The Usefulness of Statistical Financial Distress Prediction Models for Supplier Risk Management

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Executive Summary

Over the past few years supply chains have become more global and complex. This made supply chains particularly sensitive to disruptions. A high impact disruption is a defaulting critical supplier. Defaulting suppliers can cause the production to stop resulting in lost sales, high switching costs, high legal fees and damages to the buyer's reputation. In order to avoid and mitigate such events supply managers have to accurately predict financial distress of their suppliers. However this is very difficult in practice. Firm performance is influenced by various internal and external factors. This makes the detection of an early warning signal complicated. So far supply managers have mainly relied on qualitative tools. While this might work sufficiently well for small buyers this is not a very practical approach for buyers with numerous suppliers. Usually those buyers do not have the time and resources to investigate all their suppliers in detail. Thus, a tool is needed that predicts suppliers' financial distress and helps prioritize suppliers for a more detailed assessment in a second step.

This thesis investigates the opportunity of employing a statistical tool to predict suppliers' financial distress. A tool is suggested as a first of a several step screening procedure that narrows down the list of critical suppliers to those that have an elevated probability of experiencing financial distress. Only critical suppliers in the high-risk category are then further evaluated in later screening steps.

A logit analysis based on accounting variables shows a high suitability for the decision context of supply managers. The method is promising due to its high predictive accuracy, ease of application and straightforwardness of the evaluation. The developed models produce accurate, reliable and valid results that are stable for different timeframes and across industries. Thus, logit models show high potential to advance the financial distress prediction of suppliers. Employing statistical tools, like the one developed in this study, is expected to make the supplier risk management process more efficient and effective for buyers with numerous suppliers.

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Abbreviations

AIE	Artificial intelligence expert system
CUSUM	Cumulative sum
DEA	Data envelopment analysis
EBITDA	Earnings before interest, taxes, depreciation and amortization
EBIT	Earnings before interest and taxes
FD	Financially distressed
FIFO	First in, first out
LA	Logit analysis
LPM	Linear probability model
MDA	Multiple discriminant analysis
NN	Neural networks
OLS	Ordinary least square
PA	Probit analysis
SEC	Securities and Exchange Commission
SIC	Standard industry classification
SME	Small and medium sized enterprises

1 Introduction

This paper evaluates whether employing statistical financial distress prediction models can advance supplier risk management. This chapter describes the motivation for this topic and outlines its analysis.

1.1 Motivation

In the past few years many companies have implemented strategies that make their supply chains more lean resulting in fewer suppliers, outsourced manufacturing, lower levels of inventory and the elimination of duplicate assets (Christopher & Peck 2004; Fisher 1997; Hult et al. 2004; Lee 2004). These initiatives not only managed to lower costs and increase asset utilization, they also increased supply chain complexity and the degree of dependence among supply chain entities (Narasimhan & Talluri 2009; Lin et al. 2006). Consequently the supply chain vulnerability to unexpected disruptions is much higher than it used to be (Kraljic 1983; Treleven & Bergman Schweikhart 1988; Sheffi & Rice 2005). With fewer suppliers, less in-house production and lower inventory levels it is much more difficult for buying organizations[1] to compensate, when a critical supplier goes bankrupt. In such cases the supply chain is interrupted resulting in large foregone profits and high adjustment costs.

The strong dependence on suppliers exposes buyers to operational, environmental, ethical, social, labor-related and financial risks (PriceWaterhouseCoopers 2009).
Nonetheless not all risks are formally acknowledged and accounted for in strategic supply chain decision-making. Historically the industry focused its supplier risk management on operational aspects such as quality and costs. The analysis of the financial stability of suppliers has been neglected (PriceWaterhouseCoopers 2009; Finley 2009).

The economic crisis in the year 2008 and a slow subsequent recovery increased the financial distress risk of suppliers resulting in many disruptions of the supply chains. For example Edscha, a German manufacturer of sunroofs, door hinges and other car parts, filed for bankruptcy at the beginning of 2009. This forced BMW to make undisclosed payments to Edscha to enable continued operations of their supplier so that the BMW could do their planned product launch (Bode & Wagner 2012). Such disruptions cost the buyer a lot of money due to legal fees, damages to the reputation and production

[1] In this document the term ‘buyer’ specifies a company, which is buying services and manufacturing parts from suppliers for their product production process.

delays. Experiences like the described case prompted companies to take steps to avoid, to the extent possible, future unexpected supply chain failures.
Since then supplier risk management programs and particularly the financial viability of suppliers receives more attention to promote the longevity and viability of their business relationships (Finley 2009; Bode et al. 2014).

1.2 Problem Statement

Early and accurate financial distress detection is crucial for buying organizations to enable preventive measures and an efficient allocation of their resources. In practice this is very difficult. First, there is no clearly defined event or sign that indicates a supplier will experience financial problems in the near future. Predicting a company's performance is very difficult due to the complexity of business operations and numerous internal and external factors influencing it. Nevertheless, a supplier's crisis does not occur suddenly. It is a gradual process. If its signals are recognized, amplified and responded to, then corporate failure can be prevented and financial losses avoided (Jüttner 2005; Bode & Wagner 2012). Second, buyers with many suppliers usually do not have the resources to investigate the financial viability of every supplier. So those suppliers that are the most risky candidates need to be filtered out for a more detailed assessment. How to filter out the critical suppliers with an elevated risk of financial distress is a big challenge in practice. The supply chain literature focuses on qualitative models of supplier risk management so far. This conceptual approach also reflects in the methods used in the industry. Qualitative methods are the most frequently used tools to assess suppliers' financial distress (Jüttner 2005). However, qualitative tools make comparisons and thus a filtering process difficult.

It seems many strategic sourcing departments are unaware of the statistical tools available to predict the financial distress likelihood of suppliers and prioritize suppliers based on their risk level. This thesis therefore investigates the potential of predictive models to help supply managers prevent unexpected supplier defaults.

1.3 Research Question

Predictive models are not widely used by supply managers (Jüttner 2005). Therefore this thesis investigates the following research question: *"How can predictive models advance the prevention of unexpected supplier bankruptcy?"*

The research question will be answered by investigating the following aspects:
First, it is assessed which statistical method is of practical value to predict financial distress of suppliers and filter out suppliers with a particularly high risk.

Second, the amount of data needed for the selected method is a barrier in practice. In order for predictive models to have a strong business case the costs of collecting the necessary data has to be minimized and the models applicability maximized (Hamer 1983). Casey (1980) showed that a greater amount of accounting information does not necessarily improve predictive power. Furthermore, the choice of which information to use turned out to be more important than its processing to derive accurate models (Abdel-Khalik & El-Sheshai 1980). Thus, the second aspect that is investigated is how the quantity of variables impacts the predictive accuracy of the models. If less complex models perform equally well, then simpler models could be used lowering the barrier for using corporate financial distress prediction models in supplier risk management.

Third, a crucial issue that has not received a lot of attention yet is to assess the stability of statistical models over time and across industries. Supply managers will most likely prefer to keep the number of times a statistical model needs to be rerun as low as possible. In order to determine whether this is possible temporal and industry-specific effects need to be assessed. This is important to ensure models do not loose their classification accuracy over time or when applied to different industries.

Together these three aspects answer how predictive models can advance the prevention of unexpected supplier bankruptcy.

1.4 Scientific Approach

This thesis investigates the practical issue of how supply managers can assess their supplier's financial viability with statistical tools. The aim of the analysis is to develop a practical and parsimonious monitoring solution. The tool should ease classifying suppliers into different financial risk categories that enable effective countermeasure. That way stability in the supply chain can be maintained. Thus, practical considerations and implications are a core element of this solution-oriented investigation.

A functionalist approach is used that builds on the ontological view, that reality is external and exists independent from an individual's perception of it (Burrell & Morgan 1980). Hence, the social world is composed of relatively concrete empirical relationships, which can be identified, studied and measured with natural science techniques. In line with the sociological positivist perspective insights that explain and predict financial distress are researched by searching for relationships and patterns in business behavior. Rational human actions are assumed to be the driver of this business behavior.

First the relationship between business' behavior and financial distress is explored inductively based on findings of previous empirical studies and then tested deductively via econometric methods with a dataset. This way the empirical findings of previous studies can be used as basis for an econometric model that caters to supply managers' needs.

The analysis is designed to be objective and nomothetic. An objective risk assessment can best be provided via a quantitative approach that enables a value-free assessment and comparison. This is crucial from a practical perspective to filter out the suppliers with the greatest risk exposure and effectively use the limited resources of the buyer. The combination of the quantitative approach and a representative dataset contribute to generalizable results.
Alternatively a qualitative approach could have been chosen analyzing individual cases of supplier's financial distress, which could have given insights into the decision processes of the management. However, the practical advantages of generalizable results and objective risk comparisons, that are possible with quantitative analysis tools, are expected to outweigh the additional insights possible with a qualitative case study approach.

1.5 Limitations

This thesis only looks at buyers who have so many critical suppliers, that assessing the financial viability of each of them individually is not feasible. Smaller buyers are also expected to benefit from an accurate financial distress prediction tool, but they do not face the problem of finding a filtering mechanism to the same extent. Thus, the analysis takes the perspective of buyers with many suppliers. In order to avoid distortions in the statistical analysis due to geographic variations only companies that have their headquarter in the USA are included in the dataset. This group of companies is further narrowed down to public firms, as their financial information is easily accessible for supply managers.

A core element of this study is the usefulness of statistical prediction methods. Artificial intelligence expert systems and theoretical models are not investigated due their difficult application in practice, which is expected to be too complicated for supply managers with little statistical knowledge. Time series methods are also not considered, as they require much larger amounts of data than single period models. The data acquisition for time series methods is therefore assumed to be too time-consuming for a practical tool.

This study investigates the potential of statistical tools to make supplier risk management more efficient and effective. Barriers to using statistical tools in practice such as implementation issues, organizational barriers (e.g. management engagement, company culture) and lack of resource (time, expertise and funds) are not assessed in detail. Such barriers are very company-specific and a general evaluation is therefore not possible. The study solely focuses on filtering out those suppliers that are most at risk to experience financial distress. No interpretations and recommendations are made as to what actions should be taken to avoid or mitigate a supplier's financial distress. A general catalogue of potential reactions is discussed but as the selection of the most suitable option depends on numerous supplier- and buyer-specific aspects no general conclusions can be formed.

1.6 Contributions

Previous accounting research focused on developing the most accurate corporate bankruptcy prediction models. A key aspect for future corporate failure prediction is to consider the applicability of models to a concrete decision context of businesses. Taking the perspective of the user (buyer) it needs to be understood what criterion event is of most relevance to his/her decision context and how it is possible to build models, which are more applicable to that (Keasey & Watson 1991). Usually researchers assume the position of a financial analyst that assesses a corporation's performance relative to its peers. However, the analysis of a supply chain manager differs from a financial analyst.

The supply chain manager needs the supplier to have sufficient financial resources so that it can stay viable in the future, but it does not matter to him how profitable the supplier is. Besides, unlike financial institutions, buying firms are not interested in predicting the likelihood of a supplier's default. They rather focus on financial distress, which normally precedes a supplier's default by some time, because they are interested in uninterrupted supply chains and hence focus on an early intervention (Hertzel et al. 2008; Bode & Wagner 2012). This thesis will apply the research findings of corporate bankruptcy prediction models to the financial distress prediction of suppliers. Thereby the bankruptcy prediction literature will be advanced towards concrete practical applications (besides the financial service sector). In addition, the supply chain research field benefits from the statistical findings of the accounting and finance literature that can advance the currently mainly qualitative supplier risk management literature.

In previous studies non-representative samples, purely statistical variable selection and little assessment of model stability have been frequent. Therefore particular attention is paid to representative data selection, qualitative variable selection and model stability over time and across industries. Furthermore, the existing literature does not provide an investigation of how the quantity of explanatory variables used in corporate bankruptcy prediction models impacts predictive performance (Fejér-király 2015; Yazdipour & Constand 2011). These issues are therefore further investigated in this study.

1.7 Structure of Thesis

First the decision context of a supply manager is described to provide a deeper understanding of the relevance of supplier risk management for buying organizations and the role of financial viability assessments. The general four-step process of supplier risk management is elaborated and fundamental business considerations related to it are discussed. Second, in order to determine whether suppliers are at risk to experience financial distress a financial distress event is defined and located in the corporate failure process. In order to be able to predict financial distress various causes and symptoms of corporate failure need to be understood. Previous bankruptcy prediction research is used as a foundation for this. Later the findings of this investigation form the basis of the variable selection for the models that are used to predict suppliers' financial distress.

Selecting a suitable statistical tool that supply managers can utilize to identify suppliers with a high financial distress risk is a core element of the analysis. Therefore a brief overview of the historic development of corporate failure prediction models is provided to give the reader a sense of where my chosen topic fits into the line of research. Afterwards the most popular statistical models are assessed in more detail for their statistical and practical usefulness. This analysis is the basis for the selection of a statistical method that is most suitable for the decision context of supply managers.

After the theoretical groundwork has been laid a dataset is selected that supply managers are able to replicate in practice. Then a statistical method and suitable variables for the suppliers' financial distress prediction tool are picked. The findings are afterwards provided and discussed to draw conclusions on the usefulness of statistical screening tools to predict suppliers' financial distress and filter out those suppliers that have a particularly high risk. Afterwards recommendations for future research are outlined.

2 Literature Review

This chapter presents the literature review for the supplier risk management process, the corporate failure research and predictive modeling.

2.1 Supplier Risk Management Process

Supplier risk management is a continuous process of identifying, assessing and controlling threats to corporations' capital and earnings that have their source in the supply chain (Bode & Wagner 2012). The source is mainly related to a supplier's operational performance and financial distress (Carter & Giunipero 2010). These two are often linked but do not necessarily have a cause and effect relationship. Since most corporations have good systems in place to assess a supplier's operational performance this thesis focuses on the financial distress aspect of supplier risk management.

Practically the supply manager identifies potential negative events, assesses their likelihood of happening, undertakes preventive measures to avoid their occurrence, estimates their impact on the buyer's performance and makes contingency plans for the case that a supplier actually defaults. A supplier's default can have a significant impact on operating performance causing foregone revenues as well as increased expenses due to search and switching costs which negatively affect profits.

Buyers use financial distress symptoms as a warning signal that a supplier might go bankrupt. Financial distress can for instance arise due to reduced cash flow, broken lending covenants and more limited access to credit (Deloitte 2011). The range of actions available to a buyer to help the supplier and avoid potential losses are greatly reduced and often more costly once a supplier has filed for bankruptcy. Thus, with an early warning system the buyers can anticipate and manage their risks much more efficiently (Carter & Giunipero 2010; Bode & Wagner 2012).

Generally, researchers know surprisingly little about what firms practically do to avoid supply chain disruptions and even less about how buyers deal with supplier's financial distress, because the supply chain literature focuses on conceptual frameworks and risk construct developments (Bode et al. 2014). A survey of 138 supply managers done by Jüttner showed that there is a focus on "softer" tools like brainstorming, while scenario planning and the Six Sigma method are at the bottom of the list of tools used (Jüttner 2005). The analysis does not reveal whether less formal processes receive increasing attention because of a lack of understanding of the statistical tools, insufficient actionable insights of quantitative methods or other reasons. Nevertheless, the study highlights the hesitance of supply managers to using statistical tools.

Since corporations face a trade-off between risk reduction and costs for risk management it is neither efficient nor necessary to continuously analyze all suppliers. Instead an analysis is only done for critical suppliers. Critical suppliers are those "that the buying firm identifies as having the potential to have a significant impact on the buying firm's ability to meet its goals" (Carter & Giunipero 2010). Whether this is the case depends on different factors including whether the supplier under consideration is a strategic supplier, single or sole supplier, a supplier with parts/services in several product lines or programs, a supplier with long qualification times and the percentage of business done with the supplier (Carter & Giunipero 2010). The process for managing financial distress risk of critical suppliers has four steps: screening, interpreting, acting and learning (Carter & Giunipero 2010).

2.1.1 Screening

First, the suppliers are scanned for warning signals. These signals are related to their *probability to default*, the *buying firm's exposure* (at default) and *suppliers' default dependencies* (Wagner et al. 2009). Delayed or missed supplier deliveries happen frequently but they normally have relatively little impact on the operations of a buyer. Supplier default is a more unusual event but it can have a significant impact on the buyer's business resulting in production delays, damage to the buyer's reputation and high switching costs. Buyer's exposure measures the potential impact in terms of foregone profits and incurred costs when a supplier defaults. The extent of the buying firm's exposure depends on the direct and indirect costs of a supply chain disruption. Indirect costs include ripple effects in the supply chain as a consequence of a supplier's default. Suppliers' default dependence describes effects of a supplier's default on other suppliers. Buyer's exposure and supplier's default dependencies are very company-specific and need to be assessed on a case-by-case basis. Therefore, this analysis focuses on the probability to default going forward.

In order to scan critical suppliers for their probability of financial distress appropriate data needs to be collected. Most corporations have around 20-40 known critical suppliers (Ernst&Young 2014), which makes a qualitative assessment of each not feasible. Thus, a systematic early detection system is needed that cost-effectively prioritizes which suppliers are most likely to encounter financial distress (Ernst&Young 2014; Wagner & Johnson 2004; Bode & Wagner 2012). Quantifiable measures are easy to allow comparisons across entities. The most popular quantitative methods to evaluate the financial viability of a supplier are Ohlson's O-score, Altman's Z-score and Dun & Bradstreet's stress score (Bode & Wagner 2012; Altman 1968; Ohlson 1980). Accounting data is accessible for free via the

Securities and Exchange Commission (SEC) for publicly traded firms in the USA. Privately held companies are not required to publicly report their financial statements in the United States. Therefore obtaining data for those suppliers can prove to be challenging. Possibilities to get access to this data include asking for it or requiring it as a prerequisite for doing business. More recently third parties[2] offer to analyze the supplier's financial data based on the buyer's scoring models (Carter & Giunipero 2010). This way the buyer gets the needed information and the supplier can protect its financial reports, which if disclosed could adversely affect the supplier's negotiation power with the buyer.

Generally the scope (breadth and depth) and intensity (frequency and intrusiveness) of the analysis depends on the trade-off between information processing needs to get a detailed picture of the supplier's situation and the time and expenses required for it (Wagner & Johnson 2004). Information overload and an inefficient use of resources need to be avoided. Hence, a supply manager should ask himself the following questions: How accurate does the scanning have to be? How high are the costs of making an interpretation error that gathering more data is warranted to avoid such an error?
The extensiveness of the financial distress analysis correlates most with the industry of the buyer and less with the size of the buyer's organization (Bode & Wagner 2012). Business sectors like aerospace, health care, energy and automotive that strongly depend on their suppliers do especially extensive analysis (Deloitte 2011; Wagner et al. 2009; PriceWaterhouseCoopers 2009). Therefore, the business sector is more important than the size to determine the scope and intensity of the analysis. Depending on the urgency and reliability needed, the calculated score or rating information is complemented with additional information. This could for instance be personal interviews with the management team of a supplier (Bode & Wagner 2012).

2.1.2 Interpreting

In the second step of the supplier risk management process the collected and scanned information is analyzed and interpreted. Based on all available information a watchlist is created for critical suppliers that have an elevated probability of experiencing financial distress (Carter & Giunipero 2010). Depending on the level of risk different actions are then considered.

[2] For a detailed overview of third parties and their offers please see (Carter & Giunipero 2010)

2.1.3 Acting

In the third step action is taken. Depending on the severity of the financial distress problem actions range from more frequent or more detailed assessments to adjustments in the purchasing process. A buyer can for instance improve a supplier's liquidity by paying early, taking early deliveries, buying raw material for the supplier, helping the supplier fix his problems, investing in the supplier's business, facilitating credit, buying the supplier or deciding to move the business to another supplier (Bode et al. 2011; Tomlin 2006; Carter & Giunipero 2010).

Bode et al. (2014) identified four archetypes of supply managers. The *reactor* is rather passive and waits until a clear signal indicates the financial distress of a supplier. *Guards* are more proactive; they scan the supplier base vigorously for warning signals so that they can implement countermeasures early on. *Observers* are in between the two, they perform qualitative but not so sophisticated quantitative analyses (Bode & Wagner 2012). Which archetype is most appropriate depends on the decision context.

The choice of supply manager guides the strategy selection. Bode & Wagner (2012) describe four generic strategies buyers use to react to financial distress of their suppliers: avoidance, control, cooperation and flexibility. The most common strategies include *buffering, bridging* and *substitution*.
Buffering is an uncooperative approach that aims to reduce the buyer's resource dependence and increases its autonomy (Bode et al. 2014). This is usually done through diversifying the supplier base or building slack (inventory, flexibility or time buffer).
The buffer makes the supply chain less sensitive to temporary supply disruptions. Bridging is a more cooperative approach that targets managing the supplier relationship more actively. This includes forming links with influential people in the supplier's organization for a vertical integration.
Substitution is a response mainly chosen by organizations that produce standard products and services and have low switching barriers. A more cooperative approach is chosen when a higher degree of dependency and trust exists. Buyers with very complex products or services only switch supplier if it is completely unavoidable, because finding a suitable alternative is very complicated and costly then (Choi et al. 2002; Doney & Cannon 1997). If the supplier is already bankrupt then it is too late for preventive measures and crisis management needs to be done. Implementing a contingency plan limits the reputational damage and financial loss (Martha & Subbakrishna 2002). This includes quick and honest communication with stakeholders, backup operational plans and an immediate search for alternative suppliers to avoid prolonging supply chain interruptions (PriceWaterhouseCoopers 2009).

2.1.4 Learning

The last step involves a learning process. Supply chain crisis are a valuable source of organizational learning. It exposes flaws and vulnerabilities in the processes that help improve the buyer' supply chain in the long-run (PriceWaterhouseCoopers 2009).

The return on investment of supplier risk management is a lower loss. A risk-based supply chain management approach could thereby also lead to a competitive advantage, as companies do not only compete for customers but also for capable suppliers (Bode & Wagner 2012). Furthermore, after action is taken a learning process should take place (Sitkin 1992). Documentation systems need to translate the findings into explicit knowledge, so that the buyer does not repeat errors (Hult et al. 2004). Problems in the supplier risk management process can be eliminated that way.

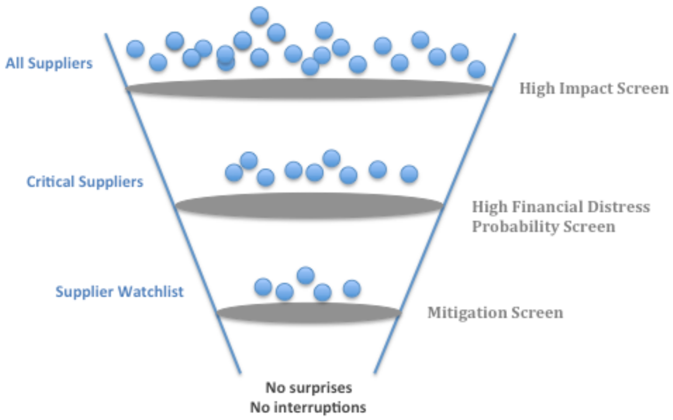

Figure 1 Screening suppliers based on Carter & Giunipero (2010)

The statistical tool that is considered in this study would be used in the second screening stage of Figure 1. It is expected to ease the process of filtering out suppliers with an elevated financial distress risk. Next the concept of financial distress and its role in the corporate failure process is discussed.

2.2 Corporate Failure

Previous accounting literature used varying definitions of corporate failure. First, those different definitions are briefly outlined and then the definition used in this thesis is specified.

Theory related to the causes of corporate default is limited and mainly built on case studies and expert interviews that date back to the 1980's and 1990's. The literature review focuses on the main internal and external factors causing corporate failure. Previous literature frequently mixed causes and symptoms. This is problematic, as symptoms do not have a direct causal relationship with financial distress. Hence, conclusions that can be drawn from the analysis of causes are different from those of symptoms. Therefore this thesis attempts a clear distinction between causes and symptoms. Not all the factors that will be discussed in this section are useful for predictive purposes. Only visible, measurable, objective, reliable, available and accessible factors are useful for predictive modeling. Nevertheless it is important to have a comprehensive understanding of all the major factors to build well-founded models and assess their limitations.

2.2.1 Corporate Failure Process

So far no unified definition of corporate failure exists. The terms "default", "insolvency", "liquidation", "bankruptcy" and "failure" are frequently used. Sometimes they refer to the same concept but they are not all interchangeable as they describe different stages in the corporate failure process.

Financially distressed → *Financial default* → *Insolvency* → *Legal bankruptcy*

A firm is considered *financially distressed* when it has problems to meet its debt payments. Once a firm cannot pay the liabilities and debt payments that are due it experiences *financial default*. If there is no way to find new liquidity then the *insolvency* process is initiated that aims to cover all outstanding claims either by *reorganizing* the company or *liquidating* its assets. *Legal bankruptcy* occurs when a company files for bankruptcy, which is highly dependent on national law and therefore the prerequisites vary by country. Most studies understand bankruptcy as "ultimate failure" (Bellovary et al. 2007; Bode & Wagner 2012). Practically, most definitions focus on bond default or bankruptcy as those dates are publicly known, which eases the application of statistical models. A detailed overview of these terms and their exact definitions can be found in Altman (1983) and Argenti (1976).

Balcaen and Ooghe (2006) point out that the time of the legal failure does not necessarily reflect the 'real' failure event. Some companies that show signs of a failing company do not change their legal status at all, delay changing their status, merge with another company or initiate reorganization. Seemingly healthy companies might file for bankruptcy for strategic reasons (e.g. to eliminate rising debt) or because they cannot meet their payments. Bankruptcy is a process, the legal definition does not account for the interim stages and does not state a clear cut-off rule (Argenti 1976; Laitinen 1993).

Supply managers are much more interested in detecting financial distress in its early stages to prevent costly supply chain disruptions and changes (Blome & Schoenherr 2011; Finley 2009; Wagner et al. 2009). Hence, instead of a legal event an economic turning point is of interest. The increasing interest in early detection to enable preventive measures resulted in papers focusing on financial distress, like Pindado et al. (2008) and Sanz & Ayca (2006). Focusing on financial distress also avoids distortions of the sample through strategic bankruptcies and corporations that experience high levels of financial distress but do not file for bankruptcy (Keasey & Watson 1991; Platt & Platt 2002). Therefore this thesis builds on the findings of bankruptcy prediction research but focuses on financial distress (using the definition stated above) as it is the earliest and most relevant stage in the corporate failure process for supply managers.

2.2.2 Causes of Corporate Failure

There are multiple company-specific, industry-specific and macroeconomic factors that influence corporate performance. These are important to understand in order to identify the source of financial distress. This is not only relevant for an accurate prediction but also to take appropriate countermeasures.

The impact of internal and external factors on firm performance depends on the characteristics of the firm. Two views dominate the corporate failure literature: one deterministic, the other voluntaristic (Mellahi & Wilkinson 2004). The deterministic view believes corporate failure largely results from industry and macroeconomic factors, while the voluntaristic view sees the source more in the company-specific factors (Heracleous & Werres 2015). Both perspectives will be discussed in this chapter.

First a brief overview is given of the firm-specific characteristics that have been analyzed in the literature. Then the main industry-specific and macroeconomic factors are outlined that are expected to influence firm performance.

2.2.2.1 Company-specific Factors

The corporate failure process differs depending on firm-specific characteristics. Particularly the role of a *firm's age, size, industry, corporate governance* and *leadership team* have shown to be of importance (Ooghe & De Prijcker 2006).

Young firms have to build external legitimacy and relationships with stakeholders, which makes them more vulnerable than more established companies. This is called the "liability of newness" (Freeman et al. 1983; Sutton 1987).

Halliday, Powell, and Granfors (1987) find that size may affect survival chances. Larger firms are more likely to have scale-effects, more negotiation power with their business partners and are more likely to benefit from their experience. This however is a comparatively minor issue compared to being new in the market.

Platt, Platt and Pedersen (1994) show that the probability of failure varies with industry. So despite a similar financial profile companies will have a different probability of default due to industry-specific risk factors that can play a dominant role in a very volatile industry.

Greening and Johnson (1996) find that leadership team characteristics such as functional heterogeneity of the board of directors and the top management team, their experience and organizational tenure are good proxies for decision-making quality in a corporation, which in turn determines firm performance. Daily and Dalton's (1995) findings support the relevance of governance structures as significant difference that can be identified between the governance systems of failing and non-failing firms. The managerial focus of failing firms differs from their healthy competitors as they deny crisis and focus on the company's internal environment, while successful firms pay equal attention to the external and internal environment (D'Aveni & McMillan 1990).

2.2.2.1.1 Management Team

According to Altman & Hotchkiss (2011) the primary cause of corporate failures is bad management performance. A poor management team does not sufficiently take changes in demand, supply and macro-economic factors into account and lacks an overview of the company's financial situation. This could be due to lack of management experience, education, motivation, social skills or leadership quality (Lussier 1996; Balcaen & Ooghe 2006). A high degree of turnover in a management team can be an indicator of unresolvable conflicts. Short retention periods make a thorough understanding of the business difficult (Gilson 1989; Barniv et al. 2002). Thus, management turnover can be used as a proxy for the ability of the management to give the firm direction. Similarly, Lussier & Halabi (2010) recommend the use of total years of education, difficulty of staffing and existence of a specific strategy as variables to measure the management's capabilities. Park & Han (2002) complement such internal data with information about stakeholder relationships. They assess the price competitive advantage, working conditions and the relationship between labor and capital.

Interestingly John, Lang and Netter (1992) find that managers of financially distressed firms see the cause of negative earnings in bad economic conditions rather than their own performance. Khanna and Poulsen (1995) find supporting evidence. They analyzed the decisions of managers whose companies' undergo insolvency processes under Chapter 11 (in the USA) and compared them to decisions of managers of financially viable companies. Neither group of managers had an adverse effect on value creation of the firm. Thus, they conclude that managers serve as scapegoats, when a firm is in financial distress.

Various academics (including Beer et al. 2005; Miles & Snow 1984; Porter 1996; Powell 1992) oppose this view. They argue that a company's long-term success depends on its ability to ensure internal and external alignment. Poor management teams fail to maintain this alignment of the company's strategy with the environment (Voelpel et al. 2006; Ginsberg & Venkatraman 1985; Porter 1980; Barney 1991). The different views on whether the management is to blame for corporate failure or not highlight that the answer depends on whether a deterministic or voluntaristic perspective is taken.

External events trigger corporate failure but "being normal hazards of any business" (Argenti 1976, p.137), they ought not to cause bankruptcy. A good management team would prepare the company for them. Therefore, the predominant perception in the academic literature is that companies' performance is heavily influenced by the management team's ability to foresee such problems (Ooghe & De Prijcker 2006).

2.2.2.1.2 Board of Directors

The central role of the management team for firm performance raises the question why management teams of companies that go bankrupt perform more poorly than management teams of companies that do not go bankrupt. The stakeholder group with the greatest gain and loss potential, shareholders, should be most motivated to monitor the corporation. They are incentivized to implement governance processes that assess the management's performance and incentivize managers to act in their interest (Coase 1993; Jensen & Meckling 1976; Shleifer & Vishny 1997). In order to overcome agency issues a board of directors is usually created. The board of directors then supervises the executive management team.

The board of directors' tasks include monitoring the executives, hiring/firing them, providing expertise and network and advising on the corporate strategy (Hermalin & Weisbach 2003).

Depending on the life-cycle stage of the corporation different tasks are more important for the board of directors (Filatotchev et al. 2006). For a startup, governance focuses on value creation. The board members mainly provide access to resources such as network and support the strategy development (Hermalin & Weisbach 2003). A more mature corporation on the opposite requires more value protection. Here the board of directors pays more attention to monitoring and control (Hermalin & Weisbach 2003).

Whether a board fulfills its value creation and value protection tasks well depends on balancing several trade-offs: First, the composition of the board of directors is vital aspect to an efficient governance process. An independent board is more likely to critically assess the management performance. At the same time it can also contribute to the board of directors' performance to have a few managers on the board that can provide a more detailed picture of what is happening inside the corporation (Hermalin & Weisbach 2003; Coles et al. 2008). Board members with various backgrounds and experiences are expected to contribute with well-rounded solutions. If the corporation is very complex (due to its size, business model or products) the knowledge of experts might prove to be more relevant than the professional diversity of its board members (Hermalin & Weisbach 2003; Coles et al. 2008).
Second, the larger and more diversified a board is the more topics can be assessed but it will also take more time to find consensus (Coles et al. 2008). This can impair the efficiency of this governance institution and adverse affect the corporate performance.
Third, the members of the board need to be critical but also complement each other in terms of team dynamics to avoid deadlock, as this would inevitably harm the corporation's performance.

Besides the conventional monitoring and control systems the board of directors can use incentives schemes to align the management's interest with those of the shareholders. Their existence and specification can therefore give an indication about the effectiveness of the board. Explicit incentive tools include options, which allow the management to financially benefit from corporate value creation as well as more implicit opportunities such as later career options (Tirole 2001; Goergen & Renneboog 2011). Corporate performance measures that only reflect management's value creation and are difficult to manipulate are practically non-existent, since corporate performance is influenced by various unobservable factors. Nevertheless, the existence of incentive schemes reflects the efforts of the board of directors to increase firm performance. The board of directors is strongly influenced by the largest shareholders and their incentives (Bertrand & Schoar 2006; Bennedsen & Nielsen 2010; Holderness 2003; Laeven & Levine 2008). Hence, there is no one-type-fits all corporate governance system making its impact on firm performance difficult to assess.

2.2.2.2 Industry-specific Factors

While the voluntaristic perspective, constituted by organizational studies, emphasizes internal factors including strategy, resources, capabilities and leadership (Argenti 1976; D'Aveni & McMillan 1990) the deterministic view is grounded in the natural selection model developed by Hannan & Freeman (1977). The deterministic view sees one of the main sources of corporate financial distress in unexpected changes in the environment. It views corporate failure as a natural phenomenon that depends on varying market efficiencies (Klepper 1996).

An increase in *competitive pressure* due to new market entrants and an overcapacity in an industry force established firms to improve their offer for the customer, in order to maintain their previous market position. Particularly the creation of competition among suppliers through bidding processes have pushed high quality suppliers out of the market (Bode & Wagner 2012). Buyers tend to have more negotiation power, because they are relatively few compared to the more numerous suppliers, putting additional pressure on the margins suppliers are able to earn. This misbalance can push suppliers to the verge of financial distress (Bode & Wagner 2012). Asset specificity increases the dependence of a supplier on the buyer. When the supplier invests in assets that can only be utilized for one buyer that buyer can force prices down and the supplier is under very high pressure to assent these demands, as the assets cannot be used for another customer (Buvik & Grønhaug 2000). Opportunistic buyers that abuse this situation will face the long-term consequence of diminishing quality products/services provided by fewer suppliers.

Chronically struggling industries such as textiles, department stores or agriculture battle with adjusting their business models to *changes in customer's interests* (Altman & Hotchkiss 2011). New competition can be the result of innovation but also a political agenda. Deregulation in industries like airlines, financial services, health care and energy forced established players to compete with new market entrants. Lang and Stulz (1992) find that in some industries a bankruptcy announcement by one firm has a significant (positive or negative) impact on the valuation of other firms in that industry, depending on the estimated contagion risk. Jones & Hensher (2004) find that new economy sectors such as biotechnology firms, Internet firms and high technology firms are more prone to financial distress. Platt & Platt (1990) conclude based on their analysis that companies in the construction and financial service sector are more likely to experience corporate bankruptcy. The most vulnerable industry according to their analysis is the retail industry. All these cases illustrate the importance of knowing what competitors, supplier's supplier, customers and new market entrants do, in order to identify profitable market opportunities and position the company respectively.

Chava & Jarrow (2004) tested industry specific effects for various industries. The only model with an industry dummy that had some significance was the financial industry model. Campbell et al. (2008) only find insignificant industry effect variables when modeling corporate default. Thus, the findings are arbitrary and no final conclusions can be made as to whether industry-specific effects actually play a role or not.

2.2.2.3 Macroeconomic Factors

Political changes are highly relevant. Politicians may affect access to resources, markets and financing (Argenti 1976). Denis and Denis (1995) find that especially unexpected regulatory and macroeconomic changes are key causes for financial distress. Observing trends in political programs favoring or limiting business opportunities is vital. Thus, the political environment has a varying impact by industry, which can put companies in financial distress if not anticipated.

Managers need to consider *economic change* irrespective of whether they do business nationally or internationally. Events such as the devaluation of a major currency, financial crisis, economic cycles, interest rate changes, inflation and changes in disposable income affect their business performance directly and indirectly (Argenti 1976; Vassalou & Xing 2004). The modern supply chains become increasingly sensitive to such exogenous shocks, due to the international scope of business activities. The capital structure determines a company's sensitivity to changes in the real interest rates. Companies with high leverage are more exposed to interest rate risk than companies with less gearing (Altman & Hotchkiss 2011). If *real interest rates* rise and the interest payments exceed the cash generated by operating activities, then a default is more likely (Balcaen & Ooghe 2006). Opler and Titman (1994) find that the capital structure is of particular importance in industry downturns. Very leveraged firms loose a substantial market share to their more conservatively financed competitors then. This effect is stronger in concentrated industries and for companies with very specialized products.

A longer foresight is needed to anticipate *changes in society* such as life-style trends, the composition of the population and the attitude towards topics like sustainability and consumer protection (Argenti 1976).

Technological change is disrupting industries. With a shortening of product life cycles companies have to be very attentive and react quickly to new trends and technical advances, in order to avoid that products and processes become outdated (Klepper 1996). The resulting discontinuity and high velocity of change makes suppliers more receptive for financial distress (Balcaen & Ooghe 2006).

2.2.3 Symptoms of Corporate Failure

Symptoms are the financial and non-financial signs that show when a company struggles with one or several of the failure causes discussed above. Corporate failure is a process, identifying where in this process a company is and whether there is still an opportunity for a turnaround requires a detailed assessment. Bode and Wagner (2012) identify symptoms that reflect five different stages of a supplier's financial distress: the strategic, operative, revenue and liquidity crisis (see Figure 2). The signals for each indicate an increasing urgency for countermeasures in order to avoid supplier default.

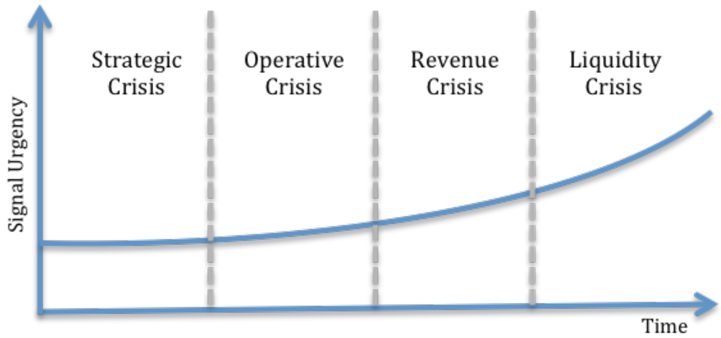

Figure 2 Signal urgency and stages of supplier crisis based on Bode & Wagner (2012)

Issues in the corporate governance system and management team reflect in the *strategic positioning* of the corporation and operational procedures. A disadvantageous market position with an insufficient product/service portfolio is visible in a declining market share, increasing interest of competitors to purchase the organization, dependency on a few key customers and/or suppliers and extraordinarily high or low capital expenditures (Lehmann 2003). These signs of trouble can but do not have to indicate that a corporation is about to experience financial distress. A competitor could simply be interested in a merger or acquisition to benefit from economies of scale and scope, which does not have to have something to do with the financial viability of the corporation. Symptoms have to be assessed with care. Their interpretation is not as clear as that of causes since symptoms are based on correlation not causation. (Bode & Wagner 2012)

A decline in *operating performance* can show in less products being produced, technical problems, higher scrap rates, higher inventory of materials and low capacity utilization (Becchetti & Sierra 2003). Decreasing order numbers and increasing customer complaints reflect issues in the product market fit.

Once a corporation reaches the *revenue crisis* stage the profits start collapsing, while costs are exploding. The management then often responds with cost-cutting programs, short-time work and postponing scheduled investments. Information about such events should therefore be considered a warning signal.

The longer the revenue crisis the more likely it is that a *liquidity crisis* occurs. When the company starts to run out of money it will delay the payments of obligations and try to change the payment terms with customers, get additional liquidity from its shareholders or banks and consider the liquidation of non-essential land and equipment (Hall 1994). Hence, cash flow figures that show shrinking cash reserve, increasing leverage and delayed payments to suppliers are a warning signal.
With the revenue crisis and particularly liquidity crisis changes in the stakeholder behavior will be more apparent. Key employees might choose to leave the corporation (Lussier 1996; Hall 1994), financial investors assume more control, ownership changes and unions get more involved. (Bode & Wagner 2012)

2.3 Background Predictive Modeling

This section gives an overview of the development of predictive modeling. It focuses on its methodological development, its application and recent research trends. The aim of this section is not to provide an exhaustive overview of all publications; instead it provides the reader with an overview of the major findings and positions the thesis in the research field. Financial distress prediction has only recently gained attention. So the majority of the papers are related to bankruptcy prediction.

2.3.1 Methods

The first studies used univariate models to identify the characteristics that distinguish failed and non-failed companies. For this the means of financial ratios of failing and non-failing firms were compared individually (Gepp & Kumar 2012) or in pairs (Fitzpatrick 1932). These studies focused on identifying the explanatory variables that best explain business failure, so that stakeholders could avoid those business partners. Chudson (1945) found industry-, size- and profitability-specific clusters of ratios, which were considered good indicators of bankruptcy.

Building on previous findings Beaver (1966) compared the means of 30 ratios of a sample of 79 failed and 79 non-failed companies in various industries. He was the first to test the predictive abilities of the individual ratios. Business failure was defined as liquidation, empty bank accounts, default on debt and missed preferred stock dividends. He picked his ratios based on the concept that bankruptcy is related to a lack of liquidity to cover the liabilities. Thus, he assessed several cash flow ratios beside the conventional accrued accounting ratios. The variable net income divided by total debt and cash flow divided by total debt had the highest predictive ability with 87 percent accuracy one year before the corporate failure (Beaver 1966). He recommended the combination of multiple ratios in one model to encompass the complexity of business failure, improve the models' predictive accuracy and avoid the problem of conflicting predictions for the individual ratios. This triggered the development of predictive statistical models and the search for the sets of explanatory variables with the highest predictive abilities.

The first multivariate study was published by Altman (1968). His five-factor model for manufacturing firms is called the Z-score. It combines five ratios into a single weighted score for each business. With specific cut-off values a relative measure of probability can be calculated. His analysis was based on a sample of 66 matched firms with financial ratios for 18 years. The model had a high predictive ability one year prior to failure (95 percent accuracy in the estimation sample and 79 percent in the hold-out sample[3]), which outperformed that of Beaver (1966). However the predictive accuracy dropped for two years (72 percent) and three year (48 percent) prior to failure. This is not surprising as uncertainty increases with the prediction horizon. Interestingly Altman found no cash flow ratios to be significant in contrast to Beaver (1966). Moyer (1977) replicated Altman's model and only achieved a 75 percent predictive accuracy one year prior to the outcome (Keasey & Watson 1991). Since then the number and complexity of the models has increased exponentially in the pursuit of developing the most accurate business failure prediction models possible.[4] Deakin (1972) increased the number of independent variables, Edmister (1972) applied Altman's model to small businesses and Blum (1974) used the change in ratios over time as independent variables. Different discriminant scores were developed to classify firms (Gepp & Kumar 2012) and various techniques were tested to fulfill the statistical assumptions of multiple discriminant analysis (MDA), which are often violated by financial datasets (Laitinen & Kankaanpää 1999). These issues are discussed in detail in chapter 2.4.1. With increasingly more complex models and larger datasets the variable selection process advanced. Factor analysis, principal component analysis and cluster analysis were explored (Ganesalingam & Kumar 2001).

Logit and probit models became more popular with the 1980's as the output of the model, the probability of bankruptcy, is more intuitive than the MDA. More importantly the dataset requirements of the logit and probit models are less restrictive than the MDA improving model validity. Furthermore the models build on a non-linear function, which seemed promising as it more accurately reflects the non-linear corporate failure process. Ohlson (1980) was the first to use a logit model and Zmijewski (1985) the first to use a probit model for bankruptcy prediction purpose. The two models function very similarly and since logit models were easier to compute back then than probit model the logit analysis prevailed. Ohlson's first empirical results for a sample of 105 bankrupt and 2058 non-bankrupt companies were promising with 93% and several subsequent studies were able to show equal or superior performance of this method compared to MDA (Laitinen & Kankaanpää 1999). Generally the overall classification accuracy of MDA and logit models did not differ significantly (Martin 1977; Collins & Green 1982; Hamer 1983). Despite similar performance logit analysis became more popular than MDA, due to its higher statistical validity and intuitive interpretation.[5] Linear probability models (LPM) were suggested as another alternative to MDA as its score takes a value

[3] A hold-out sample is a separate set of observations that has not been use to develop the model. The extra dataset is used to test the external validity of a model.

[4] For a detailed list please see Bellovary et al. (2007)

[5] For a more detailed comparison please see Chapter 2.4.2

between 0 and 1, also allowing an easier interpretation but its inferior empirical performance constrained its use (Theodossiou 1991).
In the late 1980's sequential procedures and human information processing became popular. Cumulative sum (CUSUM) procedures are a dynamic time-series extension of the MDA. They are used to detect shifts in a series of variables' values (Healy 1987). These shifts are then used as financial distress signals. This method showed a high accuracy and applicability in later research by Theodossiou (1993) and Kahya (1999) but never got widely used because it is quite complex to compute (Gepp & Kumar 2012). In the same time period survival analysis started being used more. It accounts for the time dimension of corporate failure and does not assume failure is a steady state. This method determines the effect of the independent variables on the hazard rate and not necessarily the actual hazard rate (Balcaen & Ooghe 2006). Since the method requires a homogenous length of failure processes in the sample, which is normally not the case, this method received less attention in the bankruptcy prediction literature.

Neural networks (NN) became a prevalent artificial intelligent technique used in the 1990's when new information technology enabled the simulation of human pattern recognition (Anandarajan et al. 2001). Using sample cases the network "learns" the decision-making process in the training mode. Once sufficiently trained the neural network model is used on a hold-out sample. Trainng NN is complex and involves a lot of 'try-and-error'. Messier et al. (1988) were the first to apply NN to failure prediction. A key advantage of NN is that they do not have normality, linearity and independence requirements for the input variable like the conventional statistical tools do (Bellovary et al. 2007). They can therefore handle outliers, missing data and multicollinearity much better. In addition they are able to learn from and adapt to a dataset and can capture non-linear relationships between variables. A major disadvantage of the method is that it is a black-box approach making it hard to understand which variables are most relevant (Lee & Choi 2013). Hence, recent research investigates means to make the internal logic of the NN more transparent (Gepp & Kumar 2012). Other intelligence techniques used since include fuzzy set theory, decision trees, rough sets, case-based reasoning, support vector machines, data envelopment analysis (DEA) and soft computing. [6]

With various methods being available the search for the 'best' empirical method for business failure prediction gained increasing attention. Meaningful comparisons of methods are only possible by assessing their performance on the same dataset. Thus, various papers have been published comparing artificial intelligence expert models and other new methods to the more conventional

[6] For a detailed overview of and introduction to all major intelligent techniques please see Ravi Kumar & Ravi (2007).

statistical models (Premachandra et al. 2009; Korol et al. 2011; Gupta et al. 2014). A review of these studies by Ravi Kumar & Ravi (2007) showed that artificial intelligence expert systems (AIE) outperformed statistical techniques in the vast majority of studies, but not all academics agree with that view due the mixed findings (Bellovary et al. 2007).

Besides the artificial intelligence techniques studies still investigate alternative methods. Recently Bayesian, hazard (Shumway 2001; Chaudhuri 2013) and mixed logit models (Jones & Hensher 2004) have been used as more advanced statistical alternatives to AIE and conventional statistical models. (Xu & Zhang 2009) looked into the application of option-pricing techniques for bankruptcy prediction models. They all aim to identify the most accurate models with a tendency towards more focused models. Models are applied to different timeframes, geographic regions and prediction horizons (Begley et al. 1996; Grice 2001).

2.3.2 Focused Models

Several more focused models emerged for specific target groups such as banks (e.g. Meyer & Pifer 1970; Alam et al. 2000) or manufacturing firms (Taffler 1984; Theodossiou 1991). More industry specific models have been developed since 2000 (Bottazzi et al. 2011). For example papers focused on computer/software firms (Shah and Murtaza 2000), casinos (Patterson 2001) and Internet firms (Wang 2004). Most of the studies developed models for U.S. firms. With increasing data availability more paper also use datasets for other countries (Bellovary et al. 2007).
The most frequently used prediction timeframe is on year prior to failure. Some models like that of Deakin (1972) managed to achieve a 96 percent accuracy rate two years prior to failure. However, in general there is still a lot of uncertainty about determining and optimizing the prediction horizon (Bellovary et al. 2007).

2.3.3 Independent Variables

The number of explanatory variables used in the starting models ranged from one to 57. Bellovary et al. (2007) identified 752 different variables that have been used, in a review of 160 papers between 1930 and 2004. However, 674 of them were only used in one or two studies. The most frequently used explanatory variables include return on assets, current ratio and asset turnover in the mentioned order. Early models focused on accounting variables while later studies tested the usefulness of market variables, corporate governance measures, industry effects and macroeconomic factors (Campbell et al. 2008; Tian et al. 2015; Laitinen & Suvas 2016). The average number of independent variables used in the final models between the years 1970 and 2007 was eight (Bellovary et al. 2007). For models with 100 percent classification accuracy the number of factors ranged from 2 to 21. A higher number of factors therefore does not seem to ensure a higher predictive ability. Since the dataset characteristics, estimation methods, variables used and prediction horizon of the papers were not identical this is only indicative and not sufficient to determine, whether more or less variables perform better and why. This topic is therefore further explored in this thesis.

Future research will further assess the use of non-financial ratios, estimation methods, sampling methods, impact of the prediction horizon and model stability over time, industries and countries.

2.3.4 Research Focus

Previous literature developed general prediction tools that could potentially be used by any practitioner. Their limited use in practice however questions the appropriateness of this approach. Therefore more decision context specific models, like the one this study attempts, are suggested. Sample selection, variable selection and model stability are key elements that are assessed in the process. Furthermore, the usefulness of frequently used approaches in previous research is challenged for practical applications. In addition, it is investigated how the number of independent variables impacts predictive accuracy in order to contribute to developing parsimonious model that optimizes the trade-off between information needs and the involved effort.

2.4 Predictive Statistical Models

Academic researchers worldwide have used various modeling types and estimation techniques with varying computational complexity and different underlying assumptions. The three main groups of models are statistical models, artificial intelligence expert systems (AIE) and theoretical models. Statistical and AIE models focus on the symptoms of failure, while the theoretical models mostly investigate qualitative causes for failure. 64 percent of models that have been used for corporate failure prediction are statistical models followed by AIE models with 25 percent and theoretical models with 11 percent (Bellovary et al. 2007).

This paper aims to ease the application of financial distress prediction models for professionals with little econometric knowledge. This thesis therefore does not aim to provide an exhaustive overview of all the models that have been developed. Instead the analysis focuses on statistical models. Statistical models are easier to apply, compute and interpret for laymen than AIE models, which require extensive training. Since theoretical models make comparisons between companies difficult when results are of purely qualitative nature, these models are not investigated here. The statistical methods that are outlined in this section are selected based on them being used by papers that have been published in well-respected journals and them being considered as having added significant value in the empirical literature on corporate failure.
Classical cross-sectional statistical models have been widely used. They classify firms into a failing and non-failing group. The most well-known analysis types are discriminant analysis and conditional probability models.

2.4.1 Discriminant Analysis

Discriminant analysis was the most popular method in the 1960' and 1970's. This group of statistical analysis includes simple univariate discriminant analysis and multivariate discriminant analysis.

2.4.1.1 Univariate Discriminant Analysis

Beaver (1966) was the first to build corporate failure prediction models with financial ratios. Univariate discriminant analysis focuses on the signaling value of each variable individually using a dichotomous classification test with different cut-off points to minimize the misclassification rate. Beaver identified those ratios that had the highest accuracy in classifying companies of a paired sample of failing and non-failing companies. The underlying rationale is that if financial ratios exhibit significant differences in failing and non-failing firms then they could be used for predictive purposes.

Univariate analysis is based on the assumption that the relationship between each variable and the failure status is linear. Keasey & Watson (1991) however found that in practice this relationship is often non-linear questioning the accuracy of the model. Univariate analysis is very simple, does not require statistical knowledge as each variable is compared to the cut-off point and classified respectively. Since the classification can only be done for one ratio at a time different ratios can result in inconsistent classifications (Altman 1968; Zavgren 1985) making final conclusions difficult. Generally it is questionable whether one ratio can capture the complex multidimensional concept of firm performance. Thus, this method is susceptible to omitted variable bias, because the correlation between the variables, which tends to be high for financial ratios, is neglected.

Univariate analysis was the first method used for corporate failure prediction. Its ease of implementation is attractive but limits the performance of the models. Therefore models incorporating several variables, became more popular.

2.4.1.2 Multivariate Discriminant Analysis

In 1968 Altman introduced the Z-score. The Z-score is based on multiple discriminant analysis (MDA), which is a method that attempts to derive a linear (or quadratic) combination of a firm's individual characteristics, which gives a score that classifies observations into a failing and non-failing group. In 1977 Altman adjusted the Z-score to account for new financial reporting standards and named the new model "zeta analysis" (Altman et al. 1977). The score can take a value between $-\infty$ and $+\infty$ and is used to generate an ordinal ranking. In most studies a low discriminant score indicates poor financial health. The Z-score and zeta analysis are frequently used as benchmark method for comparative studies. Just like the univariate analysis MDA is strictly speaking no predictive model. It simply classifies firms based on their resemblance to firms that fail or do not fail.

MDA is based on four assumptions: First, MDA assumes that the dataset is dichotomous meaning that the groups, into which the observations are classified, are discrete, non-overlapping and identifiable. The arbitrary separation concerns the definition of failure as well as its application to assessing the predicted probability of failure. In reality this distinction is less trivial, as corporate failure is a process that takes place gradually without a universal tipping point. Some researchers therefore propose to classify firms in more than two groups to specify more stages of a corporation's financial health. This would allow varying levels of response to the risk of corporate failure (Martin 1977; Zavgren 1985) and enable adjustments to the risk premium required to do business with a company (Chesser 1975). However, statistical methods are not designed for such multiple outcome predictions. Furthermore the issue of determining a cut-off point for the outcome variable that determines whether an observation is financially distressed or not remains.

Second, the independent variables need to be multivariate normally distributed. Multivariate normality of the independent variables is often violated (Deakin 1972; Taffler 1984; Barnes 1987), which results in biased significance tests and error rates (Eisenbeis 1977; Richardson & Davidson 1984). Multivariate normality requires univariate normality (Karels & Prakash 1987). Financial ratio variables, which are the most frequently used variables, generally exhibit non-normal distributions (Barnes 1987; Mcleay & Omar 2000). Some researchers try to approximate univariate normality by transforming the variables before estimating their model. The literature has no general guidelines about the appropriate transformation process (Barnes 1987). Altman et al. (1977) used a log-transformation, Deakin (1972) used a square root and log-normal transformation, while Taffler (1984) transformed variables with reciprocals and logarithmic transformations. Other techniques include trimming and winsorising. Trimming means deleting outliers based on the normal distribution. Winsorising changes an outlier's value into the closest non-outlier (Beaver, William H; McNichols, Maureen F.; Rhie 2005). Even when the variables are univariate normally distributed it is not guarantee that the assumption of multivariate normality is not violated anymore. In addition, transformation can impair the interrelations among variables resulting in distorted models with inaccurate predictions (Lo 1986). Thus, multivariate normality is very difficult to achieve and assess.

Third, the groups' 'dispersion matrices' or 'variance-covariance matrices' need to be equal for the failing and non-failing group (Ohlson 1980; Zavgren 1985). When the dispersion matrix is not equal a quadratic discriminant method should be used to receive unbiased estimators (Eisenbeis 1977; Zavgren 1985). Some studies like Taffler (1984), and Izan (1984) applied this quadratic discriminant method but Altman's original linear model has been shown to perform better than the quadratic model (Altman et al. 1977).

Fourth, the probability of failure and misclassification costs need to be specified prior to running the model. The probabilities of a company belonging in the failing or non-failing group and the costs if misclassifying them need be determined to get unbiased MDA models that are representative for the total population. According to Deakin (1972) the cut-off point should be determined by minimizing the total loss function, which includes error rates, population proportions and misclassification costs. Most researchers do not specify error costs and/or population proportions. Instead they assume that the misclassifications costs are equal and that the sample proportions are equal to the population's proportions. This is often incorrect as in practice the costs of misclassifying failing firms (Type I error) are much greater than misclassification costs for non-failing firms (Type II error). Doing business with a firm that goes bankrupt usually results in greater losses than avoiding business with a firm that is expected to go bankrupt but does not. In the population the number of bankruptcies is very small compared to the non-bankruptcies. When this proportionality is neglected then reducing Type I errors is stressed too much, which results in relatively low Type I error rates but relatively high Type II error rates (El-Zayaty 1987). Moreover, estimating the total loss function is practically very difficult because the costs of errors are often immeasurable, intangible and depend on the decision-makers risk profile. Due to these practical issues most researchers only minimize the total error rate instead of the entire total loss function (Altman et al. 1977; Taffler 1984). Consequently the MDA technique is often applied inappropriately and conclusions from the analysis are questionable.

Some authors discuss the importance of the second and third assumption and resulting biases but most do not analyze whether the data satisfies these assumptions. According to Eisenbeis (1977), Richardson & Davidson (1984) and Zavgren (1985) data rarely satisfies these assumptions.

Although MDA is the most popular statistical technique for corporate failure prediction it has several disadvantages, besides the frequent violation of its assumptions. MDA classifies corporations based on a linear model, but most variables do not have a linear relationship with firm health. Furthermore the discriminant score is an ordinal measure, which is used to create an ordinal ranking. For its interpretation as probability of default a subjective and potentially incorrect assessment of the likelihood of corporate failure needs to be made (Zavgren 1985). The MDA technique is similar to multiple regression analysis, but it is not equivalent. The ordinary least-square (OLS) method is not suitable for estimating the coefficients for a linear relation with a binary dependent variable (Bellovary et al. 2007). Thus, the coefficients cannot be interpreted like β-coefficients of a regression and do not reflect the relative importance of each variable (Altman 1968; Blum 1974; Taffler 1984; Keasey & Watson 1991). This can lead to confusions for laymen and make the interpretation difficult (Zavgren 1985). As MDA is a static model it can only predict corporate failure one step ahead. This results in neglecting the risk trend of a firm over time (Bellovary et al. 2007). MDA is more sophisticated than univariate analysis but the method has various assumptions that are difficult to meet in practice, resulting in biased results that involve a very subjective assessment.

2.4.2 Conditional Probability Models

In the 1980s and 1990s conditional probability techniques including logit analysis (LA), probit analysis (PA) and linear probability modeling (LPM) became popular. The models vary concerning the probability distribution they employ. Ohlson (1980) was the first to use a logit analysis with financial ratios, which assumes a logistic distribution, while Zmijewski (1985) was the pioneer for probit analysis in this field, which assumes a cumulative normal distribution. Linear probability models on the opposite assume the relationship between variables and the failure probability is linear. LA is the most popular method of the three. PA has been used less frequently because the technique requires more computations (Gepp & Kumar 2012) but given their theoretical similarities their estimates are very similar (Stock & Watson, 2012). Linear probability models have only been applied in a limited number of studies like Platt (1989) as they cannot capture the expected nonlinear nature of the true population regression function. Specifically this means that the probability of default by linear models is expected to change by the same amount for an equal change in one of the explanatory variables (Stock & Watson, 2012). In reality this is usually not the case. The non-linear shape of the logit function is particularly realistic as it implies that a firm that is very healthy must experience a proportionally larger decline in one of its variables in order to experience a higher logit score than a financially distressed firm (Laitinen & Kankaanpää 1999; Platt & Platt 1990). Therefore this section focuses on logistic regressions to assess the benefits of conditional probability models with non-linear probability functions.

Logit models combine several company characteristics into a multivariate probability score, which is the predicted failure probability. Because the regression function is a nonlinear function of the coefficients these coefficients cannot be estimated by OLS estimation. Instead the maximum likelihood estimation is used. The logistic function implies that the logit score has a value between 0 and 1. When the failed status is coded as one a higher score indicates a higher probability of failure and hence poorer financial health of the corporation. If the logit score exceeds (is less than) the cut-off point then the corporation is classified into the failing group (non-failing group).

For LA no assumptions related to the distribution of the independent variables and prior probabilities of failure need to be made (Ohlson 1980; Zavgren 1985). It is therefore a lot less restrictive and demanding than MDA. It also allows for disproportional samples. However, the LA method has two assumptions, which need to be fulfilled. First, the dependent variable needs to be dichotomous, with all groups being discrete, non-overlapping and identifiable. Second, the cost of Type I (bankrupt firms classified as health) and Type II error rates (healthy firms classified as bankrupt) should be accounted for when selecting the optimal cut-off probability. Issues related to this have already been discussed in chapter 2.4.1 LA has the advantage that its output is the failure probability of the company, which eases the interpretation. Furthermore, the significance of each variable can be interpreted provided that the variables are not multicollinear. In addition, it allows for categorical and continuous variables.

Nevertheless LA also has disadvantages. First, logit models are very sensitive to multi-collinearity so that the inclusion of highly correlated variables needs to be avoided (Balcaen & Ooghe 2006). As most LA models are based on financial ratios that often contain the same denominator or numerator this problem can be severe. Secondly, LA models are very sensitive to outliers and missing values, which need to be corrected. Lastly, even though the model does not require normally distributed variables Mcleay & Omar (2000) show that models are sensitive to extreme non-normality. Prior to estimation the data with extreme non-normality needs to be transformed or deleted in order to approximate normality.

3 Data

This chapter discusses the sample selection process. Afterwards the sample's characteristics are presented and the data preprocessing explained.

3.1 Sample Selection

A dataset has been extracted from Compustat – Capital IQ (via the Wharton Research Data Service) that contains publicly traded companies in the *USA* between *2000-2015*. Since previous studies (Laitinen & Suvas 2016; Altman & Hotchkiss 2011; Bellovary et al. 2007) found varying impact for country-specific effects this study focuses on the USA to avoid any biases. The timeframe of the data is large enough to generate sufficient data but recent enough to be representative for future business activities. As the data is from 2000 and later it accounts for advances in the information technology, latest (lean) supply chain trends and recession as well as expansion periods.

Since only *public companies* are obliged to publish their financial statements the thesis focuses on those. The data collected in Compustat is equivalent to the data that is publicly available through the homepage of the SEC. Anyone can get access to this data for free through EDGAR, the search tool of the SEC. Whether public firms are a representative target group for a buyer depends on its supplier base. This can vary a lot by industry, but frequently suppliers are SMEs, which are not publicly traded. In such cases the buyer would need to inquire the financial information from its suppliers, in order to be able to do statistical analysis.

Suppliers provide a variety of services and goods to the buyer. In order to account for the range of industries with which buyers do business *all industries*, based on the 'Standard Industry Classification' (SIC) code, except finance, insurance and real estate (SIC 6000-6799) and non-classifiable (SIC 9900-9999), are included. Financial services are normally not a crucial part of the supply chain and have a very different business model compared to industrial and service firms. Thus, they are not included. Also non-classifiable companies have been excluded from the sample, because their relevance as a supplier is unclear and therefore could cause distorted results.

A major concern in corporate failure prediction is the sample composition. Various previous studies used non-random samples with a modified proportion of failed corporations so that the proportion of failed companies is higher than in the overall population (e.g. Altman 1968, Deakin 1972, Foreman 2003, Ohlson 1980, Zavgren 1982).

The higher proportion of defaulting companies has either been caused by picking out some observations from the population or deliberately matching failing firms with healthy firms, based on similar characteristics like size and industry (e.g. Altman 1968; Zavgren 1985; Blum 1974). This results in a 'choice-based' sample bias and is a risky approach as it impairs the reliability of the results (Zmijewski & Dietrich 1984; Platt & Platt 2002; Hillegeist et al. 2004). With matched firms it is possible to control for implicit factors (Zavgren 1985) but it is very likely that characteristics are over- or underrepresented, resulting in sample specific failure prediction models that lack representativeness. If size is used as a selection criterion, then the number of small firms is higher than it would be in the total population, as small firms are more likely to experience financial distress. Furthermore, if the selection criterion is linked to the probability of financial distress then 'selection bias' is the consequence (Eisenbeis 1977). Consequently the sample violates the random sample assumption. Besides the mentioned statistical issues, modified proportions are probably not practical for supply managers, as they require a lot of manual pre-selection. This would be very time consuming. Hence, in order to ensure reliable and representative results and use an approach that is practical feasible, observations are not further preselected on any criterion and no adjustments to the proportionality are undertaken.

Most researchers use static single-period classification models that use one observation of one point in time per firm. This does not account for the fact that firms change over time. Thereby they introduce 'sample selection bias'. Hence, Shumway (2001) expects the estimates of those models are biased and inconsistent. This can be remedied by using time series data for each firm or by including one observation per firm year over a series of years. Balcaen & Ooghe (2006) suggest using extended timeframes. Only those firms are included as non-failing that have non-failure characteristics for up to five years after the considered timeframe. This is not possible in a practical setting. Therefore this study follows Shumway's (2001) approach and includes one observation per firm per year. When a company has been traded in several years then the company has one observation for each year. Consequently the dataset is relatively large and generates more consistent and accurate predictions, when the dependence of the observations is correctly accounted for.

3.2 Sample Specifications

The dataset contains 62,746 observations for 8,082 companies that are traded at a stock exchange in the USA between 2000 and 2015. Only companies which have their headquarter in the USA are included. The sample has not been matched or modified so that the proportion of financially distressed firms is expected to reflect the population. The majority of the observations are in the manufacturing, service, transportation, communication and utilities sector.

SIC Code	Industry	Percentage of sample	Number of observations	Percentage with FD	Standard deviation of FD
0100-0999	Agriculture, Forestry and Fishing	0%	255	25%	12%
1000-1499	Mining	5%	3136	36%	10%
1500-1799	Construction	1%	749	25%	15%
2000-3999	Manufacturing	48%	29949	31%	4%
4000-4999	Transportation, Communications, Electric, Gas and Sanitary service	12%	7606	20%	10%
5000-5199	Wholesale Trade	4%	2493	18%	6%
5200-5999	Retail Trade	7%	4599	15%	4%
7000-8999	Services	22%	13959	32%	10%
	Total	100%	62746		

Table 1 Overview of dataset by industry

The number of observations varies per year. There are 6656 observations for 2000 and 2895 in 2014. Since financial statement information for 2015 was only available up to November 2015 most firms have not published their annual report for that year yet. Thus, 2015 only has 201 observations. The statistical models using this data will therefore put a larger weight on earlier years because they reflect a larger proportion of the observations. Models' stability over time will therefore be a central element of the robustness assessment. For a detailed overview of the total observations per year please see appendix 1.

A firm is considered financially distressed if its EBITDA is less than its financial expenses for two consecutive years. The selection of this definition is elaborated in detail in chapter 4.2.1. In the sample 29 percent of the observations are considered financially distress. Whether this is comparatively high or low is difficult to assess. The financial distress definitions other studies used and the timeframe of their data differs from the one chosen here. Generally the rate of financially distressed firms ranges between 1 and 24 percent (Hillegeist et al. 2004; Pindado et al. 2008). Since these studies focus on later stages in the corporate failure process it is not surprising that the percentage of distressed firms in those studies is lower than in this study, where an early stage warning indicator is used.

The percentage of financially distressed firms in this sample varies by industry and year under consideration. Mining, service and manufacturing firms seem to experience financial distress most. The least distressed industries are wholesale trade and retail trade. Construction, agriculture, mining, services, transportation, communication and utilities industries have relatively high fluctuations in the average percentage of observations that are considered financially distress in each year. This highlights that financial distress is strongly influenced by industry-specific factors. Thus, models need to be tested for their predictive ability across industries.

In 2001 and 2002 40,6 percent of the observations are classified as financially distressed. The financial distress rate then declined to around 30 percent for 2003 to 2009. The years 2010 to 2012 have the lowest financial distress rate with around 22 percent. Since 2013 the financial distress rate has increased again and is at 31 percent at the end of 2014. The highs and lows in the financial distress rate vary with economic cycles with a one-year time lag.[7] This shows that financial distress also depends on macroeconomic factors. This questions the temporal stability of statistical models and needs to be accounted for in the model development and robustness assessment.

60 percent of all quantitative bankruptcy prediction studies use financial ratios as the only explanatory variable, while the remaining 40 percent use a combination of financial and other variables (Aziz & Dar 2006). This paper focuses on the use of accounting variables and a measure for macroeconomic changes. The variable selection process and chosen variables are discussed and presented in detail in chapter 4.2. Therefore not detailed overview is provided here. Generally the dataset contains a range of accounting variables from the balance sheet and profit and loss statement, that enable the construction of profitability, operating performance, liquidity and leverage ratios.

[7] For a detailed overview please see appendix 1.

3.3 Data Preprocessing

Like Altman & Hotchkiss (2011) say "there is nothing more important in attracting rigorous and thoughtful research than data". Therefore particular care is taken to prepare the data for the analysis and get further insights into the nature of the data.

The data from Compustat contains the 10-K reports that have been filed with the SEC. All financial reports are audited and frequently assessed by analysts, so that their accuracy is expected to be high. The data for each fiscal year-end report is usually published within three months from the selected fiscal year end. Most of the observations in the sample use December as fiscal year end month. In order to account for the time lag between the reporting date and actual availability of the financial reports in the database *a time lag of one year* is used. So in any year only the annual report of the previous year is available. All financial input figures are denominated in million US dollar. Even though all companies reporting with the SEC have to follow its reporting regulations, a different application of guidelines and industry-specific reporting standards can impair the comparability. This will be considered in the variable selection chapter.

Logit models struggle with multi-collinearity, are sensitive to *outliers, missing values* and *extreme non-normality* (Balcaen & Ooghe 2006).

The logit analysis is sensitive to *outliers* as they influence the averages and covariance matrices. Outliers are data points at the far end of the tails of a distribution. These are quite frequent for financial ratios and corporate failure data. In order to identify outliers each financial ratio is assessed with summary statistics and histograms. Histograms have the advantage that they provide a deeper insight into the distribution of the values. Analogue to Shumway (2001), observations at the 99th and 1st percentile were excluded from the sample, to ensure outliers do not heavily influence statistical results. Furthermore, observations with illogical values such as negative sales and duplicate data were eliminated.

Misleading values include ratios that have a denominator that is negative or zero. Only total assets and current liabilities are used as denominator, which both cannot take negative values. Furthermore the number of observations with a numerator or denominator equal to zero accounts for 201 observations, which is equivalent to 0,3 percent of the total observations. This is not considered large enough to bias the statistical models, therefore the observations remain part of the dataset.

Missing financial data points for an observation can be partial or total. One opportunity to deal with this is to use the mean ratio of the sample for empty cells, so that the observation is not dropped in the

modeling process. However, in previous studies this did not particularly improve the results (Zmijewski & Dietrich 1984). Other studies only used those observations that had complete data. This however would result in sample selection bias as failing companies are more likely to have incomplete data, since many of them stop reporting before they default. When statistical models are estimated conditional on complete data then results understate the population's probability of financially distressed firms. This is the case because the probability of distress of an observation with complete data is less than the probability of distress of a randomly drawn observation (Zmijewski & Dietrich 1984). As adjustment methods have not contributed to improving models accuracy in the past missing data points are not eliminated or replaced in this study.
The distribution analysis via histograms shows that all variables have a slight left or right skew but no *extreme non-normality* is detected. Thus, the selected statistical tool should not experience estimation problems.

In conclusion, the final dataset contains 6656 observations for the timeframe 2000-2015. Extreme outliers have been excluded but observations with missing data points remain part of the dataset. No extreme non-normality has been detected.

In order to objectively assess the statistical models the dataset is split into an estimation and a testing sample. 80 percent of the observations are used to develop models that are then run on the remaining 20 percent of the sample. In order to ensure that the two samples have a representative percentage of financially distressed observations the random sample function in SAS is used, with the financial distress variable as strata[8] variable.

[8] Using a strata variable in the process of creating two samples ensures that both samples have the same proportion as the total sample based on a specified variable. Here the financial distress criterion is used that classifies observations either as financially distressed or financially viable based on the chosen financial distress definition (EBITDA less than financial expenses for two consecutive years).

4 Methodology

In this chapter the method selection and variable selection are discussed in detail. Based on the selected method and variables different models are then developed.

4.1 Method Selection

A variety of models have been used in the past to predict corporate bankruptcy. Each of them has strengths and weaknesses that make the selection for an empirical application difficult. Researchers disagree on what method generates the best predictive models. However, two types of statistical models are the most frequently used in the accounting literature: multivariate discriminant analysis and logit models. Both have been assessed in detail in chapter 2.4.1 and 2.4.2. Which method is most suitable as a screening tool for supply managers depends on their predictive accuracy, ease of application and straightforwardness of the evaluation.

4.1.1 Predictive Accuracy

The predictive ability and performance reported in studies has been mixed. Lennox (1999) confirmed that a single period logit model outperforms an MDA model. Muller et al. (2009) state that MDA has a higher classification accuracy than logit models. There are studies, where MDA outperforms and others where the logit model outperforms but generally their performance is perceived to be similar (Martin 1977; Collins & Green 1982; Hamer 1983). Their performance has also proven to be high or even superior when compared to AIE systems (Zavgren 1985; Chava & Jarrow 2004; Muller et al. 2009). In which settings the respective methods perform better has not been assessed yet and is not the aim of this paper. The purpose of this study is to identify a good method, which can be used as an early warning screening tool to identify financially distressed critical suppliers. The screening tool is the first of several screening steps. Thus, the predictive accuracy does not need to be 100 percent. It needs to be more efficient than the existing methods employed and help supply managers focus the limited resources of the buyer's organization on those suppliers that are most at risk. A benchmark with the quantitative and qualitative tools currently used for supplier risk management is not possible, as such data has not been collected yet. Since MDA and LA have a similar predictive accuracy the ease of computing the model and interpreting it are going to be the decisive factors for the method selection.

4.1.2 Ease of Application

MDA accounts for the fact that numerous factors influence the financial distress likelihood and combines them in a linear model. However, the relationship between the explanatory variables and financial distress are rarely linear in practice (Bellovary et al. 2007). In addition, the statistical assumptions of multivariate normality and similar variance-covariance matrices method are difficult to meet. Thus, this method will prove to be challenging when applied to a range of suppliers. Several researchers assessed the normality of ratios after removing outliers and transforming the data. Many of the distributions remained non-normally distributed (including Deakin, Barnes and Lee). Hence, it is questionable whether the preprocessing procedures of this dataset would be sufficient to achieve the normality required for MDA. As elaborated in chapter 2.4.2 the logit analysis also has assumptions but they are easier to assess and to achieve than the ones of the MDA, as the normal distribution of the independent variables is not a requirement for logit analysis.

Both, MDA and LA, are easily applied once the data is prepared and tend to be part of the readily available statistical packages. However, only LA can include categorical variables in the model providing the supply chain manager with a wider range of variables that can be included. Therefore the LA outperforms the MDA in terms of ease of data selection and preparation requirements. LA is preferable for the supply chain managers as it requires less upfront effort to prepare the data and there are less statistical validity and variable selection considerations that need to be made.

4.1.3 Straightforwardness of Evaluation

An intuitive interpretation is crucial to convince supply managers from the benefits of statistical analysis. Logit models have the advantage that their output is the predicted probability of default. Just having a ranking based on a MDA score does not indicate in how much trouble the respective candidates might be. With a probability as output a practical measure is used that conveys the likelihood that a supplier's operating income is not sufficient to cover its financial expenses. Several groups can be created based on the risk-averseness of the buyer, so that different actions can be taken for each group. The suppliers with a higher probability could be assessed first and more extensively than those in a lower risk group. This continuum of alternative judgments and actions reflects the reality of decision-making more accurately (Lau 1987). Furthermore the estimated coefficients for LA, allow a more detailed interpretation than MDA. For LA the impact of a change in an independent variable on the financial distress likelihood can be estimated. Since the dependent variable of the MDA is not a probability this is not possible with MDA models. Thereby the logit model itself could give indications about the core drivers that should be looked at more closely in the next screening step.

LA outperforms MDA in terms of ease of application and interpretability, while no clear superiority in predictive accuracy could be identified for either method. Therefore a logistic regression model[9] will be used to predict the financial distress likelihood of critical suppliers in this paper. The probability of financial distress is given by

$$Pr_i\ (Y_i = 1) = 1/[1 + \exp\ -(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik})]$$

where Y_i equals one if the firm (i) experiences financial distress (EBITDA less than financial expenses for two consecutive years). The β_k are the estimated coefficients for the independent variables X_k known at the end of the previous year.

4.2 Variable Selection

The choice of the dependent variable Y_i and the independent variables X_k used in the logistic function is elaborated in the next chapters.

4.2.1 Dependent Variable

So far no unified definition of financial distress exists. Platt & Platt (2002) define that a financially distressed firm has one or several of the following symptoms: several years of negative operating income, suspension of dividend payments, major restructurings or layoffs. Mcleay & Omar (2000) suggested a firm is considered financially distressed, when it makes losses, issues additional shares, initiates capital restructuring or reorganization. Both author teams base their definition on visible external events.

In order to accommodate different types of financial distress researchers either built a different model for each distress type (Keasey & Watson, 1991) or developed a more general financial distress model (Lau, 1987).

Lau (1987) accounts for the different financial distress types by including five financial states that approximate the range of corporate financial viability states: i) omitted or reduced dividend payments, ii) technical default and default on loan payments, iii) protection under chapter 10 and 11 bankruptcy

[9] The terms logit model and logistic model are often used interchangeable in research. They are basically the same as the logistic model is just the inverse of the logit model.

act, iv) bankruptcy and liquidation and v) financially viable. Since supply chain managers are most interested in early stages of financial distress only i) and ii) would be of interest for this study.
Alternatively the different outcomes can also be combined into one variable. For instance, Pindado et al. (2008) combine several criteria into one financial distress predictor. They classify a firm as financially distressed when it files for bankruptcy or its EBITDA are lower than its financial expenses for two consecutive years and its market value decreased for two consecutive years. Thereby they account for trends by only considering a warning signal, when it has been prevalent for at least two years in a row.

This analysis only considers ii) default on loan payments, as it is one of the earliest signs of financial distress. In that situation a firm's operating income is not sufficient to cover its financial expenses. This is a crucial turning point as creditors are one of the first stakeholder groups that collect their claims. Therefore based on Pindado et al. (2008) a firm is considered financially distressed, if its EBITDA are less than its financial expenses in two consecutive years. This criterion is the earliest indicator in the corporate failure process outline by Lau (1987). This economic event sends a clear signal related to a firms financial performance and as the symptom has been visible for two years in a row it is very likely that the firm suffers from a more substantial problem.
Changes in dividends (i) are not considered as useful for the supply manager's decision context. Dividends can be issued as cash payments, shares of stock or other property. This makes their comparison difficult. Furthermore dividends are considered a weaker signal than comparing earnings and expenses. The later is purely related to the financial viability of the corporation and not impacted by industry- or company-specific payout policies.
Pindado et al. (2008) also include a measure of change in the market value. This is not included in the definition of financial distress for this study, as this model is supposed to be applicable to public as well as private firms. Besides the availability of an external market valuation, it is questionable whether the market valuation chosen for a certain fiscal year only reflects firm performance. This matter is discussed in more detail in chapter 4.2.2.4. For the mentioned reasons only the default on loan payments is part of the financial distress definition.

In conclusion, a firm is considered financially distressed in the year that immediately follows the occurrence of two consecutive years in which EBITDA were less than the financial expenses (interest and related expenses for short- and long-term debt). Since this definition of financial distress occurs in an early stage in the corporate failure process it is considered to be a strong early warning indicator. This warning indicator gives the supply manager the early opportunity to analyze the supplier's financial situation in more detail and take appropriate action.

4.2.2 Independent Variables

Financial distress prediction models are usually based on financial information about a firm's solvency, operating performance, profitability and leverage. Despite the fact that many studies reported a high predictive accuracy with their ratios, the optimal combination of financial ratios has not been found yet. A model's composition depends on the data availability, data quality and method of analysis. Useful variables need to be *visible, measureable, objective, reliable, available* and *accessible* in order to identify root-causes and symptoms of financial distress. Only variables that fulfill these rather technical criteria can contribute to valid and reliable models. Decisive factors such as a management's abilities are not directly visible and therefore often approximated for example with years of experience. The further away from the root-cause a variable is the more likely other factors influence this variable. This can impair the variables validity. Objective criteria are preferable over variables that involve subjective assessments. The data's correctness is assessed by checking the data for potential manipulations, by involved parties. Data should always be verified for correctness before usage. Especially aspects such as the availability of data and access to it can be limiting factors.

The most relevant root-causes and symptoms often do not fulfill at least one of these data quality factors. A careful assessment of the resulting trade-offs thus needs to guide the variable selection process.

4.2.2.1 Selection Approach

Relevant variables can either be selected based on theoretical considerations and/or statistical selection techniques. The theoretical foundation for variable selection is relatively thin so that most studies, like Ohlson (1980), only employ statistical methods to select the most useful variables from a list of potentially relevant variables. They select variables based on the statistical significance of the estimated parameters, individual discriminating ability of each variable, the sign of the variables coefficients, principal components analysis, factor analysis and stepwise methods (Keasey & Watson 1991). This approach stresses the statistical characteristics of variables but ignores their economic importance. Consequently very sample specific and unstable models are created, which makes the models' applicability to other datasets and decision contexts difficult (Zavgren 1985; Edmister 1972). Zavgren (1985) therefore recommends using theory to determine the important dimensions and avoid overfitting. The variable selection of this study is therefore guided by theoretical and practical considerations. First the key dimensions are identified based on a literature review and then the most relevant variables for each dimension are selected. Which variables turn out to be the best predicting ones is then tested statistically.

4.2.2.2 Variable Types

As outlined in chapter 2.2.2.1 management performance is seen as one of the core company-specific drivers of corporate performance. However measuring management performance is difficult. Either "input" factors such as management's educational background and work experience can be used or "output" parameters that describe the firm's performance and indirectly reflect management performance such as profitability, liquidity and alike can be utilized. The aim of the analysis is to provide the supply manager with a good understanding of the financial viability of its suppliers. For first he/she is most interested in understanding the status quo of the supplier's performance and only when that performance is predicted to be poor considers investigating its source. Hence "output" measures are the more practically relevant measures for a first screening step. These "output" measures are equivalent to the financial and non-financial symptoms that a financially distressed firm experiences. They have been discussed in chapter 2.2.3.

4.2.2.3 Variable Categories

Symptoms can be non-financial and financial. Financial variables have been most frequently used because they are more accessible through various databases. Furthermore they are comparable, performed well in the past and are easier to integrate in statistical models. When only financial ratios are included it is implicitly assumed they include all relevant failure or success indicators (internal and external). However this is clearly not the case as financial ratios cannot capture many relevant non-financial firm-specific characteristics, industry-specific factors or macroeconomic trends, which determine a corporations vulnerability to financial stress (Hillegeist et al. 2004). It is not necessarily true that insolvent firms always fail and solvent firms survive (Bulow & Shoven 1978). This depends on the relative claims, economic interests and power of different stakeholders. So it is more than a simple mechanic relationship that exists between a firm's financial condition as reflected in its ratios, and the chosen criterion event. So far no theory has been developed to assess the process of a firm that becomes insolvent and the agents that decide to not continue operations (Keasey & Watson 1991). Argenti (1976) therefore stated "while these ratios may show that there is something wrong ... I doubt whether one would dare to predict collapse or failure on the evidence of these ratios alone." However, so far there are only a few papers that combine variables from several categories.

Either qualitative financial distress measures should be integrated into the statistical model or they need to be assessed in a second screening step.

Previous literature concentrated on the first option and integrated more qualitative measures in their models. This study raises the question, whether that is necessarily the best approach in practice. Including all potentially relevant variables in one analysis tool results potentially in a more accurate model but as the literature review showed, the classification accuracy has been already quite high in the past, when only financial variables were used. Besides a 100 percent accuracy is not needed for supply managers, they are merely interested in identifying which of their numerous suppliers might have a particularly high risk to experience financial distress. So if the accuracy is not the core factor, then the interpretability is the only factor left that could justify the inclusion of all potentially relevant financial, non-financial, industry-specific and macroeconomic factors despite the additional data acquisition costs that would create. Particularly the selection of industry-specific and non-financial variables requires a deep understanding of the sample's business environment, to determine the relevant variables. Otherwise no explanatory power is gained and overfitting occurs. It is not reasonable to assume that a supply manager knows the entire range of supplier industries sufficiently well to be able to do that. Furthermore, non-financial factors like management performance are often not visible and measurable. Since such information is not publicly available it needs to be inquired via a survey, which opens up the analysis to additional sampling issues, data mining problems and a lack of objectivity. When these unobservable factors are approximated by more distant variables no clear conclusions can be made about whether they actually influence financial distress or only introduce bias. The interpretational advancements possible by including more explanatory variables in a model seem very constraint by the availability of variables.

Statistical methods have proven to be valuable in terms of their consistency and ability to determine the optimal weight for different variables (Dawes et al. 1989) but they are not designed for qualitative environments, where the cause-effect relationship is only vaguely known or cannot be measured. Accordingly a generic model cannot reflect non-financial company-specific and industry-specific factors sufficiently accurate to warrant the effort involved with including them in a statistical model.

It does not seem economically necessary and statistically sensible for a first screening step to force all potential variable categories into one model. Instead, a stepwise analysis approach is proposed to supply managers. The first screening step employs a logistic regression based on financial variables and a macroeconomic indicator to assess suppliers' probability of financial distress. The non-financial and industry-specific factors are analyzed in a later analysis step for companies that show strong signs of struggling.

4.2.2.4 Financial Variables

In order to determine which financial variables will be included a decision needs to be made whether accounting or market variables or a combination of both will be used. Accounting figures can be accrual or cash flow figures. Studies that found accounting variables to be relevant predictors for financial distress include Altman (1968), Beaver (1966), Ohlson (1980), Shumway (2001) and Hillegeist et al. (2004).

Accounting information is not based on current market values. Thus, accounting information can give a distorted view of the financial viability of a firm if the actual value of assets and liabilities differs significantly from the book value. Factors responsible for this include inflation and asset price volatility, which are both not accounted for (Platt et al. 1994). Hence, assets could be under- or overvalued compared to their market value.

Furthermore the quality of financial reports is questionable. Arbitrary cost allocation (e.g amortization of intangible assets), accounting estimates (e.g. estimation of uncollectible accounts receivable) and alternative accounting policies (e.g. inventory accounting using FIFO or average cost) give the managers room for window dressing of key financials to hide telltale signs of declining performance (Petersen & Plenborg 2012). Thus, it is questionable whether annual reports give a fair and true view of the financial situation of a company. It is generally believed that failing firms manage their earnings upwards and give a more positive presentation of their financial situation (Argenti 1976). Thus, key financials are at risk to be manipulated (Agarwal & Taffler 2008). This generally raises the question how comparable accounting ratios are across industries and countries. Since the dataset, used in this study, focuses on U.S. companies traded on U.S. stock exchanges sufficient comparability can be assumed, because all publicly traded firms are audited and obliged to follow the SEC reporting requirements.

Besides the accrual variables, cash flow variables are frequently used accounting variables. Cash flow variables are less subjective than accrual earning. They provide valuable information about the earnings quality, financial flexibility and liquidity risk. However, cash-flow-based performance measures also have their flaws. They do not account for uncompleted transactions, which is a severe issue for businesses with long operating cycles such as in the aerospace and shipyard industry (Petersen & Plenborg 2012). Accrual measures can therefore be seen as better indicators for long-term operating performance while cash-flow variables give a better insight into the liquidity and financial flexibility of the business. Based on their informational value, accrual and cash flow figures are therefore seen as complementary.

Even though several studies suggest the utilization of market variables the studies using them is limited. In an efficient capital market the market-based models would be expected to outperform the accounting-based models, since the market also includes expectations of non-financial nature such as changes in the market environment (Agarwal & Taffler 2008). This non-financial information is expected to include the probability of bankruptcy. Hillegeist et al. (2004) found that the Black-Scholes-Merton option-pricing model offers significantly more information about the probability of bankruptcy than Altman's Z-score and Ohlson's O-score. Shumway (2001) and Chava & Jarrow (2004) view accounting and market variables as complementary and hence combine the two categories in their paper. However, there is also opposing evidence. Beaver et al. (2010) find that the accounting-based model has a slightly better predictive accuracy. Agarwal & Taffler (2008) compared market-based and accounting-based bankruptcy prediction models and found that the predictive accuracy based on accounting ratios is not inferior to KMV[10] structural models and option-based models.
Since the number of papers that compare accounting and market variables is limited and findings are arbitrary no final conclusion can be made. Generally market variables focus more on the current value of a firm oppose to the accounting variables. However, the market price of a stock is also exposed to market variations that do not necessarily have their source in firm performance constraining its informative content.

So basically the main disadvantages of the two variable types are that accounting variables are based on historic information that can be manipulated while market variables have a forward looking perspective but they are affected by random noise in the market that is not related to company performance. The bias introduced by limitations of accounting figures is expected to be less than the impairments by noise in the market. Besides, a large proportion of suppliers is expected to be SMEs that are not traded on a stock exchange. Since the model needs to be applicable to them as well, the analysis focuses on accounting variables only.

4.2.2.4.1 Types of Accounting Variables

Accounting variables are usually included as financial ratios, because they enable comparisons across companies by adjusting for size (Barnes 1987). Nevertheless this only generates unbiased results if the numerator and denominator are strictly proportional. Furthermore, ratios can be used to control for industry-wide factors by comparing them to industry mean ratios, facilitating a more informative comparison (Platt & Platt 1990).

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[10] Structural model developed by Kealhofer, McQuown, and Vasicek that is now owned and used by Moody's

The meaningfulness of financial ratios has been subject to major criticism. Previous studies showed that financial ratios are non-normal distributed (Horrigan 1968; Deakin 1972). If there is non-normality then the ratio distribution is skewed (Barnes 1987). The distribution is of high relevance to assess ratios individually and to facilitate their use in statistical models that require multivariate normality. This is not an issue for this study, as a logit analysis is applied, which does not require normally distributed independent variables. Thus, financial ratios can be used unless they show extreme non-normality. The skewness can be accounted for by using histograms in the descriptive analysis. Generally Beaver (1966) suggests studying financial components instead of ratios. Alternatively financial components (Beaver 1966), a change in components' values and ratios can be assessed over time, to spot turning points in the financial viability of an individual firm (Blum 1974). Another way to account for changes over time is to include a trend variable (Edmister 1972).

Which approach is most useful depends on whether an individual firm should be assessed over time or whether multiple firms should be compared at one point in time. For time series analysis financial components and variables that measure change seem most valuable, while for inter-firm comparisons ratios are expected to provide more insights. Since the purpose of the statistical model is to filter out those critical suppliers that have a high risk of financial distress ratios are perceived as more valuable and are therefore used in the model.

4.2.2.4.2 Variable Description

The statistical model chosen needs to capture the dimensions of financial health, which are relevant for the decision context (Keasey & Watson 1991). Supply managers are interested in an early detection and prevention of future liquidity problems. The likelihood of such issues depends on the ability to generate sufficient excess cash flow via operating activities to cover financing expenses, which depend on the amount of borrowed funds. *Profitability, operating performance, liquidity* and *capital structure* are therefore the core dimensions that describe corporate performance and are most relevant to predicting financial distress (Altman 1968; Ohlson 1980; Pindado et al. 2008; Zmijewski & Dietrich 1984; Campbell et al. 2008; Shumway 2001). Basically firms with low profits, low sales, low liquidity and high financial leverage are more likely to experience financial distress. All these categories are important determinants, but they are symptoms rather than causes. They all do not lead to financial distress on their own. However they all indicate the competitiveness of a corporation and poor performance in one or several of these dimensions creates uncertainty about the firm's future performance.

For each of those dimensions ratios are selected. The choice of ratios depends on whether they have been used in a study before and shown to be significant. Bellovary et al. (2007) created a list of the range of explanatory variables that have been used in five or more studies between 1965 and 2006 (excluding replicative studies). These 64 variables have been assessed for their usefulness as predictors in these four dimensions. A parsimonious selection is pursued to generate more stable models in terms of applicability, coefficients' sign and significance of the variables. Previous models did not require a large set of variables to achieve their maximum predictive accuracy (Zmijewski 1984; Pindado et al. 2004). Therefore only a few financial ratios are selected, that are closely linked to financial distress. The average quantity of variables used in bankruptcy prediction models is 8. This is therefore also the number of variables targeted in this study. Since financial distress is defined as credit default liquidity is particularly important. Thus, more ratios are included for this category than for the other categories. Next the four dimensions and financial ratios that are used for each dimension in this study are presented.

Profitability: Profitability ratios reflect the ability of a corporation to generate profits by efficiently employing its corporate assets. The larger and more stable the profits are over time the higher the ability of the corporation to generate liquidity from its operating cash flows. This eases to get external financing and accumulate profits to increase the equity. Just like Ohlson (1980), Zmijewski (1984) and Shumway (2001) this study uses the ratios *net income/total assets (NI/TA)* and *EBIT/total assets (EBIT/TA)* to assess a firm's profitability. The net income measures the profit made after all expenses are paid for. EBIT[11] is a relevant benchmark as it captures the true earning power of a firm's assets excluding the effect of leverage and taxes. A higher ratio reflects a higher profitability and lower probability of financial distress. Given this, profitability will negatively influence the financial distress likelihood.

> Hypothesis 1: The profitability ratios have a negative relationship with the financial distress likelihood.

[11] EBIT = earnings before interest and tax

Operating performance: A firm's sales generating ability of assets is one measure of the management's ability to position the firm well in its competitive environment. The asset turnover ratio, *sales/total assets* (*S/TA*) is a frequently used ratio to measure this (e.g. Altman 1968). It is an indicator for the ability to raise capital for future investment opportunities and increase profits. The higher the ratio the more efficiently the firm utilizes its resources to generate sales. Operating performance will therefore negatively influence the financial distress likelihood of a firm.

> Hypothesis 2: The operating performance measure has a negative relationship with the financial distress likelihood.

Liquidity: Liquidity ratios capture how easily a firm can cover its short-term financial obligations. Whether a firm is able to pay back its debt and interest determine the corporation's default risk. Just like Chava & Jarrow (2004), Lennox (1999), Deakin (1972), Hillegeist et al. (2004) and Jones & Hensher (2004) *cash and cash equivalents/current liabilities (CS/CL)*, *working capital/total assets (WCAP/TA*), *current assets/current liabilities (CA/CL)* and *operating cash flows/current liabilities (OCF/CL)* are used to measure solvency. Higher ratios indicate more liquidity (Beaver 1966, Altman 1968, Campbell et al 2008). Thus, liquidity will negatively influence the financial distress likelihood.

> Hypothesis 3: The liquidity ratios have a negative relationship with the financial distress likelihood.

Capital structure: The capital structure of a company reveals the degree of financial leverage a firm is exposed to. The higher the leverage the more sensitive the firm is to changes in external factors, such as interest rates, that impact the cash reserves of the firm (Opler & Titman 1994). Just like Jones & Hensher (2004) and Campbell et al. (2008) the ratio *liability/total assets (TL/TA)* will be used. This ratio reflects the proportion of firm assets that are provided via debt. Hence, firms with low leverage ratios are associated with a lower risk of failure. Leverage will therefore positively influence the financial distress likelihood.

> Hypothesis 4: The leverage measure has a positive relationship with the financial distress likelihood.

4.2.2.5 Macroeconomic Variables

Macroeconomic variables describe general changes in the business environment that are not industry-specific. Their use is recommended by several academics to capture systemic risk factors (Dimitras et al. 1996; Keasey & Watson 1991). Nam et al. (2008) and Bonfim (2009) find that macroeconomic variables improved the predictive ability of their dynamic logit model. Macroeconomic factors have the advantage that they cannot be manipulated by the management and are relatively easy to include in time-varying models. As they are publicly available they can be used for private and public firms. They can be selected based on the geographic area a corporation is active in.

Since the dataset used in this study includes every available firm-year observation the observations are likely to be temporally related. Temporal dependence can come from the baseline hazard rate fluctuating over time. This has been identified in the analysis of the specifications of this dataset. During recessions corporations are more likely to experience financial distress than during economic expansion periods (Lennox 1999). In order to account for this a time-varying baseline hazard rate is included. Ideally a macroeconomic factor that causes the temporal dependence in the data should be used. However, because there are so many potential factors Hillegeist et al. (2004) proxy for this with an economy-wide bankruptcy rate. Alternatively a time indicator variable could be added to the model to complement or replace the system-wide variable. Similar to Hillegeist et al. (2004) an economy-wide financial distress measure is included in each model of this study to capture the temporal dependence in the data. This baseline hazard rate is not a conventional macro-economic variable. Instead the baseline hazard rate is defined as the economy-wide number of financially distressed observations divided by the total number of observation in the sample in a given year. This rate directly relates to the economic situation and financial distress in a given year, but has no cause-effect relationship. The baseline hazard rate is therefore expected to influence the financial distress likelihood positively.

> Hypothesis 5: The baseline hazard rate has a positive relationship with the financial distress likelihood.

If the macroeconomic variable turns out to have predictive power, then temporal stability is not given. This is a highly relevant issue for model robustness. If temporal stability is not the case, then variables significance and relation with the dependent variables might change over time. In order to account for that, the model would have to be redone frequently as its performance would be negatively affected otherwise (Keasey & Watson 1991).

4.2.2.6 Descriptive Statistics

Nine variables have been selected that are used to develop a model that predicts financial distress of suppliers. Eight variables are accounting variables and one variable is a macroeconomic variable. In Table 2 an overview of the summary statistics of the variables is provided based on already preprocessed data. They form the basis for the models developed in this study.

		Mean		Std Dev		Minimum		Maximum		N	
	Variables	FD	no FD	FD	no FD	FD	no FD	FD	no FD	FD	no FD
Profitability	NI/TA	-0.76	0.04	1.56	0.28	-14.76	-14.87	9.94	8.81	17656	35513
	EBIT/TA	-0.62	0.08	1.19	0.20	-9.98	-8.00	0.49	5.18	17639	35505
Operating performance	S/TA	0.86	1.24	1.07	1.00	0.00	0.00	19.73	19.72	17656	35513
Liquidity	CA/CL	3.05	2.49	4.04	2.39	0.00	0,00	33.51	34.15	17536	34831
	CS/CL	2.14	0.96	3.80	1.85	0.00	0,00	29.59	29.66	17554	34874
	WCAP/TA	-0.17	0.21	1.79	0.37	-19.94	-18.13	1.00	1.00	17373	34807
	OCF/CL	-1.09	0.61	2.37	0.93	-19.89	-18.37	76.50	49.49	17526	34792
Leverage	TL/TA	1.08	0.54	2.28	0.44	0.00	0.00	66.56	18.13	17605	35526

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Baseline hazard rate	4%	41%	40%	37%	34%	31%	31%	30%	29%	29%	25%	22%	22%	32%	31%

Table 2 Summary statistics of the explanatory variables

As expected the mean net profitability ratios (*NI/TA, EBIT/TA*), sales performance (*S/TA*) and operating cash flow (*OCF/CL*) are lower for the as financially distressed classified observations (FD). Firms in financial distress also seem to have a much higher leverage (*TL/TA*) and negative working capital (*WCAP/TA*). Interestingly the liquid assets held by financially distressed firms (*CA/CL, CS/CL*) are higher than for the as financially viable classified firms. This could be the case because business partners require cash payments or liquidity is build up in order to cover the overdue interest and principal payments. The standard deviation of the liquidity variables is quite high reflecting the wide range of liquidity ratios financially distressed firms have. The right tail of the distribution seems to be particularly long limiting the representativeness of this average.

The variables make intuitively sense. Difference-in-means tests are not computed, as they allow no conclusion about whether variables are valuable for predictive purposes (Beaver, 1966). Thus, the general usability of the variables for the model development is solely based on their theoretic relevance, performance in the past and intuitive correctness based on the summary statistic. All variables fulfill these criteria and are therefore considered for the model development.

4.3 Model Development

The aim of the modeling process is to build accurate and consistent models that predict the financial distress of a supplier one year in advance. Based on Hosmer et al. (2013) "successful modeling of a complex dataset is part science, part statistical methods, and part experience and common sense" (Hosmer et al. 2013, p. 89). Therefore the variable selection has been made based on theoretical considerations, that identified four firm performance dimensions and a macroeconomic indicator, which are measured by nine ratios. However, once it comes to the selection of which variables should be contained in a model for each category, statistical tests prevailed in previous studies.

4.3.1 Quantity of Variables

The statistical approach is to develop the most parsimonious model that still accurately reflects the true outcome. Models with a limited number of variables are more stable and easier to apply in practice, but they are more likely to suffer from omitted variable bias. A larger number of variables provide an opportunity to capture more information but the risk of modeling variation not related to financial distress also increases. The model basically becomes more of a specialist opposed to a generalist. In addition, with more (particularly financial) variables a higher correlation between the variables is expected, as the key financial figures are closely related. This tends to complicate computations and increases the processing time. Therefore statistical methods were frequently employed to ease this process. T-tests, stepwise methods (Zavgren 1985), principle component analysis (Couderc & Renault 2005) and factor analysis (Barnes 1987) have been frequently used. Back et al. (1996) found that the prediction accuracy varies greatly with the variable selection method. However, the number of studies, which thoroughly investigate this are limited, so that a generalization of these findings is problematic. In order to investigate the effect of the quantity of independent variables on model's predictive accuracy models of various sizes are built and tested. Particularly when models are based on financial ratios it seems possible to achieve very good result with a limited number of variables, because the variables tend to be highly correlated. Thus, a few variables are expected to already capture a lot of the variation in the dependent variable.

> Hypothesis 6: A larger quantity of explanatory variables increases the accuracy of predictive models.

When researchers select variables for their models based on the statistical significance of the estimated coefficients, their individual discriminating abilities, the signs of their coefficients or by employing one of the above mentioned techniques then the statistical characteristics of the variables are stressed, while their economic importance is disregarded (Keasey & Watson 1991). Neglecting the economic meaning and simply including as many variables as the statistical method suggests increases the likelihood of unstable estimates. Financial ratios tend to be highly correlated. If there is too little variation between the explanatory variables, then this can result in counter-intuitive signs for coefficients jeopardizing their interpretation. Mechanical procedures rely on the dataset characteristics of the chosen sample. Thereby they potentially produce sample specific and unstable models that are not suitable for an application to other datasets (Edmister 1972; Zavgren 1985). Hence, this study aims for a more theoretical selection process that might impair the predictive ability but produces more consistent results by limiting the risk of overfitting. This is called a 'purposeful selection process' by Hosmer et al. (2013). Bursac et al. (2008) compared the purposeful selection and stepwise selection via simulations. They found that the purposeful selection outperforms the stepwise selection. Since no actual theoretical framework exists up to now (Balcaen & Ooghe 2006) considerations will be based on representing the four dimensions, *profitability, operating performance, liquidity and leverage,* accurately in the models.

4.3.2 Correlation Analysis

Each of the four dimensions contains different variables. Because variables from the same group are expected to contain very similar information, their combination should be avoided to prevent redundancy and multicollinearity that can distort results. In order to assess the degree of this, a correlation matrix is created (see Table 3).

Prob > |r| under H0: Rho=0

	NI/TA	EBIT/TA	S/TA	CA/CL	CS/CL	WCAP/TA	TL/TA	OCF/CL
NI/TA	1,00	0,87	0,06	0,10	0,02	0,51	-0,52	0,31
EBIT/TA	0,87	1,00	0,09	0,08	-0,01	0,53	-0,53	0,38
S/TA	0,06	0,09	1,00	-0,19	-0,25	-0,04	0,07	0,14
CA/CL	0,10	0,08	-0,19	1,00	0,92	0,28	-0,22	-0,20
CS/CL	0,02	-0,01	-0,25	0,92	1,00	0,21	-0,86	-0,02
WCAP/TA	0,51	0,53	-0,04	0,28	0,21	1,00	-0,86	-0,03
TL/TA	-0,52	-0,53	0,07	-0,22	-0,86	-0,86	1,00	-0,03
OCF/CL	0,31	0,38	0,14	-0,20	-0,02	-0,03	-0,03	1,00

Table 3 Pearson correlation coefficients for the explanatory variables

A correlation coefficient is the result of a mathematical comparison of how closely two variables are related. Two variables are considered highly correlated if a movement in one variable results or takes place at the same time as a comparable movement in another variable (Tsai, 2009). Correlation therefore does not imply that a causal relationship drives the changes in the two variables. The correlation matrix shows Pearson correlation coefficients greater than 0,8 or smaller than -0,8 for several variables. This is considered sufficiently high to warrant that the respective variables should not be included in the same model to avoid multicollinearity[12]. As expected, variables of the same dimension capture very similar information and are thus highly correlated. The two profitability measures *NI/TA* and *EBIT/TA* should not be included together in one model. The same holds for the liquidity measures *CA/CL* and *CS/CL*. The leverage measure *TL/TA* should not be in the same model as the liquidity measures *CS/CL* and *WCAP/TA* since a higher leverage seems to have an inverse relationship with liquidity measures. Therefore all variables can be combined in models except the ones mentioned above. This will create more stable models (Edmister 1972).

4.3.3 Dependency of Observations

As discussed in the previous chapter temporal dependence can arise due to temporal changes in the economy. Temporal dependence can also arise due to the inclusion of multiple observations from the same firm. The fact that the individual firm's observations are not independent can result in understated standard errors. To account for this firm dependence, Huber-White standard errors can be used. These standard errors are a generalization of White (1980) standard errors that are robust to serial correlation and heteroskedasticity[13] (Huber 1967). The estimator procedure of the variance accounts for the dependence of the observations by dividing the observations in M groups. One group is equivalent to one firm. Each group is assumed to be independent from other groups. The Huber-White correction is conservative; it may bias the t-statistic downward (Hillegeist & Keating 2002). The Huber-White estimation method should therefore provide unbiased and consistent coefficient estimates and prevent overstated t-statistics. The Huber-White standard errors are not readily available in SAS. They can only be activated by invoking a matrix (Liu n.d.). Unfortunately for the SAS version available through the Copenhagen Business School the respective matrix function cannot be invoked. Therefore conventional standard errors have been used. Thus, standard errors are assumed to be understated, leading to overstated t-statistics. However, because the sample size is so large this is expected to be a minor issue in this dataset. Even when the standard errors get adjusted for M their significance is still expected to be very high (Laitinen & Suvas 2016).

First a univariate analysis is performed for each independent variable to test whether the variables have some level of association with the dependent variable. In the next step models with more than

[12] Multicollinearity occurs when independent variables in a multiple regression model are highly correlated. Then one can very accurately be linearly predicted from the others.

[13] Heteroskedasticity of the error term refers to a regression model's inability to predict the dependent variable consistently across all values of the dependent variable.

one variable are developed. Those models should include each dimension with at least one variable, if the model size allows and avoid the inclusion of variables that are highly correlated. The result of this process are 27 models:

- eight models with two explanatory variables
- seven models with three explanatory variables
- four models with four explanatory variables
- four models with five explanatory variables
- four models with six explanatory variables

Thus, the 27 models (see Table 4) cover a range of different variable combinations and model sizes. The results for the various models are going to show how stable the models are for different specifications. Furthermore, they provide an answer to the question how the predictive accuracy of the models changes with the quantity of variables included.

	NI/TA	EBIT/TA	S/TA	CA/CL	CS/CL	WCAP/TA	OCF/CL	TL/TA	baseline hazard
Model 1	x								x
Model 2		x							x
Model 3			x						x
Model 4				x					x
Model 5					x				x
Model 6						x			x
Model 7							x		x
Model 8								x	x
Model 9	x		x						x
Model 10		x	x						x
Model 11	x					x			x
Model 12	x							x	x
Model 13		x						x	x
Model 14		x					x		x
Model 15	x					x			x
Model 16	x		x		x				x
Model 17	x		x	x					x
Model 18	x		x				x		x
Model 19		x	x			x			x
Model 20	x		x	x				x	x
Model 21	x		x				x	x	x
Model 22		x	x	x				x	x
Model 23		x	x				x	x	x
Model 24	x		x	x		x		x	x
Model 25	x	x	x	x				x	x
Model 26		x	x	x		x		x	x
Model 27		x	x		x		x	x	x

Table 4 Overview of models

4.3.4 Misclassification Costs

Misclassification costs are the direct and indirect costs a buyer incurs when a firm is classified as financially distress or financially viable even though that is not the case. The Type I error measures the percentage of observations that are classified as financially viable but are actually experiencing financial distress based on the financial distress definition (EBITDA less than financial expenses). The Type II error measures the percentage of observations that are classified as financially distressed but turn out to be fine.

As discussed in chapter 2.4.1 most studies assume misclassification costs are equal for Type I and Type II errors but that is not the case in practice. Type I errors are usually more costly than Type II errors because a financial loss tends to be incurred (Looney et al. 1989; Whalen 1991). Classifying a financially distressed firm as financially viable results in the buying firm losing a supplier. This impacts and potentially disrupts the supply chain. Type II errors (financially strong firms are classified as distressed) on the opposite only create lost opportunity costs from assessing suppliers in detail that do not turn out to experience severe financial distress. Thus, the misclassification costs differ, which should be captured by a higher penalty for Type I errors.

However, the difference in misclassification costs has not been uniformly quantified yet. It varies with the decision environment and therefore highly depends on subjective decision making (Gepp & Kumar 2012). Muller et al. (2009) expect Type I error costs to be 20 to 38 times greater than Type II error costs. Nevertheless, there is not sufficient empirical evidence on the misclassification costs of both error types to derive a concrete estimate for this data set.

Changing the relative Type I and Type II error costs results in different prediction accuracies (Hillegeist et al. 2004). Thus, no cut-off value is selected up front. For each model the *percentage correctly classified, Type I* and *Type II error* are generated for different cut-off values. Then the most suitable cut-off value can be chosen by each buyer individually to account for its business environment. This is not only done for the models that are built on the estimation sample but also for the output of the models that have then been run on the testing sample. The "CTABLE" function in SAS is used to generate this output (Karp n.d.).

5 Empirical Results

In this chapter the developed models are assessed for their predictive accuracy and robustness.

5.1 Model Assessment

For each of the 27 models a logistic regression has been run. First the models' performance is assessed by evaluating their estimated coefficient, standard error, p-value, global null hypothesis and measure of fit. Then classification rates are used to evaluate the classification accuracy of each model.

5.1.1 Logistic Regression Results

For each of the 27 models a logit model is run.[14] A significance level of five percent is chosen initially. Bendel & Afifi (1977) argue that it is better to use a higher significance value in the beginning to avoid not capturing relevant variables that turn out to be important in larger models. As the eight models, that only contain one explanatory variable and the baseline hazard rate, already achieve a p-value of less than 0,0001 based on the Wald Chi-Square this is not an issue with this sample. The high significance level achieved speaks in favor of the purposeful selection approach chosen. Even though the p-values are a bit overstated, because Huber-White standard errors are not used, all eight models are expected to easily meet the five percent threshold. All variables achieve a one percent significance level in all the models they are included in except the variable *WCAP/TA*. For *WCAP/TA* three out of the five models are not significant at the five percent level. It is also the only variable for which the coefficient takes different signs in the models. Thus, this variable seems to be a less stable predictor than the other variables. Generally the coefficients of all the significant variables have the sign that was expected based on their theoretical analysis in the variable selection chapter. Thus, hypothesis 1 to 5 can be approved.

The coefficients of the variables are quite stable, unless two highly correlated variables are included in the same model. Model 25 is the only model in which *NI/TA* and *EBIT/TA* are both included. This resulted in a much lower *NI/TA* coefficient, while the *EBIT/TA* coefficient remained similar to the level it takes in other models. This supports the concept of not including highly correlated variables in one model, as the coefficients are not meaningful then.

For logistic regressions the size of the estimated coefficient cannot be interpreted on its own, due to the non-linear function underlying the logit analysis. A ten percent increase in a ratio will have a different effect on a corporation that is not financially distressed oppose to a financially distressed

[14] The logistic regression results for all 27 models are available in appendix 3.

corporation. In order to assess the impact of a specific change in a ratio on the probability of financial distress the financial distress likelihood should be computed for the respective values separately, holding all other factors constant. The difference between the two probabilities can then be attributed to the change in the ratio.

The global null hypothesis is, that at least one of the predictor's regression coefficients is equal to zero in the model. In that case this variable would not explain any variation in the dependent variable. Based on the Wald Chi-Square Test all models can reject this hypothesis supporting the relevance of the selected variables.

The models statistical fit is assessed using the popular goodness-of-fit measurement for likelihood-based model selection, the Akaike Information Criterion (AIC).
It is calculated as $AIC = -2\ Log\ L\ +\ 2((k-1)+s$. $Log\ L$ is the log likelihood value and k is the number of levels of the independent variable, while s is the number of predictors in the model (SAS Annotated Output 2016). AIC therefore penalizes the log likelihood by the number of predictors included in the model. In general a good model aims to balance its accuracy and complexity. These two are often a tradeoff between bias and variance by statisticians. A financial distress model with a larger number of explanatory variables is expected to yield a better in-sample likelihood but not necessarily a better AIC Tian et al. (2015). The AIC value itself has no meaning, but the model with the smallest AIC has the best statistical fit. Therefore the AIC is mainly used to compare the statistical fit of the 27 models. Other assessment options include Receiver Operating Characteristics (ROC) curve (Chava & Jarrow 2004; Agarwal & Taffler 2008), information content (Zavgren 1985; Agarwal & Taffler 2008), trade-off function (Balcaen & Ooghe 2006), the Gini-coefficient (Balcaen & Ooghe 2006), log-likelihood ratio (Zmijewski & Dietrich 1984) and pseudo R square (Stock & Watson, 2012). The AIC is a well-recognized goodness-of-fit measure and since the output does not give any reason for concern no additional statistical measures are applied. Instead, attention is paid to the classification accuracy in the estimation and testing sample.

5.1.2 Classification Accuracy

Most frequently classification rates are used to test the validity of failure prediction models (e.g. Altman 1968; Ohlson 1980; Zavgren 1985; Lennox 1999; Agarwal & Taffler 2008). The measure 'fraction correctly predicted' measures how many observations were classified correctly (Miller 2009). The misclassification costs determine the cut-off point, the probability of financial distress for which an observation is classified as financially distressed. These misclassification costs are driven by the buying firm's exposure when a supplier defaults and the supplier's default dependencies (Wagner et al. 2009). Buyer's exposure measures the potential impact a resulting supply chain disruption has such as foregone sales, switching costs and the damages to the buyer's reputation. In addition, suppliers' default dependence is a crucial aspect to consider, as other suppliers of the buyer might also depend on the struggling supplier, so that its financial distress could trigger other critical suppliers to experience financial distress as well, which could further harm the buyer. How high these direct and indirect costs are will vary for each company. No empirical data about the direct and indirect costs a buyer would incur are available so far. So no cut-off value can be empirically determined in advance. Instead the choice of an individual cut-off value is delayed until after the model output is generated. This allows each buyer to tailor the models to his/her needs.

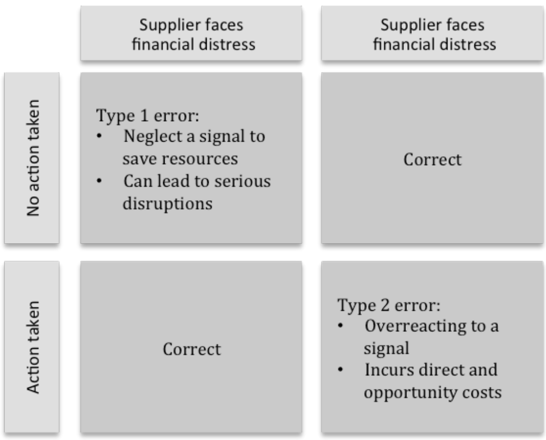

Figure 3 Misclassification costs based on Bode & Wagner (2012)

At a cut-off point of 0,5 the Type I and Type II errors are expected to be equally costly. With a lower (higher) cut-off point a lower (higher) Type I but higher (lower) Type II error is the result. As outlined Figure 3 if the cut-off value is chosen low by a more cautious buyer then the Type 1 error is low because most of the critical suppliers that are predicted to experience financial distress are detected. This highly sensitive approach also means that a lot of resources will be used to investigate corporations that the statistical tool classifies as financially distressed that turn out to be fine in a later investigation. Thus, a very low cut-off value will result in a more sensitive model. If the buyer is less worried about a supply chain disruption and choses a higher cut-off value then the statistical model might not recognize as many of the financially distressed firms (higher Type I error) but also investigate less firms that do not need an investigation (lower Type II error). Which approach is more appropriate for a buyer will depend on the buyer's exposure, suppliers' default dependence and buyer's general risk-averseness.

Since an empirical determination of the cut-off value is not possible a statistical evaluation has been done to see which cut-off value is most frequently resulting in the most accurate classification of observations. This cut-off value will be called 'optimal cut-off value'. The optimal cut-off value that is most frequent for the 27 models is 0,30. Thus, any observation that has a probability of experiencing financial distress above 30 percent is classified as financially distressed[15]. With this threshold the largest proportion of firms is correctly classified as financially distress or financially viable based on the explanatory variables of the model.

In order to illustrate this, Table 5 shows the classification table of model 13, the model with the highest classification accuracy out of the 27 models. Model 13 includes *EBIT/TA, TL/TA* and the *baseline hazard rate*. If the cut-off value that maximizes the percentage of observations that are correctly classified is chosen, then 91.7 percent of the observations are classified correctly as financially distressed or not distressed based on the explanatory variables. 3.7 percent of the as financially viable classified observations are actually distressed (Type I error) and 16.3 percent of the as financially distressed classified observations are actually financially viable (Type II error).

[15] For a more detailed overview of the analysis please see appendix 2.

	Percentages		
Probability	Correct	Type I error	Type II error
0	33.3	.	66.7
0.05	44.6	0.2	62.5
0.10	59.6	0.2	54.8
0.15	77.3	0.4	40.4
0.20	88.0	1.3	25.6
0.25	91.7	3.7	16.3
0.30	91.5	6.6	12.4
0.35	90.4	9.2	10.5
0.40	89.6	10.9	9.0
0.45	88.6	12.5	8.3
0.50	87.8	13.8	7.4
0.55	86.9	15.0	6.7
0.60	86.2	15.9	6.4
0.65	85.4	16.9	6.3
0.70	84.6	17.8	6.0
0.75	83.9	18.7	5.6
0.80	82.9	19.7	5.6
0.85	81.8	20.8	5.4
0.90	80.4	22.2	5.4
0.95	79.0	23.6	4.8
1.0	66.7	33.3	.

Table 5 Classification chart of model 13

The 27 models[16] showed that on average 84.6 percent of the estimation sample and 84.0 percent of the testing sample were correctly classified, when a cut-off value was chosen that maximizes the percentage of correctly classified observations. 91.8 percent was the highest, while 68.1 percent was the lowest achieved classification accuracy of the models. The average Type I and Type II error for the 27 models are 14 percent and 19 percent respectively. Aziz & Dar (2006) analyzed the results of 46 articles reporting 89 empirical studies of corporate bankruptcy prediction. Even though financial distress is not exactly the same, their findings help to put the results into perspective. Across all statistical and AIE models the average predictive accuracy (geometric mean) ranged between 67 and 94 percent. Logit models had an accuracy of 87 percent on average (for 19 models). The average type I error and type II error are 15 and 10 percent respectively. The papers that used a dataset of the USA had a geometric mean of 83.5 percent accuracy. However, most of those studies did not use a holdout sample. Thus, the presented results are probably biased upwards. They all mainly use a one-year prediction horizon, which is equivalent to the prediction horizon chosen in this study. Particularly

[16] The classification results for all 27 models are available in appendix 4.

older studies used smaller samples so that their results might not be as representative. Despite the mentioned limitations the results of the models in this study seem in line with the findings of previous studies and the performance can be ranked in the group of well performing models. This speaks in favor of the dataset, variable selection and model development that have been chosen.

5.1.3 Impact of the Quantity of Explanatory Variables on Predictive Accuracy

One research question is to test the impact of the number of variables used on the predictive accuracy of the models. Since accounting ratios are highly correlated (as shown in the model development chapter) it is hypothesized that models with more explanatory variables do not necessarily lead to a higher predictive accuracy. In order to test this hypothesis the predictive accuracy of the 27 models has been plotted against the number of variables the respective models contain.

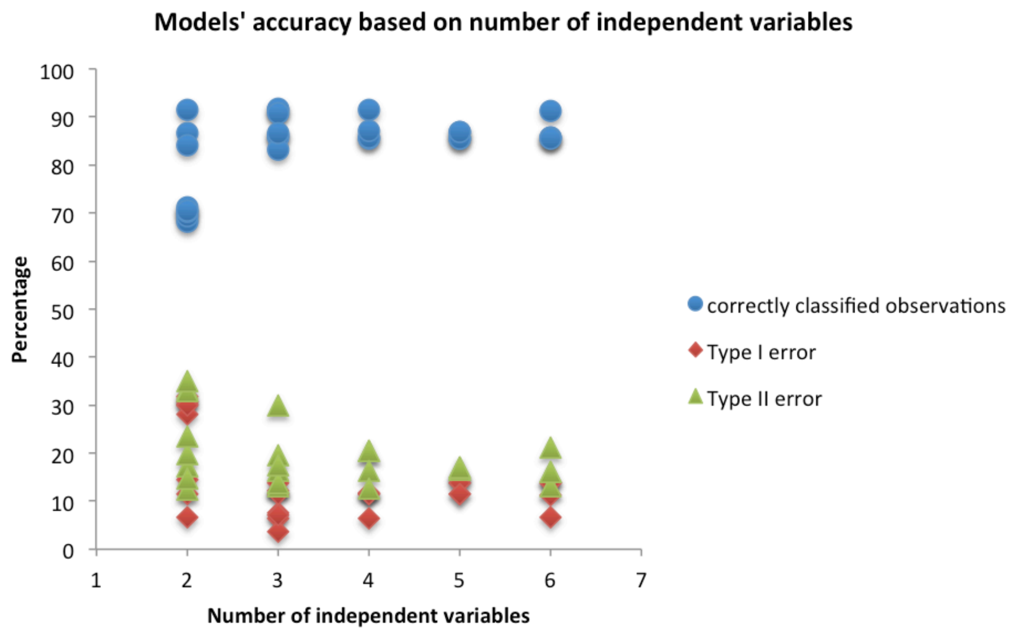

Figure 4 Quantity of explanatory variables and models' classification accuracy

As shown in Figure 4, the predictive accuracy increases for 1 to 3 variables but then it stagnates once three explanatory variables are included. The mirrored effect holds for the Type I error and Type II error. Because only up to nine variables are included in the models this might only be a local maximum and not a global maximum. Nevertheless, it seems reasonable to conclude that for models that only contain accounting ratios, models with more than 3 variables do not improve predictive accuracy. Thus, hypothesis 6 can be rejected.

5.2 Model Robustness

It is important to test whether the estimation results are robust to changes in the model's specifications. If the results are robust then inferences a researcher makes with respect to the prediction do not change. This is of practical importance for supply managers. They need to know the validity and stability of the models they use in order to apply them appropriately.

5.2.1 Internal Validity

Internal validity measures how well a model captures the cause-and-effect relationship or covariation of the dependent and independent variables (Gordon & Porter 2009). Since empirical data is used a variety of causes of corporate failure have not been included in the models. These include company-specific, industry-specific and macroeconomic factors that influence the likelihood that a company experiences financial distress. Only company-specific information in terms of accounting information and a macroeconomic indicator are included in the models. Thus, there clearly are various variables omitted, that limit the internal validity.

In this sample the two groups, financially distressed and financially viable firms, are clearly separated based on the financial distress definition (EBITDA is less than financial expenses for two consecutive years). This clear-cut rule contributes to the good classification results. In reality the financial distress criterion might not be so clear, because firms that hardly make their financial expense payments cannot really be considered financially viable. A model that distinguishes between more than two groups and reflects reality more accurately, might not achieve the classification accuracy of the models described here. Thus, the use of a dichotomous dependent variable has practical limitations. A decision-maker has a more continuous classification option than assumed in the choice of the dependent variable of this study (Hillegeist & Keating, 2002).

5.2.2 External Validity

External validity refers to the applicability of the results to other settings. Validation issues were first pointed out by Jones (1987). He recommended the use of hold-out samples to test external validity. Nevertheless, only 50 percent of the studies used hold-out samples as external validation tool. Many studies also use the Lachenbruch method (also called jackknife method), where one observation is excluded from the estimation sample to predict its classification (Bellovary et al. 2007). This process is then repeated for each observation in the sample. This method is very useful for small samples, where a hold-out sample would be too small but since the dataset of this study is sufficiently large a hold-out sample is used. The hold-out sample has been referred to as testing sample before. The hold-out sample used for the 27 models contains observations from the same sample period, industries and overlapping pool of corporations as the modeling sample. This can potentially bias the hold-out sample's accuracy rates upwards.

5.2.2.1 Temporal Stability

The 'stationarity assumption' implies that the relationship between the independent variables and the dependent variable are stable over time (Platt & Platt 1990; Jones 1987) Since the variables that have been use in the models have also shown significance in previous studies, covering various timeframes, this is expected to be a minor issue. However, the problem of non-stationarity is closely related to data instability. When the mean values of the independent variables differ for the estimation period and the forecast period then non-stationarity is the case (Stock & Watson 2012). Previous studies provide a lot of evidence of data instability and non-stationarity. Barnes (1987) and Richardson & Davidson (1984) suggest that the relationships between financial ratios are unstable over time because they might be sensitive to changes in factors like accounting methods, inflation, interest rates, business cycles and the competitive environment. Moyer (1977) finds that such economic idiosyncrasies of the observed period are ignored in many studies. Subsequently many classical statistical models have stationarity problems, which can negatively affect the predictive abilities of the model for subsequent periods. In that case the corporate failure prediction models would be unstable and would need frequent redevelopment in order to remain useful.

Timely variation of the economy-wide rate of financially distressed firms has been shown in the data chapter. Pooled data and a time-varying baseline hazard rate were used in this study, in order to account for this timely variation. Whether this was sufficient to account for the data instability needs to be assessed. Beaver, William H; McNichols, Maureen F.; Rhie (2005) achieved a high robustness with their three-factor prediction model over a 40 years timeframe using a hazard model. Therefore there is evidence of studies, where models hold for different years and some where this is not case. Therefore this section tests the best performing model, model 13, on portions of the testing data to test its stability when applied to different years. Ideally data for a year that has not been part of the modeling sample is used. Therefore the model is estimated excluding the observations available for the years 2014 and 2015 and then tested on the data for those two years.[17] Because the baseline hazard rate is 0.31 for 2014 and 2015 and thus has no discriminating power, this variable is excluded by SAS when running the model on the hold-out sample. Comparing the classification tables for the

[17] For an overview of the results please see appendix 5

estimation dataset and testing dataset a difference in performance is noticeable. Both models achieve a maximum classification accuracy for a cut-off value of 25 percent. Interestingly the classification for 2014-2015 has a classification accuracy of 94.2 percent while the classification accuracy for the data from 2000-2013 is 91.7 percent. The model therefore seems to perform even better on more recent data. The difference in the classification accuracy of 2.5 percent is not considered large enough to raise doubt about the stability of this model for supplier screening purposes. The model can therefore be used in the recent future.

5.2.2.2 Industry Variability

All models were develop with and tested on datasets that contained observations from various industries. Industry differences were not accounted for assuming they would not be sufficiently strong to impair the model. Grice & Dugan (2001) find that Zmijewski's and Ohlson's models are not transferable to other industries. The testing sample results are still biased upward when the industries included in the estimation sample are the same as those in the testing sample (see Begley et al. 1996; Zavgren 1985; Altman 1968). Therefore one industry, services (SIC 7000-8999), is excluded from the estimation sample and model 13 is then assessed on its performance for that excluded industry.[18] The model achieves an accuracy for the estimation sample of 92.6 percent, while the application of the model to the service industry results in a slight decline of the classification accuracy to 87.9 percent, when the same cut-off value of 25 percent is chosen. The maximum accuracy of the testing sample is 89.4 percent for a cut-off value of 0.35. This highlights the relevance of carefully selecting the cut-off value, based on the misclassification costs of the buyer, as it strongly influences the classification accuracy. These findings do not raise concern about applying the model to different industries.

5.2.3 Reliability

Reliability refers to the ability to get the same result when repeating the analysis (Carmines & Zeller 1979). As outlined in the model assessment chapter the predictive accuracy, the Type I and Type II errors are very similar to those of previous studies that also used accounting ratios. Therefore the reliability is assumed to be no issues for the models.

[18] For an overview of the results please see appendix 6

Models	Number of explanatory variables	Percentage of observations correctly classified
Model 13	3	91.7
Model 12	3	91.7
Model 10	3	91.4
Model 19	4	91.5
Model 2	2	91.4
Model 25	6	91.2
Model 14	3	90.7
Model 27	6	85.5
Model 21	5	86.9
Model 23	5	86.9
Model 15	3	86.7
Model 17	4	85.6
Model 1	2	86.7
Model 18	4	87.0
Model 16	4	85.5
Model 11	3	85.6
Model 9	3	86.2
Model 20	5	85.5
Model 22	5	85.5
Model 24	6	85.6
Model 26	6	85.6
Model 7	2	84.0
Model 3	2	71.1
Model 8	2	70.4
Model 5	2	69.3
Model 6	2	70.2
Model 4	2	68.1

Top 25% based on chosen criterion

Bottom 25% based on chosen criterion

Table 6 Overview of 27 models ranked by their classification accuracy

Even when the independent variables included in the models differ from one model to the other, the results are very similar (see Table 6). When comparing the results of the 27 models the performance of the best performing 25 percent is very similar and then 50 percent of models following are very similar again. Only the bottom quarter of models has more variation in its predictive accuracy. All except one of these models in the bottom quarter only have one variable besides the baseline hazard rate. So these models are simply too small to capture enough of the variation in the dependent variable to perform as well as the other models. Thus, the performance of models with at least three variables is very reliable no matter which combination of accounting variables is chosen.

6 Discussion

The financial default of a critical supplier is a rare but high impact event that strongly affects the buying organization. When a critical supplier defaults costly supply chain disruptions are very likely. Assessing the financial viability of suppliers is therefore a vital part of supplier risk management. Practically this can be challenging as corporate failure is a complex process and investigating all suppliers in detail is often not feasible for buyers with many suppliers.

This thesis investigated the opportunity of using a several step screening procedure. The first screening step involves a statistical screening tool that identifies and filters out those critical suppliers that have an elevated probability of experiencing financial distress in the next year. For each of the risk classes, that suppliers have been classified into by the statistical tool, subsequent screen steps are applied. These have varying scopes and intensities of investigation depending on the risk class. The last screening step is then used to decide which of the high-risk critical suppliers need intervention or mitigation. Thus, the statistical tool only applies to the first step of the scanning stage in the supplier risk management process (scanning, interpreting, acting and learning). The major tasks of the tool are to ease the screening process of the numerous suppliers and promote an efficient allocation of the buyer's resources in the process.

The discussion of the statistical tools showed that logit analysis outperforms multivariate analysis in terms of its applicability and interpretability in the decision context of supply managers. The selected variables are significant in all models, except two models that included the working capital measure. This highlights that all other profitability, operating performance, liquidity and leverage measures are strong predictors of firms' financial distress. The estimated coefficient of each of them shows the expected positive or negative relationship with the financial distress likelihood. The predictive accuracy turned out to be very stable for the different variable combinations. Thus, the range of the correctly predicted observations and the two error types are very narrow. This is attributed to the high correlation between the different variables being selected. Consequently, the hypothesis that the quantity of variables has a positive effect on the accuracy of predictions is rejected for models based on accounting ratios. The models have shown a limited internal validity due to the wide range of possible causes and mediating factors that are not included in the models. However, the external validity has proven to be very high as the models turn out to be very stable over time and among industries. This significantly simplifies the application, as industry-specific and timeframe-specific models do not seem necessary. The fact, that the costs for data acquisition, variable selection and model development can thereby be reduced strengthens the argument to consider statistical tools.

For the results that have been elaborated above limitations and weaknesses are discussed. This discussion focuses on the following three topics: theoretical foundation, decision context of the supply manager and statistical refinements.

6.1 Theoretical Foundation

As outlined, the theoretical foundation for financial distress predictions is very limited.
The difference between financial distress and bankruptcy has received little attention so far. Bankruptcy reflects a later stage in the corporate failure process. Thus, not all findings for bankruptcy prediction necessarily hold for financial distress prediction. These differences should be investigated in more detail in future research.

Most empirical studies, including this one, assume the failure process is uniform for different corporations. However, this is practically not the case due to various company-specific characteristics that mediate the impact of external influences. Particularly factors like a supplier's relationships with its stakeholders can strongly affect the financial distress likelihood. Furthermore, the chosen dataset only includes public corporations in the USA. However, most of the suppliers tend to be SMEs that are located all over the world. The failure process of SMEs might be very different from a public corporation. Omitting these factors can result in omitted variable bias and inadequate countermeasures. A deeper understanding of when which company-specific factor has a strong or weak mediating effect could advance the development of statistical models that provide more concrete recommendations to decision-makers about what actions to take.

This touches upon a core issue that has not received sufficient attention in this and previous research: How can a supply manager take the step from understanding that a critical supplier is at risk to deciding what actions he/she should take? Information about company-specific factors causing financial distress is usually not publicly available, reliable, objective, quantifiable or already outdated by the time it is provided. The statistical tools therefore mainly employ symptoms as variables in their models. This however has the disadvantage that the models do not capture cause-effect relationships. Therefore they are not useful for identifying the root-cause of the financial distress situation of a supplier. However, this is needed in order to undertake effective countermeasures. Thus, statistical tools show potential for generic screening solutions, that predict the financial distress likelihood of critical suppliers, but they are not helpful in providing actionable insights about the source of the financial distress.

6.2 Decision Context

This thesis highlights the importance of taking the decision context into consideration when developing financial distress prediction models. However, the supply chain literature has primarily developed conceptual models. In order to ensure that the financial distress models can serve supply managers well more insights into what supply managers actually do need to be generated.

This particularly relates to the characteristics of the decision-maker and how he/she reaches decisions so far. What information is currently used? Which processes and methods are currently adopted? Why are they used? What are their advantages and disadvantages? Is credit default actually the most relevant economic event or is there another one? What are the costs of misclassification?

Only with a clear understanding of these factors it is possible to conclusively assess and quantify if and by how much statistical tools, like the one developed in this thesis, can outperform the current process and methods in place. The current empirical research is not sufficient to allow final conclusions on this matter.

Besides the accuracy of different tools and processes a cost-benefit trade-off needs to be made. However, calculating the return on investment for a more accurate financial distress prediction tool is difficult. The main cost block would involve the data collection and model development for the geographic area of interest. Afterwards the model can be applied to the pool of critical suppliers for the near future. Thus, the recurring costs for this analysis method are expected to be minor. If the tool works effectively then it will avoid costs, which are not readily measured. Efficient supplier risk management ensures that a critical supplier's financial distress can be prevented or protective measures can be implemented in time, so that the supply chain is not adversely affect by a defaulting critical supplier. Determining how many critical events have been prevented due to countermeasures is practically very difficult. Nevertheless, concrete data needs to be generated to verify and complement the theoretical and statistical usability of the developed screening tool with a solid business case. These results should be benchmarked to the current and alternative solutions, like partially or completely outsourcing the analysis to a third party.

In order to develop a practical approach it was briefly discussed for which parts of the analysis a statistical assessment might be superior to a qualitative assessment and the other way around.

The theoretical discussion should be complimented with reports about practitioners experience with various tools. This feedback should not only be constraint to supply managers. Potentially other departments such as export financing also employ screening techniques to assess the financial viability of customers. Leveraging their experience could support the tool and process development.

Thus, a close collaboration with supply managers is necessary not only to understand the existing processes but also to explore how new processes can be put in place that advance supplier risk management.

6.3 Statistical Refinements

The 27 models that have been developed showed a very high level of stability and consistency across industries and time. This speaks in favor of the representative sample chosen and the theory based variable selection. Even though the models only contain a limited number of predictors and omit various other factors a very high classification accuracy has been achieved. Of course, the accuracy could potentially be further improved with more focused models. However, the main benefit of more focused models is not the accuracy but their contribution to a deeper understanding of how the supplier's environment affects its financial distress likelihood. More specific models with *different financial distress types*, *different geographic regions, more specific industries segmentations, different prediction horizons* and *more time series data* could give a better understanding of the business environment of suppliers.

Different geographic regions: According to Laitinen & Suvas (2016) there are a number of factors, which weaken the international applicability of country-specific models. These factors include accounting legislation and practice (Choi & Levich 1991), creditor rights and investor protection (Stulz & Williamson 2003), law enforcement (Radebaugh and Gray 1993) and corporate governance (Doidge et al. 2007). However, these factors have only been assessed for bankruptcy prediction so far and should also be assess for financial distress prediction.

Industry segmentation: The choice of industry groups limits the identification of different industry effects. The larger the group the more likely the industry effect disappears in the group (Berkovitch & Israel 1998). The groups chosen in this study are based on the SIC groups. These groups are not very specific. Thus, the groups chosen for the models might have simply been too broad to capture the industry-specific effects. Furthermore, this assessment only compared all industry SIC groups with the services SIC group and not the individual segments. In order to investigate this effect further smaller industry groups are expected to be better to receive more accurate industry effects.

Prediction horizon: This study employs an annual prediction horizon. It should be assessed in case studies whether this is an appropriate timeframe for supply managers to predict financial distress and implement countermeasures.

Time series data: The use of more information from previous quarterly and annual reports would enable the identification of trends. Assessing those trends and accounting for industry averages in the process could facilitate more insights into the differences of corporate failure processes. Furthermore, company-specific fixed effects could be excluded by only looking at changes in ratios over time.

7 Conclusion and Recommendations

In the last decade supply chains have become more lean, global and complex. This made supply chains particularly sensitive to disruptions. A rare but high impact disruption is a defaulting critical supplier. In order to avoid and mitigate such events supply managers have to accurately predict and react to the financial distress of their suppliers. So far supply managers have mainly relied on qualitative tools. This is particularly difficult for buyers with numerous suppliers. Due to resource and time constraints these buyers cannot investigate all suppliers in great detail. Thus, a prediction and prioritization tool is needed.

This thesis investigated the opportunity of employing a statistical tool to predict supplier's financial distress. A statistical tool is suggested as a first step of a several step screening procedure that narrows down the list of critical suppliers to those that have an elevated probability of experiencing financial distress in the next year. Only the critical suppliers in the high-risk category are then further assessed in subsequent screening steps.

The logit analysis demonstrated a high suitability for the decision context of supply managers due to its high predictive accuracy, ease of application and straightforwardness of the evaluation. Several logit models based on accounting information were developed. They produced accurate, reliable and valid results that are expected to be representative for the suppliers of buying firms. Further tests confirmed the models' performance for different timeframes and industries. Based on the statistical and theoretical assessment, accounting based logit models show high potential to advance the financial distress prediction of suppliers' financial viability.

After the first screening step a more detailed assessment needs to be done of those corporations that show a high risk of experiencing financial distress. This involves an analysis of non-financial firm-specific factors and industry-specific factors. For this step a qualitative approach is recommended, as it seems to provide a more accurate and less costly way to investigate the causes of a supplier's financial distress. In the last step a decision is made whether actions are undertaken to avoid or mitigate the impact of financial distress of a supplier.

Future research should investigate the corporate failure process and the difference between financial distress and bankruptcy predictors. This would help advance the theoretical foundation for practical prediction models.

In order to promote the application of predictive models, research needs to move away from the abstract decision-maker and tailor the predictive models to the decision-maker context. Besides statistical considerations, the business case of using statistical tools should be investigated further. For this case study based research is recommended.

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Appendices

Appendix 1: Observations Per Year

Year	Number of observations	No FD	With FD	percentage with FD
2000	6656	5111	240	4%
2001	5906	2774	1894	41%
2002	5363	2601	1734	40%
2003	4915	2500	1462	37%
2004	4598	2415	1265	34%
2005	4259	2353	1061	31%
2006	3954	2175	968	31%
2007	3662	2039	877	30%
2008	3417	1922	798	29%
2009	3264	1836	766	29%
2010	3155	1898	631	25%
2011	3154	1982	550	22%
2012	3196	2018	557	22%
2013	3160	1828	680	27%
2014	2895	1574	737	31%
2015	201	112	43	31%
				29,0%

Appendix 2: Most Frequent Optimal Cut-off Value

Optimal cut-off value	Frequency estimation sample	Frequency testing sample
0,25	2	2
0,3	16	11
0,35	1	8
0,4	3	1
0,45	5	5
	27	27

Appendix 3: Logistic Regression Results All Models

	Intercept		NI/TA		EBIT/TA		S/TA		CA/CL		CS/CL		WCAP/TA		OCF/CL	
	p-value	α	p-value	β_1	p-value	β_2	p-value	β_3	p-value	β_4	p-value	β_5	p-value	β_6	p-value	β_7
Model 1	<0.0001	-2.0936	<0.0001	-5.5041												
Model 2	<0.0001	-1.8334			<0.0001	-12.8409										
Model 3	<0.0001	-1.559					<0.0001	-0.5239								
Model 4	<0.0001	-2.0739							<0.0001	0.053						
Model 5	<0.0001	-2.2086									<0.0001	0.1705				
Model 6	<0.0001	-1.9247											<0.0001	0.5555		
Model 7	<0.0001	-1.3082													<0.0001	-2.3434
Model 8	<0.0001	-2.4809														
Model 9	<0.0001	-1.746	<0.0001	-5.3829			<0.0001	-0.4381								
Model 10	<0.0001	-1.6304			<0.0001	-12.7002	<0.0001	-0.2661								
Model 11	<0.0001	-2.317							<0.0001	0.0883						
Model 12	<0.0001	-2.1562	<0.0001	-5.4649												
Model 13	<0.0001	-1.992			<0.0001	-12.8599										
Model 14	<0.0001	-1.6203			<0.0001	-10.3183									<0.0001	-0.7626
Model 15	<0.0001	-2.1036	<0.0001	-5.4753									0,0736	0.055		
Model 16	<0.0001	-2.034	<0.0001	-5.1656			<0.0001	-0.3065			<0.0001	0.1342				
Model 17	<0.0001	-1.9549	<0.0001	-5.3122			<0.0001	-0.3788	<0.0001	0.0664						
Model 18	<0.0001	-1.1993	<0.0001	-2.7074			<0.0001	-0.3653							<0.0001	-1.6925
Model 19	<0.0001	-1.6218			<0.0001	-12.5698	<0.0001	-0.264					0,3823	-0.0323		
Model 20	<0.0001	-2.3201	<0.0001	-5.1265			<0.0001	-0.422	<0.0001	0.0934						
Model 21	<0.0001	-1.4425	<0.0001	-2.4825			<0.0001	-0.4166							<0.0001	-1.7005
Model 22	<0.0001	-2.0301			<0.0001	-12.429	<0.0001	-0.2787	<0.0001	0.0462						
Model 23	<0.0001	-1.5406			<0.0001	-10.0672	<0.0001	-0.3297							<0.0001	-0.8014
Model 24	<0.0001	-2.3357	<0.0001	-5.126			<0.0001	-0.4242	<0.0001	0.0917			0,4546	0.0427		
Model 25	<0.0001	-2.0278	0,7093	-0.0281	<0.0001	-12.4006	<0.0001	-0.279	<0.0001	0.0461						
Model 26	<0.0001	-2.2281			<0.0001	-12,4094	<0.0001	-0.3108	<0.0001	0.0252			<0.0001	0.5486		
Model 27	<0.0001	-2.2554			<0.0001	-12.2881	<0.0001	-0.2734			<0.0001	0.0678	<0.0001	0.436		

	TL/TA		baseline hazard		AIC Intercept & Covariates	Global Null Hypothesis
	p-value	β_8	p-value	β_9		ChiSq
Model 1			<0.0001	2.9117	38382.234	<0.0001
Model 2			<0.0001	2.8199	28508.884	<0.0001
Model 3			<0.0001	4.7715	52037.169	<0.0001
Model 4			<0.0001	4.2605	52781.849	<0.0001
Model 5			<0.0001	4.4083	51425.385	<0.0001
Model 6			<0.0001	4.4313	51337.252	<0.0001
Model 7			<0.0001	2.8639	35273.261	<0.0001
Model 8	<0.0001	0,6442	<0.0001	4.6161	51506.102	<0.0001
Model 9			<0.0001	3.2967	37594.536	<0.0001
Model 10			<0.0001	3.0783	28282.967	<0.0001
Model 11			<0.0001	2.8231	37104.817	<0.0001
Model 12	0,0002	0,1024	<0.0001	2.9326	38288.852	<0.0001
Model 13	<0.0001	0,2752	<0.0001	2.8309	28383.133	<0.0001
Model 14			<0.0001	2.6005	27026.022	<0.0001
Model 15			<0.0001	2.9056	37610.189	<0.0001
Model 16			<0.0001	3.217	36146.488	<0.0001
Model 17			<0.0001	2.4041	36552.951	<0.0001
Model 18			<0.0001	2.782	31466.377	<0.0001
Model 19			<0.0001	3.051	27703.717	<0.0001
Model 20	<0.0001	0,5362	<0.0001	3.3265	36196.796	<0.0001
Model 21	<0.0001	0,4373	<0.0001	2.9215	31145.796	<0.0001
Model 22	<0.0001	0,5158	<0.0001	3.0564	27437.183	<0.0001
Model 23	<0.0001	0,3514	<0.0001	2.9134	26583.593	<0.0001
Model 24	<0.0001	0,5569	<0.0001	3.3337	36198.239	<0.0001
Model 25	<0.0001	0,5121	<0.0001	3.0525	27439.044	<0.0001
Model 26	<0.0001	0,7915	<0.0001	3.1298	27375.181	<0.0001
Model 27	<0.0001	0,7757	<0.0001	3.1266	27292.575	<0.0001

Appendix 4: Overview Classification Accuracy All Models

	Estimation data				Testing data			
	correct	Type I error	Type II error	cut-off value	correct	Type I error	Type II error	cut-off value
Model 1	87.2	11.3	16.4	0.30	86.7	11.6	17.3	0.30
Model 2	91.5	6.6	12.3	0.30	91.4	6.7	12.5	0.30
Model 3	71.0	28.8	30.5	0.45	71.1	28.2	33.4	0.45
Model 4	67.4	32.5	35.7	0.45	68.1	31.8	33.0	0.45
Model 5	68.9	30.7	35.9	0.45	69.3	30.2	35.1	0.45
Model 6	70.1	30.7	12.6	0.45	70.2	30.6	14.8	0.45
Model 7	84.4	14.1	19.3	0.40	84.0	14.6	19.7	0.40
Model 8	70.6	30.0	21.5	0.45	70.4	30.0	23.5	0.45
Model 9	87.3	10.4	17.7	0.30	86.2	13.7	13.9	0.35
Model 10	91.5	6.5	12.5	0.30	91.4	6.4	13.0	0.30
Model 11	86.5	11.5	18.0	0.30	85.6	12.1	19.5	0.30
Model 12	86.9	11.3	16.4	0.30	83.2	7.5	30.0	0.25
Model 13	91.8	4.0	15.5	0.25	91.7	3.7	16.3	0.25
Model 14	91.0	6.9	13.2	0.30	90.7	7.0	13.8	0.30
Model 15	87.2	11.3	16.4	0.30	86.7	11.5	17.5	0.30
Model 16	86.4	11.3	18.6	0.30	85.5	11.7	20.4	0.30
Model 17	86.8	10.9	18.3	0.30	85.6	11.5	20.4	0.30
Model 18	87.5	11.3	15.5	0.35	87.0	11.6	16.4	0.35
Model 19	91.5	6.5	12.4	0.30	91.5	6.4	12.7	0.30
Model 20	86.6	10.8	18.9	0.30	85.5	13.7	16.5	0.35
Model 21	87.4	12.7	12.3	0.40	86.9	11.4	17.1	0.35
Model 22	86.6	10.8	18.9	0.30	85.5	13.7	16.5	0.35
Model 23	87.4	12.7	12.3	0.40	86.9	11.4	17.1	0.35
Model 24	86.6	10.8	18.9	0.30	85.6	13.8	16.0	0.35
Model 25	91.5	6.5	12.4	0.30	91.2	6.7	13.1	0.30
Model 26	86.6	10.8	18.9	0.30	85.6	13.8	16.0	0.35
Model 27	86.6	11.0	18.6	0.30	85.5	11.2	21.1	0.30
Average/mode	84.6	13,8	18.1	0.30	84.0	14.2	19.13	0.30

Appendix 5: Temporal Stability

	Estimation sample			Testing sample		
Probability	Correct	Type I error	Type II error	Correct	Type I error	Type II error
0.00	33.2	.	66.8	31.8	.	68.2
0.05	46	0.1	61.9	53.8	0	59.2
0.10	62.6	0.3	52.9	72.5	0.1	46.4
0.15	79.2	0.6	38.3	86.8	0.5	29.1
0.20	88.8	1.7	24.1	93.3	1.1	16.3
0,25	91.7	4.0	15.8	94.2	3.4	10.7
0.30	91.5	6.7	12.4	93.6	5.7	8.0
0.35	90.6	8.9	10.6	93.1	7.0	6.8
0.40	89.7	10.6	9.5	92.3	8.4	5.9
0.45	88.9	12.1	8.4	91.6	9.4	5.4
0.50	88.1	13.4	7.7	91.0	10.3	5.1
0.55	87.3	14.5	7.3	90.4	11.2	4.6
0.60	86.6	15.4	6.8	89.9	11.9	4.4
0.65	85.8	16.4	6.4	89.1	12.8	4.4
0.70	85.1	17.2	6.0	88.4	13.6	4.3
0.75	84.4	18.1	5.6	88.0	14.3	3.7
0.80	83.6	19.0	5.3	87.2	15.2	3.5
0.85	82.6	20.0	5.0	86.7	15.8	3.4
0.90	81.5	21.1	4.6	85.9	16.7	2.9
0.95	79.9	22.7	4.2	84.5	18.1	3.1
1.00	66.8	33.2	.	68.2	31.8	.

Appendix 6: Industry Variability

	Estimation sample			Testing sample		
Probability	Correct	Type I error	Type II error	Correct	Type I error	Type II error
0.00	31.8	.	68.2	38.2	.	61.8
0.05	48.9	0.1	61.7	43.3	0.6	59.8
0.10	66.8	0.1	51.1	53.5	0.3	54.9
0.15	82.6	0.5	35.3	68.2	0.8	45.4
0.20	90.5	1.6	21.6	81.4	1.8	32.3
0.25	92.6	3.8	14.3	87.9	4.2	21.5
0.30	92.2	6.2	11.4	89.4	7.4	15.4
0.35	91.4	8.1	9.7	88.8	10.4	12.8
0.40	90.6	9.6	8.8	87.4	13.3	11.2
0.45	90.0	10.8	7.8	86.1	15.5	10.3
0.50	89.2	12.0	7.0	85.1	17.1	9.4
0.55	88.4	13.1	6.5	84.3	18.4	8.6
0.60	87.8	13.9	6.1	83.3	19.7	8.0
0.65	87.2	14.8	5.7	82.4	20.8	7.4
0.70	86.4	15.7	5.5	81.5	22.0	6.9
0.75	85.8	16.4	5.1	80.4	23.2	6.7
0.80	85.1	17.2	4.8	79.3	24.3	6.3
0.85	84.2	18.2	4.5	77.9	25.7	6.1
0.90	83.2	19.2	4.2	76.7	26.9	5.5
0.95	81.7	20.8	3.8	74.8	28.6	5.4
1.00	68.2	31.8	.	61.8	38.2	.