organization and control structure [and] means that the firm has fully recovered, is making 'good' profit and is unlikely to face another crisis in the foreseeable future" (Slatter & Lovett 1999).

For our purposes, *decline* precedes *failure* (or insolvency), and bankruptcy is an extreme form of *failure*. Furthermore, we propose two sub-stages of *decline*, namely *business distress* and *financial distress*. *Business distress* denotes the early stages of decline, where the firm must reorient itself to deal with changes in its competitive environment in order to avoid *financial distress*, which is the inability to meet its financial obligations in the foreseeable future. *Financial distress* can be operationalized as a de facto covenant breach or the occurrence of a default. It can also occur in the form of substantial losses to shareholders, or in the form of low cumulative profitability compared to other investments with similar risk profiles. The table below summarizes these definitions and can be used as a point of reference for the concepts discussed throughout the paper.

TABLE 1 – DEFINITIONS AND CHARACTERISTICS OF KEY CONCEPTS

Key term	Definition	Characteristics
Decline	A stagnant business in a changing product-market environment	Under-utilized assets and ineffective management
Business Distress	The early stages of decline, where the firm must reorient itself to deal with changes in its competitive environment	Operationalized using predominately qualitative key developments indicating Red Flags, see Table 4
Financial Distress	The inability to meet financial obligations in the foreseeable future	De facto covenant breaches and/or reported debt defaults
Turnaround Situation	When the firm's financial performance indicates that it will fail in the foreseeable future unless short-term corrective action is taken	Profitability below industry average, can be measured using return on assets, cumulative profitability, etc.
Short-term Recovery	Below average performance, and short-term survival followed by insolvency	Continuous below-average performance
Sustainable Recovery	Achieving a viable and defensible business strategy supported by an adequate organization and control structure	Good profits, unlikely to face another crisis in the foreseeable future
Failure	Non-reversible insolvency.	Bankruptcy, defaults, buyouts, hostile takeovers, other types of firm exit.

2.3 A brief overview of bankruptcy prediction models

Bankruptcy prediction first gained traction as a research discipline in the 1960s when Beaver (1966) established the empirical usefulness of accounting ratios for the purpose of predicting failure. Altman (1968) then pioneered the use of multivariate analysis to predict bankruptcy using matched pairs of bankrupt and non-bankrupt firms within the same industries. In 1977, Altman, Haldeman & Narayanan updated the multivariate model, creating the Zeta model in response to the need for a more relevant bankruptcy prediction model given the ongoing changes in the business and regulatory environments at the time. Specifically, the new model was a response to changes in the following five contingencies:

1. The increasing size of failing companies in the 1970s.
2. The need to create a current model given the evolving nature of data.
3. The industry-specific focus of past failure models.
4. Changes in financial reporting standards and accepted accounting practices, notably the capitalization of all non-cancellable operating and financial leases.
5. The introduction of recent advances in discriminant analysis.

In order to fairly assess and compare the Zeta model to other existing models today, it is important to be aware of these contingencies as well as the sample selection methodology and the ratios used. The Zeta model was applied to publicly held American firms in the manufacturing and retailing industries, with an average asset size of approximately $100 million in the two annual reporting periods immediately prior to failure. No firm had less than $20 million in assets. Furthermore, every bankrupt firm in the sample failed in the seven years prior to the publication date (Altman, Haldeman & Narayanan 1977), and bankrupt firms were defined as those that had filed bankruptcy petitions. The result was a sample of 53 bankrupt firms and 58 non-bankrupt firms matched by industry and year of data. The utilization of matched pairs results in a sample where the ratio of bankrupt to non-bankrupt firms is overrepresented compared to the actual population, and that companies are chosen arbitrarily using size and industry.

Zmijewski (1984) (cited in Ko, Blocher & Lin 2001, p. 72) investigated the problems associated with "sample selection bias" and "choice-based sample bias", and found that choice-based sample bias, or the bias associated with overstating failed firms in the sample, decreased as the failure/non-failure ratio approached the population probability. On the same note, Skogsvik (2005) concluded that choice-based sample bias in probabilistic bankruptcy models using matched data with limited sample sizes could be corrected for without re-estimating the models. It is unclear whether this approach would correct the choice-based sample bias in models using multivariate discriminant analysis, such as the Z-score and ZETA models.

Ohlson's (1980) probabilistic model redressed many problems associated with previous models, such as the use of matched samples, the arbitrary nature of size and industry classifications, and the lack of acknowledgement of timing issues of prior bankruptcy research. He distanced himself however, from attempting to define business failure or bankruptcy, and from assessing the relative usefulness of the ratios used. Notable conclusions from his study were that the robustness of the predictive power of ratios is positively related to sample size, and that significant improvements in the predictability of models likely require additional predictors beyond ratios pertaining to *company size, financial structure, performance measures,* and *liquidity measures*. He also hypothesized that it would be more useful to include *industry* as a predictive measure rather than to use it as a screening factor in data collection.

While both Altman, Haldeman & Narayanan (1977) and Ohlson (1980) explicitly concerned themselves with a two-state bankruptcy prediction model and distanced themselves from making a general claims about failure, Grice and Dugan (2001) suggested that prior models are still widely used in various applications in spite of the fact that extant literature provides minimal evidence as to their generalizability. According to Grice & Dugan (2001), careful attention should be paid to the time periods and industries used when the models were created, as well as the type of financial distress situation currently dealt with when attempting a wider application. They evaluated the generalizability of the probabilistic bankruptcy prediction models created by Ohlson and Zmijewski using a wider definition of distress, including chapter 11 bankruptcy, chapter 7 liquidation, bond ratings below CCC, and stock ratings at "lower B" and below. The ratio of distressed to non-distressed firms in their study was 17.87%. Since their definition of distress encapsulated bankruptcy, the danger of having an upwardly biased "bankrupt" sample was minimized using this approach. Furthermore, they used samples from different time periods, industries, and financial conditions than those originally used to design the models or chosen as the holdout samples for the respective studies. The findings were that the overall accuracy of the models when applied to alternative samples significantly declined, ranging from 34.8% to 81.3%. However, a notable finding was that the models tested were not sensitive to different distress situations within the sample, which indicated that they are more generally useful for identifying *financially distressed* firms rather than bankruptcies in particular.

2.4 Implications on current research design

Altman's re-assessment of the Z-score and ZETA models in 2001 led him to conclude that the Z-score and, in particular, the revised ZETA model was able to separate bankrupt firms from below-average performers in 52 cases out of a sample of 66 poorly performing firms. This suggests that in theory, closely observing the differences in Ohlson and Altman, Haldeman & Narayanan choices of ratios should be helpful in identifying the distinguishing factors between firms likely to declare bankruptcy and firms in a more general distress situation. If this is the case, a general model utilizing a broader "failure" definition could be made to capture both "bankrupt" and "distressed" firms, acknowledging that "bankruptcy" is a severe form of "distress", and only one of many exit alternatives for shareholders of distressed firms. It also suggests that a sample that reasonably reflects the actual rate of default in the population has the potential to be generalized in order to detect distressed firms, rather than just failing ones. The general trend within the bankruptcy prediction discipline is moving toward the utilization of broader definitions of failure and multiple states of distress (Chancharat et al. 2010), as well as the earlier identification of financial distress in order to minimize losses to stakeholders (Ko, Blocher & Lin 2001).

TABLE 2 – RATIOS USED IN DIFFERENT HISTORICAL BANKRUPTCY PREDICTION MODELS

Altman Z-Score (1968)		Altman, Haldeman & Narayanan ZETA Analysis (1977)		Ohlson (1980)		Skogsvik (1988)	
Variable	Formula	Variable	Formula	Variable	Formula	Variable	Formula
R1	(Current assets-Current liabilities)/Total Assets	**ROA**	EBIT/Total assets	**SIZE**	Ln(total assets /GNP price-level index)	**R1**	EBIT/Average total assets
R2	Retained earnings/Total assets	**Earnings Stability**	Standard error of estimate around a 10-year trend in ROA	**TLTA**	Total liabilities/Total assets	**R2**	Interest expense/Average liabilities and deferred taxes
R3	EBIT/Average total assets	**Debt Service (ICR)**	EBIT/Total interest payments	**WCTA**	Working capital/Total assets	**R3**	Average inventory/Sales
R4	MV(equity)/BV(liabilities)	**Cumulative Profitability**	BV (Retained earnings)/Total assets	**CLCA**	Current liabilities/Current assets	**R4**	BV (equity)/Total assets
R5	Sales/Average total assets	**Liquidity (Current ratio)**	Current assets/Current liabilities	**OENEG**	1 if Total liabilities exceeds Total assets, 0 otherwise	**R5**	Change in owner's equity (BV)
		Capitalization	Common equity/Total capital	**NITA**	Net income/Total assets	**R6**	Diff (R2)
		Size	Total assets	**FUTL**	Funds from operations/Total liabilities		
				INTWO	1 if Net income was negative for the last 2 years, 0 otherwise		
				CHIN	Change in Net income		

Most models include return on assets, the current ratio, and equity-related ratios while size and working capital related factors are less prevalent. The models also differ in the degree of ratio specificity. This paper will follow Ohlson's (1980) approach of relying on general, standardized ratios, without reflecting on how different profitability ratios differ from each other, for instance.

2.5 Financial distress in credit risk models

While bankruptcy prediction models have been successful in establishing the links between accounting data and the occurrence of bankruptcy, the broad application of generalizable bankruptcy prediction models is problematic for practitioners[4] for a number of reasons. Firstly, most bankruptcy prediction models rely on financial predictors using data from the two years immediately preceding bankruptcy. This is problematic given that bankruptcy is the end-stage of a long, unwinding decline process, and it is likely that any data from those years is a result of various late-stage rescue attempts. Furthermore – and this is particularly expected when corporate banking is primarily relationship-driven – most lenders and shareholders should already know that firms are headed for insolvency at that point in time (Slater & Lovett 1999). Secondly, most commonly used bankruptcy prediction models do not incorporate any market data, even though it can be expected that the inclusion of such data would enhance predictability (Ohlson 1980). For our purposes, strong parallels can be drawn between the explicit purpose of probabilistic bankruptcy prediction models and the purpose of credit risk models, which are predominately concerned with the possibility of financial losses due to changes in a firm's financial strength. The focal point of a credit risk model is to map out the probability of *default*, which as previously mentioned, is the inability of a firm to meet its debt servicing obligations, and which could ultimately result in insolvency if left unrectified. Given that default precedes insolvency, any attempt at pinpointing early-stage decline, which precedes financial distress, should take both approaches into account in order to enhance the predictive ability of such a model.

Credit risk models focus on the relative rankings of market participants' credit worthiness as a function of both current strength <u>and</u> expectations of future performance, which is the part that makes them fundamentally different from accounting-based bankruptcy prediction models (Metz & Cantor 2006). Koopman et al. (2009, p. 54) found that changes in the level of economic activity, bank lending conditions, and financial market variables are important determinants of default, while Metz and Cantor (2006) found that ratings distributions are stable over time. While this is seemingly counterintuitive if ratings are meant to approximate the probability of default, it supports Amato & Furfine (2004), who found that credit ratings are not pro-cyclical when examining a complete set of firms and ratings. This means that for a broad sample of firms of varying financial strength, ratings are not conditional on financial, business, and macroeconomic characteristics. One could argue that this is logical given that firms in a particular market

[4] "Practitioners" will in this paper refer to lenders, shareholders, and turnaround industry professionals, among others.

environment are all exposed to the same macroeconomic factors, so any ordinal ranking system meant to establish the relative credit worthiness of firms within a given market would have to have the ability to rate *through* cyclical factors in order to be useful for lenders.

Metz & Cantor (2006) introduced a new method of predicting credit ratings by using a model that weighs five financial factors based on the leverage ratio of the firm. They found that this model outperformed both linear regression and ordered probit models in both in-sample and hold-out sample tests, which supports their idea that certain factors become more or less important in determining a given firm's credit rating depending on how leveraged the firm is. They found that two-thirds of the weights were always distributed across the interest coverage ratio, the return on assets, or a variable capturing the interaction between the two, whereas the remaining third was distributed over the remaining factors. The ratios used in their model as well as in Amato and Furfine's procyclicality study (2004) are summarized below. While it is useful to bear the credit risk model approach in mind when evaluating the factors that determine business distress, it is important to note that the more commonly used credit migration models cannot be applied to the Nordic market, since Nordic non-financial firms tend to lack credit ratings from large ratings agencies due to the high costs of obtaining ratings (Andersson, Selinus, & Zettergren 2011).

TABLE 3 – RATIOS USED IN CHOSEN CREDIT RISK MODELS

Amato and Furfine (2004)		**Metz and Cantor (2006)**	
Variable	Formula	Variable	Formula
Interest Coverage Ratio	Unspecified	**Interest Coverage Ratio**	[(EBIT-Interest Capitalized) + (1/3)*Rental Expense)] / (Interest Expense + (1/3)* Rental Expense + Preferred Dividends)/0.65
Operating Margin	Unspecified	**Leverage**	(Total Debt + 8*Rental Expense) / (Total Debt + 8*Rental Expense + Deferred Taxes + Minority Interest + Total Equity)
Long-term Debt	Unspecified	**Return on Assets**	Net After-Tax Income Before X-Items / 2 Year Average Assets
Total Debt	Unspecified	**Volatility Adjusted Leverage**	(5 Year Average Asset Growth + Equity/Assets) / 5 Year Standard Deviation Asset Growth
Market Value	Unspecified	**Revenue Stability**	5 Year Average Net Sales / 5 Year Standard Deviation Net Sales
Market-Model Beta	Unspecified		
Market-Model Standard Error	Unspecified		

2.6 Non-financial factors

Reported financial information is automatically subject to a time lag of three to fifteen months depending on the time of year. Hence there is a need to look for trends and build-ups in non-financial factors to facilitate the identifications of firms in early stages of decline (Slatter & Lovett 1999). The idea of including qualitative factors in predicting company distress was further supported by Grunert, Norden & Weber (2005) who demonstrated that the combined use of financial and non-financial factors leads to a more accurate prediction of future default events than use of any of those factors on their own. Beyond the inclusion of dummy variables to capture variance due to sector, country and recession year, we will also examine *changes in executive management*, *changes in the board of directors*, *company size* as a function of national gross domestic product, *firm age*, and the occurrence of certain key developments that indicate distress.

2.6.1 Changes in executive management and the Board of Directors

It has been widely documented in qualitative business failure research that companies achieve successful turnarounds through 'reorientation of positioning, strategy, structure, control systems and power distribution' (Pretorius 2009). Executive leadership initiates and directs these reorientations, and when accompanied by executive succession, strategic reorientations result in better performance (Tushman, Virany & Romanelli 1985). Management characteristics are commonly used as qualitative predictors in internal credit scoring systems by a wide variety of institutions (Grunert, Norden & Weber 2005). When assessing management for the purpose of credit scoring, S&P incorporates a 'management' variable, and Moody's uses 'quality of management' which consists of *planning and controlling, managerial track record, organizational structure and entrepreneurial succession.* Banks commonly rely on variables pertaining to management quality, measured by *years of experience*, *succession*, *quality of accounting and control systems*, *customer relationships*, as well as *account management* (Krahnen & Weber 2001).

Some researchers suggest that executive management must be changed when companies are in need of a strategic reorientation in order to recover from a decline (Arogyaswamy et al. 1995; Hofer 1980; and Starbuck et al. 1978, all cited in Barker III & Barr 2002, p. 976). The underlying argument is that executive managers that have been active within a given firm or industry for a long time move up the hierarchical ranks and are more likely to feel committed to current strategic initiatives (Wanous 1980, cited in Barker III & Barr 2002, p. 966). When the company enters a decline, such managers are more reluctant to implement strategic changes. They are likely to perceive external problems as the source of decline rather than internal problems, in contrast to newly appointed executives. Restructuring experts point out that rapid change of the CEO and high turnover in senior management are early symptoms of decline (Slatter & Lovett 1999), although it is unclear whether this correlation supports or refutes the causal argument made by Barker III & Barr (2002). The second group of executives involved in managing the strategic reorientation of a company is the Board of Directors, which establishes boundaries for strategy formulation and decision-making. Changes in the Board during the decline phase may result in the implementation of new ideas, the trumping of strategic inertia, and the realization of strategic changes (Goodstein & Boeker 1991 and Grinyer et al. 1988, both cited in Barker III & Barr 2002, p. 967). It was found out that the level of Board turnover is positively correlated with the extent of strategic reorientation during decline which can be explained by the fact that high turnover in Board of Directors leads to the addition of new directors that possess the knowledge and skills essential to affect change (Barker III & Barr 2002). In contrast, restructuring professionals cite the occurrence of "brain-drain", or the subsequent loss of top talent the further the company descends into decline. This study will refrain from making causal claims as to the relationship between changes in key persons, and will instead focus on establishing whether such changes are correlated with early-stage decline.

2.6.2 Firm size, age, and time to failure

The level of stakeholder network complexity affects probability of failure. Balcaen, Manigart & Ooghe (2011) found that it takes longer for companies with a higher degree of stakeholder dependence to exit after distress. The level of complexity is measured by firm size, business group membership, supplier relationships, and leverage. These factors determine the length and complexity of the liquidation procedure, since more stakeholder claims result in a lower freedom of action for executive management. Size can be used as a proxy for the scope of the stakeholder network since larger firms tend to have more stakeholders in the form of employees, shareholders, banks, business partners, et cetera. Age, measured by the number of years since establishment, was also found to prolong the time from initial distress symptoms to bankruptcy, possibly as a result of older firms having more competent employees, stable social relations, and a greater skill set (Balcaen, Manigart & Ooghe 2011).

2.6.3 Key developments related to distressed firms

Additional factors that are especially important in identifying early decline include covenant breaches, restructuring talks, the issuance of new debt to finance losses, and the lack of investment in people, capital, or technology (Slatter & Lovett 1999). More detailed information on key developments and their use in our sampling methodology will be included in the next section.

3. RESEARCH DESIGN

The purpose of our study is two-fold: we (1) specifically seek to explore whether the notion of *business distress* can be <u>objectively identified</u> at a given point in time using quantitative measures, and (2) to evaluate whether the occurrence of *business distress* can be <u>reliably predicted</u> using statistical techniques.[5] In this section we will describe the step-by-step development of the empirical method used to create our model. We will begin by covering our choice of market, time period, and operationalization of business distress, followed by an outline of our methodology, factors analyzed, and the use of specific statistical tests applied to check statistical robustness. We will conclude by describing our data collection process.

3.1 Why the Nordics?

As previously mentioned, large Nordic firms tend to be highly export-focused and thereby highly sensitive to diminishing global demand. During unraveling of the Eurozone crisis, the Nordics have fared relatively well, and Nordic banks are currently regarded as a safe haven for European depositors and fixed-income investors as a result of their high credit ratings (Sandstrom, 2012). The region's success in warding off the perils of the financial crisis are widely attributed to the regulatory measures instituted during the financial crisis in the early 1990s, which have played a pivotal role in maintaining institutional and market stability. As far as reporting regulations are

[5] Given the exploratory nature of this study, the term "reliably" is explicitly meant to refer to a prediction model that performs better than chance using robust statistical techniques.

concerned, Denmark, Finland, Sweden, and Norway all adopted the International Financial Reporting Standards for large listed firms in 2005. Furthermore, the primary stock exchanges in Stockholm, Copenhagen, and Helsinki are all owned by the NASDAQ OMX Nordics, with Oslo Børs being the exception. While distinctions certainly exist between the countries, their economic structure is homogenous relative to other regions within Europe, the European Economic Area as a whole, and the OECD. Notwithstanding these facts, the most compelling reason for grouping these countries together as a single market is the competitive landscape of large firms. The development of a Nordic firm follows the following pattern: it begins in the domestic economy, expands to neighboring Nordic countries (and in more recent years, to the Baltics), and continues to Germany and/or the United Kingdom en route to the rest of the world. As such, the "home market" for large, established firms in the Nordics usually consists of the entire region rather than a single country. This especially tends to be the case for industrial firms and manufacturers of consumer goods and durables, as well as the agricultural sector. As a result, resources are sourced, produced, distributed and sold across the region, and large firms within a given industry compete with each other within the region, not just the individual country. In order to effectively assess distress in large companies both within and irrespective of industry, all four countries must be accounted for. [6]

3.2 Choice of time period

Our sample consists of observations of distress occurring in the time period from 2006 to 2011 for a number of reasons. Firstly, we chose to focus on large listed firms because they are expected to be more comparable across borders within the region as described above. This is partly due to the fact that reporting standards for large firms listed on primary stock exchanges in the Nordics were harmonized in 2005 through the uniform implementation of IFRS for large, listed firms, whereas different rules prevail in different countries for firms that are unlisted or classified as SMEs. This makes the financials of large listed firms more comparable across the Nordics than SMEs or unlisted firms, and the comparability of financial ratios is a necessary requirement of model design.[7] Secondly, in order to objectively classify firms as "large", we

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[6] NOTE: Although Iceland is also a part of the Nordics, it differs significantly in terms of size and economic circumstances and is therefore excluded.

[7] Large firms are also more interesting from a research perspective, since they have been found to be less likely to *fail* and to have greater bargaining power with lenders.

used an exclusionary approach in which firms too large to be considered Small and Medium Enterprises (SMEs) were classified as “large”. We relied on the European Commission’s report on the classification of Small and Medium Enterprises (SME), which classifies SMEs as firms with less than € 50 million in turnover or less than € 43 million in total assets. This framework was introduced during the year 2005, so we applied it to the outgoing balances in 2005, and proceeded to the last period for which annual reports were available.

The benefit of this approach is that it enables us to design a model *through* the crisis, rather than developing a model that is only useful given the particular contingencies of a unique financial period. A noteworthy drawback is that the prediction models utilize data from up to five periods (T-5) prior to the earliest occurrence of *distress* (T=0), to 2001 at the earliest. No common set of accounting rules for the whole Nordics was in place before 2005 and country rules were applied. This runs the risk of reducing model effectiveness as ratios in financial statement might have been reported in different manner in different countries and discrepancies are possible.

3.3 Operationalization of business distress

The operationalization of *business distress* poses a significant challenge since it is a vaguely defined concept. *Business distress*, *financial distress*, and overall *decline* can take various forms in different sectors, and even in different firms within a sector.[8] *Distress* prediction is fundamentally different from bankruptcy prediction owing to the fact that *bankruptcy* is a legal term that denotes a terminal, irreversible state. A firm cannot revert from being bankrupt to not being bankrupt, but it can revert from *distress* to non-distress. The occurrence of *distress* is not bound by time nor defined using financial bright-line rules, and it can occur with or without the presence of a cash crisis, both in firms with declining sales and in firms that outgrow their own financing potential (Slatter & Lovett 1999). As a result, *business distress* cannot be operationalized in legal or financial terms. Furthermore, selection on the basis of financial performance could lead to an unclear distinction between independent and dependent variables. Bearing these limitations in mind, we ran several screenings using Standard & Poor’s Capital IQ database in order to identify the most appropriate operationalization of distress. The result was a

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[8] For the sake of simplicity, we decided to exclude the financial and utilities sector since they are fundamentally different from other sectors in terms of financial structure and insolvency procedures.

business distress operationalization based on two criteria. Firstly, the firm must have experienced a "Potential Red Flag/Distress Indicator" in a particular year. Secondly, the terms "*failure*", "*default*", or "*restructuring*" must have been included in the firm's list of reported key development situations during that year. The following table includes the exhaustive list of key developments that trigger a potential red flag or distress indicator in the Capital IQ database. This was found to be the most objective and inclusive method available to operationalize *business distress*. It is also comparable across countries, sectors, and companies.

TABLE 4 – POTENTIAL RED FLAGS/DISTRESS INDICATORS AS DEFINED IN S&P CAPITAL IQ

Key Developments	Definitions
Accounting Issues/SEC Inquiries	Includes announcements that the Securities and Exchange Commission (SEC) is launching an inquiry into a company, changes in accounting policy of a company, or a change in the auditor of a company.
Auditor Going Concern Doubts	This is when an auditor for a company has doubts for the accounting statement for their client company's reaffirmation that it will continue its business.
Bankruptcy Related	Events involving federal court proceedings in which an insolvent debtor's assets are to be liquidated, and the debtor is seeking relief of further liability. Rumors regarding a potential bankruptcy filing are also tracked under this event type. Also includes court rulings that might have an adverse or favorable impact on the company's bankruptcy case. For example: A major court ruling involving a company's labor union, shareholders, debt holders etc. Also includes other important court rulings, such as when the disclosure statement or the reorganization plan is filed and approved by the court.
Business Reorganization	The reorganization of a division, management, or operations of a company or corporation for efficiency or cost saving purposes. This may increase the earnings of the company.
Credit Watch-Credit Watch/Outlook Action	When a company's credit rating is being monitored for a possible downgrade in credit rating.
Credit Watch-Non-Rated Action	When a company's credit rating is being monitored, possibly for a downgrade, with no rating having been issued
Delayed Earnings Announcement	When a company postpones the release of its earnings to the public.
Delayed SEC Filings	When a company does not file appropriate corporate documents or filings with the SEC at the appropriate deadline.
Delisting	This development is used when a company's common stock, whether voluntarily or involuntarily, is removed from the exchange it trades on. This also includes companies that have filed for Form 15 and companies that have received non-compliance notices from their respective stock exchanges.
Discontinued Operations/Downsizings	Phasing out of a product line, closing of an individual facility, such as a plant, branch, division or subsidiary, or a reduction in the work force of a company.
Events Triggering Accelerated Debt Repayment	Usually companies borrow money, based on some standard and agreed upon repayment schedule. Sometimes debt providers demand the company to repay the debt before scheduled maturity date in situations where the company fails to perform its obligations under the Indenture. This pertains to these situations, which are cause for the accelerated debt payment. These situations may lead a company to cash crunch and may also lead to a change in the company's debt structure.
Impairment/Write-Offs	A reduction in the value of an asset or earnings by the amount of an expense or loss. This is usually reduced because of poorly estimated losses or gains. Generally companies write off their assets to ensure that their assets are not overstated in the financial statements. Whenever a company recognizes an impairment loss, there will be a change in assets of the company as well as it will affect the earnings of the company.
Index Constituent Drop	An announcement that a company has been removed from a stock index.

Labor-Related Announcements	Various announcements pertaining to the labor force of a particular company, including changes in agreements between a company and it employees' union and when a company enters an agreement with the U.S. Labor Department in relation to the workers contract.
Lawsuits	This pertains to actions or suits brought before a court against the company, as to recover a right or redress a grievance.
Restatements of Operating Results	This pertains to whenever there is a revision in a company's earlier financial statements. The need for restating financial figures can result from fraud, misrepresentation, change of accounting policy or a simple clerical error.

3.4 Variables used in the model

Since early-stage decline has not been explicitly or extensively analyzed in previous quantitative models, we have decided to include all factors identified by the extant literature and practitioners as potential identifiers or predictors of *business distress*. In line with Ohlson's (1980) methodology, we have chosen specific variables based on simplicity, without attempting to assess the relative usefulness of particular types of ratios that indicate, for instance, profitability, financial gearing, or liquidity. We use two main groups of variables in our analysis: qualitative ones incorporated as dummy variables, such as crisis year, sector, country, and key developments, and quantitative ones such as age, size, and financial ratios. The variables used have been summarized in the following tables, along a description of how their values were calculated and a column denoting our expectations for the sign of the coefficients based on the literature.

TABLE 5 – QUALITATIVE VARIABLES USED IN OUR RESEARCH

Category	Variable	Operationalization	Expectations (Sign)
Business environment related factors	Crisis year	Dummy variable with value 1 if the occurrence of *distress* is during the financial crisis (2007-2009) and 0 otherwise.	Positive
	Sector	A set of 7 dummy variables for 8 sectors where Telecommunication is the chosen base case scenario in order to avoid the dummy variable trap.	Unspecified
	Country	3 dummy variables for 4 countries: Finland, Denmark, Norway and Sweden, where Finland is the chosen base case scenario in order to avoid the dummy variable trap.	Unspecified
Key development related factors	Seeking to Sell/Divest	Dummy variable with value 1 if the event occurred and 0 if it did not.	Positive
	Executive/Board Changes – CEO, Executive/Board Changes – CFO, Executive/Board Changes – Other	One dummy variable for each event, with value 1 if event occurred and 0 if it did not.	Unspecified
	Corporate guidance lowered	Dummy variable with value 1 if event occurred and 0 if it did not.	Positive

TABLE 6 – QUANTITATIVE VARIABLES USED IN OUR RESEARCH

Category	Variable	Operationalization (all values in EURm at historical rates)	Symbol	Expectations (Sign)
Company characteristics	Age	Years since establishment	Age	Negative
	Relative size	Log (total assets/GNP). GNP adjusted for purchasing power parity; Value calculated for the end of 2005 and kept constant over the whole period	RS	Negative
Market factors	Capitalization	1-year MV of common equity/(Equity + Debt)	MF1	Negative
	Price risk	Beta, 1-year	MF2	Positive
Profitability related	Sales growth	Total Revenues, 1 year Growth %	P1	Negative
	Gross margin	(Revenue-COGS)/Revenue	P2	Negative
	ROA	EBIT/Total Assets	P3	Negative
	Cumulative profitability	Retained Earnings/Total Assets	P4	Negative
Liquidity related	Current ratio	Current assets/Current liabilities	L1	Negative
		NWC/Sales	L2	Positive
	Cash conversion cycle	Cash conversion cycle in days	L3	Positive
Covenants related	Interest coverage ratio	(EBIT + Financial income)/Financial expense	CC1	Negative
		ND/EBITDA	CC2	Positive
Financial gearing		Debt/Equity	FG1	Positive
	Relative interest	Financial Expense/Total Debt	FG2	Positive
		LTD due +1/Total LTD	FG3	Positive
		LTD due +2/Total LTD	FG4	Positive
Investment level related	Investment level	(Net $PPE_{t=0}$ - Net PPE_{t-1})/ Net PPE_{t-1}	IL1	Negative
		CAPEX as % of Revenues	IL2	Negative

Note: LTD is an abbreviation for long-term debt.

3.5 Test design

Using an exploratory approach, we utilize various methods to answer the two central questions of our study:

1. DISTRESS IDENTIFICATION: What quantitative factors can help an independent analyst distinguish between distressed and non-distressed companies?
2. DISTRESS PREDICTION: Is it possible to predict *business distress*, and which factors are useful when making this prediction?

To answer the first question we will check whether the means of quantitative variables differ between distressed and non-distressed firms using three methods: t-tests with equal variances, t-test with unequal variances, and the Kruskal-Wallis test. The most appropriate test is chosen depending on the statistical features of the samples being compared. To answer the second question we apply logistic regression in order to distinguish factors that are statistically significant in predicting the occurrence of *distress* at T=0 using data from T-1 to T-5, respectively.

We have decided to apply a significance level of 0.1 in all the methods utilized. A significance level of 0.1 indicates that there is a 10% likelihood that a result is due to chance, which indicates that the finding has a 90% chance of being non-random. The interpretation procedure for statistical tests used is as follows: when the p-value of a test is less than 0.1, then the null hypothesis is rejected. If the p-value is greater than 0.1, then the null hypothesis cannot be rejected.

3.5.1 Distress identification: comparing the means of two groups

The most commonly used test to compare the arithmetic means of two groups is a t-test. In our case we apply a t-test for two independent groups – distressed firms and non-distressed firms. This type of test can be applied when the independent variable is a ratio or interval and when dependent variable is binary. In this case, the dependent variable is a binary variable for which a value of 1 indicates distress, and 0 indicates non-distress.

The underlying assumptions of a t-test are that observations are independent, sample variances are equal, and the underlying population distributions are normal for both groups being compared (Newbold, Carlson & Thorne 2010). Independence of samples means that observations are mutually exclusive. If the sample is not normally distributed, the t-statistic will have an unknown distribution and the t-test may return inaccurate results. Furthermore, skewness and kurtosis can have a substantial impact on results, although this risk is reduced in samples with over 200 observations (Tabachnick & Fidell 2007, pp. 80-81). Skewness provides an indication of the symmetry of the distribution, with negative values indicating scores clustered to the right at the high values whereas kurtosis provides information on the peak of the distribution, with negative values for relatively flat distributions (Pallant 2007, p. 56). Since our sample sizes will be relatively small – notably within specific sectors – we check all the assumptions before choosing an appropriate method.

Another concern with small sample sizes is the possibility of getting insignificant results due to insufficient power. The power of a test measures its ability to detect an alternative hypothesis and is measured as the probability that the null hypothesis will be rejected when it should not be. In line with Stevens (cited Pallant 2007, p. 205) we decided to use higher alpha (0.1 instead of 0.05 or 0.01) to compensate for the risk of incorrectly rejecting null hypothesis.

The method of mean comparison for each respective quantitative factor examined is as follows: firstly, we examine the sample distribution using the Shapiro-Wilk test, which hypothesizes that the data is normally distributed. Secondly, we run Levene's test of homogeneity to determine whether or not the two groups have equal variances. Thirdly, quantitative factors are split into three groups: (i) the ones for which populations are distributed normally and variances are equal, (ii) the ones for which populations are normally distributed but variances are unequal, and (iii) the ones for which populations are not normally distributed.

For groups (i) and (ii), t-tests with equal and unequal variances are conducted, respectively. T-tests are used to test the null hypothesis that arithmetic mean of a factor is equal for both groups analyzed. We use one of the following statistics, where $\bar{Y}$ and $\bar{Z}$ are sample means, s_1^2 and s_2^2 are variances, and N_1 and N_2 are number of observations in two groups:

Equal variances

$$t = \frac{\bar{Y} - \bar{Z}}{s\sqrt{\frac{1}{N_1} + \frac{1}{N_2}}}$$

Variances not equal

$$t = \frac{\bar{Y} - \bar{Z}}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}$$

We use the t-statistic to calculate p-values and test the null hypothesis.

For group (iii), a non-parametric Kruskal-Wallis test is performed. Non-parametric tests have lower power than t-tests, but they have less strict statistical requirements in terms of underlying assumptions. Non-parametric tests are well suited to analyze data when the presence of outliers is expected. The Kruskal-Wallis test assumes that there are independent samples of n_1, n_2, ..., n_k observations from K populations. Let n denote the total number of sample observations and R_1, R_2, …, R_k the sums of ranks for the K samples when all observations are pooled together and ranked in ascending order. We test the null hypothesis that samples are drawn from the same population (or equivalently, from different populations with the same distribution) based on the following statistics:

$$W = \frac{12}{n(n+1)} \sum_{i=1}^{K} \frac{R_i^2}{n_i} - 3(n+1)$$

We use the W statistic to calculate p-values and test the null hypothesis. This non-parametric test was chosen owing to the fact that it is valid for samples with more than 5 observations (Newbold, Carlson & Thorne 2010, pp. 695-697).

3.5.2 Distress prediction using logistic regression

Grounds for choosing logistic regression

For the purpose of predicting *business distress*, or early-stage decline, logistic or probabilistic regression is preferable to other types of statistical regression models. The benefit of logistic regression is that it avoids many of the problems associated with alternatives, such as multivariate discriminant analysis (MDA) (Ohlson, 1980). The efficacy of MDA depends on the statistical requirements of the properties of independent variables, such as multivariate normality and equal variance-covariance across groups. Furthermore, interpretation of the numerical score returned by MDA models is less intuitive than the interpretation of the percentage probability of an event occurring given in logistic regression models. Additionally, the logistic model overcomes the limitations of the linear probability model, where fitted probabilities can be more than 1 or less than 0 (Wooldridge 2009, p. 575).

Model description

A logistic regression model is a binary response model that makes it possible to establish a relationship between a binary outcome and a vector of independent variables. The model of logistic regression (before logit transformation) is presented below (Hosmer & Lemeshow 2000):

$$\pi\,(x) = p = \frac{exp(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k)}{(1 + exp(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k))}$$

In our case, p denotes the probability of distress. If the value of the logistic function is greater than or equal to 0.5, then the company is classified as distressed; if the value is lower it is classified as non-distressed. Logistic regression models depict the logit-transformed probability as a linear relationship with predictors. The logistic function can only be expressed in values between 0 and 1 for all real numbers – ensuring that the probabilities computed using the model are always between 0 and 1.

Let us assume that Y represents a binary variable that indicates an event occurring or not occurring, with values 1 and 0 respectively. P is the probability of the event occurring and $X_1, \dots, X_k$ is the vector of k predictors. Logistic regression estimates the parameter values for coefficients β_0, β_1, …, β_k using the maximum likelihood method of the following equation:

$$logit(p) = \log\frac{\pi\,(x)}{1-\pi\,(x)} = \;log\;\frac{p}{1-p} = \;\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k,$$

where $\frac{p}{1-p}$ in the model represents the odds that distress will occur given a particular exposure (set of predictor values), compared to the odds of the event occurring in the absence of that exposure. The maximum likelihood method returns the values of the unknown coefficients that make the probability of observed data most likely. To calculate the estimates of coefficients, the likelihood function is constructed, representing the probability of the observed data as a function of the set of unknown parameters. For the purpose of mathematical simplification, the log likelihood function is used:

$$L(\boldsymbol{\beta}) = \ln[l(\boldsymbol{\beta})] = \;\sum_{i=1}^{n}\{y_i \ln[\pi(x_i)] + (1 - y_i)\ln[1 - \pi(x_i)]\},$$

If dependent variable Y is coded as 1 or 0, then function π (x) provides, for an arbitrary value of vector of parameters β, the conditional probability that Y=1 given X. This is denoted as P (Y = 1|x). In cases where Y=0, the conditional probability given X is equal to 1 - π(x). [9] Thus, the contribution of each pair (x_i, y_i) to the likelihood function equals:

$$\pi(x_i)^{y_i}[1 - \pi(x_i)^{1-y_i}]$$

Parameter estimation is an iterative process (Hosmer & Lemeshow 2000). The log likelihood function is also important when comparing models and assessing the goodness-of-fit, which will be described in the diagnostics section.

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[9] The conditional probability that Y=0 given X is denoted P (Y = 0|x).

Model interpretation

In a logistic regression, coefficients reflect the change in the logit function due to a unit increase in an independent variable ($\beta_k = g(x+1) - g(x)$). The interpretation of coefficients depends on the type of independent variable used. The coefficients themselves are log-odds ratios, where odds ratio is odds of being distressed to odds of being non-distressed. Taking the exponent of the coefficient ($e^{\beta k}$) returns the odds ratio, which is interpreted as the multiplicative change in odds related to a one-unit change in the independent variable *ceteris paribus*. For dummy variables, coefficients are interpreted directly as the odds ratio between two groups. For example, the odds ratio for Executive/Board Changes – Other of 0.36 indicates that companies where such changes occurred (x=1) are 64% less likely to be distressed than companies where such changes did not occur (x=0) *ceteris paribus*. For continuous variables, coefficients are interpreted as the odds ratio between observations with the same values for all variables apart from the variable analyzed (Hosmer & Lemeshow 2000). For example, if odds ratio equals 1.2 then a one-unit change in ROA will increase odds of being distressed by 20% *ceteris paribus*.

The log-odds ratio for a change of c units is obtained from the logit difference and equals $c\beta_k$. Accordingly, odds ratio equals $e^{(c\beta k)}$ (Hosmer & Lemeshow 2000). Positive values of coefficients indicate a positive relationship between the independent variable and the probability of *distress* occurring, and vice versa. For odds ratios, the dividing line is 1: an odds ratio greater than 1 indicates a positive relationship, whereas an odds ratio less than 1 indicates a negative relationship.

Model Estimation

Since our study is exploratory, we have decided to apply a backward stepwise regression. This procedure is based on the sequential iterations in which least significant variables are removed from a full model. Stepwise procedures have been criticized since they are susceptible to be influenced by random variation in the data, resulting in the removal of predictors from the model on purely statistical grounds (Pallant 2007 p. 166). However, Hosmer & Lemeshow (2000) argue that this approach is particularly useful when "the outcome being studied is relatively new, important covariates may not be known, and associations with the outcome [are not] well understood" as is the case with predicting *business* distress.

We begin our analysis for each period *from T-5 to T-1* with a model incorporating all variables described in section 3.4. The least significant variables – with the highest p-values – are eliminated from the model one-by-one through consecutive iterations. The fit of the model is tested after the elimination of each variable in order to ensure that the model still fits the data adequately. When all variables in the model are statistically significant at the 0.1 level, the analysis is complete and the final model has been generated. In stepwise logistic regressions it is recommended to use higher significance levels (up to 0.2), since the use of stringent ones often result in the exclusion of important variables from the model (Lee & Koval 1997, cited in Hosmer & Lemeshow 2000).

3.5.3 Diagnostics: Assessing model quality

The application of logistic regression requires the data to follow certain distributional assumptions in order for the results to be robust (Ko, Blocher, & Lin 2001, p. 70). Post-estimation evaluation of the model plays an important role in identifying the statistical problems that would result in low reliability of the model. Below we present four methods that we will use and their implications on the models.

Goodness-of-fit measures

To generally assess whether a model fits the data, a few methods can be used. To check if the model as a whole is statistically significant we examine the log likelihood chi-squared that is presented as part of the basic output of logistic regression in STATA. It is two times the difference between the log likelihood of the current model and the log likelihood of a model with no independent variables, known as “iteration 0”. The degrees of freedom used to calculate the statistic equal the number of independent variables included in the model. A statistically significant result with a p-value lower than 0.1 in our case, allows us to conclude that the model generally fits the data well (Chen et al. 2012).

FIGURE 2 – EXAMPLE OF STATA OUTPUT FOR LOGISTIC REGRESSION

```
Iteration 0:   log likelihood = -221.78321
Iteration 1:   log likelihood = -160.98589
Iteration 2:   log likelihood = -159.03136
Iteration 3:   log likelihood = -159.01211
Iteration 4:   log likelihood =  -159.0121

Logistic regression                               Number of obs   =        341
                                                  LR chi2(10)     =     125.54
                                                  Prob > chi2     =     0.0000
Log likelihood =  -159.0121                       Pseudo R2       =     0.2830
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Sect_Energy	-1.424137	.6453678	-2.21	0.027	-2.689034	-.1592391
Sect_Information_Technology	1.460598	.4411218	3.31	0.001	.5960154	2.325181
Sweden	-.8922076	.3749416	-2.38	0.017	-1.62708	-.1573356
Norway	-1.350907	.4623584	-2.92	0.003	-2.257113	-.4447013
Denmark	-1.084258	.4360862	-2.49	0.013	-1.938971	-.2295448
Finland	0	(omitted)				
Key_Changes_Other	-1.019586	.3194699	-3.19	0.001	-1.645736	-.3934368
MF2	.9424769	.3238085	2.91	0.004	.3078238	1.57713
RS	.803177	.1117188	7.19	0.000	.5842121	1.022142
P1	-1.890208	.6152562	-3.07	0.002	-3.096088	-.6843284
CC1	-.0007513	.0003661	-2.05	0.040	-.0014688	-.0000338
_cons	4.902385	.8107765	6.05	0.000	3.313292	6.491477

Unlike in OLS regressions where R^2 represents the proportion of variance explained by the model, the Pseudo R^2 in logistic regression is not measured in terms of variance since the variance is fixed. The Pseudo R^2 is mainly used to compare alternative models, with a higher value indicating better fit, however its meaning is limited when taken out of context (Chen et al. 2012).

In our study, we test the goodness-of-fit of the final models using Pearson's chi-squared test, which is expressed mathematically as follows (Hosmer & Lemeshow 2010, pp. 145-146):

$$\chi^2 = \sum_{j=1}^{J} r(y_{j,}\hat{\pi}_j)^2,$$

where *r* is the symbol for residual, and j denotes the covariate pattern combination. Pearson's chi-squared statistic compares the differences in outcome frequencies to establish whether or not an observed frequency distribution differs from a theoretical distribution. Generally if the p-value for the test is higher than the significance level of 0.1, we conclude that model fits the data well.

Classification tables and ROC curves

A classification table presents a summary of observed and predicted outcomes, classifying companies as distressed if the probability of distress is equal or higher than 0.5, and non-distressed if the probability is less than 0.5. It can be used to assess how well the model predicts the correct outcome for each observation (Hosmer & Lemeshow 2000, pp. 156-160).

FIGURE 3 – EXAMPLE OF STATA OUTPUT FOR CLASSIFICATION TABLE

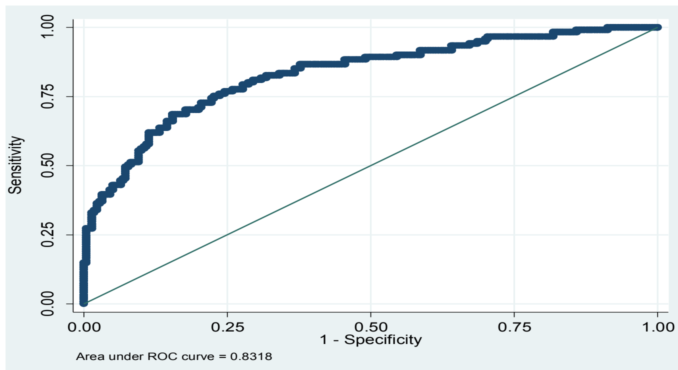
```
Logistic model for Distress

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        75            27  |        102
     -     |        46           193  |        239
-----------+--------------------------+-----------
   Total   |       121           220  |        341

Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   61.98%
Specificity                     Pr( -|~D)   87.73%
Positive predictive value       Pr( D| +)   73.53%
Negative predictive value       Pr(~D| -)   80.75%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   12.27%
False - rate for true D         Pr( -| D)   38.02%
False + rate for classified +   Pr(~D| +)   26.47%
False - rate for classified -   Pr( D| -)   19.25%
--------------------------------------------------
Correctly classified                        78.59%
```

The sensitivity of the model refers to the percentage of companies that were correctly classified as distressed out of all distressed firms in the sample, whereas the specificity shows the percentage of companies that were correctly classified as non-distressed out of all non-distressed firms in the sample.

The positive predictive value is the percentage of firms correctly classified as distressed out of all firms classified as distressed according to the model. For example 73.53 per cent means that out of the companies predicted to be distressed, our model correctly identified 73.53 per cent of them. The negative predictive value is the percentage of companies correctly classified as non-distressed out of all firms classified as non-distressed (Pallant 2007, p. 175). In our research we use the number of correctly classified companies to compare prediction accuracy in the models.

Sensitivity and specificity rely on the same cut-off point to determine whether to classify companies as distressed or non-distressed. A Receiver Operating Characteristic (ROC) curve shows how well the model discriminates between companies that are distressed and companies that are not distressed for all possible cut-off points. Discrimination is measured as the likelihood that a non-distressed company will have a higher probability of being distressed than the company that is actually distressed. It is important to note that values higher than 0.9 are extremely unusual in practice (Hosmer & Lemeshow 2000, pp. 160-164).

FIGURE 4 – ROC CURVE AND ASSESSMENT OF MODEL DISCRIMINATION ABILITIES



Area under ROC curve	Interpretation
ROC = 0.5	No discrimination
0.7 ≤ ROC < 0.8	Acceptable discrimination
0.8 ≤ ROC < 0.9	Excellent discrimination
ROC ≥ 0.9	Outstanding discrimination

Specification error

When creating the logistic regression model we assume that: (i) the logit function is a linear combination of predictors, (ii) logit is the correct function to use, (iii) all relevant variables are included in the model, and (iv) no irrelevant variables are included in the final model. If the logit function is not the correct one to use, or if the relationship between the logit of the dependent variable and the independent variables is not linear, then specification error occurs. The occurrence of a specification error strongly indicates that the aforementioned assumptions are not met, and that the model needs to be re-specified (Chen et al. 2012).

To check whether that is the case a linktest in STATA can be performed. It assumes that if all statistically significant variables were included in the model then finding additional statistically significant variables would not be possible except by chance. Entering the linktest command after logistic regression rebuilds the model using its linear predicted value _hat and its square _hatsq as independent variables. The predictor _hat should be significant since it is the fitted value of the model. Additionally, if the model is correctly specified '_hatsq' should not have predictive power. If this is not the case then it is possible that some important variables are omitted or that the logit function is not the correct one to use, in which case the model has to be re-specified (Chen et al. 2012).

FIGURE 5 – EXAMPLE OF STATA OUTPUT FOR LINKTEST

```
. linktest, nolog

Logistic regression                               Number of obs   =        341
                                                  LR chi2(2)      =     126.35
                                                  Prob > chi2     =     0.0000
Log likelihood = -158.60956                       Pseudo R2       =     0.2848

------------------------------------------------------------------------------
    Distress |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   1.055512   .1380881     7.64   0.000      .784864     1.32616
      _hatsq |   .0591698   .0641349     0.92   0.356    -.0665324     .184872
       _cons |  -.0720505   .1703232    -0.42   0.672    -.4058779     .261777
------------------------------------------------------------------------------
```

Multicollinearity

Ideally in models, independent variables should be strongly related to the dependent variable but not to each other. When perfect collinearity is said to occur it means that one predictor is a perfect linear combination of other predictors, and it is impossible to get a unique estimate of coefficients. In such cases STATA automatically takes out such a predictor from the regression. Any correlation among the independent variables is an indication of collinearity hence moderate levels are very common. However, if the level of multicollinearity is high, standard errors may be inflated and estimates of the coefficient unreliable. We perform tolerance analysis to check the level of multicollinearity in the models. Tolerance is an indicator of the level of variability in one independent variable that is not explained by other independent variables. Very low values of tolerance (lower than 0.1) suggest correlations and the possibility of high multicollinearity (Pallant 2007, p. 156). STATA presents also an inverse value of tolerance, so called Variance inflation factor.

FIGURE 6 – EXAMPLE OF STATA OUTPUT FOR VARIANCE INFLATION FACTOR ANALYSIS

Variable	VIF	1/VIF
Norway	1.87	0.535417
Sweden	1.76	0.568815
Denmark	1.56	0.642275
Sect_Energy	1.30	0.766513
RS	1.28	0.782434
MF2	1.19	0.842769
Key_Change~r	1.14	0.873974
Sect_Infor~y	1.13	0.888835
P1	1.03	0.972223
CC1	1.02	0.980803
Mean VIF	1.33	

3.6 Data Collection

Our primary source of qualitative and quantitative data is Standard & Poor's Capital IQ database and we rely on Oxford Economics for comparable GNP data for the four countries. The boundaries we have imposed on the data mean that there is no distinction between the sample and the actual population. All observations meet the following constraints: (i) primary equity listing on OMX Nordic Exchange Copenhagen (CPSE), OMX Nordic Exchange Helsinki (HLSE), Oslo Børs (OB) or OMX Nordic Exchange Stockholm (OM), (ii) total revenue greater than 50 EURm or total assets exceeding 43 EURm using the historical exchange rates at the end of fiscal year 2005, and (iii) representative of all sectors excluding financial and utilities firms. The size criterion (ii) is only checked at the beginning of the period (closing balance 2005) in order to avoid excluding firms that became distressed and experienced shrinking turnover and balance sheets during the period, since these would be companies that we want to include. We ran company screens for each year during the time frame using the following screening criteria to obtain a sample of distressed firms[10]:

[10] The resulting list of distressed and non-distressed firms can be found in Table B and Table C in the appendix, respectively.

TABLE 7 – SCREENING CRITERIA FOR SAMPLE SELECTION

Screening criterion 1:	Geographic Locations: Sweden, Denmark, Norway, Finland
Screening criterion 2:	Industry Classifications: NOT Financials (Primary), NOT Utilities (Primary)
Screening criterion 3:	Exchanges (All Listings): CPSE, HLSE, OB, OM
Screening criterion 4:	Total Revenue (FY 2005) is greater than 50 EURm
	(OR) Total Assets (FY 2005) is greater than 43 EURm
Screening criterion 5:	Key Developments by Category: Potential Red Flags/Distress Indicators [one of calendar years: 2006-2011]
Screening criterion 6:	Key Development Situation [one of calendar years: 2006-2011] Keyword: default
	(OR) Key Development Situation [one of calendar years: 2006-2011] Keyword: restructuring
	(OR) Key Development Situation [one of calendar years: 2006-2011] Keyword: failure

Since we are interested in early-stage prediction, we account only for the first occurrence of distress for a given company. This means that if a firm was distressed in 2007, 2009, and 2010 for example, T=0 for distress is only in 2007. The dependent variable "distress" equals 1 if a company is distressed at any point during the years 2006 – 2011, and 0 if the company is never distressed during the period. We ran criteria 1-4 above to obtain the total list of firms, which returned a population of 343 firms. We then applied criteria 5 and 6 to obtain the list of distressed firms, which we then crosschecked with the list of 343 firms to remove duplicates. We ended up with a list of 122 distressed firms and 221 non-distressed firms for the period. The following tables provide an overview of the sample characteristics for distressed firms.

TABLE 8 – DISTRESSED COMPANIES BY YEAR AND PRIMARY SECTOR

Sector / Year	2006	2007	2008	2009	2010	2011	Total
Consumer discretionary	4	3	2	3	1	3	**16**
Consumer staples	2	1	1	2	2	1	**9**
Energy	0	1	1	2	1	1	**6**
Industrials	13	3	7	9	11	2	**45**
Information technology	4	2	1	5	4	3	**19**
Materials	7	0	5	0	0	1	**13**
Telecommunication services	0	2	1	0	0	1	**4**
Healthcare	3	1	1	3	0	2	**10**
Total	**33**	**13**	**19**	**24**	**19**	**14**	**122**

TABLE 9 – DISTRESSED COMPANIES BY YEAR AND COUNTRY

Year	Sweden	Norway	Denmark	Finland	Total
2006	10	6	3	14	**33**
2007	3	3	3	4	**13**
2008	7	1	4	7	**19**
2009	9	2	7	6	**24**
2010	6	6	2	5	**19**
2011	4	3	2	5	**14**
Total	**39**	**21**	**21**	**41**	**122**

The highest rate of distress is observed in years 2006 at 27% and in 2009 at 20%, however it is important to bear in mind that multiple distress observations for a given firm were eliminated, meaning that the number of distressed firms in 2006 is likely to be overstated. Furthermore we see that distress is unevenly spread across countries, with approximately 40 observations for Finland and Sweden and 21 observations for Norway and Denmark. Industrial firms experience the highest occurrence of distress at 45 observations, with Information Technology firms experiencing the second highest at a distant 19 observations. The most commonly observed key developments are discontinued operations (55.7% of distressed sample) and reorganization (36% of distressed sample).

TABLE 10 – DISTRESSED COMPANIES BY KEY DEVELOPMENT AT T=0

Distressed companies by key development at T=0 as in screening criterion 5 (Note: More than one key development can be assigned to one observation)							
Key development	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Total**
Auditor Going Concern Doubts	0	0	0	0	1	0	**1**
Business Reorganization	12	3	7	9	8	5	**44**
Delayed Earnings Announcement	1	1	3	0	1	0	**6**
Delisting	0	1	0	1	0	1	**3**
Discontinued operations/Downsizings	20	6	15	16	7	4	**68**
Impairment/Write-Offs	5	1	2	3	5	2	**18**
Index Constituent Drop	0	0	1	0	1	3	**5**
Labor-Related Announcements	5	1	0	1	2	0	**9**
Lawsuits	8	5	2	5	2	2	**24**
Restatements of Operating Results	1	0	0	0	0	0	**1**

In the next step, we randomly distributed the remaining 221 firms that were non-distressed on a per year basis using a randomization function and the ratio of failed firms in a particular year to total sample of distressed firms. This procedure is described as follows:

Firstly, we calculated the ratio of distressed companies in a particular year to the total distressed sample (x%). Secondly, we calculated the corresponding number of non-distressed companies by multiplying the distress ratio per year by the total number of non-distressed firms to obtain the annual non-distress distribution throughout the period. Thirdly, we put the list of all non-distressed companies in random order using the RAND() function in Excel, and assigned specific non-distressed companies to particular years.

During this process, one non-distressed industrial company was removed due to the fact that we could not extract data on it from the database, resulting in a total sample of 342 firms comprised of 220 non-distressed firms and 122 distressed firms.

TABLE 11 – DISTRIBUTION OF DISTRESSED AND NON-DISTRESSED COMPANIES IN THE PERIOD

	2006	2007	2008	2009	2010	2011	Totals
NON-DISTRESSED distribution	60	23	34	44	34	25	**220**
DISTRESSED	33	13	19	24	19	14	**122**
Ratio of DISTRESS per year to total (x%)	27%	11%	16%	20%	16%	11%	**342**

In the last step, the data was normalized so that the year when the dependent variable is observed is T=0 for all companies. For distressed firms, T=0 is the first year that distress is observed and for the control group, T=0 represents the year the firm was allocated to in the aforementioned procedure. We then screened for qualitative factors manually and extracted financial ratios directly using the Capital IQ Excel plug-in. Some of the quantitative variables listed in **Table 6** were left blank if data was missing in the database, or if they could not be computed due to denominators of "0", notably FG3 and FG4. In these instances, observations with missing variables were excluded *pairwise*, meaning that they were excluded from the analysis only when data needed for this specific analysis was missing. For the logistic regression, it means that as variables are eliminated from the model during the backward stepwise process, the sample size increases since previously excluded observations are reintroduced when they have no missing data for the variables being tested. We found this to be less restrictive to the sample than *listwise* exclusion[11] and less distortive than replacing the missing data points with the mean values.

[11] In listwise exclusion, observations with missing data are eliminated from the sample, thus reducing the sample size for the entire study.

4. RESULTS AND ANALYSIS

4.1 Distress Identification

We analyzed the differences in means between the distressed and non-distressed companies at T=0 from two perspectives: (i) the sample as a whole, and (ii) companies within particular sectors. The attempted quantification of *business distress*, which is inherently a qualitative phenomenon[12], aims to facilitate the process of screening for distressed companies out of a large group of both distressed and non-distressed firms. It should be noted that no causal relationships are indicated in this type of comparison, rather it indicates whether a particular factor differs significantly between the groups.

4.1.1 Distress Identification for the entire sample

We evaluated the underlying statistical assumptions of parametric methods for comparing means between two groups and found that for the sample as a whole, none of the variables were normally distributed according to the Shapiro-Wilk test of normality. As a result, the non-parametric Kruskal-Wallis test was applied. As we can see in Table 12, ratios from all categories of factors[13] were considered relevant in distinguishing between distressed and non-distressed firms. In general, distressed firms are characterized by higher mean values of *beta*, *investment level*, *LTD due in 2 years/total LTD*, and *relative size.* Moreover, they are characterized by lower mean values of *sales growth*, *return on assets*, *interest coverage ratio*, and *LTD due in 1 year/Total LTD* than non-distressed firms. Due to the fact that outliers were not excluded from the analysis[14], the means are affected. To compensate for the resulting distortion of means for some of the factors, we have decided to also report median values to provide a better overview for the reader.

---

[12] See Section 2.2: Key Definitions
[13] Refers to the grouping of factors analyzed in our study, see Table 5 and Table 6 for reference.
[14] For a detailed explanation on why outliers are included, see Section 4.4: Limitations.

TABLE 12 – COMPARISON OF MEANS FOR DISTRESSED AND NON-DISTRESSED COMPANIES AT T=0 (ALPHA= 0.1)

Variable	Group	Mean	Median	Standard deviation	Test used	Test statistic	p-value
Beta (MF2)	Distressed	.6663	.7040	.4357	Kruskal-Wallis test	$\lambda^2 = 5.858$	0.0155
	Non-distressed	.5562	.5055	.4650			
Sales growth (P1)	Distressed	.1198	.0470	1.0923	Kruskal-Wallis test	$\lambda^2 = 5.172$	0.0230
	Non-distressed	6.2526	.0824	89.3748			
ROA (P3)	Distressed	.0477	.0586	.1000	Kruskal-Wallis test	$\lambda^2 = 4.480$	0.0343
	Non-distressed	.0705	.0724	.09652			
Interest coverage ratio (CC1)	Distressed	15.4666	4.5558	98.9079	Kruskal-Wallis test	$\lambda^2 = 3.378$	0.0661
	Non-distressed	45.5081	6.151	243.4241			
Investment level (IL1)	Distressed	4.0333	.0000	42.0293	Kruskal-Wallis test	$\lambda^2 = 11.151$	0.0008
	Non-distressed	.0149	-0.0429	.7902			
LTD due +1/Total LTD	Distressed	.6788	.1425	2.7211	Kruskal-Wallis test	$\lambda^2 = 12.144$	0.0005
	Non-distressed	1.3582	.0468	10.0818			
LTD due +2/Total LTD	Distressed	.2009	.1371	.2173	Kruskal-Wallis test	$\lambda^2 = 16.230$	0.0001
	Non-distressed	.1329	.0275	.2255			
Relative size (RS)	Distressed	-5.13	-4.87	1.7630	Kruskal-Wallis test	$\lambda^2 = 52.742$	0.0001
	Non-distressed	-6.57	-6.82	1.3482			

Analysis

All variables presented in Table 12 are significant according to the Kruskal-Wallis test. Looking at means, medians and standard deviations, we can distinguish between two categories of variables. The first category is composed of variables with similar standard deviations for both distressed and non-distressed companies, with a visible difference in both the means and medians of the two groups (*Beta*, *ROA*, *LTD due +2/Total LTD, relative size*). Those variables can be reasonably analyzed using the mean values. The second category consists of variables with very high standard deviations (*Sales growth*, *Interest coverage ratio*, *Investment level* and *LTD due 1 /Total LTD*). The latter group should be analyzed using the median values, since they are less susceptible to distortion due to outliers.

Company characteristics

A comparison of the relative size of companies indicates that distressed firms tend to be larger than non-distressed firms. At first glance, this seems counterintuitive since larger firms are correlated with a lower probability of failure in bankruptcy prediction models, and longer time to failure in qualitative failure research. However, there are two plausible explanations for this phenomenon. The first is what we have chosen to call the 'inefficient bureaucracy syndrome', which refers to oversized firms that can be characterized by heavy administration and a low degree of flexibility. Such firms are susceptible to downsizings and reorganizations, since they must often reorient themselves and institute organizational efficiency schemes in order to stay competitive. However, due to their sheer size and presumably high degree of stakeholder network complexity, they are "too big to fail", hence stakeholders prevent them from reaching the terminal state of bankruptcy, in line with the findings from previous research. Another more simple explanation would be that generally, larger firms are more diversified and more likely to experience the key developments used in our research to operationalize *business distress*, such as lawsuits, reorganizations, or downsizings for example.

Market factors

Distressed firms exhibit higher average values of *beta* than non-distressed firms, at 0.666 and 0.556, respectively. This is in line with our expectation that distressed companies are also characterized by higher price risk. It may also suggest that the market is efficient at assessing firm distress, and adjusts expectations of price movements accordingly.

Profitability related factors

Both *return on assets* and *sales growth* are lower on average for distressed firms. In terms of *ROA*, a higher mean value is expected for non-distressed firms, since this particular measure of profitability has consistently proven to be a robust indicator of company performance in previous research. Distressed firms have on average roughly 2/3 the *return on assets* of non-distressed firms, which lends support to the argument that *business distress* can be identified in quantitative terms by evaluating profitability.

An analysis of *sales growth* shows that the median for non-distressed companies is approximately 2 times higher indicating that, in general, non-distressed companies are characterized by higher top-line growth than distressed ones. The difference in means for the two groups is substantial, at 625% for non-distressed firms and 11.98% for distressed firms. The high means and standard deviations are reflective of the presence of outliers both on the negative side and the positive side, where the minimum value is at -99%, and the maximum value is at

132570%, with 7 firms experiencing triple-digit sales growth or higher. This is partially owed to the fact that the companies are at different starting points in terms of sales value and size, which favors the relatively smaller companies since it is easier for a company in the 50 EURm turnover range to achieve double-digit sales growth than it is for national giants such as Statoil ASA or AP Møller-Maersk. It could also be attributed to differences in company strategy both within and between sectors.

Covenant related factors

The median value of *interest coverage ratio* for non-distressed firms (6.15) is approximately 35% higher than for distressed ones (4.55). This is in line with the expectation that debt servicing is less of a concern for non-distressed firms. Very high standard deviations are indicative of the wide range of values for this ratio. For distressed firms, the values range from minimums of -307.15 to maximums of 906.82, and for non-distressed firms, they range from -33.9 to 3162.59.

Investment level related factors

The interpretation of *investment level* results is less intuitive. The median for distressed firms is higher than for non-distressed firms, at 0% and -4.29% respectively. As mentioned, the *investment level* in a given period is measured as the annual percentage change in Net PPE. This suggests that there is no year-on-year change in *investment level* for distressed firms, and that the investment level for non-distressed firms decreases on an annual basis. This counters our initial expectation that companies that are doing relatively well would tend to invest more. A possible explanation could be that non-distressed firms are better and faster at adjusting expectations about future demand growth, and subsequently, the amount of investment in fixed assets required to produce.

Financial gearing

The interpretation of the results for *LTD maturing in 1 year/Total LTD* and *LTD maturing in 2 years/Total LTD*, referred to as FG3 and FG4 respectively, is more difficult due to timing differences in the extracted data. The numerators are calculated on a current year basis, while the denominators are calculated on a fiscal year basis within the database, which complicates matters since it results in seemingly counterintuitive cases where ratios are considerably greater than 100% for some companies. Nevertheless, we decided to include these factors to get a general idea of the impact of maturity schedules on distressed and non-distressed firms. We find that both vary significantly between the groups and that distressed companies tend to have higher values of both *LTD maturing in 1 year/Total LTD* and *LTD maturing in 2 years/Total LTD* than non-distressed companies. We can see that in general impending debt maturities are more prevalent among distressed companies.

4.1.2 Distress Identification by sector

We began the sector analysis by evaluating the underlying assumptions of the parametric methods used to compare the means between groups, and found most variables to be not normally distributed, for which we again applied the Kruskal-Wallis non-parametric test. For a few of the factors however, the null hypothesis of normal distribution in Shapiro-Wilk test could not be rejected. For those factors we examined the equality of variances using Levene's test. Adjustments for t-tests with unequal variances were made where necessary.

Analysis

Table 13 presents the result matrix of mean comparisons between distressed and non-distressed firms within each sector, excluding the Telecommunication sector since there was only one non-distressed firm in the control sample. The table highlights the fact that, unsurprisingly, various factors affect companies within particular sectors to a different degree. The important thing to bear in mind is that while the methods used are statistically robust in spite of cases where the data is abnormally distributed, the nominal values of means should be interpreted cautiously since they are taken from one point in time (T=0) and no distinction is made between firms for which T=0 took place during a crisis year (2007-2009) and firms for which T=0 did not occur during a crisis year according to this method. It is thus unclear how much of the variation is due to industry-specific cyclical factors and the presence of outliers, respectively. We can only take note of the general patterns of variation in factors affecting *business distress* within sectors, without making long-run generalizations.

TABLE 13 – DISTRESS IDENTIFICATION BY SECTOR

T=0	Consumer Staples		IT		Materials		Energy		Industrials		Consumer Discretionary		Healthcare	
Significant Variables	Distressed	Non-distressed	Distressed	Non-distressed	Distressed	Non-distressed	Distressed	Non-distressed	Distressed	Non-distressed	Distressed	Non-distressed	Distressed	Non-distressed
Relative size	-4.7615 (1.4789)	-6.0796 (0.8717)	-6.1898 (0.0235)	-7.5592 (0.7610)	-3.8249 (1.6647)	-6.3054 (1.3550)			-5.2271 (1.5312)	-6.5058 (1.4851)	-5.1430 (1.0649)	-7.0436 (1.1037)		
Capitalization			7.6316 (8.6791)	19.3791 (23.6657)	4.9883 (5.3099)	8.4275 (7.1181)	16.1409 (8.8508)	6.0584 (6.9537)						
Beta							1.1872 (0.4226)	0.7510 (0.5772)	0.6948 (0.5044)	0.4996 (0.4394)				
Debt/Equity	1.0060 (0.4649)	0.7810 (0.9255)												
Financial Expense/Total Debt					0.0607 (0.0294)	0.0453 (0.0252)	0.1154 (0.0919)	0.0460 (0.0273)						
LTD due +1/ Total LTD					0.3650 (0.5223)	0.2108 (0.4081)			0.3793 (0.5433)	0.9799 (3.3695)	2.7808 (7.1584)	4.7585 (24.7435)		
LTD due +2/ Total LTD					0.1209 (0.1018)	0.1061 (0.2471)			0.2313 (0.2520)	0.1477 (0.2365)	0.2304 (0.2854)	0.0652 (0.1246)		
ND/EBITDA			5.0953 (4.2766)	1.1364 (0.4800)	7.3627 (14.9970)	2.3043 (1.3389)	1.5330 (1.7178)	9.9562 (0.0273)	3.9752 (7.5945)	4.3286 (5.3973)				
Interest coverage ratio	3.4764 (3.0977)	8.4942 (7.4514)	54.5026 (242.171)	138.9101 (318.467)										
Sales growth	-0.0865 (0.2578)	0.0921 (0.1598)	0.0150 (0.2605)	0.1483 (0.2029)										
ROA	0.0466 (0.0349)	0.0964 (0.0716)	0.0230 (0.1035)	0.1097 (0.1107)										
Current ratio	1.1852 (0.4268)	1.9018 (0.8002)					0.7196 (0.3725)	3.3490 (4.8580)					3.1484 (1.7881)	1.8769 (0.8408)
NWC/Sales	0.0920 (0.0913)	0.2429 (0.2089)	0.1524 (0.1192)	0.0623 (0.1067)			-0.8636 (1.5130)	-0.0542 (0.7578)						
Cash conversion cycle	52.6461 (43.7328)	151.4741 (166.153)												
CAPEX as % of Revenues			0.0457 (7.7404)	0.0189 (0.0084)										
Investment level											0.1156 (0.3176)	-0.0597 (0.2634)	0.2778 (0.5046)	-0.1422 (0.1931)

A note on relative size

The analysis shows that for all sectors except Energy and Healthcare, distressed companies are larger, on average, than non-distressed firms. This is particularly interesting given that the sample itself is already limited to the largest 342 listed firms in the region. It begs the question whether firms that are "too big to fail" are also too big to be efficient, and is something that should be evaluated further in future research in light of the current crisis.

Consumer Staples

Consumer Staples is the only sector for which the *Debt/Equity* ratio varies significantly between the groups at T=0. The mean is generally higher for distressed firms, although non-distressed firms display twice the standard deviation of distressed firms. In terms of *return on assets*, *sales growth*, and *interest coverage*, these are all higher for non-distressed firms, in line with expectations. However, in terms of working capital-related factors it is the opposite. Distressed firms exhibit significantly lower cash conversion cycles, a lower percentage of net working capital to sales, and a lower ratio of current assets to current liabilities. According to the traditional view, these characteristics taken together would imply working capital efficiency, which is associated with better performance rather than worse. The fact that the opposite is true within the sector supports Slatter & Lovett's (1999) assertion that the existence of a cash crisis is not a prerequisite for distress.

Information Technology

The IT sector exhibits the same characteristics as Consumer Staples with regards to *return on assets*, *sales growth*, and *interest coverage* although the scale varies. Non-distressed firms have almost 3 times the *interest coverage* of distressed firms and the range is considerably wider. *Capitalization* is on average more than double for non-distressed firms, which again suggests that the market has the ability to account for the additional risk associated with *business distress*. Mean *ND/EBITDA* is almost 5 times higher for distressed IT firms, indicating that they may experience problems generating the cash necessary to amortize debt assuming that debt levels are kept constant. For IT firms, the mean value of *NWC/Sales* for distressed firms is 3 times greater in line with the view that distressed firms are less cash efficient than their non-distressed counterparts. A distinguishing feature of IT firms is that they represent the only sector where *CAPEX as % of Revenues* is statistically significant between the two groups. For non-distressed firms it averages around 1.89% with a standard deviation of 0.84%, whereas for distressed firms it is at 4.57% with a 770% standard deviation, suggesting the presence of extreme values within the distressed group only. This suggests that *CAPEX as % of Revenues* tends to remain stable in non-distressed firms, whereas distressed firms may suffer from either overinvestment or underinvestment relative to turnover.

Materials

The Materials sector displays the same characteristic for *Capitalization* as the IT sector but to a lesser degree (~2x distressed = non-distressed), and with far less in-group variance. *ND/EBITDA* is considerably higher on average for distressed firms at 7.36, with a standard deviation of 14.99, whereas the standard deviation is substantially lower for non-distressed firms, at 1.33. The difference in means for *Financial Expense/Total Debt* is statistically significant, showing that distressed firms have slightly higher interest costs than non-distressed firms even before the occurrence of a default. The short-term and medium-term maturity of debt is also higher on average for distressed firms.

Energy

The Energy sector is distinct from other firms in terms of the combination of factors found to be significant. *Financial Expense/Total Debt* is on average roughly 7% higher for distressed firms, and *beta* is substantially higher as one would expect. Mean *ND/EBITDA* for non-distressed firms is the highest for all sectors at 9.95, with a low standard deviation, which indicates that cash flow generation is generally not a problem in this particular industry. In terms of the *current ratio* and *NWC/Sales*, they are higher and lower, respectively, for distressed firms, similar to the Consumer Staples sector.

Industrials

For Industrial firms, only debt-related factors and *beta* are significant, indicating that leverage and cash generation in relation to leverage are the key determinants of distress in this industry. It is the only sector in which mean *ND/EBITDA* is greater among distressed firms than non-distressed firms.

Consumer Discretionary

Short-term debt maturity is relevant for this sector, as well as *investment level*. The change in fixed assets is significantly higher for distressed firms at 11.5%, compared to negative investment for non-distressed firms at -5.9%.

Healthcare

Firms in the Healthcare sector display similar traits when it comes to *investment level* as Consumer Discretionary firms, with the year-on-year change being negative for non-distressed firms and positive for distressed firms. Furthermore, the current ratio is higher for distressed firms than vice versa. This may be attributable to the payment terms in the Healthcare sector, where there is usually a higher level of accounts receivable due to insurance agreements resulting in longer time to payment, whereas payments to suppliers are usually made on regular terms.

4.2 Logistic Regression

In our study 20 variables turned out to be statistically significant in at least one out of the five prediction models spanning the time period from T-1 to T-5. The significant variables cover all the different categories of factors included in our study.

TABLE 14 – COEFFICIENTS AND ODDS RATIOS FOR VARIABLES IN PREDICTION MODELS (ALPHA= 0.1)

	Time span									
	1 year		2 years		3 years		4 years		5 years	
Variable	**Coefficient**	**Odds ratio**	**Coefficient**	**Odds ratio**	**Coefficient**	**Odds ratio**	**Coefficient**	**Odds ratio**	**Coefficient**	**Odds ratio**
Sector IT	1.4605	4.3085	1.2464	3.4780	1.2636	3.5382	1.3809	3.9785	1.5364	4.6479
	(0.4411)	(1.9005)	(0.3924)	(1.3648)	(0.4354)	(1.5407)	(0.4233)	(1.6843)	(0.6891)	(3.2032)
Sector Healthcare					1.7389	5.6911				
					(0.6240)	(3.5517)				
Sector Industrials									0.6717	1.9576
									(0.3461)	(0.6777)
Sector Energy	-1.4241	0.2407								
	(0.6453)	(0.1553)								
Sweden	-0.8922	0.4097								
	(0.1536)	(0.1536)								
Norway	-1.3509	0.2590	-0.7458	0.4743						
	(0.4623)	(0.1197)	(0.3356)	(0.1592)						
Denmark	-1.0842	0.3381								
	(0.4360)	(0.1474)								
Executive/Board Changes – Others	-1.0195	0.3607					-0.9001	0.4065		
	(0.3194)	(0.1152)					(0.3584)	(0.1457)		
Capitalization					-0.0320	0.9685				
					(0.0150)	(0.0145)				
Beta	0.9424	2.5663								
	(0.3238)	(0.8309)								
Relative size	0.8031	2.2326	0.7778	2.1767	0.8529	2.3465	0.9538	2.5956	0.7793	2.1800
	(0.1117)	(0.2494)	(0.0983)	(0.2140)	(0.1076)	(0.2525)	(0.1177)	(0.3056)	(0.1212)	(0.2643)
Sales growth	-1.8902	0.1510			-0.9494	0.3869	0.8800	2.4110		
	(0.6152)	(0.0929)			(0.4849)	(0.1876)	(0.3380)	(0.8151)		
Gross margin							1.3170	3.7324		
							(0.6979)	(2.6052)		
ROA									9.0102	8186.907
									(4.3442)	(35565.9)
Cumulative profitability			-0.9208	0.3981	-1.3028	0.2717	-0.9138	0.4009		
			(0.3316)	(0.1320)	(0.4503)	(0.1223)	(0.3774)	(0.1513)		
Cash coversion cycle					-0.0045	0.9954				
					(0.0019)	(0.0018)				
Interest	-0.0007	0.9992							-0.0789	0.9240

coverage ratio	(0.0003)	(0.0003)							(0.0408)	(0.0377)
ND/EBITDA									0.0476	1.0487
									(0.0273)	(0.0287)
Capex							-3.6484	0.0260		
/Revenues							(1.5575)	(0.0405)		
Debt/Equity					-0.4579	0.6325				
					(0.2235)	(0.1414)				
Constant	4.9023	134.6104	4.2900	72.9680	5.7066	300.8714	5.1424	171.1331	3.4944	32.9318
	(0.8107)	(109.1389)	(0.6165)	(44.9895)	(0.7875)	(236.9536)	(0.7840)	(134.1718)	(0.7253)	(23.8867)

Business environment related factors

Both dummy variables for sector and country turned out to be statistically significant in our models. The aim of including those variables was to check whether the probability of distress is correlated with a company's primary listing location and the sector in which it operates. The results confirm our hypothesis that companies in some sectors are more or less prone to being distressed. Hence, it can be concluded that even though universal models can be estimated, sector-specific analysis is also of great importance.

The variables for country were designed to capture the macroeconomic, legislative, and environmental distinctions that exist from country to country in spite of the fact that the Nordics are considered a relatively homogenous region. This shows that the distinctions in the overall business environment do indeed affect the probability of distress for large listed firms.

Key development related factors

Executive/Board Changes – Others was the only key development that turned out to be significant in our prediction models (in T-1 and T-4). The odds ratios indicate that distress is approximately 60% less likely to occur among companies experiencing changes in Executives or Board than those who are not in the study population *ceteris paribus*. This is in line with previous research, indicating that changes in key personnel are positively correlated with the implementation of new ideas and strategic reorientation.

Company characteristics

Relative size is significant in all prediction models and is positively correlated with the probability of distress. Firstly, it may be due to the fact that some companies tend to grow too fast and at some point it becomes difficult to control, integrate, or reorient them. Secondly, it may be due to the fact that such companies are more complex and hence experience key developments used to operationalize business distress in our study more often.

Market factors

Both of the market factors included in the model turned out to be statistically significant. It is in line with Ohlson's (1980) expectations that those variables could be helpful in predicting distress. Capitalization (present in model T-3) turned out to be negatively correlated with the probability of distress whereas Beta (present in model T-1) turned out to be positively correlated. Annual Beta being significant one year prior to business distress may be an indication that market has already adjusted its expectations to incorporate the perceived riskiness of the company due to the difficulties it is experiencing.

Profitability

The profitability ratios used in our study display different patterns during different time periods within our models. Sales growth is present in the T-1, T-3, and T-4 models. It should be noted that the sign of coefficients differ in T-3 and T-4 models. The interpretation of coefficients is as follows: companies with higher values of sales growth are more prone to be distressed in 4 years and less prone to be distressed in 3 years *ceteris paribus*. The change of sign may indicate that some companies tend to grow too fast and at some point they have to slow down. Aggressive growth strategies may mask problems of the company in the short term, and they may then resurface in the medium term when *business distress* occurs. Hence, the reversal of signs may be an indication that the company reached a performance peak and subsequently entered decline. This hypothesis is supported by the observed coefficients for gross margin and return on assets. The T-5 model indicates that companies with higher ROA are more prone to become distressed in the future and the T-4 model indicates the same for companies with higher gross margins.

The only profitability factor that turned out to be negatively correlated with distress (T-4, T-3, T-2) is cumulative profitability, meaning that companies with higher values for this variable are less likely to become distressed in the future. It suggests that performance stability is negatively correlated with *business distress*, which is in line with expectations.

Liquidity related factors

The only liquidity ratio that turned out to be significant in our models is the *cash conversion cycle* in T-3. The odds ratio indicates that on average an increase of 1 day in CCC makes a company 0.5% less likely to become distressed in 3 years *ceteris paribus*. While this result is surprising, one possible explanation could be that companies that are in a good financial standing are able to extend credit to their buyers (higher days sales outstanding) and keep larger inventories to facilitate faster distribution, hence a longer CCC is not an indication of problems.

Covenant related factors

Both *ND/EBITDA* and the *interest coverage ratio* turned out to be significant in our models. It suggests that covenant ratios are good indicators of future *business distress* as suggested by lenders and practitioners. The results are in line with our original expectations, namely that (i) the higher the *ND/EBITDA* the higher the probability of distress and (ii) the higher the *interest coverage ratio* the lower the probability of distress.

Investment related factors

Capex/Revenues turned out to be statistically significant in T-4 and negatively correlated with distress. The odds ratio for a percentage point change equals 0,964173 (calculated as $e^{3.64*0.01}$) meaning that on average, a percentage point increase in the ratio makes the risk of being distressed on average 3.5 percent lower *ceteris paribus*.

Financial gearing

The only ratio from this group that turned out to be significant is *Debt/Equity* (T-3). It is negatively correlated with distress meaning that the more debt the company has relative to equity, the less prone it is to become distress. A one percentage point increase in this ratio results in a company being on average 0.45 percent less likely to be distressed *ceteris paribus*. Here it should be noted that Liabilities/Equity, Liabilities/Assets, and Debt/Asset ratios are also commonly used in related studies. Since we made no judgment as to the relative benefits of certain gearing ratios over others, we cannot conclude that financial gearing in general is unimportant in periods other than T-3.

4.3 Diagnostics

Goodness-of-fit

Table 15 presents the summary of the results of diagnostics related to goodness-of-fit. It can be concluded that all prediction models fit the data well. Reported values of log likelihood chi-squares indicate that all prediction models from T-1 to T-5 are statistically significant (p-value = 0). Additionally, results of Pearson's chi-squared test do not lead us to reject the null hypothesis that the model fits the data well in any of the analyzed cases.

TABLE 15 – COMPARISON OF RESULTS FOR FINAL MODELS - GOODNESS-OF-FIT DIAGNOSTICS

Diagnostic	**Time span**				
	T-1	**T-2**	**T-3**	**T-4**	**T-5**
Log likelihood chi-square	125.54	90.99	114.30	114.86	63.76
Prob > chi2	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Pseudo R^2	**0.2830**	**0.2058**	**0.2612**	**0.2643**	**0.2173**
Pearson's chi-squared test					
Number of observations	341	338	333	331	219
Number of covariate patterns	341	338	333	331	219
Pearson chi2	336.88	332.21	324.61	320.12	205.96
Prob > chi2	**0.3851**	**0.5019**	**0.4800**	**0.5347**	**0.6040**

Classification tables and ROC curves

Classification tables were presented to give an overview on how good a model is at distinguishing distressed and non-distressed firms. Sensitivity ranged from 54.10% to 65.29% with the best results in the T-4 model. The models performed better in terms of specificity ranging between 82.71% and 88.15%, with the best results in the T-3 model. Out of the firms classified as distressed by models, the number of firms that were distressed in reality ranged between 67.35% and 74.75%. For non-distressed companies, it ranged between 74.32% and 80.75%.

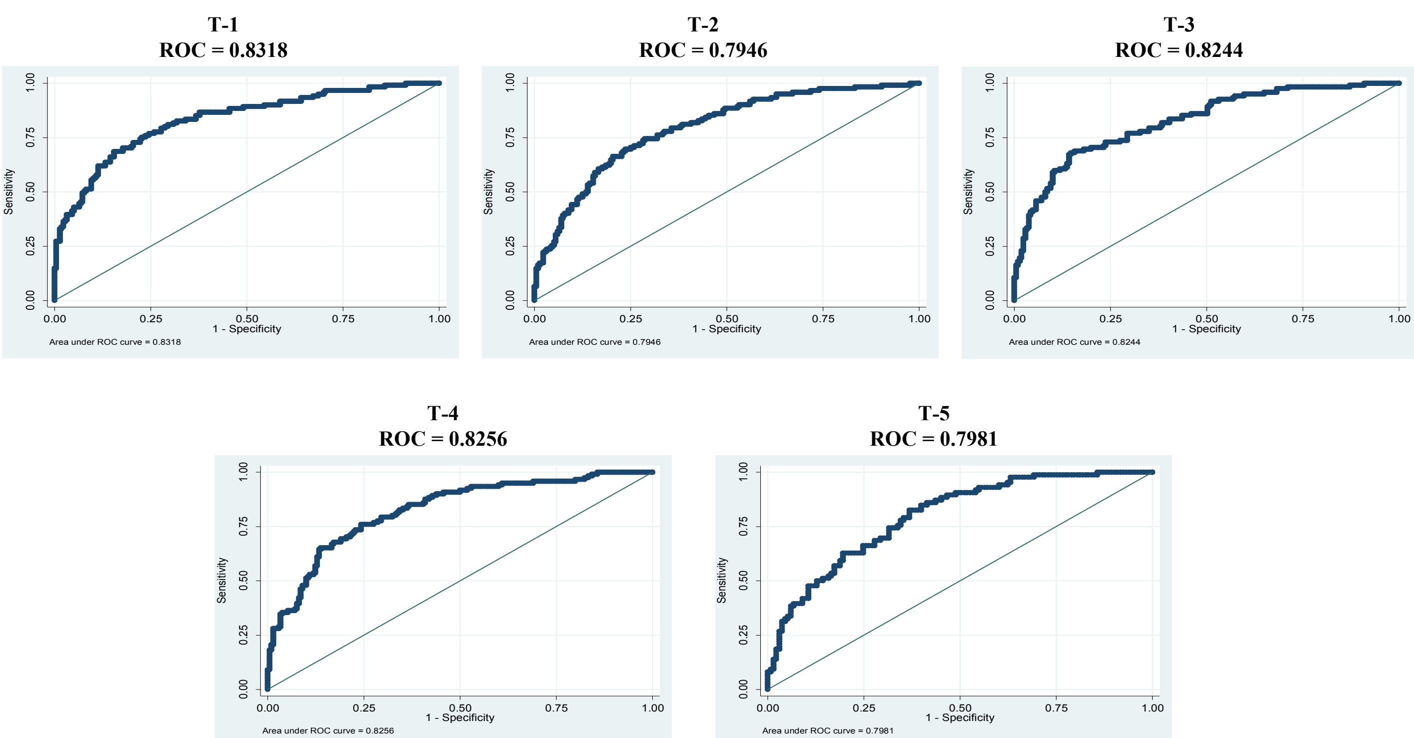
The models perform better for non-distressed companies, however this was expected since "classification is sensitive to the relative sizes of the two component groups and always favors classification into the larger group" (Hosmer & Lemeshow, 2000). Taking that into account, the models are balanced in terms of performance regarding both distressed and non-distressed companies, indicating a high quality of classification. The overall performance of the models varies between 72.15% and 78.59% of correctly classified companies, which substantially exceeds the results obtained by random classification.[15]

TABLE 16 – COMPARISON OF RESULTS FOR FINAL MODELS - CLASSIFICATION TABLES

Classification table	Time span				
	T-1	T-2	T-3	T-4	T-5
Sensitivity	61.98%	54.10%	60.66%	65.29%	55.81%
Specificity	87.73%	85.19%	88.15%	86.19%	82.71%
Positive predictive value	73.53%	67.35%	74.75%	73.15%	67.61%
Negative predictive value	80.75	76.67%	79.49%	81.17%	74.32%
Correctly classified	**78.59%**	**73.96%**	**78.08%**	**78.55%**	**72.15%**

The area under the ROC curve varies from 0.7946 to 0.8318. This indicated that the models with a predictive time span of 1, 3 and 4 years can be described as having excellent discrimination capability, while the ones with a predictive time span of 2 and 5 years can be described as having acceptable discrimination capability. All the models discriminated between companies that are distressed and non-distressed well, indicating good quality.

FIGURE 7 – ROC CURVES FOR PREDICTION MODELS



[15] Random classification refers to results obtained by chance, which are mathematically estimated to be correct 50% of the time.

Specification Error

For all the prediction models *_hat* is a significant variable and *_hatsq* is a non-significant one. This allows us to conclude that the models are correctly specified; meaning that no important variables were omitted and that the logit function is the correct one to use for this research problem.

TABLE 17 – COMPARISON OF SPECIFICATION ERROR IN FINAL MODELS

Linktest	Time span				
	T-1	T-2	T-3	T-4	T-5
P > |z| for_hat	0.000	0.000	0.000	0.000	0.000
P > |z| for _hatsq	0.356	0.702	0.891	0.855	0.312

Multicollinearity

Variance inflation factors for all the independent variables within the models range from 1.02 to 2.08 indicating that the variability in particular independent variables cannot be explained to a high extent by other independent variables. This means that the models do not display negative effects associated with high multicollinearity, such as inflated standard errors and unreliable coefficient estimates.

TABLE 18 – COMPARISON OF VARIANCE INFLATION FACTOR IN FINAL MODELS

VIF	Time span				
	T-1	T-2	T-3	T-4	T-5
Minimum value	1.02	1.02	1.03	1.06	1.07
Maximum value	1.87	1.09	1.23	1.15	2.08
Average	**1.33**	**1.05**	**1.13**	**1.11**	**1.40**

4.4 Limitations

As mentioned previously, we excluded observations with missing data on a pairwise basis in our research, so the initial model is estimated using a smaller sample than the final model. Changes in the size of the sample during the estimation process let us estimate final models of good quality, however it cannot be established whether these are the best models that could be estimated for this data. As a result, we can only comment on significance of the variables in the final models, however we cannot conclude that the excluded variables could not be significant in alternative models.

Pairwise exclusion not only results in differences between estimation sample sizes between initial and final models but also in differences in estimation sample sizes between final models with different time span. Final estimation samples for models with different time spans are summarized in Table 19. For time spans from 1 to 4 years prior to distress, the volatility of the sample is not so significant, especially taking into account that almost all distressed companies were included. However, the T-5 model significantly differs from the rest in this respect, having an estimation sample of less than 100 companies compared to other models. Consequently, the comparability of results for the T-5 model and the other models is reduced. In this model, it can no longer be claimed that almost the whole population was analyzed, so the estimation results may be less robust.

TABLE 19 – SAMPLE SIZE FOR PREDICTION MODELS WITH DIFFERENT TIME SPAN

Estimation sample	**Time span**				
	T-1	**T-2**	**T-3**	**T-4**	**T-5**
Distressed	121	122	122	121	86
Non-distressed	220	216	211	210	133
Total	**341**	**338**	**333**	**331**	**219**

We have decided not to exclude outliers in our sample for two reasons. Firstly, we estimated our models on almost the entire population of large, listed, non-financial and non-utilities Nordic firms, hence observations with outliers reflect the reality of the phenomenon rather that an error due to sample selection. Secondly, the diagnostic tests performed did not indicate problems with the quality of the models, in which case it would have been necessary to investigate outliers due to the possibility that the model would not explain those cases well. Nevertheless, we do not exclude the possibility that further investigation of outliers could improve the model and enhance its quality.

An additional problem in model estimation was the number of events per variable (EVP) in the logistic regression. Peduzzi et al. (1996) suggest that an EPV lower than 10 may result in biased coefficients and sample variance, confidence intervals with inadequate coverage, overly conservative Wald statistics, and incorrect signs of significant variables. On the other hand, an EPV larger than 10 was not connected with any major problem. This is not a problem in our final models since all of them have at least 10 distressed companies in the sample per variable, however it is a problem in the initial models in which all original variables from Section 3.4 are included. This problem could be solved in the future by increasing the sample of distressed companies or by conducting a preliminary analysis of ratios and limiting the number of variables in the logistic regression model itself.

Finally, we have only analyzed the performance of our models in-sample. It would be useful to check how the models perform out-of-sample to validate the results.

Due to all the reasons discussed above, our models should be treated as a starting point for the further research rather than optimal solution to the research question.

5. CONCLUSION

Quantitative research on troubled firms has largely focused on bankruptcy prediction or credit risk modeling, with both research disciplines employing widely varying definitions of failure, the process of decline, and the distress phenomenon itself. Distress as a distinctive research field is gaining traction, partially due to the ongoing crisis and the resulting pressures on the banking sector, and partially due to a shift in bankruptcy regimes that favors reorganization rather than liquidation. However, not a lot of research has explicitly focused on the conditions of firms in the early stages of decline.

In this paper, we have made an attempt to delineate the different stages of decline and to clarify whether the early stage of decline - herein referred to as *business distress* - can be conceptually defined without the use of financial bright-lines and subjective determinants. Owing to the fact that *business distress* is neither a legalistic term nor a terminal state with clearly defined boundaries, we investigated whether it was possible to operationalize the *business distress* stage using qualitative means. We then assessed whether this stage could be distinguished using quantitative measures and predicted using both quantitative and qualitative factors. In order to do so, we have implicitly examined whether statistical models that primarily rely on accounting ratios for bankruptcy prediction can be modified using factors from related research disciplines to create a model that captures distressed firms in the early stages of decline. We have focused on large public firms listed on primary exchanges in Denmark, Finland, Norway, and Sweden, using data from the years 2001 to 2011.

One conclusion with major implications is that *business distress* is indeed a distinguishable phenomenon that can be operationalized using qualitative factors (selected key developments). Secondly, it can be predicted up to 5 years in advance, with 72% to 78% prediction accuracy, using cross-disciplinary factors that incorporate company characteristics, market factors, profitability, liquidity, commonly used covenant tests, financial gearing, and investment levels.

In addition, we find that qualitative factors, specifically key developments reflecting the changes in executive management and the board of directors are useful in predicting *business distress*. In our study such changes turned out to be negatively correlated with distress, in line with previous research.

Furthermore, we have established that the decline phase is a progression with different sub-stages, which can be identified using different types of factors. We have conceptualized three sub-stages of decline: *business distress*, *financial distress*, and *failure*. Evidence suggests that the decline progression goes from broad to narrow, meaning that *failure*, for instance, is more narrowly defined than *financial distress*, which is more narrowly defined than *business distress.* Although we make no attempts to limit these sub-stages by time, we find evidence that suggests a certain degree of overlap between *business distress* and *financial distress*. Notably, we see a reversal in firm performance from T-5 to T-1, during which firms classified as *distressed* (note: the model explicitly concerns *business distress*) experience a reversal in profitability, going from higher profitability to lower profitability compared to their non-distressed peers. This reversal occurs between 4 and 3 years prior to the distress classification in our data sample.

In order to contribute to the quantitative research methodology with regards to sample selection and matching procedures, we found that the inclusion of previously used matching criteria, such as firm size, country, and sector are more useful as variables in the prediction model, in line with Ohlson's reasoning. We found size to be particularly interesting, given that size is negatively correlated with *bankruptcy* according to previous studies but positively correlated with *business distress* in our study. Contrary to expectations, we found that a higher debt-to-equity ratio was negatively correlated with business distress, although higher leverage is also positively correlated with bankruptcy in subsequent stages.

Our final conclusion with regards to the identification and prediction of distress is that market factors show promise in the early-stage identification of decline, as do covenant-related factors. This suggests that the combination of academic and practical approaches lend substantial synergies to *business distress* research, which has huge potential in helping key stakeholders identify troubled firms early on in order to achieve successful turnarounds.

5.1 Suggestions for further research

Our study is exploratory in nature and has only been tested for in-sample data. It should be treated as an initial step; further research in a number of areas pertaining to *business distress* analysis is needed going forward. Attempts should be made to identify the "optimal" set of ratios that could be used to predict distress.

Another suggestion concerns the overlap between *business distress* prediction and business life-cycle research. There is a need to explicitly map the progression from the point when a firm enters decline to the point of failure. An interesting dimension to add would be to analyze the type of turnaround interventions necessary for the firm to recover during different stages within this progression. Furthermore, the role of financial gearing and debt maturity schedules should be examined more closely in order to pinpoint differences between *business* distress and *financial* distress, and to determine the interrelations between leverage and profitability as a firm approaches a *turnaround situation*.

The research could also be expanded to different size categories within the Nordics as financial data becomes more comparable. Additionally, comparisons could be made to determine whether there exists such a thing as an "optimal size", after which the firm experiences diminishing marginal profitability.

REFERENCES

Altman EI 1968, “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy”, *The Journal of Finance*, vol. 23, no. 4., pp. 589-609.

Altman, EI 1971, “Corporate bankruptcy in America”, Heath Lexington Books, Lexington, Mass.

Altman, EI, Haldeman, RG & Narayanan, P 1977, "ZETATM analysis A new model to identify bankruptcy risk of corporations", *Journal of Banking and Finance,* vol. 1, no. 1, pp. 29-54.

Amato, J & Furfine, C 2004, “Are credit ratings procyclical?”, *Journal of Banking and Finance*, vol. 28, pp. 2641–2677.

Andersson, R, Selinus, M & Zettergren C, “VAD VET VI OM SVENSKA ICKE-FINANSIELLA FÖRETAGS KAPITALSTRUKTUR?”, Accounting Issues 30 hp HT-11, Företagsekonomiska Institutionen, Uppsala Universitetet.

Balcaen, S, Manigart, S & Ooghe, H 2011, "From distress to exit: Determinants of the time to exit", *Journal of Evolutionary Economics,* vol. 21, no. 3, pp. 407-446.

Barker III, VL & Barr, PS 2002, "Linking top manager attributions to strategic reorientation in declining firms attempting turnarounds", *Journal of Business Research,* vol. 55, no. 12, pp. 963-979.

Beaver, WH 1966, “Financial Ratios as Predictors of Failure”, Empirical Research in Accounting: Selected Studies*, Journal of Accounting Research*, Supplement to vol. 4, pp. 71-111.

Campbell, JY, Hilscher, J & Szilagyi, J 2008, "In search of distress risk", *Journal of Finance,* vol. 63, no. 6, pp. 2899-2939.

Chancharat, N, Tian, G, Davy, P, McCrae, M & Lodh, S 2010, "Multiple States of Financially Distressed Companies: Tests using a Competing-Risks Model", *Australasian Accounting Business and Finance Journal*, vol. 4, no. 4, pp. 27-44.

Chen X, Ender P, Mitchell M & Wells Ch 2012, *Logistic Regression with Stata. Logistic Regression Diagnostics*, UCLA: Statistical Consulting Group, viewed 25.10.2012, <http://www.ats.ucla.edu/stat/stata/webbooks/logistic/chapter3/statalog3.htm>.

Ernst & Young 2012, *Battle for capital, battle for growth. Implications for restructuring*.

Ernst & Young 2012, *Eurozone Forecast*, Autumn Edition, Oxford Economics.

European Commission 2005, *The new SME definition: User guide and model declaration,* viewed 10 October 2012, <http://ec.europa.eu/enterprise/policies/sme/files/sme_definition/sme_user_guide_en.pdf>.

Financial Times 2012, *Special Report: Business Turnarounds*, viewed 21 September 2012, <www.ft.com/turnarounds-sept-2012>.

Gilson, SC, John, K & Lang, LHP. 1990, "Troubled debt restructurings. An empirical study of private reorganization of firms in default", *Journal of Financial Economics,* vol. 27, no. 2, pp. 315-353.

Grice, JS & Dugan, MT 2001, "The limitations of bankruptcy prediction models: Some cautions for the researcher", *Review of Quantitative Finance and Accounting,* vol. 17, no. 2, pp. 151-166.

Grunert, J, Norden, L & Weber, M 2005, "The role of non-financial factors in internal credit ratings", *Journal of Banking and Finance,* vol. 29, no. 2, pp. 509-531.

Hosmer, DW & Lemeshow, S 2000, *Applied Logistic Regression*, 2nd edn, Wiley Series in Probability and Statistics, New York.

Ko, LJ, Blocher EJ & Lin PP 2001, "Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System", *The International Journal of Digital Accounting Research*, vol. 1, No. 1, pp. 69-85.

Koopman, SJ, Kräussl, R, Lucas, A & Monteiro, AB 2009, "Credit cycles and macro fundamentals", *Journal of Empirical Finance,* vol. 16, no. 1, pp. 42-54.

Krahnen, JP & Weber, M 2001, "Generally accepted rating principles: A primer", *Journal of Banking and Finance,* vol. 25, no. 1, pp. 3-23.

Metz A & Cantor R 2006, *Moody's Credit Rating Prediction Model*, Moody's, Inc., viewed 15.10.2012, <http://www.moodys.com/sites/products/DefaultResearch/2006200000425644.pdf>

Miller, D & Friesen, PH 1984, "A longitudinal study of the corporate life cycle", *Management Science,* vol. 30, no. 10, pp. 1161-1183.

Moody's Global Corporate Finance 2008, *Corporate Default and Recovery Rates, 1920-2007,* viewed 20 October 2012, <http://www.moodys.com/sites/products/DefaultResearch/2007000000474979.pdf>.

Newbold, P, Carlson W & Thorne B 2010. STATISTICS FOR BUSINESS AND ECONOMICS: GLOBAL EDITION, 7th edition, Pearson Higher Education.

Ohlson, JA 1980, "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research*, vol. 18, no. 1 (Spring, 1980), pp. 109-131.

Pallant J 2007, *SPSS Survival Manual. A Step-by-Step Guide to Data Analysis using SPSS version 15*, 3rd edition, Open University Press, Berkshire.

Peduzzi, P, Concato, J, Kemper, E, Holford, TR & Feinstem, AR 1996, "A simulation study of the number of events per variable in logistic regression analysis", *Journal of clinical epidemiology,* vol. 49, no. 12, pp. 1373-1379.

Pretorius, M 2009, “Defining business decline, failure and turnaround: a content analysis”, *New Series of The Southern African Journal of Entrepreneurship and Small Business Management,* vol. 2, no. 1.

Sandstrom, G 2012, “Nordic Banks Gain New Status: Haven”, *The Wall Street Journal*, viewed 02 November 2012,
< http://online.wsj.com/article/SB10000872396390444813104578016182740070640.html>.

Skogsvik, K 1988, "Predicting failure by means of financial ratios", *Skandinaviska Enskilda Banken Quarterly Review*, vol. 2, pp. 30-37.

Skogsvik, K 2005, “On the Choice-Based Sample Bias in Probabilistic Business Failure Prediction", *Working Paper Series in Business Administration*, 2005:13, Stockholm School of Economics, revised 09 Jan 2006.

Slatter, S & Lovett, D 1999, *Corporate Turnaround: Managing Companies in Distress*, 2nd edn, Penguin UK.

Strömberg, P & Thorburn, K 1996, “An empirical examination of Swedish Corporation in liquidation bankruptcy”, EFI research report, Stockholm School of Economics.

Tabachnick, BG, & Fidell, LS (2007). *Using multivariate statistics,* 5th edn, Allyn and Bacon, Boston.

Tushman, ML, Virany, B & Romanelli, E 1985, "Executive succession, strategic reorientations, and organization evolution. The minicomputer industry as a case in point", *Technology in Society,* vol. 7, no. 2-3, pp. 297-313.

Wooldridge, JM 2009, *Introductory Econometrics. A modern Approach,* 4th edn, South-Western, Cengage Learning.

APPENDIX

Table A – Definitions in previous literature

A brief overview of commonly used criteria for defining *decline* and *failure* are summarized in the table below.

Construct	Criteria	Description	Supporting reference
DECLINE	Decreasing internal resources	Decreasing financial and human resources over time.	D'Aveni (1989)
	Change in direction	Going from good performance to poor performance.	
	Worsening performance	ROI decline for two consecutive years; average pre-tax ROI of less than 10% in the same period. Independent of industry.	Chowdhury & Lang (1993)
	Value destruction	Loss of company value; unprofitability.	Probst & Raisch (2005)
	Financial distress	Debt accumulation to the point that it threatens survival. Unprofitability, loss of market leadership position.	
FAILURE	Bankruptcy	Legal bankruptcy filing.	Altman (1971); Ohlson (1980).
	Shareholder losses	A loss to creditors, owners or any other relevant constituency.	Keasy & Watson (1991) and Lussier (1995)
	Loss-cutting	Appears to be similar to exiting at threshold performance.	Gimeno et al. (1997)
	Loss-cutting	Firms are disposed of to avoid losses.	Liao (2004)
	Earnings	A firm is viewed as a failure if it is not earning an adequate return on invested capital, which is significantly and continually below prevailing rates on similar investments.	
	Discontinuing operations	Includes exit or closure for any reason, excluding deliberate exits for alternative motives.	
	Bankruptcy	The firm is deemed to be legally bankrupt or has ceased operation with resulting losses to creditors.	

Table B – List of distressed firms in the sample

DISTRESSED FIRMS				
No.	**Company name**	**Year (T=0)**	**Country**	**Primary Sector**
1	AB SKF	2006	Sweden	Industrials
2	AB Volvo	2010	Denmark	Industrials
3	A.P. Møller - Mærsk A/S	2008	Sweden	Industrials
4	Ahlstrom Oyj	2006	Finland	Materials
5	Aker Seafoods ASA	2010	Norway	Consumer Staples
6	Aker Solutions ASA	2009	Norway	Energy
7	Alfa Laval AB	2009	Sweden	Industrials
8	Alma Media Oyj	2011	Finland	Consumer Discretionary
9	Anoto Group AB	2010	Sweden	Information Technology
10	Aspiro AB	2009	Sweden	Information Technology
11	Aspo Oyj	2006	Finland	Industrials
12	Aspocomp Group Oyj	2007	Finland	Information Technology
13	Assa Abloy AB	2006	Sweden	Industrials
14	Atria Oyj	2008	Finland	Consumer Staples
15	Austevoll Seafood ASA	2011	Norway	Consumer Staples
16	Autoliv, Inc.	2008	Sweden	Consumer Discretionary
17	Bang & Olufsen Holding A/S	2009	Denmark	Consumer Discretionary
18	Bilia AB	2006	Sweden	Consumer Discretionary
19	Biotage AB	2009	Sweden	Healthcare
20	Bong AB	2006	Sweden	Industrials
21	Cargotec Corporation	2008	Finland	Industrials
22	Carlsberg A/S	2007	Denmark	Consumer Staples
23	Cision AB	2006	Sweden	Industrials
24	Coloplast A/S	2006	Denmark	Healthcare
25	Comptel Oyj	2011	Finland	Information Technology
26	Dalhoff Larsen & Horneman A/S	2008	Denmark	Industrials
27	Dantherm A/S	2009	Denmark	Industrials
28	Digia Oyj	2009	Finland	Information Technology
29	Efore Oyj	2007	Finland	Industrials
30	Elanders AB	2007	Sweden	Industrials
31	Electrolux AB	2006	Sweden	Consumer Discretionary
32	Elektrobit Oyj	2009	Finland	Information Technology
33	Eltek ASA	2006	Norway	Information Technology
34	Enea AB	2007	Sweden	Information Technology
35	Eniro AB	2008	Sweden	Consumer Discretionary
36	Ericsson	2006	Sweden	Information Technology
37	EVRY ASA	2010	Norway	Information Technology

38	Exel Composites Oyj	2006	Finland	Industrials
39	Finnair Oyj	2006	Finland	Industrials
40	FLSmidth & Co. A/S	2011	Denmark	Industrials
41	Genmab A/S	2009	Denmark	Healthcare
42	Getinge AB	2008	Sweden	Healthcare
43	GN Store Nord A/S	2006	Denmark	Healthcare
44	Gunnebo AB	2010	Sweden	Industrials
45	H. Lundbeck A/S	2007	Denmark	Healthcare
46	Haldex AB	2007	Sweden	Industrials
47	Hexagon AB	2009	Sweden	Information Technology
48	HKScan Oyj	2006	Finland	Consumer Staples
49	Holmen AB	2008	Sweden	Materials
50	Huhtamaki Oyj	2008	Finland	Materials
51	Husqvarna AB	2009	Sweden	Consumer Discretionary
52	Incap Oyj	2006	Finland	Industrials
53	Jason Shipping ASA	2010	Norway	Industrials
54	Kemira Group	2008	Finland	Materials
55	Kesko Oyj	2006	Finland	Consumer Staples
56	Kitron ASA	2011	Norway	Information Technology
57	Københavns Lufthavne A/S	2010	Denmark	Industrials
58	Konecranes Plc	2009	Finland	Industrials
59	Kongsberg Automotive Holding ASA	2007	Norway	Consumer Discretionary
60	Lindab International AB	2010	Sweden	Industrials
61	Loomis AB	2009	Sweden	Industrials
62	Medivir AB	2011	Sweden	Healthcare
63	Metsa Board Oyj	2006	Finland	Materials
64	Metso Corp.	2010	Finland	Industrials
65	Modern Times Group Mtg AB	2011	Sweden	Consumer Discretionary
66	NCC AB	2009	Sweden	Industrials
67	Nederman Holding AB	2010	Sweden	Industrials
68	Neurosearch A/S	2011	Denmark	Healthcare
69	NKT Holding A/S	2008	Denmark	Industrials
70	Nobia AB	2010	Sweden	Consumer Discretionary
71	Nokia Corporation	2006	Finland	Information Technology
72	Nokian Tyres Oyj	2011	Finland	Consumer Discretionary
73	Nordic Aluminium Oyj	2006	Finland	Materials
74	Norse Energy Corp. ASA	2010	Norway	Energy
75	Norsk Hydro ASA	2006	Norway	Materials
76	Norske Skogindustrier ASA	2006	Norway	Materials
77	North Media A/S	2009	Denmark	Consumer Discretionary
78	NOTE AB	2008	Sweden	Information Technology
79	Novo Nordisk A/S	2009	Denmark	Healthcare
80	Odfjell SE	2006	Norway	Industrials
81	Outokumpu Oyj	2008	Finland	Materials
82	Outotec Oyj	2010	Finland	Industrials
83	PartnerTech AB	2010	Sweden	Information Technology
84	PKC Group Oyj	2009	Finland	Industrials
85	Pöyry PLC	2010	Finland	Industrials
86	Ramirent Oyj	2008	Finland	Industrials

87	Rapala VMC Corp.	2007	Finland	Consumer Discretionary
88	Rederi AB TransAtlantic	2011	Sweden	Industrials
89	Renewable Energy Corporation ASA	2010	Norway	Information Technology
90	Reservoir Exploration Technology A.S.	2009	Norway	Energy
91	Rockwool International A/S	2009	Denmark	Industrials
92	Royal Unibrew A/S	2009	Denmark	Consumer Staples
93	Ruukki Group Oyj	2011	Finland	Materials
94	Saab AB	2006	Sweden	Industrials
95	Sandvik AB	2009	Sweden	Industrials
96	Sanistål A/S	2008	Denmark	Industrials
97	Sanoma Oyj	2006	Finland	Consumer Discretionary
98	SAS AB	2006	Sweden	Industrials
99	Schibsted ASA	2006	Norway	Consumer Discretionary
100	Sevan Marine ASA	2011	Norway	Energy
101	Statoil ASA	2007	Norway	Energy
102	Stockmann Oyj ABP	2007	Finland	Consumer Discretionary
103	Stora Enso Oyj	2006	Finland	Materials
104	Suominen Oyj	2010	Finland	Consumer Staples
105	Svenska Cellulosa Aktiebolaget SCA	2009	Sweden	Consumer Staples
106	TDC A/S	2007	Denmark	Telecommunication Services
107	Tecnotree Oyj	2009	Finland	Information Technology
108	Tele2 AB	2011	Sweden	Telecommunication Services
109	Telenor ASA	2007	Norway	Telecommunication Services
110	TeliaSonera Aktiebolag	2008	Sweden	Telecommunication Services
111	Tieto Oyj	2006	Finland	Information Technology
112	Tomra Systems ASA	2006	Norway	Industrials
113	TopoTarget A/S	2006	Denmark	Healthcare
114	TORM A/S	2008	Denmark	Energy
115	Trelleborg AB	2006	Sweden	Industrials
116	UPM-Kymmene Oyj	2006	Finland	Materials
117	Uponor Oyj	2008	Finland	Industrials
118	Vacon plc	2010	Finland	Industrials
119	Vaisala Oyj	2011	Finland	Information Technology
120	Wärtsilä Oyj Abp	2009	Finland	Industrials
121	Wilh. Wilhelmsen Holding ASA	2010	Norway	Industrials
122	Yara International ASA	2008	Norway	Materials

Table C – List of non-distressed firms in the sample

NON-DISTRESSED FIRMS				
No.	**Company name**	**Year (T=0)**	**Country**	**Primary Sector**
1	A/S Det Østasiatiske Kompagni	2007	Denmark	Consumer Staples
2	AarhusKarlshamn AB	2010	Sweden	Consumer Staples
3	AB Fagerhult	2008	Sweden	Industrials
4	Acando AB	2008	Sweden	Information Technology
5	ACAP Invest AB	2009	Sweden	Industrials
6	Active Biotech AB	2011	Sweden	Healthcare
7	Addnode Group AB	2008	Sweden	Information Technology
8	Addtech AB	2009	Sweden	Industrials
9	ÅF AB	2006	Sweden	Industrials
10	AF Gruppen ASA	2009	Norway	Industrials
11	Affecto Oyj	2008	Finland	Information Technology
12	AGR Group ASA	2006	Norway	Energy
13	Aker Philadelphia Shipyard ASA	2009	Norway	Industrials
14	Aktiebolaget Geveko	2007	Sweden	Materials
15	Aktieselskabet Schouw & Co.	2009	Denmark	Industrials
16	ALK-Abelló A/S	2010	Denmark	Healthcare
17	Ambu A/S	2011	Denmark	Healthcare
18	Amer Sports Corp.	2009	Finland	Consumer Discretionary
19	Andersen & Martini A/S	2010	Denmark	Consumer Discretionary
20	AQ Group AB	2011	Sweden	Industrials
21	Arkil Holding A/S	2010	Denmark	Industrials
22	Atea ASA	2011	Norway	Information Technology
23	Atlantic Airways	2011	Denmark	Industrials
24	Atlas Copco AB	2006	Sweden	Industrials
25	Auriga Industries A/S	2007	Denmark	Materials
26	Axfood AB	2008	Sweden	Consumer Staples
27	Axis AB	2007	Sweden	Information Technology
28	B&B Tools AB	2006	Sweden	Industrials
29	Bavarian Nordic A/S	2008	Denmark	Healthcare
30	BE Group AB	2008	Sweden	Industrials
31	Beijer Electronics AB	2010	Sweden	Information Technology
32	Belships ASA	2009	Norway	Industrials

33	Bergs Timber AB	2010	Sweden	Materials
34	Betsson AB	2006	Sweden	Consumer Discretionary
35	Billerud AB	2011	Sweden	Materials
36	Blom ASA	2010	Norway	Information Technology
37	BoConcept Holding A/S	2006	Denmark	Consumer Discretionary
38	Boliden AB	2009	Sweden	Materials
39	Bonheur ASA	2006	Norway	Energy
40	Brødrene A. & O. Johansen A/S	2008	Denmark	Industrials
41	Brødrene Hartmann A/S	2006	Denmark	Materials
42	Brøndbyernes IF Fodbold A/S	2006	Denmark	Consumer Discretionary
43	BWG Homes ASA	2009	Norway	Consumer Discretionary
44	Byggma ASA	2006	Norway	Materials
45	Cermaq ASA	2006	Norway	Consumer Staples
46	Clas Ohlson AB	2011	Sweden	Consumer Discretionary
47	Columbus A/S	2007	Denmark	Information Technology
48	Componenta Corp.	2008	Finland	Industrials
49	Concordia Maritime AB	2006	Sweden	Energy
50	Consilium AB	2006	Sweden	Industrials
51	Cramo Oyj	2006	Finland	Industrials
52	Dampskibsselskabet Norden A/S	2006	Denmark	Industrials
53	DFDS A/S	2006	Denmark	Industrials
54	DNO International ASA	2007	Norway	Energy
55	DOF ASA	2009	Norway	Energy
56	Domstein ASA	2009	Norway	Consumer Staples
57	Doro AB	2010	Sweden	Information Technology
58	DSV A/S	2006	Denmark	Industrials
59	Duni AB	2007	Sweden	Consumer Discretionary
60	egetæpper a/s	2006	Denmark	Consumer Discretionary
61	Eidesvik Offshore ASA	2010	Norway	Energy
62	Eitzen Chemical ASA	2006	Norway	Industrials
63	Ekornes ASA	2009	Norway	Consumer Discretionary
64	Electra Gruppen AB	2010	Sweden	Consumer Discretionary
65	Elekta AB	2009	Sweden	Healthcare
66	Elisa Oyj	2010	Finland	Telecommunication Services
67	Elos AB	2008	Sweden	Healthcare
68	Etteplan Oyj	2010	Finland	Industrials
69	Expedit A/S	2010	Denmark	Industrials
70	F-Secure Oyj	2009	Finland	Information Technology
71	F.E Bording A/S	2008	Denmark	Industrials
72	Farstad Shipping ASA	2009	Norway	Energy
73	Fenix Outdoor AB	2010	Sweden	Consumer Discretionary
74	Finnlines Oyj	2007	Finland	Industrials

75	Fiskars Oyj	2009	Finland	Consumer Discretionary
76	Flügger A/S	2006	Denmark	Materials
77	Fred Olsen Energy ASA	2009	Norway	Energy
78	G&L Beijer AB	2006	Sweden	Industrials
79	Ganger Rolf ASA	2009	Norway	Energy
80	Glaston Oyj Abp	2008	Finland	Industrials
81	Glunz & Jensen A/S	2009	Denmark	Industrials
82	Götenehus Group AB	2009	Sweden	Consumer Discretionary
83	Grieg Seafood ASA	2009	Norway	Consumer Staples
84	Gyldendal ASA	2006	Norway	Consumer Discretionary
85	Gyldendalske Boghandel Nordisk Forlag AS	2011	Denmark	Consumer Discretionary
86	H & M Hennes & Mauritz AB	2006	Sweden	Consumer Discretionary
87	H+H International A/S	2006	Denmark	Materials
88	Harboes Bryggeri A/S	2006	Denmark	Consumer Staples
89	Havila Shipping ASA	2006	Norway	Energy
90	Hemtex AB	2011	Sweden	Consumer Discretionary
91	Hexagon Composites ASA	2009	Norway	Industrials
92	Hexpol AB	2010	Sweden	Materials
93	HiQ International AB	2006	Sweden	Information Technology
94	Höegh LNG Holdings Ltd.	2009	Norway	Energy
95	Höganäs AB	2008	Sweden	Materials
96	Højgaard Holding A/S	2008	Denmark	Industrials
97	Honkarakenne Oyj	2006	Finland	Consumer Discretionary
98	Hurtigruten ASA	2011	Norway	Consumer Discretionary
99	I.A.R. Systems Group AB	2009	Sweden	Information Technology
100	IC Companys A/S	2006	Denmark	Consumer Discretionary
101	Ilkka Yhtyma Oyj	2007	Finland	Consumer Discretionary
102	IM Skaugen SE	2006	Norway	Energy
103	Industrial & Financial Systems IFS AB	2008	Sweden	Information Technology
104	Indutrade	2008	Sweden	Industrials
105	Infratek ASA	2010	Norway	Industrials
106	InterMail A/S	2008	Denmark	Industrials
107	Intrum Justitia AB	2009	Sweden	Industrials
108	Itab Shop Concept AB	2009	Sweden	Industrials
109	JM AB	2008	Sweden	Consumer Discretionary
110	Kabe Husvagnar AB	2011	Sweden	Consumer Discretionary
111	KappAhl AB	2009	Sweden	Consumer Discretionary
112	Keskisuomalainen Oyj	2008	Finland	Consumer Discretionary
113	Know IT AB	2006	Sweden	Information Technology
114	Kone Oyj	2011	Finland	Industrials
115	Kongsberg Gruppen ASA	2009	Norway	Industrials
116	Lagercrantz Group AB	2006	Sweden	Information Technology

117	Lammhults Design Group AB	2009	Sweden	Industrials
118	Lännen Tehtaat Oyj	2007	Finland	Consumer Staples
119	Lassila & Tikanoja Oyj	2009	Finland	Industrials
120	Lastas A/S	2009	Denmark	Consumer Discretionary
121	Lemminkainen Oyj	2010	Finland	Industrials
122	Lerøy Seafood Group Asa	2008	Norway	Consumer Staples
123	Lundin Petroleum AB	2009	Sweden	Energy
124	Malmbergs Elektriska AB	2008	Sweden	Industrials
125	Marimekko Oyj	2008	Finland	Consumer Discretionary
126	Marine Harvest ASA	2009	Norway	Consumer Staples
127	Martela Oyj	2010	Finland	Industrials
128	Meda AB	2007	Sweden	Healthcare
129	Mekonomen AB	2010	Sweden	Consumer Discretionary
130	Micronic Mydata AB	2006	Sweden	Information Technology
131	Midsona AB	2010	Sweden	Consumer Staples
132	Midway Holding AB	2006	Sweden	Industrials
133	Mols-Linien A/S	2008	Denmark	Industrials
134	Monberg & Thorsen A/S	2007	Denmark	Industrials
135	Neo Industrial Plc	2010	Finland	Industrials
136	Neste Oil Corp.	2011	Finland	Energy
137	New Wave Group AB	2007	Sweden	Consumer Discretionary
138	NIBE Industrier AB	2006	Sweden	Industrials
139	Nolato AB	2006	Sweden	Information Technology
140	Norway Royal Salmon AS	2010	Norway	Consumer Staples
141	Norwegian Air Shuttle ASA	2011	Norway	Industrials
142	Norwegian Car Carriers ASA	2006	Norway	Industrials
143	Novozymes A/S	2006	Denmark	Materials
144	NTR Holding AS	2006	Denmark	Industrials
145	Nurminen Logistics Oyj	2007	Finland	Industrials
146	OEM International AB	2010	Sweden	Industrials
147	Okmetic Oyj	2006	Finland	Information Technology
148	Olvi Oyj	2011	Finland	Consumer Staples
149	Orkla ASA	2006	Norway	Industrials
150	PA Resources AB	2009	Sweden	Energy
151	PARKEN Sport & Entertainment A/S	2006	Denmark	Consumer Discretionary
152	Peab AB	2010	Sweden	Industrials
153	Per Aarsleff A/S	2006	Denmark	Industrials
154	Petroleum Geo Services ASA	2009	Norway	Energy
155	Petrolia E&P Holdings SE	2009	Norway	Energy
156	Pohjois-Karjalan Kirjapaino Oyj	2009	Finland	Consumer Discretionary
157	Polaris Media ASA	2006	Norway	Consumer Discretionary
158	Ponsse Oyj	2006	Finland	Industrials
159	Poolia AB	2009	Sweden	Industrials

160	ProAct IT Group AB	2009	Sweden	Information Technology
161	Proffice AB	2009	Sweden	Industrials
162	ProfilGruppen AB	2010	Sweden	Materials
163	Q-Free ASA	2006	Norway	Information Technology
164	Raisio plc	2011	Finland	Consumer Staples
165	Rautaruukki Corporation	2006	Finland	Materials
166	Raute Oyj	2008	Finland	Industrials
167	Rella Holding A/S	2008	Denmark	Consumer Discretionary
168	Rieber & Søn ASA	2010	Norway	Consumer Staples
169	Rieber Shipping ASA	2008	Norway	Energy
170	RNB Retail and Brands AB	2006	Sweden	Consumer Discretionary
171	Rocksource ASA	2011	Norway	Energy
172	Rorvik Timber AB	2010	Sweden	Materials
173	Rottneros AB	2010	Sweden	Materials
174	RTX A/S	2008	Denmark	Information Technology
175	Saga Furs Oyj	2010	Finland	Industrials
176	SalMar ASA	2007	Norway	Consumer Staples
177	Scana Industrier ASA	2007	Norway	Materials
178	Scandinavian Brake Systems A/S	2008	Denmark	Consumer Discretionary
179	Scania AB	2006	Sweden	Industrials
180	Sectra Aktiebolag	2006	Sweden	Healthcare
181	Securitas AB	2011	Sweden	Industrials
182	Semcon AB	2011	Sweden	Industrials
183	Siem Offshore Inc.	2006	Norway	Energy
184	Sigma AB	2007	Sweden	Information Technology
185	SimCorp A/S	2011	Denmark	Information Technology
186	SinOceanic Shipping ASA	2011	Norway	Energy
187	SKAKO A/S	2009	Denmark	Industrials
188	Skanska AB	2007	Sweden	Industrials
189	SkiStar AB	2006	Sweden	Consumer Discretionary
190	Solar A/S	2010	Denmark	Industrials
191	Solstad Offshore ASA	2009	Norway	Energy
192	Solvang ASA	2007	Norway	Industrials
193	SP Group A/S	2007	Denmark	Materials
194	SRV Group Plc	2008	Finland	Industrials
195	SSAB AB	2008	Sweden	Materials
196	Studsvik AB	2008	Sweden	Industrials
197	Sweco AB	2006	Sweden	Industrials
198	Swedish Match AB	2006	Sweden	Consumer Staples
199	Swedish Orphan Biovitrum AB	2011	Sweden	Healthcare
200	Systemair AB	2007	Sweden	Industrials
201	Talentum Oyj	2010	Finland	Consumer Discretionary
202	Teleste Corp.	2010	Finland	Information Technology

203	TGS Nopec Geophysical Co. ASA	2007	Norway	Energy
204	Tide ASA	2010	Norway	Industrials
205	Tivoli A/S	2007	Denmark	Consumer Discretionary
206	TradeDoubler AB	2008	Sweden	Information Technology
207	Transit Invest ASA	2011	Norway	Industrials
208	TTS Group ASA	2006	Norway	Industrials
209	Tulikivi Corporation	2009	Finland	Industrials
210	Vaahto Group plc Oyj	2008	Finland	Industrials
211	VBG Group AB	2006	Sweden	Industrials
212	Veidekke ASA	2006	Norway	Industrials
213	Venue Retail Group AB	2009	Sweden	Consumer Discretionary
214	Vestas Wind Systems A/S	2006	Denmark	Industrials
215	Viking Line ABP	2011	Finland	Consumer Discretionary
216	William Demant Holding A/S	2010	Denmark	Healthcare
217	Wilson ASA	2008	Norway	Industrials
218	Wulff-Group Plc	2011	Finland	Consumer Discretionary
219	XANO Industri AB	2006	Sweden	Industrials
220	YIT Oyj	2006	Finland	Industrials

Table D – S&P Financial Glossary of items used in data extraction

Item	Definition
Beta	Excel Formula: IQ_BETA_1YR Beta - 1 Year is a measurement of the sensitivity of a company's stock price to the overall fluctuation of a given benchmark index. Capital IQ's betas are levered, unadjusted and derived from a least squares regression analysis using stock and benchmark index returns based on a monthly or weekly frequency. Beta - 1 Year is calculated using 52 weekly returns (each as of Friday). Capital IQ uses four different benchmark indices to better estimate a stock's volatility against a respective market: the S&P 500 for all US stocks, the S&P/TSX index for all Canadian Stocks, and the MSCI EAFE (Developed Markets) and MSCI Emerging Markets for all other international stocks. The MSCI EAFE (Developed Markets) index includes equities from the following countries: Japan, UK, France, Switzerland, Germany, Australia, Italy, Spain, Netherlands, Sweden, Hong Kong, Finland, Belgium, Singapore, Denmark, Ireland, Norway, Greece, Austria, Portugal, New Zealand.
Capital expenditure	Capital Expenditure (Excel Formula: IQ_CAPEX) is a line item in the Standard template that represents cash outflows towards purchase of plant, property and equipment by the company and has the following components: Capital Expenditure - (Template Specific), Nuclear Fuel Expenditures,
COGS	Cost of Goods Sold, Total (Excel Formula: IQ_COGS)is a line item in the Standard template with the following components: Amortization Of Deferred Charges, Amortization of Deferred Policy Acquisition Costs, Commissions, Cost of Goods Sold, Cost of Services Provided, Deferred Policy Acquisition Costs, Dividends to Policy Holders - Life Insurance, Dividends to Policy Holders - P&C, Fuel Expenses, Fuel & Purchased Power - (Collected), Lease and Rent Expenses, Non-Insurance Activities Expenses, Policy Benefits - Accident &Health, Policy Benefits - Life Insurance, Life Reserve Transfers, Policy Benefits – Other, Policy Benefits - P&C Insurance, Underwriting Costs, Policy Benefits (Insurance & Annuity), Allowance for Inventory, Policy Acquisition / Underwriting Costs, Policy Acquisition Costs / Underwriting Costs – Other, Cost of Sales, Stock-Based Compensation COGS (Standard / REIT Template), Operations And Maintenance, Maintenance & Repair Expenses, Provision For Loan Losses - (Ins. / REIT / Utility Templates). This item excludes Excise Taxes Included in Sales (Revenue Breakup) and the corresponding supplemental Item. Also included in this Cost of Goods Sold, Total are items relating to changes in inventory. The reason for including these items is that normally a commercial entity which is dealing in goods and merchandise may have some amount of inventory balance at the beginning and closing of the accounting period and these opening and closing inventory amounts are adjusted while calculating Cost of Goods Sold, Total. However some organizations may present the net effect of opening and closing inventory as separate line items in the income statement. As a result the following items are included in Cost of Goods Sold, Total as well: (Increase) / Decrease in Stock in Trade (Increase)/decrease in project related work in progress, Change in inventories, Change in metal stocks, Variation in raw, accessory and ancillary materials and goods, (Increase)/decrease in finished and semi-finished stocks (Increase)/Decrease in Software Projects in Progress, (Increase)/Decrease in WIP Provision for loss on inventory and Inventory write-down are not included however.
Current assets	Total Current Assets (IQ_TOTAL_CA) is subtotal line item in the Standard template with the following components: Total Cash & ST Investments, Total Receivables, Inventory, Prepaid Exp., Finance Div. Loans and Leases, ST, Finance Division Other Current Assets, Total, Other Current Assets, (Summary Subtotal).
Current liabilities	Total Current Liabilities (Excel Formula: IQ_TOTAL_CL) is a subtotal line item in the Standard template with the following components: Accounts Payable, Total, Accrued Expenses, Total, Short-term Borrowings, Current Portion of Long Term Debt/Capital Leases, Finance Division Debt Current, Finance Division Other Current Liabilities, Total, Other Current Liabilities, Total.
EBIT	EBIT (Excel Formula: IQ_OPER_INC) is a subtotal line item in the Standard template with the following components: Total Revenues - Total Operating Expenses. Where Total Operating Expenses is a line item in the Standard template with the following components: Cost of Revenues, Other Operating Expenses, Total.
EBITDA	EBITDA (Excel Formula: IQ_EBITDA) is the headline EBITDA number in Capital IQ. It is a line item in the Standard, Real Estate, Insurance and Utility templates with the following components: EBIT [400], D&A for EBITDA [2206]. Where D&A for EBITDA (Excel Formula: IQ_DA_EBITDA) is a line item added back to EBIT to arrive at

	EBITDA and is a sum of the following components: Depreciation - Disclosure in Footnotes - (For D&A), Amortization of Intangibles - Disclosure in Footnotes - (For D&A), Impairment of Oil, Gas & Mineral Properties - (For D&A), Amortization of Goodwill - Disclosure in Footnotes - (For D&A), Amortization of Goodwill - (For D&A), Amortization of Intangible Assets - (For D&A), Depreciation & Amortization - (For D&A).
Interest and Investment Income	Interest and Investment Income (Excel Formula: IQ_INTEREST_INVEST_INC) is a line item in the Standard template with the following components: Interest and Dividend Income, Interest and Investment Income - (Expense Block). Additionally, based on information provided in the filings it is determined whether this item is part of operating or non-operating income.
Interest expense	Interest Expense, Total (Excel Formula: IQ_INTEREST_EXP) is a line item in the Standard template with the following components: Debt Issuance Costs, Interest Expense, Preferred Stock Dividend of Subsidiary, After Tax portion of Pref. Stock Dividend of Subsidiary, Dividend on Trust Pref. Securities, After Tax portion Dividend on Trust Pref. Securities.
Net Debt	Net Debt (Excel Formula: IQ_NET_DEBT) is a supplemental line item across all templates with the following components: Total Debt - Total Cash & Short-term Investments.
Net PPE	Net Property Plant And Equipment (Excel Formula: IQ_NPPE) is a subtotal line item across all templates (excl. Real Estate) with the following components: Gross Property Plant And Equipment, Accumulated Depreciation.
Net working capital	Net Working Capital (Excel Formula: IQ_NET_WORKING_CAP)] is a supplemental line item for the Standard, Insurance, Real Estate and Utility templates that represents working capital net of non-operating current assets and liabilities (Total Current Assets - Total Cash And Short Term Investments) - (Total Current Liabilities - Short-term Borrowings - Current Portion of Long-Term Debt - Current Portion of Capital Lease)
Retained earnings	Retained Earnings (Excel Formula: IQ_RE) is a line item across all templates that represents earnings not distributed to shareholders nor apportioned for any specific purpose and can therefore be reinvested in the business. This item includes: Unrestricted Retained Earnings and in the absence of breakdown includes: Earnings reinvested in business, Legal reserve, Income reinvested in the business, Deficit accumulated during development stage.
Revenues	Excel Formula: IQ_TOTAL_REV Total Revenues is subtotal line item in the Standard template with the following components: Revenues & Other Revenues, (Summary Subtotal) Where Revenues (Excel Formula: IQ_REV) are: Revenues is a line item in the Standard template with the following components: Accident and Health Premiums Earned, Asset Management Fee, Brokerage Commission, Credit Card Fee, Commission and Fees, Income (Loss) on Equity Invest. (Income Block) - (Bank Template), Fees and Other Income, Foreign Exchange Gain (Loss) – Income, Gain (Loss) on Sale of Assets - (Revenue Block), Gain (Loss) On Sale Of Investments and Securities (Rev), Gain (Loss) on Sale of Loans - (Revenue Block) - (Bank Template), Other Premiums Earned, Underwriting & Investment Banking Fee, Interest and Dividend Income Corporate Segment, Interest and Dividend Income Other than Corporate Segment, Income (Loss) on Real Estate Held for Investment – Income, Income (Loss) From Foreclosed Properties - (Rev), Life Insurance Premiums Earned, Loan Servicing Revenue, Mortgage Banking Activities, Mortgage Banking, Property Management Fee, Non-Insurance Activities Revenues, Non-operating Income (Expenses) - (Income Block) - (Bank Template), Property & Casualty Premiums Earned, Trading and Principal Transactions, Tenant Reimbursements, Rental Revenues, Service Charges On Deposits, Revenues - (Collected), Cargo Revenues, Franchise Revenues, Gain (Loss) on Sale of Loans & Receivables - (Revenue Block) - (Collected), Management Fee, Passenger Revenues, Product Revenues, Research and Development Revenues, Royalty Income - (Rev), Rental Revenues, Service Revenues, Income From Trading Activities, Trust Income, Deductions from Sales, Insurance And Annuity Revenues, Excise Taxes Excluded from Sales, Other Non-interest Income (Collected), Excise Taxes Included in Sales (Supple) is excluded from Revenues. Where Other Revenues (Excel Formula: IQ_OTHER_REV) are: Other Revenues, (Summary Subtotal) is a summary line item in the Standard template that is the sum of the following data items: Finance Div. Revenues, Insurance Division Revenues, Gain (Loss) on Sale of Assets, Total (Rev), Gain (Loss) on Sale of Investment, Total (Rev) Interest and Invest. Income (Rev).
Total assets	Total Assets is subtotal line item across all templates with the following components: Total Current Assets, Net Property, Plant & Equipment, Long-term Investments, Goodwill, Other Intangibles, Total, Finance Div. Loans and Leases, LT, Finance Division Other Long-Term Assets, Total, Other Assets, Total.

Table E – Distress Identification by sector

CONSUMER DISCRETIONARY			
Variable	Test used	Test statistic	p-value
Relative size (RS)	Kruskal-Wallis test	$\lambda^2 = 20.348$	0.0001
Investment level (IL1)	Kruskal-Wallis test	$\lambda^2 = 4.200$	0.0404
LTD due +1/Total LTD (FG3)	Kruskal-Wallis test	$\lambda^2 = 4.447$	0.0350
LTD due +2/Total LTD (FG4)	Kruskal-Wallis test	$\lambda^2 = 7.136$	0.0076

CONSUMER STAPLES			
Variable	Test used	Test statistic	p-value
Relative size (RS)	T-test with unequal variances	t = -2.4574	0.0318
Interest coverage ratio (CC1)	T-test with unequal variances	t = 2.4107	0.0242
Sales growth (P1)	Kruskal-Wallis test	$\lambda^2 = 3.068$	0.0798
ROA (P3)	Kruskal-Wallis test	$\lambda^2 = 4.306$	0.0380
Current ratio (L1)	Kruskal-Wallis test	$\lambda^2 = 4.765$	0.0290
NWC/Sales (L2)	Kruskal-Wallis test	$\lambda^2 = 4.765$	0.0290
Cash conversion cycle (L3)	Kruskal-Wallis test	$\lambda^2 = 5.705$	0.0169
Debt/Equity (FG1)	Kruskal-Wallis test	$\lambda^2 = 3.260$	0.0710
Capex as % of Revenues (IL2)	Kruskal-Wallis test	$\lambda^2 = 2.882$	0.0896

ENERGY			
Variable	Test used	Test statistic	p-value
Beta (MF2)	T-test with equal variances	t = -1.7241	0.0961
Capitalization (MF1)	Kruskal-Wallis test	$\lambda^2 = 7.539$	0.0060
Current ratio (L1)	Kruskal-Wallis test	$\lambda^2 = 10.786$	0.0010
NWC/Sales (L2)	Kruskal-Wallis test	$\lambda^2 = 6.348$	0.0118
ND/EBITDA (CC2)	Kruskal-Wallis test	$\lambda^2 = 3.481$	0.0621
Financial expense/Total Debt (FG2)	Kruskal-Wallis test	$\lambda^2 = 3.757$	0.0526

INDUSTRIALS			
Variable	Test used	Test statistic	p-value
Beta (MF2)	Kruskal-Wallis test	$\lambda^2 = 5.596$	0.0180
Relative size (RS)	Kruskal-Wallis test	$\lambda^2 = 18.614$	0.0001
ND/EBITDA (CC2)	Kruskal-Wallis test	$\lambda^2 = 3.094$	0.0786
LTD due +1/Total LTD (FG3)	Kruskal-Wallis test	$\lambda^2 = 2.851$	0.0913
LTD due +2/Total LTD (FG4)	Kruskal-Wallis test	$\lambda^2 = 6.428$	0.0112

INFORMATION TECHNOLOGY			
Variable	Test used	Test statistic	p-value
NWC/Sales (L2)	T-test with equal variances	t = -2.6352	0.0117
ND/EBITDA (CC2)	T-test with equal variances	t = -2.6019	0.0209
Capitalization (MF1)	Kruskal-Wallis test	$\lambda^2 = 6.131$	0.0133
Sales growth (P1)	Kruskal-Wallis test	$\lambda^2 = 6.855$	0.0088
ROA (P3)	Kruskal-Wallis test	$\lambda^2 = 6.980$	0.0082
Interest coverage ratio (CC1)	Kruskal-Wallis test	$\lambda^2 = 5.143$	0.0233
Capex as % of Revenues (IL2)	Kruskal-Wallis test	$\lambda^2 = 5.558$	0.0184
Relative size (RS)	Kruskal-Wallis test	$\lambda^2 = 5.228$	0.0222

MATERIALS			
Variable	Test used	Test statistic	p-value
Relative size (RS)	T-test with equal variances	t = -4.6354	0.0001
Capitalization (MF1)	Kruskal-Wallis test	$\lambda^2 = 9.072$	0.0026
ND/EBITDA (CC2)	Kruskal-Wallis test	$\lambda^2 = 3.788$	0.0516
Financial expense/Total Debt (FG2)	Kruskal-Wallis test	$\lambda^2 = 3.905$	0.0482
LTD due +1/Total LTD (FG3)	Kruskal-Wallis test	$\lambda^2 = 6.981$	0.0082
LTD due +2/Total LTD (FG4)	Kruskal-Wallis test	$\lambda^2 = 4.333$	0.0374

HEALTHCARE			
Variable	Test used	Test statistic	p-value
Current ratio (L1)	Kruskal-Wallis test	$\lambda^2 = 3.888$	0.0486
Investment level (IL1)	Kruskal-Wallis test	$\lambda^2 = 5.732$	0.0167

STATA outputs for prediction models

1. Model T-1

Initial model

```
Logistic regression                               Number of obs   =        233
                                                  LR chi2(35)     =     118.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -95.461631                       Pseudo R2       =     0.3820
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Crisisyear	-.4539628	.452184	-1.00	0.315	-1.197739	.2898137
Sect_Consumer_Discretionary	.1234754	1.610502	0.08	0.939	-2.525565	2.772516
Sect_Consumer_Staples	.743508	1.666989	0.45	0.656	-1.998445	3.485461
Sect_Energy	-.8688928	1.706892	-0.51	0.611	-3.67648	1.938695
Sect_Healthcare	-.2812377	1.838566	-0.15	0.878	-3.30541	2.742935
Sect_Industrials	.5350473	1.593159	0.34	0.737	-2.085465	3.15556
Sect_Information_Technology	1.018796	1.709694	0.60	0.551	-1.7934	3.830992
Sect_Materials	-.4455256	1.636536	-0.27	0.785	-3.137387	2.246336
Sect_Telecommunication_Services	0	(omitted)				
Sweden	-.6930794	.6783807	-1.02	0.307	-1.808916	.4227576
Norway	-1.503299	.7070351	-2.13	0.033	-2.666268	-.3403293
Denmark	-.6705843	.7568102	-0.89	0.376	-1.915426	.5742577
Finland	0	(omitted)				
KEY_Sell_Divest	.4164177	.8408064	0.50	0.620	-.9665857	1.799421
Key_CEO	.1886958	.6215536	0.30	0.761	-.8336689	1.21106
Key_CFO	.8321257	.6413076	1.30	0.194	-.2227314	1.886983
Key_Changes_Other	-1.732068	.5086836	-3.41	0.001	-2.568778	-.8953577
Key_Corporate_Guidance_Lowered	-.0574665	.8486588	-0.07	0.946	-1.453386	1.338453
Age	.0054582	.0025846	2.11	0.035	.0012069	.0097096
MF1	.0098273	.0369023	0.27	0.790	-.0508716	.0705262
MF2	1.171155	.5121945	2.29	0.022	.3286701	2.01364
RS	1.003591	.1819719	5.52	0.000	.7042737	1.302908
P1	-3.085148	1.205055	-2.56	0.010	-5.067286	-1.103009
P2	1.326127	1.294162	1.02	0.306	-.8025805	3.454834
P3	3.695522	5.346622	0.69	0.489	-5.098889	12.48993
P4	-1.5861	1.601285	-0.99	0.322	-4.21998	1.04778
L1	-.4582029	.450676	-1.02	0.309	-1.199499	.2830932
L2	1.822376	2.889215	0.63	0.528	-2.92996	6.574712
L3	-.0061101	.0050375	-1.21	0.225	-.0143961	.0021758
CC1	-.0249696	.0237871	-1.05	0.294	-.064096	.0141567
CC2	.0051498	.0109101	0.47	0.637	-.0127957	.0230953
IL1	.4059127	.1768292	2.30	0.022	.1150545	.6967708
IL2	-.6477697	1.324808	-0.49	0.625	-2.826885	1.531346
FG1	-.1699935	.1339771	-1.27	0.205	-.3903661	.0503792
FG2	3.757065	9.069559	0.41	0.679	-11.16103	18.67516
FG3	-.0029014	.0045904	-0.63	0.527	-.0104519	.0046491
FG4	.1095567	.0911721	1.20	0.230	-.040408	.2595214
_cons	5.986579	2.191109	2.73	0.006	2.382525	9.590633

Note: 0 failures and 1 success completely determined.

Final model – coefficients reported

```
Logistic regression                               Number of obs   =        341
                                                  LR chi2(10)     =     125.54
                                                  Prob > chi2     =     0.0000
Log likelihood =  -159.0121                       Pseudo R2       =     0.2830
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Energy	-1.424137	.6453678	-2.21	0.027	-2.485672	-.3626011
Sect_Information_Technology	1.460598	.4411218	3.31	0.001	.7350175	2.186179
Sweden	-.8922076	.3749416	-2.38	0.017	-1.508932	-.2754835
Norway	-1.350907	.4623584	-2.92	0.003	-2.111419	-.5903953
Denmark	-1.084258	.4360862	-2.49	0.013	-1.801556	-.3669601
Finland	0	(omitted)				
Key_Changes_Other	-1.019586	.3194699	-3.19	0.001	-1.545067	-.4941051
MF2	.9424769	.3238085	2.91	0.004	.4098592	1.475095
RS	.803177	.1117188	7.19	0.000	.6194158	.9869381
P1	-1.890208	.6152562	-3.07	0.002	-2.902215	-.878202
CC1	-.0007513	.0003661	-2.05	0.040	-.0013534	-.0001491
_cons	4.902385	.8107765	6.05	0.000	3.568776	6.235993

Final model - odds ratios reported

```
Logistic regression                               Number of obs   =        341
                                                  LR chi2(10)     =     125.54
                                                  Prob > chi2     =     0.0000
Log likelihood =  -159.0121                       Pseudo R2       =     0.2830
```

Distress	Odds Ratio	Std. Err.	z	P>|z|	[90% Conf. Interval]	
Sect_Energy	.2407162	.1553505	-2.21	0.027	.0832696	.6958639
Sect_Information_Technology	4.308537	1.900589	3.31	0.001	2.085518	8.901138
Sweden	.4097502	.1536324	-2.38	0.017	.2211461	.7592049
Norway	.2590052	.1197532	-2.92	0.003	.121066	.5541082
Denmark	.3381526	.1474637	-2.49	0.013	.1650419	.6928373
Finland	1	(omitted)				
Key_Changes_Other	.3607442	.1152469	-3.19	0.001	.2132975	.6101167
MF2	2.56633	.8309996	2.91	0.004	1.506606	4.371449
RS	2.232623	.249426	7.19	0.000	1.857842	2.683007
P1	.1510403	.0929285	-3.07	0.002	.0549015	.4155294
CC1	.999249	.0003658	-2.05	0.040	.9986475	.9998509
_cons	134.6104	109.1389	6.05	0.000	35.47314	510.8077

Diagnostics for the final model

- *Goodness-of-fit test*

Logistic model for Distress, goodness-of-fit test

```
       number of observations =       341
 number of covariate patterns =       341
             Pearson chi2(330) =       336.88
                   Prob > chi2 =         0.3851
```

- *Classification table*

Logistic model for Distress

Classified	True D	True ~D	Total
+	75	27	102
-	46	193	239
Total	121	220	341

Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0

Sensitivity	Pr(+| D)	61.98%
Specificity	Pr(-|~D)	87.73%
Positive predictive value	Pr(D| +)	73.53%
Negative predictive value	Pr(~D| -)	80.75%
False + rate for true ~D	Pr(+|~D)	12.27%
False - rate for true D	Pr(-| D)	38.02%
False + rate for classified +	Pr(~D| +)	26.47%
False - rate for classified -	Pr(D| -)	19.25%
Correctly classified		78.59%

- *Specification error – linktest*

```
Logistic regression                               Number of obs   =        341
                                                  LR chi2(2)      =     126.35
                                                  Prob > chi2     =     0.0000
Log likelihood = -158.60956                       Pseudo R2       =     0.2848
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_hat	1.055512	.1380881	7.64	0.000	.784864	1.32616
_hatsq	.0591698	.0641349	0.92	0.356	-.0665324	.184872
_cons	-.0720505	.1703232	-0.42	0.672	-.4058779	.261777

- *Variance Inflation Factor analysis*

Variable	VIF	1/VIF
Norway	1.87	0.535417
Sweden	1.76	0.568815
Denmark	1.56	0.642275
Sect_Energy	1.30	0.766513
RS	1.28	0.782434
MF2	1.19	0.842769
Key_Change~r	1.14	0.873974
Sect_Infor~y	1.13	0.888835
P1	1.03	0.972223
CC1	1.02	0.980803
Mean VIF	1.33	

2. Model T-2

Initial model

```
Logistic regression                               Number of obs   =        233
                                                  LR chi2(35)     =      91.35
                                                  Prob > chi2     =     0.0000
Log likelihood = -109.74771                       Pseudo R2       =     0.2939
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Crisisyear	-.1848734	.4115261	-0.45	0.653	-.8617736	.4920267
Sect_Consumer_Discretionary	1.131874	1.364464	0.83	0.407	-1.11247	3.376218
Sect_Consumer_Staples	.8145636	1.383799	0.59	0.556	-1.461584	3.090711
Sect_Energy	-.5023347	1.559354	-0.32	0.747	-3.067245	2.062575
Sect_Healthcare	.779912	1.557697	0.50	0.617	-1.782272	3.342096
Sect_Industrials	.7764261	1.325163	0.59	0.558	-1.403272	2.956125
Sect_Information_Technology	2.079182	1.528798	1.36	0.174	-.4354666	4.593831
Sect_Materials	.5702945	1.369918	0.42	0.677	-1.68302	2.823609
Sect_Telecommunication_Services	0	(omitted)				
Sweden	-.1606951	.5737663	-0.28	0.779	-1.104457	.7830665
Norway	-.957624	.6374541	-1.50	0.133	-2.006143	.0908948
Denmark	-.221686	.6324116	-0.35	0.726	-1.26191	.8185384
Finland	0	(omitted)				
KEY_Sell_Divest	-.2538228	.9474706	-0.27	0.789	-1.812273	1.304628
Key_CEO	.1035899	.6228871	0.17	0.868	-.9209682	1.128148
Key_CFO	.3460121	.6432135	0.54	0.591	-.71198	1.404004
Key_Changes_Other	-.7723981	.4717883	-1.64	0.102	-1.548421	.0036246
Key_Corporate_Guidance_Lowered	.453171	.7315007	0.62	0.536	-.7500405	1.656383
Age	.0038979	.0025046	1.56	0.120	-.0002217	.0080176
MF1	-.0182158	.0289961	-0.63	0.530	-.0659102	.0294786
MF2	.1415585	.4151492	0.34	0.733	-.5413012	.8244181
RS	.9245729	.1605079	5.76	0.000	.6605608	1.188585
P1	-.5871039	.5575296	-1.05	0.292	-1.504158	.3299507
P2	1.632831	1.240228	1.32	0.188	-.4071631	3.672825
P3	7.516233	4.45078	1.69	0.091	.1953516	14.83711
P4	-2.940756	1.223614	-2.40	0.016	-4.953423	-.9280894
L1	.2178757	.4220517	0.52	0.606	-.4763376	.9120889
L2	2.707949	2.213006	1.22	0.221	-.9321224	6.348021
L3	-.0074988	.0042529	-1.76	0.078	-.0144942	-.0005034
CC1	.0150023	.019753	0.76	0.448	-.0174885	.0474931
CC2	.040925	.0195713	2.09	0.037	.0087332	.0731169
IL1	.0649732	.0471363	1.38	0.168	-.0125591	.1425055
IL2	-.3351104	1.48141	-0.23	0.821	-2.771814	2.101593
FG1	-.2624755	.2689744	-0.98	0.329	-.7048989	.179948
FG2	12.4545	8.690855	1.43	0.152	-1.840681	26.74969
FG3	-.0856124	.0956887	-0.89	0.371	-.2430063	.0717814
FG4	-.2987387	1.218201	-0.25	0.806	-2.302502	1.705024
_cons	3.16191	1.703884	1.86	0.063	.3592712	5.96455

Note: 0 failures and 1 success completely determined.

.

Final model – coefficients reported

```
Logistic regression                               Number of obs   =        338
                                                  LR chi2(4)      =      90.99
                                                  Prob > chi2     =     0.0000
Log likelihood = -175.54578                       Pseudo R2       =     0.2058
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Information_Technology	1.246476	.3924296	3.18	0.001	.600987	1.891966
Norway	-.7458718	.33567	-2.22	0.026	-1.298	-.1937438
RS	.7778516	.0983556	7.91	0.000	.6160711	.9396322
P4	-.9208911	.3316143	-2.78	0.005	-1.466348	-.375434
_cons	4.290022	.6165655	6.96	0.000	3.275862	5.304182

Final model - odds ratios reported

```
Logistic regression                               Number of obs   =        338
                                                  LR chi2(4)      =      90.99
                                                  Prob > chi2     =     0.0000
Log likelihood = -175.54578                       Pseudo R2       =     0.2058
```

Distress	Odds Ratio	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Information_Technology	3.478066	1.364896	3.18	0.001	1.823918	6.632392
Norway	.4743206	.1592152	-2.22	0.026	.2730775	.823869
RS	2.176791	.2140995	7.91	0.000	1.851639	2.55904
P4	.3981641	.1320369	-2.78	0.005	.2307667	.686991
_cons	72.96805	44.98958	6.96	0.000	26.46602	201.1763

Diagnostics for the final model

- *Goodness-of-fit test*

Logistic model for Distress, goodness-of-fit test

```
       number of observations =       338
 number of covariate patterns =       338
            Pearson chi2(333) =       332.21
                  Prob > chi2 =         0.5019
```

- *Classification table*

Logistic model for Distress

Classified	True D	True ~D	Total
+	66	32	98
-	56	184	240
Total	122	216	338

Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0

Sensitivity	Pr(+| D)	54.10%
Specificity	Pr(-|~D)	85.19%
Positive predictive value	Pr(D| +)	67.35%
Negative predictive value	Pr(~D| -)	76.67%
False + rate for true ~D	Pr(+|~D)	14.81%
False - rate for true D	Pr(-| D)	45.90%
False + rate for classified +	Pr(~D| +)	32.65%
False - rate for classified -	Pr(D| -)	23.33%
Correctly classified		73.96%

- *Specification error – linktest*

```
Logistic regression                               Number of obs   =        338
                                                  LR chi2(2)      =      91.13
                                                  Prob > chi2     =     0.0000
Log likelihood =  -175.4742                       Pseudo R2       =     0.2061
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_hat	.9751767	.1380945	7.06	0.000	.7045165	1.245837
_hatsq	-.0331958	.0869041	-0.38	0.702	-.2035248	.1371332
_cons	.0324333	.1675188	0.19	0.846	-.2958975	.3607641

- *Variance Inflation Factor analysis*

Variable	VIF	1/VIF
RS	1.09	0.914014
P4	1.05	0.954592
Sect_Infor~y	1.05	0.956578
Norway	1.02	0.985075
Mean VIF	1.05	

3. Model T-3

Initial model

```
Logistic regression                               Number of obs   =        218
                                                  LR chi2(35)     =     111.49
                                                  Prob > chi2     =     0.0000
Log likelihood = -89.100531                       Pseudo R2       =     0.3849
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Crisisyear	-.1816756	.4862893	-0.37	0.709	-.9815504	.6181992
Sect_Consumer_Discretionary	1.809759	1.479337	1.22	0.221	-.6235337	4.243051
Sect_Consumer_Staples	1.579942	1.535961	1.03	0.304	-.9464891	4.106373
Sect_Energy	-2.546515	1.940109	-1.31	0.189	-5.737711	.6446801
Sect_Healthcare	3.188811	1.807784	1.76	0.078	.2152718	6.162351
Sect_Industrials	1.746676	1.455596	1.20	0.230	-.6475663	4.140919
Sect_Information_Technology	1.922603	1.703321	1.13	0.259	-.879111	4.724317
Sect_Materials	1.498147	1.556748	0.96	0.336	-1.062475	4.058769
Sect_Telecommunication_Services	0	(omitted)				
Sweden	-.0546885	.6163409	-0.09	0.929	-1.068479	.9591021
Norway	-.0845105	.716236	-0.12	0.906	-1.262614	1.093593
Denmark	-.3496799	.6623723	-0.53	0.598	-1.439185	.7398255
Finland	0	(omitted)				
KEY_Sell_Divest	2.616181	1.642924	1.59	0.111	-.0861878	5.31855
Key_CEO	.465775	.6936273	0.67	0.502	-.6751404	1.60669
Key_CFO	2.288161	1.363473	1.68	0.093	.0454475	4.530875
Key_Changes_Other	-.5818819	.5281949	-1.10	0.271	-1.450685	.2869213
Key_Corporate_Guidance_Lowered	.8639192	1.105786	0.78	0.435	-.9549374	2.682776
Age	.0003871	.0030694	0.13	0.900	-.0046616	.0054358
MF1	-.0263263	.0291587	-0.90	0.367	-.074288	.0216354
MF2	.7580745	.4591877	1.65	0.099	.002778	1.513371
RS	1.029546	.1891995	5.44	0.000	.7183408	1.340752
P1	-1.259517	.8763207	-1.44	0.151	-2.700937	.1819021
P2	2.405302	1.309217	1.84	0.066	.2518318	4.558772
P3	.8447081	5.279956	0.16	0.873	-7.840046	9.529463
P4	-3.481246	1.775329	-1.96	0.050	-6.401402	-.5610896
L1	.8968399	.4992322	1.80	0.072	.0756761	1.718004
L2	2.586625	2.174875	1.19	0.234	-.990726	6.163976
L3	-.0141542	.004926	-2.87	0.004	-.0222566	-.0060517
CC1	.018031	.0297788	0.61	0.545	-.0309508	.0670128
CC2	.0021098	.0903839	0.02	0.981	-.1465585	.150778
IL1	.2527234	.2433366	1.04	0.299	-.1475297	.6529765
IL2	1.211874	1.70425	0.71	0.477	-1.591367	4.015115
FG1	-.7801853	.4819029	-1.62	0.105	-1.572845	.0124744
FG2	-2.49612	7.039721	-0.35	0.723	-14.07543	9.083191
FG3	-.0590392	.1378214	-0.43	0.668	-.2857352	.1676569
FG4	-.0994923	1.651059	-0.06	0.952	-2.815243	2.616258
_cons	3.834596	2.026153	1.89	0.058	.5018707	7.167321

Note: 1 failure and 1 success completely determined.

.

Final model – coefficients reported

```
Logistic regression                               Number of obs   =        333
                                                  LR chi2(8)      =     114.30
                                                  Prob > chi2     =     0.0000
Log likelihood = -161.63082                       Pseudo R2       =     0.2612
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Healthcare	1.738907	.6240857	2.79	0.005	.7123777	2.765437
Sect_Information_Technology	1.263638	.4354638	2.90	0.004	.5473636	1.979912
MF1	-.0320051	.0150003	-2.13	0.033	-.0566784	-.0073318
RS	.8529653	.107615	7.93	0.000	.6759543	1.029976
P1	-.9494766	.4849732	-1.96	0.050	-1.747187	-.1517666
P4	-1.302804	.4503078	-2.89	0.004	-2.043495	-.5621136
L3	-.0045683	.001906	-2.40	0.017	-.0077034	-.0014332
FG1	-.4579203	.2235852	-2.05	0.041	-.8256852	-.0901554
_cons	5.706683	.7875578	7.25	0.000	4.411265	7.0021

Final model - odds ratios reported

```
Logistic regression                               Number of obs   =        333
                                                  LR chi2(8)      =     114.30
                                                  Prob > chi2     =     0.0000
Log likelihood = -161.63082                       Pseudo R2       =     0.2612
```

Distress	Odds Ratio	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Healthcare	5.691122	3.551748	2.79	0.005	2.038833	15.88598
Sect_Information_Technology	3.538269	1.540788	2.90	0.004	1.728689	7.242105
MF1	.9685017	.0145278	-2.13	0.033	.9448979	.9926951
RS	2.346595	.2525289	7.93	0.000	1.965908	2.800999
P1	.3869435	.1876572	-1.96	0.050	.1742635	.8591888
P4	.2717687	.1223796	-2.89	0.004	.1295751	.570003
L3	.9954422	.0018973	-2.40	0.017	.9923262	.9985679
FG1	.6325979	.1414395	-2.05	0.041	.4379348	.9137892
_cons	300.8714	236.9536	7.25	0.000	82.37364	1098.939

Diagnostics for the final model

- *Goodness-of-fit test*

Logistic model for Distress, goodness-of-fit test

```
      number of observations =       333
 number of covariate patterns =       333
            Pearson chi2(324) =       324.61
                  Prob > chi2 =         0.4800
```

- *Classification table*

Logistic model for Distress

Classified	True D	True ~D	Total
+	74	25	99
-	48	186	234
Total	122	211	333

Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0

Sensitivity	Pr(+| D)	60.66%
Specificity	Pr(-|~D)	88.15%
Positive predictive value	Pr(D| +)	74.75%
Negative predictive value	Pr(~D| -)	79.49%
False + rate for true ~D	Pr(+|~D)	11.85%
False - rate for true D	Pr(-| D)	39.34%
False + rate for classified +	Pr(~D| +)	25.25%
False - rate for classified -	Pr(D| -)	20.51%
Correctly classified		78.08%

- *Specification error – linktest*

```
Logistic regression                               Number of obs   =        333
                                                  LR chi2(2)      =     114.31
                                                  Prob > chi2     =     0.0000
Log likelihood =  -161.6214                       Pseudo R2       =     0.2613
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	1.00755	.1337561	7.53	0.000	.7453933	1.269708
_hatsq	.0099316	.0724504	0.14	0.891	-.1320686	.1519318
_cons	-.0113992	.1694897	-0.07	0.946	-.3435929	.3207944

- *Variance Inflation Factor analysis*

Variable	VIF	1/VIF
Sect_Healt~e	1.23	0.811381
P4	1.23	0.812249
MF1	1.20	0.833089
Sect_Infor~y	1.13	0.884555
FG1	1.10	0.907385
RS	1.08	0.922729
P1	1.06	0.943267
L3	1.03	0.969333
Mean VIF	1.13	

4. Model T-4

Initial model

```
Logistic regression                               Number of obs   =        220
                                                  LR chi2(35)     =     101.95
                                                  Prob > chi2     =     0.0000
Log likelihood = -94.823027                       Pseudo R2       =     0.3496
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Crisisyear	-1.134818	.7571917	-1.50	0.134	-2.380287	.1106516
Sect_Consumer_Discretionary	.3624243	1.626302	0.22	0.824	-2.312604	3.037453
Sect_Consumer_Staples	.86619	1.677774	0.52	0.606	-1.893503	3.625883
Sect_Energy	-.3857373	1.807491	-0.21	0.831	-3.358795	2.58732
Sect_Healthcare	1.547097	1.96519	0.79	0.431	-1.685353	4.779547
Sect_Industrials	.6329968	1.588321	0.40	0.690	-1.979559	3.245552
Sect_Information_Technology	2.326542	1.843366	1.26	0.207	-.7055241	5.358609
Sect_Materials	-.5112747	1.703635	-0.30	0.764	-3.313504	2.290955
Sect_Telecommunication_Services	0	(omitted)				
Sweden	.2996146	.6059891	0.49	0.621	-.6971487	1.296378
Norway	-.3757987	.6997506	-0.54	0.591	-1.526786	.7751887
Denmark	-.0360499	.6356382	-0.06	0.955	-1.081582	1.009482
Finland	0	(omitted)				
KEY_Sell_Divest	-.2065509	1.723423	-0.12	0.905	-3.041329	2.628227
Key_CEO	.0126171	.8740075	0.01	0.988	-1.424997	1.450232
Key_CFO	1.615514	.9688128	1.67	0.095	.0219588	3.209069
Key_Changes_Other	-1.430425	.5674076	-2.52	0.012	-2.363727	-.4971223
Key_Corporate_Guidance_Lowered	1.722253	1.242454	1.39	0.166	-.3214017	3.765907
Age	.0010306	.0033353	0.31	0.757	-.0044555	.0065167
MF1	-.0820271	.0403798	-2.03	0.042	-.148446	-.0156082
MF2	.444565	.3724385	1.19	0.233	-.1680417	1.057172
RS	1.151512	.190986	6.03	0.000	.8373678	1.465656
P1	.8317938	.7352711	1.13	0.258	-.3776196	2.041207
P2	1.465102	1.259827	1.16	0.245	-.607129	3.537333
P3	11.94264	5.971063	2.00	0.045	2.121111	21.76416
P4	.5688961	1.832742	0.31	0.756	-2.445696	3.583488
L1	.2947287	.4493232	0.66	0.512	-.4443422	1.0338
L2	-.4291046	2.02722	-0.21	0.832	-3.763585	2.905376
L3	-.0089061	.0046931	-1.90	0.058	-.0166256	-.0011867
CC1	-.0670577	.0449215	-1.49	0.135	-.1409469	.0068315
CC2	.0334158	.0987448	0.34	0.735	-.1290049	.1958366
IL1	.2741808	.2219003	1.24	0.217	-.0908127	.6391743
IL2	-5.781581	3.01299	-1.92	0.055	-10.73751	-.8256532
FG1	-.1600565	.3025868	-0.53	0.597	-.6577674	.3376544
FG2	-1.220034	6.710822	-0.18	0.856	-12.25835	9.818286
FG3	-.252448	1.252311	-0.20	0.840	-2.312317	1.807421
FG4	.2189087	2.220901	0.10	0.921	-3.434148	3.871965
_cons	5.682794	2.154928	2.64	0.008	2.138253	9.227336

Note: 0 failures and 1 success completely determined.

Final model – coefficients reported

```
Logistic regression                               Number of obs   =        331
                                                  LR chi2(7)      =     114.86
                                                  Prob > chi2     =     0.0000
Log likelihood = -159.88618                       Pseudo R2       =     0.2643
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf. Interval]	
Sect_Information_Technology	1.380907	.4233663	3.26	0.001	.6845318	2.077283
Key_Changes_Other	-.9001556	.3584751	-2.51	0.012	-1.489795	-.3105165
RS	.9538556	.1177426	8.10	0.000	.7601863	1.147525
P1	.8800701	.3380852	2.60	0.009	.3239695	1.436171
P2	1.317076	.6979827	1.89	0.059	.1689962	2.465155
P4	-.913828	.3774503	-2.42	0.015	-1.534679	-.2929775
IL2	-3.648407	1.557556	-2.34	0.019	-6.210358	-1.086455
_cons	5.142442	.7840198	6.56	0.000	3.852844	6.43204

Note: 0 failures and 1 success completely determined.

.

Final model - odds ratios reported

```
Logistic regression                               Number of obs   =        331
                                                  LR chi2(7)      =     114.86
                                                  Prob > chi2     =     0.0000
Log likelihood = -159.88618                       Pseudo R2       =     0.2643
```

Distress	Odds Ratio	Std. Err.	z	P>|z|	[90% Conf. Interval]	
Sect_Information_Technology	3.97851	1.684367	3.26	0.001	1.982843	7.982751
Key_Changes_Other	.4065064	.1457224	-2.51	0.012	.2254189	.7330682
RS	2.595698	.3056242	8.10	0.000	2.138675	3.150386
P1	2.411069	.8151466	2.60	0.009	1.382605	4.204564
P2	3.73249	2.605214	1.89	0.059	1.184116	11.76531
P4	.4009863	.1513524	-2.42	0.015	.2155249	.7460389
IL2	.0260326	.0405472	-2.34	0.019	.0020085	.3374105
_cons	171.1331	134.1718	6.56	0.000	47.12689	621.4401

Note: 0 failures and 1 success completely determined.

Diagnostics for the final model

- *Goodness-of-fit test*

Logistic model for Distress, goodness-of-fit test

```
       number of observations =       331
 number of covariate patterns =       331
            Pearson chi2(323) =       320.12
                  Prob > chi2 =         0.5347
```

- *Classification table*

Logistic model for Distress

Classified	True D	True ~D	Total
+	79	29	108
-	42	181	223
Total	121	210	331

Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0

Sensitivity	Pr(+| D)	65.29%
Specificity	Pr(-|~D)	86.19%
Positive predictive value	Pr(D| +)	73.15%
Negative predictive value	Pr(~D| -)	81.17%
False + rate for true ~D	Pr(+|~D)	13.81%
False - rate for true D	Pr(-| D)	34.71%
False + rate for classified +	Pr(~D| +)	26.85%
False - rate for classified -	Pr(D| -)	18.83%
Correctly classified		78.55%

- *Specification error – linktest*

Logistic regression		Number of obs	=	331
		LR chi2(2)	=	114.90
		Prob > chi2	=	0.0000
Log likelihood = -159.86957		Pseudo R2	=	0.2644

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.9902137	.1297688	7.63	0.000	.7358715	1.244556
_hatsq	-.0132175	.072199	-0.18	0.855	-.154725	.12829
_cons	.0158532	.1720688	0.09	0.927	-.3213953	.3531018

- *Variance Inflation Factor analysis*

Variable	VIF	1/VIF
RS	1.15	0.869568
Key_Change~r	1.15	0.872238
P2	1.12	0.889194
P4	1.12	0.893526
Sect_Infor~y	1.08	0.925934
P1	1.08	0.928108
IL2	1.06	0.939518
Mean VIF	1.11	

5. Model T-5

Initial model

Logistic regression		Number of obs	=	213
		LR chi2(33)	=	100.13
		Prob > chi2	=	0.0000
Log likelihood = -93.603368		Pseudo R2	=	0.3485

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Consumer_Discretionary	.860053	1.463472	0.59	0.557	-1.547145	3.267251
Sect_Consumer_Staples	.4098115	1.479718	0.28	0.782	-2.024109	2.843732
Sect_Energy	-.582334	1.550512	-0.38	0.707	-3.132699	1.968031
Sect_Healthcare	2.391748	1.742374	1.37	0.170	-.4742019	5.257698
Sect_Industrials	1.152853	1.387928	0.83	0.406	-1.130085	3.435792
Sect_Information_Technology	2.673124	1.658894	1.61	0.107	-.0555134	5.401761
Sect_Materials	.3840638	1.480523	0.26	0.795	-2.05118	2.819307
Sect_Telecommunication_Services	0	(omitted)				
Sweden	-.3373012	.5833399	-0.58	0.563	-1.29681	.6222076
Norway	-.8488843	.7119807	-1.19	0.233	-2.019988	.3222198
Denmark	-1.094615	.6316481	-1.73	0.083	-2.133584	-.0556466
Finland	0	(omitted)				
KEY_Sell_Divest	0	(omitted)				
Key_CEO	.0810995	1.07239	0.08	0.940	-1.682825	1.845024
Key_CFO	.3612659	1.003981	0.36	0.719	-1.290135	2.012667
Key_Changes_Other	-.0810308	.5527859	-0.15	0.883	-.9902827	.8282212
Key_Corporate_Guidance_Lowered	2.652158	1.662558	1.60	0.111	-.082506	5.386822
Age	-.0020037	.0031641	-0.63	0.527	-.0072082	.0032007
MF1	-.0594035	.037117	-1.60	0.110	-.1204555	.0016485
MF2	.0851957	.3975031	0.21	0.830	-.5686387	.7390301
RS	.9227687	.1693696	5.45	0.000	.6441805	1.201357
P1	.5645186	.5899278	0.96	0.339	-.4058262	1.534863
P2	-.2077881	1.105203	-0.19	0.851	-2.025686	1.61011
P3	16.83287	5.904271	2.85	0.004	7.121212	26.54454
P4	2.415825	1.718965	1.41	0.160	-.4116199	5.24327
L1	-.1872371	.3612528	-0.52	0.604	-.7814451	.4069708
L2	-1.854642	2.452127	-0.76	0.449	-5.888032	2.178749
L3	-.0017204	.0032991	-0.52	0.602	-.0071469	.0037061
CC1	-.1401274	.0578777	-2.42	0.015	-.2353276	-.0449271
CC2	.068786	.0331035	2.08	0.038	.0143355	.1232364
IL1	.229107	.2036329	1.13	0.261	-.1058392	.5640533
IL2	-2.910397	1.975385	-1.47	0.141	-6.159615	.3388215
FG1	.0324927	.056119	0.58	0.563	-.0598149	.1248003
FG2	-.3431605	7.323841	-0.05	0.963	-12.38981	11.70349
FG3	.6045653	.548565	1.10	0.270	-.2977438	1.506874
FG4	-1.386452	1.916429	-0.72	0.469	-4.538696	1.765793
_cons	4.799733	1.786871	2.69	0.007	1.860592	7.738875

Note: 1 failure and 1 success completely determined.

.

Final model – coefficients reported

```
Logistic regression                               Number of obs   =        219
                                                  LR chi2(6)      =      63.76
                                                  Prob > chi2     =     0.0000
Log likelihood = -114.83606                       Pseudo R2       =     0.2173
```

Distress	Coef.	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Industrials	.6717402	.346186	1.94	0.052	.102315	1.241165
Sect_Information_Technology	1.536426	.6891738	2.23	0.026	.4028363	2.670017
RS	.7793414	.1212595	6.43	0.000	.5798872	.9787956
P3	9.010291	4.344241	2.07	0.038	1.86465	16.15593
CC1	-.0789685	.040843	-1.93	0.053	-.1461493	-.0117878
CC2	.0476014	.0273696	1.74	0.082	.0025823	.0926204
_cons	3.494441	.7253385	4.82	0.000	2.301366	4.687517

Final model - odds ratios reported

```
Logistic regression                               Number of obs   =        219
                                                  LR chi2(6)      =      63.76
                                                  Prob > chi2     =     0.0000
Log likelihood = -114.83606                       Pseudo R2       =     0.2173
```

Distress	Odds Ratio	Std. Err.	z	P>|z|	[90% Conf.	Interval]
Sect_Industrials	1.957641	.6777079	1.94	0.052	1.107732	3.459643
Sect_Information_Technology	4.647951	3.203246	2.23	0.026	1.496062	14.44021
RS	2.180036	.2643501	6.43	0.000	1.785837	2.661249
P3	8186.907	35565.9	2.07	0.038	6.453679	1.04e+07
CC1	.924069	.0377417	-1.93	0.053	.8640287	.9882814
CC2	1.048753	.028704	1.74	0.082	1.002586	1.097045
_cons	32.93188	23.88676	4.82	0.000	9.987812	108.5832

Diagnostics for the final model

- *Goodness-of-fit test*

```
Logistic model for Distress, goodness-of-fit test

       number of observations =       219
 number of covariate patterns =       219
             Pearson chi2(212) =       205.96
                   Prob > chi2 =         0.6040
```

- *Classification table*

Logistic model for Distress

Classified	True D	True ~D	Total
+	48	23	71
-	38	110	148
Total	86	133	219

```
Classified + if predicted Pr(D) >= .5
True D defined as Distress != 0
```

Sensitivity	Pr(+| D)	55.81%
Specificity	Pr(-|~D)	82.71%
Positive predictive value	Pr(D| +)	67.61%
Negative predictive value	Pr(~D| -)	74.32%
False + rate for true ~D	Pr(+|~D)	17.29%
False - rate for true D	Pr(-| D)	44.19%
False + rate for classified +	Pr(~D| +)	32.39%
False - rate for classified -	Pr(D| -)	25.68%
Correctly classified		72.15%

- *Specification error – linktest*

```
Logistic regression                               Number of obs   =        219
                                                  LR chi2(2)      =      64.78
                                                  Prob > chi2     =     0.0000
Log likelihood = -114.32714                       Pseudo R2       =     0.2208
```

Distress	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.9565302	.1543989	6.20	0.000	.653914	1.259146
_hatsq	-.1039557	.1028722	-1.01	0.312	-.3055815	.0976702
_cons	.1124639	.2032394	0.55	0.580	-.2858779	.5108058

- *Variance Inflation Factor analysis*

Variable	VIF	1/VIF
P3	2.08	0.479639
CC1	1.63	0.613239
CC2	1.42	0.703389
Sect_Infor~y	1.14	0.880525
RS	1.07	0.935689
Sect_Indus~s	1.07	0.935845
Mean VIF	1.40	