The influence of firm-specific and industry-specific risk factors on the probability of bankruptcy of Dutch firms

Master Thesis

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Table of Contents

Abstract

This research tries to explain financial distress as well as predict bankruptcy, or more general the probability of default, for Dutch firms: one sample including both large firms and SMEs, and one sample focussing on SME firms. Whereas previous researches oftentimes focus on financial ratios, this research takes a step further by focusing on risk factors pertaining to credit/liquidity risk factors, and industry risk factors. Probability of default and financial distress are measured by the interest coverage ratio and Altman's Z-score of which both has been tested for their applicability in either default prediction or explanation.

The results indicate the importance of the inclusion of liquidity measures in default prediction models: having too much working capital tied up leads to a higher probability of default, due to a higher cost of capital and higher opportunity costs of not investing the money elsewhere. In addition, access to financing appears to be a problem in this sample as well, as firms that do not have a proper access to outside financing experience a higher probability of default. It even appears that this variable moderates the relationship between the cash conversion cycle and probability of default, so that firms that have less access to financing should optimize their cash conversion cycle. Regarding industry variables, the explained variance of the model did not increase significantly, thereby indicating that industry variables are less important in default prediction studies. However, some industry variables did have a significant relationship with the probability of default, i.e. barriers, more specifically financial barriers and weather risk, competition and industry sales price.

It appears that firms that have a below-average interest coverage ratio have a 1,740 times higher chance of going bankrupt. In addition, firms with a low access to financing have a 2,972 times higher chance of going bankrupt. These outcomes add to our understanding of bankruptcy prediction and might be included in future researches on bankruptcy prediction models.

The need for distinguishing between larger firms and SMEs is important, as SMEs are significantly different from larger firms: something that has been indicated in this research. This research should be perceived as the basis for bankruptcy prediction, but should in the future be extended to include other risk categories, such as management risk or market risk, as well.

This research adds to future researches by focusing on a full Dutch sample as well as on non-financial variables, two factors that are often not researched due to a limited availability of data. However, this research has shown the importance of inclusion of non-financial variables and

has indicated that both the interest coverage ratio and Altman's Z-score are good indicators of the probability of bankruptcy.

1. Introduction

Prediction of bankruptcy has been on the research agenda of accounting and finance academics for the last four decades (Kim & Partington, 2015). Decades ago, banker “expert” systems were used to assess the credit risks related to corporate loans by which bankers used information regarding borrowers’ characteristics, e.g. borrower’s character (reputation), capital (leverage), capacity (volatility of earnings) and collateral, which are called the so-called 4 “Cs” of credit (Altman & Saunders, 1998). However, this kind of measurement is rather subjective, and therefore researchers have aimed to construct credit risk models for large firms in the first place. Among the first researchers is Altman (1968), who has used historical accounting information in the prediction of bankruptcy. Altman (1968) tried to predict bankruptcy by the use of financial ratios and drew the conclusion that his Z-model was able to predict bankruptcy correctly in 94% of the cases. Another stream of bankruptcy prediction researches started by the work of Merton (1974), who used securities market information in his prediction of financial distress (Gupta et al., 2015).

The first credit models were aimed to predict the bankruptcy of large, listed firms. However, in the Netherlands, small- and medium-sized enterprises (SMEs) are the backbone of the economy, which is oftentimes the case for wealthy nations (Gupta et al., 2015; Li et al., 2016). In the European Union, SMEs contribute more than half of all value added by businesses and even comprise 99% of all enterprises (Ferreira Filipe et al., 2016). In the Netherlands, the total SME sector contributes to over 60 percent of all value-adding activities and to 70 percent of total employment (SME Servicedesk, 2017).

Small- and medium-sized enterprises differ from large firms, which has also been acknowledged by literature. Large enterprises and SMEs differ significantly as SME survival is more easily threatened by their smaller amount of financial and non-financial resources (Falkner & Hiebl, 2015). In addition, SMEs have a lower quality of financial reporting that leads to information asymmetry between lenders and SMEs, which makes banks and financial institutions hesitant to provide SME loans, which may eventually lead to inadequate financing and credit rationing (Duarte et al., 2016). Although SMEs are important in many economies, the current literature related to credit risk is heavily tilted towards larger firms as there is a limited availability of SME information and financial data (Gupta et al., 2014; Ferreira Filipe et al., 2016). The best way to ensure a sufficient flow of financing to SMEs can be achieved by improving credit information and by developing adequate risk models (Altman et al., 2010). From a credit-risk perspective, it can therefore be argued that it is important to distinguish between SMEs and large enterprises, as it is difficult to assess SME's probability of default and riskiness of the loan.

In addition to the focus on large firms when developing credit risk models, current research is also still heavily tilted towards the use financial ratios (Gupta et al., 2014). However, when including non-financial characteristics such as business type and sector, compliance and operational risk, Altman et al. (2010) were able to improve their model performance with about 13%, highlighting the importance of the inclusion of non-financial data (Gupta et al., 2015). This increase is due to qualitative variables being of great importance as financial institutions have difficulty in finding reliable information on SMEs (Ferreira Felipe, 2016), or larger firms in general. Improving credit scoring and bankruptcy prediction models could lead to an increase in profits for banks and other financial institutions (Abellán & Castellano, 2017). In addition, the Basel II Accord from 2004 requires financial institutions to correctly evaluate credit risk by assessing SME's probability of default (Fernandes & Artes, 2016), which has increased the importance of credit scoring (Li et al., 2016). As SMEs and large firms both operate in an increasingly complex environment, it is important to consider the financial as well as the non-financial risk factors they are subjected to.

Knowing what risks can influence SME's probability of default will greatly assist in handling those risks. Any firm-specific or industry-specific risk that exerts influence on the risk of financial distress, bankruptcy, or the non-repayment of loans is important to consider as a financial institution of a firm. Firm-specific risk factors are in this instance considered as risk factors that are inherently present in the firm, e.g. employee, technology or management risk. Industry-specific risk factors are exogenous and the firm cannot exert any influence on these, e.g. industry or country risk.

In line the aforementioned arguments, the following research question is constructed that aims to answer which risk factors have the most influence on the probability of financial distress:

"What are the most important risk factors, both firm-specific and industry-specific, that influence the probability of bankruptcy of Dutch firms, and more specifically of small and medium-sized enterprises?"

As there is a lack of research on bankruptcy prediction models for SMEs and as most models are focused on financial data, this research attempts to fill this gap by providing analyses on the risk factors that exert on influence on the probability of bankruptcy for all Dutch firms, as well as for SMEs specifically. This research will specifically focus on credit and liquidity risks, and business/industry risks, of which the first two are linked to firm-specific risk and the last one to industry-specific risk factors. Both the need for evaluating credit risk when engaging in lending as well as the risk factors that exert influence on firms highlight the importance of bankruptcy risk in any lending process. Having a proper framework in place that can gauge bankruptcy risk of individual firms, and more specifically SMEs, will eventually limit credit rationing practices and inadequate financing. The results of this research are therefore particularly interesting for lending institutions and firms, more specifically SMEs. Lending institutions will be better able to assess the creditworthiness of the borrowers and firms learn more about the types of risk that exert a significant influence on their organization's performance.

In line with this, SynnoFin provides financial software to Dutch SMEs by which they can gauge their performance and benchmark this with other similar SMEs. This is done by integrating financial and non-financial information of SMEs, as well as industry-data in its software. In addition, SynnoFin provides insights in the prospects of an industry, so that SMEs can gain knowledge from it and prepare for the near future. As there is much data provided in the software, it is rather unclear which type of risk factors will exert the most influence on firm performance and might cause a higher probability of default. Gaining insights in the risk factors that are the most important in explaining the probability of bankruptcy will enable SynnoFin to optimize their software and providing better insights to Dutch SME firms.

The remainder of this research is structured as follows. Section 2 will present a literature review, including outcomes of previous studies and theories. In this section, frameworks for systematically analyzing risks will be discussed. The section will end with seven hypotheses of specific risk factors that will be tested throughout this research. Section 3 will describe the research methods, the sample, and provides an explanation of the variables included. Section 4 will describe the results and show the analyses performed by regression, survival analyses and some robustness checks. Section 5 will conclude this research by stating the main outcomes, relevance, limitations and directions for future research.

2. Literature Review

This chapter will start with a description of the different types of risk factors, ranging from financial risks to frameworks for non-financial risks. In addition, it will provide a thorough understanding of the different risk factors that might exert influence on Dutch firms. The chapter will end with a hypotheses section, in which seven hypotheses related to credit/liquidity risk and business/industry risk are outlined based on the performed literature review.

2.1 Risk factors

In literature, many studies have focused on financial ratio analysis in order to find out which financial ratios have a profound influence on the chance of going bankrupt. However, we are also interested in finding non-financial risk factors that exert influence on the probability of bankruptcy. In this section, first financial risk factors will be described. Afterwards, three different risk frameworks will be presented. At the end of this section, each type of risk will be explained individually.

2.1.1 Financial risks

Previous studies are heavily tilted towards the use of financial ratios in bankruptcy prediction. One of the first researchers to investigate the relationship between financial ratios and bankruptcy is Altman (1968), who has included give financial ratios, i.e. working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total debt, and sales/total assets, in his bankruptcy prediction model for public firms. Altman (1968) has assigned a loading to these variables in order to derive the Z-score, which indicates that the lower the score, the higher a firm's chance of going bankrupt. The formula has been found to correctly discriminate in 94 percent of the cases. Probably one of the first researches that has specifically focussed on modelling credit risks for SMEs is Edmister (1972), who has developed a model to predict defaults by the use of nineteen financial ratios. Allen et al. (2004) describe that most of the studies have found evidence that financial ratios measuring liquidity, profitability, and leverage have the highest influence in differentiating bankrupt from non-bankrupt firms. Altman and Sabato (2007) have developed a distress prediction model specifically for U.S. SMEs by the use of financial measures related to liquidity, profitability, leverage, coverage and activity. Ferreira Felipe et al. (2016) include in their financial distress prediction model financial ratios from nine categories, which are profitability, liquidity, interest coverage, activity, cash flow, leverage, growth (i.e. in sales or profits), asset utilization and employee efficiency. The authors expect all ratio categories to be negatively related to the probability of distress, except for leverage. Altman et al. (2010) and Kalak and Hudson (2016) incorporate many financial variables in their research, including leverage variables, working capital variables, and profitability variables.

The success of including financial ratios is widely acknowledged, but over the last years, researchers have combined this with qualitative information. Evidence has been found that accounting and market data complement each other (Tinoco & Wilson, 2013). In addition, empirical literature has found that qualitative information, such as firm's age, location, industrial sector, and business type have a significant influence on firm's credit risk (Gupta et al., 2015). This highlights the need for inclusion of other, non-financial, risk factors. However, such risk factors are still oftentimes ignored in SME literature due to a limited availability of data. The following section will outline risk frameworks in which a firm has to operate on a daily basis to survive.

2.1.2 Risk categories

In the literature, different frameworks for systemically analyzing risks firms are subjected to are constructed. In this section, three of these frameworks will be discussed and compared.

First, risks can be classified following the framework of Everett and Watson (1998) and Miller (1992), who both distinguish between economy-based risk, industry-based risk and firm-based risk. Economy-based risk is defined as the risk inherently present in the economy where a firm is operating (Everett & Watson, 1998). According to Miller (1992), examples of these economic, or general environmental, based risks are political instability, government policy instability, macroeconomic uncertainties, social uncertainties and natural uncertainties. Industry-based risk has to do with the risk present in the industry a firm is operating (Everett & Watson, 1998). According to Miller (1992), these risks pertain to input market uncertainties, product market uncertainties and competitive uncertainties, of which the latter includes rivalry among existing competitors, new entrants, and technological uncertainty. Firm-based risk deals with risks that are unique to the business itself (Everett & Watson, 1998). These risks include operating uncertainties, i.e. labor, input supply and production uncertainties, liability uncertainties, R&D uncertainty, credit uncertainty, and behavioral uncertainty (Miller, 1992).

Second, Olsson (2002) has developed a risk framework based on the key areas that set the size and demand for the firm. This framework includes as broad factors the economic environment, physical resources, social factors, and the political climate. The economic environment can be both domestic as well as international and encompasses factors such as interest rates, exchange rates, inflation and export demand levels. Physical resources include e.g. the availability of products and geography of a country. Social factors relate to e.g. population, education levels and availability of labor. The political climate relates e.g. to the relative size of the state in economic terms as well as the attractiveness of a country for investors. The economic environment encompasses credit, market, liquidity and systemic risk. Physical resources are linked to environmental and operational (technology) risks. Social factors include operational (people) and reputational risk. The political climate covers country, political, legal/regulatory, and accounting risk. Furthermore, a business is subjected to business risk, which includes risks related to sourcing, production, selling and competition, and industry risk.

Third, a distinction can be made between systematic and unsystematic risk, of which only the former is rewarded in terms of higher returns (Everett and Watson, 1998). In this case, both firm as industry based risk can be labelled unsystematic and will therefore not be rewarded by providing higher returns as this risk is diversifiable. Economy-based specific risk can be classified as systematic and can be beneficial in terms of higher returns. Especially for smaller businesses there is almost no possibility to diversify, which highlights the importance of both studying firm and industry specific risks in an SME environment.

In Table 1, the different risk frameworks are compared and the different kinds of risks have been classified into firm-based, industry-based or economy-based risk factors. As the study takes place in the Netherlands, the need for studying economy or general environmental risk is less, as all firms in this research are subjected to the same risk factors inherently present in a country's system. In addition, unsystematic risk is labelled as diversifiable, but this is not the case for many firms, especially SMEs, as they are small and do not have the resources to do so. Therefore, this study will focus on unsystematic risk, or firm-specific and industry-specific risks.

Table 1 Risk framework

Unsystematic	Firm-based	Credit uncertainty	Credit risk
		Behavioral uncertainty	Liquidity risk
		Operating uncertainties	Operational risk
		R&D uncertainty	Reputational risk
		Liability uncertainties	Legal/regulatory risk
			Accounting risk
	Industry-based	Input market uncertainties	Business risk
		Product market uncertainties	Industry risk
		Competition uncertainties	
Systematic	Economy-based	Political instability	Market risk
		Government policy instability	Systemic risk
		Macroeconomic uncertainties	Environmental risk
		Social uncertainties	Country risk
		Natural uncertainties	Political risk

Source: Everett and Watson (1998), Miller (1992), Olsson (2002)

2.1.3 Types of risk

The firm-based and industry-based risks pertain to credit risk, liquidity risk, operational risk, reputational risk, legal and compliance risk, accounting risk, and business/industry risk.

Credit risk is defined as "the risk that a counterparty may not pay amounts owed when they fall due" (Olsson, 2002, p. 34). Credit risk is directly linked to the probability of financial distress (Tinoco & Wilson, 2013, p. 397) and eventually the chance of bankruptcy. Especially small businesses are often paid late and therefore have the possibility of having higher credit risk (Olsson, 2002). In line with this, Miller (1992) argues that credit uncertainty has to do with collectibles, and default by clients on their financial obligations to the firm can lead to direct decline in the firm's income stream. In addition, the risk of non-payment can be quite prevalent if there is a concentration risk, which is the case if a company only does a couple of large projects (Olsson, 2002). As delay in payment causes liquidity risk, both are related to each other.

Liquidity risk is defined as "the risk that amounts due for payment cannot be paid due to a lack of available funds" (Olsson, 2002, p. 45). Liquidity risks are related to cash-flow problems. According to Olsson (2002), a company has three different sources of money to rely on: existing cash balances, borrowing, and selling assets. According to Serrasqueiro and Nunes (2008), liquidity can be measured by the ratio between current assets and short term liabilities. The higher this ratio, the less liquidity risk a company faces. One important indicator of working capital management is the cash conversion cycle, which can be optimized in order to enhance firm profitability (Zeidan & Shapir, 2017).

Operational risk is “the risk of loss due to actions on or by people, processes, infrastructure or technology or similar which have an operational impact including fraudulent activities” (Olsson, 2002, pp. 35). More specifically, it deals with management and employee risk, as well as the processes and technology within the firm that may have an effect on the exposure to risk and financial distress. According to agency theory, it is assumed that managers are risk-averse and that this in turn influences firm behavior (Bromiley et al., 2017). Managers try to reduce the chance of negative outcomes so that the potential costs to the manager are lowered (Gormley & Matsa, 2016). This risk category is related to the operating uncertainties category of Miller (1992), who describes it as an overarching concept including labor uncertainty, firm-specific input supply uncertainty, and production uncertainty.

Reputational risk is “the risk that the reputation of an organization will be adversely affected” (Olsson, 2002, pp. 35). According to Walker (2010), institutional theory, competitive resource-based theory and signalling theory are widely used theories in relation to corporate reputation. Institutional theory is related to identifying factors which lead towards building a reputation (Ali et al., 2015). The resource-based view is more concerned with the consequences of corporate reputation and relates to how reputation can lead to a sustainable competitive advantage (Walker, 2010). Signalling theory relates to how stakeholders view signals send out by the firm, especially regarding social performance and its influence on corporate reputation (Ali et al., 2015). Brammer and Pavelin (2006) have found that large firm reputation is determined by the firm’s financial performance, social performance, market risk, the nature of its business activities and the extent of long-term institutional ownership. Ali et al. (2015) argue that the antecedents of corporate reputation pertain to financial performance, social performance, media visibility, firm size, firm risk, firm age and long-term institutional ownership. Fiordelisi et al. (2013) have found that, within the banking-sector, the probability of reputational damage increases as size and profits increase, and that a higher level of capital investment and much intangible assets reduce the probability of reputational damage. Although very important, according to Olsson (2002), reputational risk is very difficult to measure, if not more or less impossible.

Legal and compliance risk is “the risk of non-compliance with legal or regulatory requirements” (Olsson, 2002, pp. 35). This is linked to reporting and compliance measures such as provision of full accounts, provision of cash flow statements, audited company, filing history (i.e. late accounts and changes in directors), and auditor switching (Altman et al., 2010).

Accounting risk is "the risk that financial records do not accurately reflect the financial position of an organization" (Olsson, 2002, p. 35). The quality of these financial statement information is an important factor, as the stakeholders of the firm need to be well-informed. For example, Van Caneghem and Van Campenhout (2012) suggest that the quality of financial reporting is associated with a better access to financing. Accounting conservatism is argued to be beneficial for firm performance, as it limits agency problems, facilitates debt financing, and limits underinvestment. Accounting conservatism is argued to be a corporate governance mechanism, as it decreases managerial incentives to make negative value investments (Ahmed & Duellman, 2011). This is an important finding related to agency theory, as this serves as a monitoring mechanism, which is less costly for outside stakeholders and in turn reduces their monitoring costs. In addition, accounting conservatism is therefore argued to alleviate the information asymmetry problem inherently present in the relationship between principal and agent. In line with this, it has been found that accounting conservatism is less applied by overconfident managers, as they prefer to delay loss recognition (Ahmed & Duellman, 2013). As debt holders are better able to assess the performance of firms that apply accounting conservatism, the cost of debt will be lower for these firms (Vander Bauwhede et al., 2015). This is argued due to high quality accounting leading to a better prediction of future cash flows and less information asymmetry. The findings of Vander Bauwhede et al. (2015) indicate that outside financiers value accounting quality and reward this with a lower cost of debt. In addition, these debt holders prefer conservative accounting as managers are found to make less risky investments in such an instance (Kravet, 2014).

Business/industry risk can be defined as "the potential threats to, and unwanted impacts on a company's operations, reputational capital, market share and profitability, as a consequence of operational decisions and strategies, and the exogenous responses of other actors to these decisions and strategies" (Graetz & Franks, 2016, p. 588/589). As industry organization economics theory predicts, firms that are subjected to many industry-specific risks have a higher chance of financial distress. According to Miller (1992), industry uncertainties pertain to input market uncertainties, e.g. shifts in market supply; product market uncertainties, e.g. changes in consumer tastes; and competitive uncertainties, e.g. new entrants or rivalry among incumbent firms.

As according to Olsson (2002), it is very difficult, if not impossible, to measure reputational risk, this variable has been excluded. In addition, SMEs are oftentimes not required to have their financial statements audited, which makes the inclusion of the variable legal and regulatory risk less useful. Furthermore, operational risk is difficult to measure as this information is not available and falls out of the scope of this research. In addition, the information for accounting risk is not available and will therefore be excluded. After considering this, the variables that will be included in this research are credit risk/liquidity risk, and business/industry risk. These variables will be elaborated on in the next section and the relationship with default probability will be hypothesized.

2.2 Hypotheses development

The types of risk that will be studied pertain to credit and liquidity risk, as well as industry-specific risk factors. All of these will be discussed in turn in different subsections.

2.2.1 Credit risk/liquidity risk

To recall, the definition of credit risk is “the risk that a counterparty may not pay amounts owed when they fall due” (Olsson, 2002, p. 34). In addition, liquidity risk has been defined as follows: “the risk that amounts due for payment cannot be paid due to a lack of available funds” (Olsson, 2002, p. 45). Liquidity risk therefore has to do with cash-flow issues, which might become a problem when a firm cannot repay its loan when its due. Therefore, it is important to look at a firm’s working capital management. Furthermore, a firm that cannot easily attain capital from the external market might also be at risk for not acquiring enough funds when needed. The second risk factor that will be discussed is therefore access to financing.

Working capital management

Working capital management is important for firms as it is found to result in higher stock prices, increased cash flow, and higher profitability (Zeidan & Shapir, 2017). Most firms have large amounts of cash invested in working capital and short-term payables, which makes these an important source of financing (Deloof, 2003). Miller and Modigliani (1958) argue that in a frictionless world, decisions to offer trade credit do not influence the value of the firm. This is due to them arguing that under some circumstances, i.e. a frictionless market, capital structure is irrelevant. However, as markets are not frictionless, offering trade credit can be a fruitful source of financing, especially in the case of taxes, as the value lies in the marginal tax rates among buyers and sellers (Brick & Fung, 1984). The above arguments highlight the importance of studying working capital management as a type of credit/liquidity risk.

According to Eljelly (2004), efficient liquidity management is related to controlling current liabilities and current assets in such a way that the risk of meeting short-term obligations is eliminated, but at the same time excessive investment needs to be avoided. This excessive investment in working capital is, however, oftentimes positively viewed at, as it provides a safety cushion for short-term financiers of the company (Eljelly, 2004). However, this excessive investment cannot be invested elsewhere in order to have the company grow. This would indicate that there is an optimal point of working capital, which makes the optimal trade-off between costs and benefits, which in turn maximizes firm value (Baños-Caballero et al., 2014).

On the one hand, having a high level of inventory and a generous trade credit policy might lead to an increase in sales and receiving higher discounts (Deloof, 2003; Baños-Caballero et al., 2014; Zeidan & Shapir, 2017). Having a larger amount of inventory will lead to less stock-outs and trade credit stimulates customers to buy the product as they are enabled to assess the quality of the product before payment (Baños-Caballero et al., 2014). On the other hand, the downside is that having money locked-up in this working capital might lead to financing problems (Deloof, 2003) and a higher cost of capital (Zeidan & Shapir, 2017). According to Zeidan and Shapir (2017), overinvestment in working capital is economically inefficient. In line with this, a consistent result in literature is that working capital investments are less profitable than investments in hard assets or cash (Zeidan & Shapir, 2017). Some level of working capital is needed in terms of inventory and trade credit, but having too much working capital locked up will be economically inefficient. According to literature, therefore, there exists an optimal level of working capital.

Although literature suggests the existence of an optimal level of working capital, empirical studies have found mixed results regarding the influence of working capital management on profitability. For example, Eljelly (2004) has found a negative relationship between liquidity measures, i.e. current ratio and cash conversion cycle, and profitability, due to lost profits and unnecessary costs from holding excessive liquidity. However, many researchers did find an inverted U-shaped relationship between working capital and profitability. Examples pertain to Deloof (2003), Baños-Caballero et al. (2014) and Zeidan and Shapir (2017).

As many researchers have found evidence for their being an optimal level of working capital investment, and as this is supported by literature, the following has been hypothesized:

Hypothesis 1: The cash conversion cycle follows a U-shaped relationship with bankruptcy risk.

Access to financing

In order to decrease liquidity and credit risks, it is important that firms have acquired some level of internal funds for financing. However, firms that have not acquired enough internal funds, have to resort to outside financing as to being able to pay their financing obligations. When these funds are necessary, the pecking order theory describes that firms prefer debt over equity due to lower information costs associated with debt financing (Frank & Goyal, 2003).

Mulier et al. (2016) argue that whether a firm has proper access to external financing depends on firm's size, age, cash flow and average level of indebtedness. The relationships of each of these factors with access to financing, can be explained by the use of the agency theory. Agency theory describes the relationship between a so-called agent and principal and explains that agents, e.g. the firm or large shareholders can make decisions in their own self-interest that does not benefit the principal, e.g. respectively outside shareholders and minority shareholders. It is, therefore, important that the principal is able to control the agent in order to make sure the agent does not only act in self-interest. In cases of high information asymmetry, which occurs when the agent possesses more knowledge than the principal and it is hard to put in place a control mechanism, agency problems occur. In this state, managers can pursue their own interests, which may not be aligned to shareholder interests (Douma et al., 2006). As outside financiers must be able to properly assess the firm before providing any financing, firms having lower levels of information asymmetry can more easily attract capital from outside markets. In some of these cases, it is difficult to assess the firm, as many information is not present in the outside market (Chemla & Hennessy, 2014), and therefore lenders are hesitant to lent money to firms with high levels of information asymmetry. The reason for this is that information asymmetry is related to market illiquidity, which therefore raises the cost of capital for firms (Lambert et al., 2011), which leads in turn to higher interest payments. This problem is higher for SMEs as their information is not publicly available.

Mulier et al. (2016) argue that firms that are financially constrained pay a higher interest rate on their debt. Older firms and larger firms possess more information, and this information can easily be acquired by financial institutions, thereby alleviating financial constraints and agency problems (Mulier et al., 2016). According to these authors, the same holds true for firms with a high level of cash flows and a smaller share of debt. Financial institutions are better able to assess the performance of these firms and in turn these firms will get a lower cost of borrowing and are enabled to become more leveraged. The following is therefore hypothesized:

Hypothesis 2: Firms with a better access to external financing have a lower bankruptcy risk than firms with worse access to external financing.

When firms have low access to financing, it is argued that those firms need to optimize their working capital management as they will then be able to acquire internal funds. According to Zeidan & Shapir (2017), cash conversion cycle management could be an important part of value creation as it is a substitute for cash (Zeidan & Shapir, 2017). Therefore, Baños-Caballero et al. (2014) and Zeidan and Shapir (2017) argue that the level of firm's financial constraints moderates the relationship between the cash conversion cycle and companies' profitability. In line with this, Kling et al. (2014) argue that firms that have enough financing have less of a need to improve their cash conversion cycle, whereas this is hypothesized to create more shareholder value (Kling et al., 2014).

According to Kling et al. (2014), the relationship between trade credit, as part of the cash conversion cycle, and short-term bank financing can be explained by the use of two different theories: (1) the substitution hypothesis as developed by Meltzer (1960), and (2) the complementary view as based on the signalling theory and information asymmetry between suppliers and banks as being part of agency theory (Jain, 2001). This substitution effect can be explained as follows: firms that already have access to bank financing have less of a need to acquire trade credit, which is a relatively expensive form of financing (Bias & Gollier, 1997). The opposite also holds true: firms might substitute institutional loans for trade credit, especially if they cannot access the loan market (Fishman & Love, 2003; Wu et al., 2012). The findings of Kling et al. (2014) indicate that trade credit, as part of working capital, facilitates access to bank financing, which indicates the relationship between those two measures. The relationship with the cash conversion cycle as a measure is easily made, as an extension of trade credit triggers an increased cash conversion cycle.

Baños-Caballero et al. (2014), Kling et al. (2014) and Zeidan and Shapir (2017) argue and have found evidence that access to financing can be viewed as a moderator in the relationship between working capital management and firm's probability of bankruptcy. For example, Baños-Caballero et al. (2014), have argued that the optimal level of working capital is lower for firms that are financially constrained than for firms that are not. This might be due to those firms encountering higher financing costs, greater capital rationing, and if the investment in working capital is lower, the need for external financing is as well (Baños-Caballero et al., 2014). In line with this, the following has been hypothesized:

Hypothesis 3: Access to bank financing moderates the relationship between the cash conversion cycle and bankruptcy risk.

2.2.2 Business risk/Industry risk

Researchers have acknowledged the importance of including industry variables in bankruptcy prediction models, as for example Fernandes and Artes (2016) have found that including the spatial dependence factor, which includes information about the industry type or region a company operates in, improves credit scoring. In addition, Ferreira Felipe et al. (2016) base their research on earlier studies and argue that inclusion of both industry- and macroeconomic variables is important for explaining default likelihoods. According to Spanos et al. (2004), the industry is an important determinant of profitability.

To recall, business risk is "the risk of failing to achieve business targets due to inappropriate strategies, inadequate resources or changes in the economic or competitive environment" (Olsson, 2002, p. 34), whereas industry risk is defined as "the risk associated with operating in a particular industry" (Olsson, 2002, p. 35). The industry risks that will be investigated are industry barriers, industry growth rate, average industry sales prices, and the level of competition.

Industry barriers

It is important that management understands and identifies the key drivers for their businesses and analyze the company's vulnerability to them and be flexible in adjusting to the environment (Olsson, 2002). Therefore, managers should have a thorough understanding of risks that are inherently present in the industry. As industry organization economics theory predicts, firms that are subjected to many industry-specific risks have a higher chance of financial distress. This theory focuses on market structure and is related to the importance of including industrial structure in determining firm performance (Miloud et al., 2012). Industry organization economics theory indicates that operating in an industry with a favorable climate enhances firm performance.

The context in which a firm operates shapes the resources a firm can access and may influence entry levels (Lofstrom et al., 2014). In line with this, the resource-based view can explain why some firms might attain a competitive advantage in unfavourable industries, and while some may be subjected to the current industry climate (Peteraf, 1993). The basic argument of the resource-based view is that resources, e.g. bundles and capabilities that underlie the production, are heterogeneous within an industry, and thus across firms (Barney, 1991). This heterogeneity is therefore able to reflect superior productive factors in an industry of limited supply, but in this case it is important that these resource remain in limited supply and cannot be expanded or imitated by other firms (Peteraf, 1993).

Following Tuzel & Zhang (2017), it is important to compare industries, but also firms that are in the same industry, but in different areas. They have found that the firm's location and industry influence firm risk through local factor process, e.g. in terms of wages and rents. This result has been found by looking at the 'local-beta', which has been computed by taking the average industry betas weighted by industry shares in the local market, where the industry's beta equals the beta of the output of the industry on the aggregate GDP. In line with this, it can be argued that the industry climate, as well as the location in which a firm operates, might influence firm performance or in turn influence the probability of bankruptcy. Industry organization economics predicts that being subjected to many industry risks factor will have a positive influence on firm's chance of going bankrupt, which leads to the following hypothesis:

Hypothesis 4: Firms that operate in an industry with a high level of barriers have a higher bankruptcy risk than firms that operate in an industry with fewer barriers.

Industry growth rate

Olsson (2002) argues for inclusion of the variable 'industry's stage in the life cycle', so birth, growth, maturity or decline in assessing risks. Hansen and Wernerfelt (1989) also acknowledge the importance of including industry growth, but state that different studies have reported different outcomes on firm performance. According to industry organization economics theory, operating in a growth industry will probably lead to less barriers and firms will then be enabled to increase or at least maintain their market share. This is also in line with Olsson (2002), who argues that it is better to be in a growth-industry rather than operating in an industry with the status ‘maturity’ or ‘decline’.

In addition, Prajogo and McDermott (2014) have researched the effects of environmental aspects, e.g. the level of dynamism present in the industry, on SME innovativeness. They argue that dynamic environments are characterised by uncertainty, which leads to firms striving for new products or services. It is expected that high-growth industries face more dynamism and therefore firms try to increase market share by innovations. At some point, firms have invested much in cost reductions and quality improvements, which reduces further entry into the industry, that leads to firms facing higher demands for production (Karuna, 2007).

However, there may also be downsides to industry growth rates. As firms, and especially SMEs, do not have much resources, a rapidly changing environment could be perceived as a threat rather than an opportunity. In line with this, Ju and Sohn (2015) have found that SMEs with a high market potential have a higher probability of default as they experience heavy competition from other firms in the market. This may eventually lead to having lower profit margins and a lower market share. In addition, Karuna (2007) argues that a greater market size leads to higher price competition.

However, as firms operating in a growth industry have the possibility to expand their business or maintain their market share, which is in line with industry organization economics theory, the following has been hypothesized:

Hypothesis 5: Firms that operate in an industry with a higher growth rate have a lower bankruptcy risk than firms that operate in an industry with a lower growth rate.

Industry competition

According to Miller (1992), one of the main industry uncertainties pertains to competitive uncertainties, i.e. rivalry among incumbent firms, new entrants and technological uncertainty related to innovations. There is no consensus in literature on whether or not industry product market competition can be viewed as a substitute for managerial incentives, which is related to the question on whether competition is unidimensionally proxied by industry concentration, or whether it is a multi-dimensional concept (Karuna, 2007). This is therefore a question on whether competition can be viewed as an alleviator of agency problems or not. There is, however, agreement on product market competition being a determinant of firm profitability (Porter, 1990). When facing heavy competition, the threat-of-liquidation is higher, which should motivate managers, which will eventually improve firm performance (Schmidt, 1997). Karuna (2007) has also found evidence for there being a relationship between managerial incentives and the level of industry competition.

According to Dedman and Lennox (2009), many studies determine the degree of competition solely based on the degree of concentration. However, after conducting a large-scale survey with managers, they have found that the degree of competition depends on “(1) the number of competitors operating in the company’s main product market, (2) the threat of entry from new rivals, and (3) the company’s own price elasticity of demand” (Dedman & Lennox, 2009, p. 210). In line with this, Spanos et al. (2004), argue that the level of competition within an industry can be determined by the level of concentration and entry barriers, e.g. cost efficiency and capital. According to Bikker and Haaf (2002), the conventional view is that concentration impairs competition. However, for example Sutton (1990) argues that intense competition is associated with high concentration as inefficient companies are driven out of the market as they cannot compete efficiently and on a low price-basis. Regarding entry barriers and its influence on competition, there is also no clear consensus, but it has been found that operating in a competitive market might increase the supply of scarce resources, which might eventually lead to less competitive advantage at the side of the incumbent firms following the argument of the resource-based view (Peterof, 1993).

So one the one hand, competition can motivate managers to perform better, which improves firm performance (Schmidt, 1997). However, intense competition could also lead to being driven out of the market as firms cannot compete efficiently enough, as prices may be driven down (Sutton, 1990). As the conventional view is that competition leads to less efficient firms being driven out of the market, the following has been hypothesized:

Hypothesis 6: Firms that operate in an industry with a stronger level of competition have a higher bankruptcy risk than firms that operate in an industry with a weaker level of competition.

Industry sales prices

Industry sales price and competition are closely related to each other. Having much competition and a high threat of new entrants can lead the incumbents or monopolist to charge more competitive prices (Dedman & Lennox, 2009), but they do not always need to. Overall, Spanos et al. (2004) argue that a very concentrated industry allows for higher prices and thus a higher profitability, which will eventually have a positive effect on firm performance. In line with this, the argument that is prevailing is that competition leads to lower prices and thus lower margins. Following the argument of Sutton (1990), this may be beneficial for firms that are able to compete on price and are efficient. This is also argued by the resourced-based view, as firms have their own resources and capabilities in house, which other firms cannot easily imitate (Barney, 1991).

However, the same argument may be applied to firms that are inefficient and thus have a higher chance to be driven out of business. According to Karuna (2007), when firm's competitors charge lower prices as a consequence of increased competition, the firm loses market share and expected profits will be eroded. Consequently, making more efforts to reduce the costs may not be economically justified. Intense competition could lead to being driven out of the market as firms cannot compete efficiently enough, as prices may be driven down (Sutton, 1990).

There is no consensus in literature about the influence of the level of sales prices in an industry on bankruptcy risk. On the one hand, charging higher prices will lead to higher margins and thus might lead to higher profitability. On the other hand, firms that are very efficient and able to compete on price, might thrive in an industry with lower sales prices. As the former argument is the more conventional argument (Sutton, 1990), the following has been hypothesized:

Hypothesis 7: Firms that operate in an industry with lower sales prices, have a higher bankruptcy risk than firms that operate in an industry with higher sales prices.

The seven hypotheses as outlined and argued above will be tested in the Chapter 4. In the following section, the methods that will be applied and the variables that will be used to test the hypotheses will be discussed.

3. Methodology

This chapter will start off with a discussion of the two main research methods used in this study: ordinary least squares regression and survival analysis. In addition, their advantages and shortcomings will be discussed shortly as to show how both can reinforce each other. Afterwards, a description of the sample will be given. Furthermore, a description of the variables included in this research will be provided based on the literature review. First, the two dependent variables of this study will be discussed: the interest coverage ratio and Altman's Z-score for private firms. Afterwards, the independent variables related to credit/liquidity risk and business/industry risk will be outlined, followed by the control variables. To conclude this chapter, the analytical approach that will be used throughout this research has been described.

3.1 Research design

In this research, two complementary methods, i.e. ordinary least squares regression and Cox survival analysis, will be used that together aim to test the hypotheses as defined in the previous chapter. Oftentimes, logit regression is used in default prediction studies, as the dependent variable is binary (Altman and Sabato, 2007). The dependent variable is in that case related to an event, i.e. default, but here we are more interested in the probability of default. Therefore, ordinary least squares regressions allow the dependent variable to take on various scores, so that it fits the purpose of this research better. In addition, survival analyses will be conducted as to predict the probability of default and the time frame in which this takes place. For this, firms will be identified that have defaulted over the period 2011-2015 and this will be taken as input for the survival analyses. The two methods are complementary, as ordinary least squares regression aims to explain the probability of default, whereas survival analysis aims to predict the chance of going bankrupt over a certain time frame.

3.1.1. Ordinary least squares regression

Ordinary least squares regression (OLS) aims to explain the dependent variable with the use of known parameters, i.e. the independent variables, by reducing the level of the residuals (De Veaux et al., 2014). This is particularly useful in explanation of firms' level of financial distress as measured by the interest coverage ratio and Altman's Z-score as these variables are measured on a metric scale (Hair et al., 2012). The explained variance of the model can easily be seen by using the adjusted R^2, but one should be careful in adding too many variables, as the explained variance per variable will be lower in this case (Hair et al., 2012). When adding too many independent variables, the model will be over fitted. The adjusted R^2 controls for number of cases and number of added variables, and it explains the amount of variance in the dependent variables captured by the independent variable (Huizingh, 2007). Ordinary least squares regression is oftentimes used due to its availability (Hair et al., 2012) and its ability to translate non-metric variables intro metric ones by the use of dummy variables (Huizingh, 2007).

However, OLS regression does come with weaknesses and limitations. For example, multicollinearity might seriously alter the regression results, as it may result in less variance explained and a more difficult interpretation of the unique variance per independent variable (Hair et al., 2012). In addition, the model is sensitive for outliers, non-linearity, and non-independence, for which first needs to be tested (Hair et al., 2012). In line with this, OLS regression can only be used, in the case of non-linearity of the variables, when curvilinear relationships are transformed into quadratic or cubic polynomials (Hair et al., 2012). A downside of techniques such as regression analysis is that biased bankruptcy probabilities might be produced as it does not take into account the time-perspective (Shumway, 2001). Survival analysis does take into account the time-perspective and is therefore complementary to the regression analyses that will be performed.

3.1.2. Survival analysis

As the aim is to predict which variables are able to explain the probability of default, it would also be convenient to include a technique that is able to predict the probability of default and the time frame in which this takes place. A technique that can be used to predict the default probability of Dutch firms is called survival analysis, which can take into account attributes, environment, and firm characteristics, and can therefore be used to assess risk (Ju & Sohn, 2015).

Survival analysis, as compared to the static models that might produce biased bankruptcy probabilities, is a hazard model that accounts for the time-perspective (Shumway, 2001). Two types of models are prevalent in survival analysis, which are parametric approaches, in which one can decide on distributions such as lognormal and exponential, and proportional hazard models (Ju & Sohn, 2015). Survival analysis uses historical data to predict the future survival (Anderson, 2007) and deals with the time to a pre-defined event, which is in this case bankruptcy (Ju & Sohn, 2015; Kim & Partington, 2015). By this, the firm's operational period up to default as well as the probability of default can be considered (Ju & Sohn, 2015). Survival analysis uses a grouped population, with varying survival rates, and then rates are determined for each group for different points in time (Anderson, 2007). It has been found that the hazard model approach is superior in bankruptcy prediction compared to other models, among others the Z-score model (Bauer & Agarwal, 2014).

Survival analysis takes into account the probability of financial distress occurring at a point T that is beyond the time horizon, denoted as *t*, for different values of *t* (Kim & Partington, 2015), so a time dimension is added to the model compared to multiple discriminant analysis and ordinary least squares regression. As it allows the estimation of the probability of default at a certain point in time, *t*, survival analysis serves as a logic choice for the prediction of financial distress (Kim & Partington, 2015). One of the most used techniques of survival analysis is the Cox model, which links to the concept of the hazard rate, which can be explained as the rate of change of the probability of survival over an interval. The formal equation of the hazard is (following Kim & Partington, 2015):

Equation 1

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}$$

where *T* is the time to failure and "*h(t)* specifies the instantaneous rate of failure at time *T* = *t* given the firm survives up to time *t*" (Kim & Partington, 2015, pp. 138). In addition, the survival function, which can be denoted as *S(t)* relates to the probability that the company experiences the event, in this case the bankruptcy, *T*, after some time *t* (Kim & Partington, 2015):

Equation 2

$$S(t) = P(T > t) = exp[-H(t)] = exp\left[-\int_o^t h(u)du\right]$$

where *H(t)* is cumulative hazard rate (Kim & Partington, 2015). Survival analysis can therefore be useful in predicting the chance of a firm going bankrupt within some specific time frame and is useful in deciding on for example, whether or not to grant a loan to an SME.

3.2 Sample

This research focuses on both firm-specific variables, such as liquidity management measures and financial measures, and industry variables, such as the level of competition and perceived barriers.

The firm-specific data will be gathered via REACH, a database provided by Bureau van Dijk. This database possesses mainly financial data of Dutch firms, ranging from larger firms to even small firms with only a few employees. 4023 companies are included in this database, ranging over 5 years, i.e. 2011 until 2015. Companies needed to have at least one year of data for each variable in order to be included in this research. The total cases included pertain to 20.115. REACH makes a distinction between the companies regarding their size, i.e. ‘very large’, ‘large’, ‘medium large’, ‘medium small’, ‘small’ and ‘very small’, because a large or a very large company has an operating income above 50 million Euros, whereas a small- or medium-sized company has an operating income of less than 50 million Euros (Reach, 2017). Following the classification of the SME Servicedesk in the Netherlands, an SME has a yearly revenue of less than 50 million Euros, which fits the classification as used by REACH. An overview of the sample selection can be found in Appendix 1. The results yielded 2314 SMEs, 1695 large firms and 4 firms were not classified. A total of 4023 firms over five years will therefore be included in these analyses. Furthermore, 3804 firms have not failed over the period 2011-2015, and 219 have.

The financial data have also been extracted from REACH, as well as the components for liquidity and credit risks. The formulas have been computed manually, as they were not provided by REACH, as well as the ASCL-index, for which firms had to be selected for either the above- or below-median group per factor.

The industry-specific data has been gathered from the CBS’s ‘Conjunctuurenquête’, which provides on how managers perceive certain industry-specific risk factors, such as competition, sales prices, barriers, and productivity. According to the CBS, the ‘Conjunctuurenquête” shows the overall sentiment of Dutch managers on a monthly basis. The questions relate to developments in the past months and the expectations for the coming months regarding, among others, revenue, production levels, order levels, price developments, and barriers. This data is only available on a quarterly basis, so first yearly numbers have to be computed in order to match the data as provided by REACH.

As companies operate in different industries, but also in different locations, every company needs to be classified manually into a Dutch province and a certain industry, based on the Dutch

SIC-codes. An overview of the industry distribution can be found in Table 3. The industries included, based on the available information provided by CBS, pertain to A (Agriculture, forestry and fishing, B (Mining and quarrying), C (Manufacturing), F (Construction), G (Wholesale and retail trade; repair of motor vehicles and motorcycles), H (Transportation and storage), I (Accommodation and food service activities), J (Information and communication), L (Renting, buying and selling of real estate), M (Consultancy, research and other specialized business services), N (Renting and leasing of tangible goods and other business support activities), R (Culture, sports and recreation) and S (Other service activities).

Table 2 Industry distribution

Industry code	Industry name	Frequency	Percent
A	Agriculture, forestry and fishing	160	,80
B	Mining and quarrying	50	,25
C	Manufacturing	2545	12,65
D	Electricity, gas, steam and air conditioning supply	70	,35
E	Water supply; sewerage, waste management and remediation activities	130	,65
F	Construction	560	2,78
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	5225	25,98
H	Transportation and storage	480	2,39
I	Accommodation and food service activities	435	2,16
J	Information and communication	570	2,83
K	Financial institutions	6990	34,75
L	Renting, buying and selling of real estate	285	1,42
M	Consultancy, research and other specialized business services	1705	8,48
N	Renting and leasing of tangible goods and other business support services	360	1,79
P	Education	50	,25
Q	Human health and social work activities	135	,67
R	Culture, sports and recreation	230	1,14
S	Other service activities	135	,67

3.3 Operationalization

In this section, an overview of the different variables will be provided in order to test the hypotheses.

3.3.1 Dependent variables

As we are interested in finding out the risk factors that might influence the probability of default of Dutch firms, two dependent variables will be included that serve as proxies for firm's probability of default: the interest coverage ratio and Altman's Z-score for private firms (Baños-Caballero et al., 2014). A short explanation on the computation of those variables is outlined in Table 3.

Interest coverage ratio

Recently, the definition of bankruptcy has been extended to reflect measures of financial distress, based on financial statement information (Tinoco & Wilson, 2013). The definition of financial distress is "the inability of a firm to repay its financial obligations" (Tinoco & Wilson, 2013, p. 396). The ability to pay financial expenses is often applied by the largest ratings agencies and is therefore important to take into consideration. Tinoco and Wilson (2013) use two conditions that need to be met in order to find out and be able to predict financial distress. According to Tinoco and Wilson (2013), a "firm is classified as financially distressed (1) whenever its earnings before interest and taxes, depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years; and (2) whenever the firms suffer from a negative growth in market value for two consecutive years" (Tinoco & Wilson, 2013, p. 396). The first condition related to the ability of firms to repay loans, or in a broader sense financial obligations. Baños-Caballero et al. (2014) use this interest coverage ratio, as it is a common measure of financial constraints and bankruptcy risk. In addition, Dothan (2006) argues that some companies have put covenants in place that states that the interest coverage ratio should at all times be above K to 1, as it might help prevent financial distress from occurring. The interest coverage ratio can be computed by taking the ratio of earnings before interest and tax to financial expenses (Baños-Caballero et al., 2014), and will be used in this research as a proxy for the probability of bankruptcy.

Altman's Z-score

By far the largest number of multivariate accounting-based credit-scoring models have been based on discriminant analysis models (Altman & Saunders, 1998). Multiple discriminant analysis has first been applied to default prediction by Altman (1968), who has been able to predict bankruptcy correctly in 94% of the cases by the use of his discriminant-ratio model. Although Altman (1968) has conducted his study by using information of only public companies, his results were striking. Altman (1968) initially used five financial ratios, i.e. working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total debt, and sales/total assets, which all received a loading and together formed the overall index, or Z-score. Only the variables working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets and market value equity/book value of total debt have been found to be statistically significant in explaining differences between bankrupt and non-bankrupt firms, of which the profitability ratio contributes the most explanatory power to the model (Altman, 1968). The greater a firm's potential to go bankrupt, the lower its Z-score (Altman, 1968).

Whereas the Z-score model has been widely applied, its limitation pertains to the inapplicability to private firms' default prediction. To overcome the limitation of the Z-score model being applied only to public firms, Altman (2000) has developed a Z-score model that can be applied to SMEs, or private firms in general, as the market value of equity has been substituted for the book value of equity (X_4). The higher the Z-score, the lower the probability of default. For example, Baños-Caballero et al. (2014) use this measure to gauge firms' bankruptcy risk. Due to Altman's Z-score being applied often, it will be used in this research as a proxy for the probability of bankruptcy.

3.3.2. Independent variables

The independent variables that will be included in the research are outlined in Table 3.

Credit/liquidity risk

In order to test the first three hypotheses, two overarching variables will be used: cash conversion cycle and the ASCL-index. In addition, an interaction variable will be created that will be used to test the third hypothesis.

Cash conversion cycle

An important and often-applied measure of working capital management is the cash conversion cycle or the net trade cycle (Deloof, 2003; Baños-Caballero et al., 2014). The cash conversion cycle can be used to capture a firm's short-term liquidity needs, and is, compared to static measures such as the current or quick ratio, a dynamic measure of liquidity (Kling et al., 2014). It is expected that working capital follows a non-linear, inverted U-shaped relationship with firm performance (among others Baños-Caballero et al., 2014). Cash conversion cycle management can result in increased cash flow and eventually a higher profitability (Zeidan & Shapir, 2017). The cash conversion cycle is composed of three measures: days' inventory outstanding, days' sales outstanding and day's payables outstanding. (Zeidan & Shapir, 2017). The precise computations used can be found in Table 3. These measures will also be tested individually as to see whether they also explain a portion of the probability of firms going bankrupt.

ASCL-index

According to Baños-Caballero et al. (2014), the level of financial constraints is dependent on the level of dividends, cash flow, size, cost of external financing and the Whited and Wu Index, which is an index that measures the access to external capital markets. Mulier et al. (2016) have also constructed an index of firm level financial constraints, which has been applied to European SMEs. According to Mulier et al. (2016), access to external financing depends on the age-size-cash flow-leverage (ASCL) index. The ASCL index includes firm size, age, the average cash flow level, and the average indebtedness (Mulier er al., 2016). Mulier et al. (2016) measure whether a firm is scoring below or above industry median for each of these determinants and assign a 1 to firms that belong to the worse performers for each category. A score of 0 then means that firms have unconstrained supply of external financing and a score of 4 indicates the opposite. Firms that are financially constrained pay higher interest rates and thus have a higher probability of distress (Mulier et al., 2016). The ASCL-index as developed by Mulier et al. (2016) has been edited a bit to suit the data of this research, as the numbers are not assigned based on industry but per year including the whole sample. Furthermore, for convenience, a 1 will be assigned to the best performers of a category instead of the worst performers, as to reflect a higher ASCL-index being linked to better access to financing.

Interaction variable

Following Baños-Caballero et al. (2014), a firm's cash conversion cycle is also dependent on the level of financial constraints a firm faces. Baños-Caballero et al. (2014) compute this by the interest coverage ratio and Altman's Z-score and assign firms to two categories based on their performance. However, as these are used as dependent variables in this study, the ASCL-index is used as a classification mechanism instead. An interaction variable will be created as to reflect the moderating nature of the ASCL-index in this instance within the relationship between the cash conversion cycle and the probability of bankruptcy (Kling et al., 2014). As we are dealing with two non-dichotomous variables, it is important to first center both variables by subtracting the mean from the cash conversion cycles and ASCL-indexes per firm and multiple both in order to achieve a new interaction variable: CCC*ASCL, which will be tested on its level of significance on bankruptcy risk in the regression analyses.

Business/industry risk

In order to test the last four hypotheses regarding the influence of industry risks on the probability of bankruptcy, the following four overarching variables will be used: percentage industry risk factors, industry growth, industry competition, and industry sales price.

Perceived industry risks

The database of SynnoFin includes data on what managers perceive as risks in the near future. This data has been derived from a survey performed by the CBS, which includes risks such as lower demand, low employment levels and financial constraints. The outcomes are weighted percentages of managers who indicate that certain circumstances, i.e. risk factors, will play a role in meeting the demand as placed upon the companies. If it is expected that certain risks are going to play a profound role in the near future, the weighted percentage will be high for a certain industry in a certain location, and this will have a positive impact on the probability of experiencing bankruptcy, according to the industry organization economics theory (Miloud et al., 2012). Regarding the barriers, the CBS provides the percentage of managers that does or does not experience the barrier in daily business or expects the barrier to exert influence on the firm in the future (CBS Statline, 2017). The barriers that will be investigated are demand risk, labour market risk, materials risk, financial risk, and weather risk.

Industry growth

Operating in a growth industry leads to higher firm valuation, because firms are better able to make mistakes and firms can maintain their market share more easily (Miloud et al., 2012). This is also predicted by industry organization economics theory as the firm is then subjected to less risk in the market. Here, again the data of the CBS is used. The explanation provided by the percentage is as follows: “Our total revenue has increased, remained stable, or decreased during the last three months” (CBS Statline, 2017). A weighted percentage has been provided which is used as a proxy for industry growth rate over three months per industry per province.

Industry competition

Being exposed to a high level of competition within the industry might lead to less efficient companies being driven out of the market (Sutton, 1990). High levels of competition can lead to managers improving performance due to the threat-of-liquidation (Schmidt, 1997), but overall the consensus is that competition leads to lower price margins and thus a higher chance of going bankrupt if the company has inefficient operations (Karuna, 2007). The CBS provides data on how managers perceive their own position in comparison to other competitors in the market by providing the following explanation to the data provided: "The weighted percentage of managers stating that their position relative to their competition has improved minus the weighted percentage of managers stating that their position relative to their competition has worsened" (CBS Statline, 2017).

Industry sales price

According to Spanos et al. (2004), a concentrated industry leads to higher prices and thus a higher profitability, whereas the opposite holds true to an industry which experiences high levels of competition. In line with the previous measures, data of the CBS has been used. The explanation provided by the percentage use is as follows: "Our sales prices will increase, remain stable, or decrease over the following three months" (CBS Statline, 2017).

3.3.3. Control variables

Two main control variables will be used in this study: firm's age and growth in terms of tangible assets. In addition, size, year-, and industry dummies will be included.

Firm age

The influence of firm's age has been acknowledged in previous literature, e.g. by Gupta et al (2015), who have found that insolvency hazard among all sizes of SMEs is dependent on firm's age. According to Ylhäinen (2017), information asymmetries are most prevalent in the early stages of a firm's life cycle and these problems will become less severe as the firm matures, which relates to the theory of financial intermediation, as firms are more dependent on financial intermediaries in early life-cycle stages. Maturing will therefore go along with a decreasing cost of credit as well as an improved availability of finance (Ylhäinen, 2017). In addition, it has been found that credit risky firms are both less profitable and younger than non-credit risky firms (Li et al., 2016). So according to theory and empirical evidence, it has been argued that older firms are less risky compared to younger firms. Firm's age will be computed by the difference between the founding year and in the particular year in this study, i.e. 2011, 2012, 2013, 2014 or 2015.

Firm growth

Regarding growth, it is argued that firms, especially SMEs, may not have the necessary knowledge and resources in-house to support high growth levels (Marcelino-Sádaba et al., 2014). Therefore, it is argued that firms with high growth levels face more risks and thus have a higher probability of financial distress. Growth is in this research linked to the increase in tangible assets when controlling for the level of depreciation.

Table 3 Variable descriptions

Dependent variables	
Interest coverage ratio	Earnings before interest and taxes / financial expenses (Baños-Caballero et al., 2014)
Altman's Z-score	$Z' = .717X_1 + .847X_2 + 3.107X_3 + 0.420X_4 + .998X_5$ where X_1 equals working capital/total assets, X_2 retained earnings/total assets, X_3 earnings before interest and taxes/total assets, X_4 book value of equity/book value of total debt, and X_5 sales/total assets (Altman, 2000)
Independent variables	
Cash conversion cycle	Days' inventory outstanding + Days' sales outstanding – Days' payables outstanding (Zeidan & Shapir, 2017)
• Days' inventory outstanding	Inventory / (Cost of goods and services sold/365)
• Days' sales outstanding	Accounts receivables / (Revenue/365)
• Days' payables outstanding	Accounts payable / (Cost of goods and services sold/365)
ASCL-index	Firms are assigned a score of 1 is they perform better than the median firms of that year, and a score of 0 is it has a below-median performance in terms of age, size, cash flow and leverage (Mulier et al., 2016)
CCC*ASCL	The centered variables CCC and ASCL are taken and multiplied (Baños-Caballero et al., 2014)
Industry barriers	The percentage of firms that perceives barriers in daily operations
• Demand risk	The percentage of firms that perceived demand risk in daily operations
• Labour market risk	The percentage of firms that perceived labour market risk in daily operations
• Materials risk	The percentage of firms that perceived materials risk in daily operations
• Financial risk	The percentage of firms that perceived financial risk in daily operations
• Weather risk	The percentage of firms that perceived weather risk in daily operations
Industry growth	The industry growth rate as a weighted percentage of managers that indicated whether their revenue has increased, remained stable, or decreased.
Industry competition	The weighted percentage of perceived competitive strength as indicated by managers.
Industry sales price	The weighted percentage of managers that indicated that the sales price has increased, remained stable, or decreased.
Control variables	
Age	Current year – founding year, as computed in years (Gupta et al., 2015).
Growth	Tangible assets $_{t-1}$ + Depreciation – Tangible assets $_t$ (Mulier et al., 2016)

3.4 Model development and analytical approach

In this research, we distinguish between all firms and SMEs specifically, as previous sections have indicated that SMEs are substantially different from large firms. Therefore, two panels will be created: Panel A, which includes all Dutch firms in this sample, and Panel B, which includes only the SMEs of this sample. To recall, an SME is a firm that has an operating income of less than 50 million Euros. Both Panels include failed and non-failed firms, as the variable of our interest is the probability of bankruptcy instead of the event. However, there will be checked for survivorship bias, and the years in which the firm was non-existent have been excluded from the regression analyses.

First, regression analyses will be performed after the requirements for regression analysis have been checked for. These regression analyses aim to test the hypotheses as formulated in Chapter 2. Separate regression analyses will be conducted for SMEs as well as all firms in the sample. The full regression model that will be tested is as follows:

$$\textit{Probability of default (ICR, Z-score)}_{it} = \alpha_0 + \beta 1 \cdot CCC_{it} + \beta 2 \cdot CCC^2_{it} + \beta 3 \cdot ASCL_{it} + \beta 4 \cdot CCC \cdot ASCL_{it} + \beta 5 \cdot INDG_{it} + \beta 6 \cdot COMP_{it} + \beta 7 \cdot Price_{it} + \beta 8 \cdot Barriers_{it} + \beta 9 \cdot Age_{it} + \beta 10 \cdot Growth_{it} + \beta 11 \cdot Sizedummies_{it} + \beta 12 \cdot Yeardummies + \varepsilon_{it}$$

The cash conversion cycle measures aims to answer the first hypothesis. Both the linear variable as well as the squared variable, which is the variable of interest, will be included at the same time, following Baños-Caballero et al. (2014). The ASCL-index is used as a proxy for access to financing, and therefore included to check the second hypothesis. The interaction variable is created based on the centered CCC and ASCL and aims to test the third hypothesis. The industry variables are included to test the fourth till the seventh hypothesis. It should be noted that the different types of barriers will be tested in a separate regression analysis, as to prevent multicollinearity from occurring. Size and industry variables are often included, e.g. by Ylhaïnen (2017), who has also includes industry dummies using the SIC-version of 2008 in order to distinguish between different industries, and Gupta et al. (2014), who also included both industry and size as control variables. The inclusion of only a few control variables is encountered more often in studies using many risk variables, e.g. Altman et al. (2010) and Gupta et al. (2014). In this research, the dummy variables will be used to eliminate as many possible influences that are caused by variables not included in the regression model. Sometimes it will, however, be less beneficial to include all of them, as in some regression analyses, already a specific sample (based on size) will be used or if industry variables are already accounted for by the industry risk variables. However, year dummies will be included in every regression analysis as to account for year influences.

After the regression analyses have been conducted, the survival analyses will be conducted in order to find out which risk factors are directly able to determine the probability of going bankrupt. For this, a real event, i.e. bankruptcy, has been taken from the sample instead of a proxy of the probability of going bankrupt, i.e. the interest coverage ratio and Altman's Z-score. The survival analyses will only include firm-specific factors as these are in this case the variables of interest. The ideas of Ju & Sohn (2015) and Kim and Partington (2015) are used as input for the survival analyses, and will also guide in how the numbers and graphics should be reported. Survival analysis is also convenient in determining a time frame along with the chance of going bankrupt per category of firms, which also aims at answering the hypotheses related to credit and liquidity risk.

4. Results

In this section, the results of the different analyses will be discussed. Firstly, an overview and an explanation of the descriptive statistics will be provided, both for the full sample and the SME sample. Afterwards, the univariate statistics will be discussed by providing a correlation table of the variables included in this research. Before proceeding to the regression analyses, some assumption tests have been performed in order to make sure that the variables are suitable to use. Then, different regression analyses will be performed on two different samples: the full sample and a sample only including SME firms. Afterwards, robustness checks have been performed on the sample and variables. To end this chapter, survival analyses have been conducted that indicate which variables can predict the chance of firms going bankrupt in the future.

4.1 Descriptive statistics

An overview of the descriptive statistics of the full sample, i.e. mean, median, standard deviation, minimum, maximum and number of observations, can be found in Table 4. An overview of the descriptive statistics of the SME sample can be found in Appendix 2. All the outliers have firstly been removed based on analyses regarding skewness, kurtosis, and boxplots. Only the cases that were significantly different and deviated much from the other numbers so that they could potentially alter the regression outcomes have been deleted from the sample.

As can be seen, the interest coverage ratio is heavily skewed to the right as the mean (122,678) is much higher than the median (3,732). This is due to some companies being able to cover their financial expenses oftentimes, due to either being financially very healthy or having low financial expenses. Altman's Z-score varies less and shows a smaller dispersion of the mean (3,042) from the median (2,626) and a smaller standard deviation (2,596). As the median value is less susceptible to outliers, it is a better indicator of each variable included in this research. The interest coverage ratio and Altman's Z-score are lower for SMEs, so they are on average performing worse than large companies based on these variables, and therefore have a higher chance of going bankrupt based on these two dependent variables.

To recall, the cash conversion cycle (CCC) is compounded of three indicators: days' inventory outstanding (DIO), days' sales outstanding (DSO) and days' payables outstanding (DPO). As the DPO is subtracted from the sum of DIO and DSO, the CCC is allowed to be negative. The high dispersion in the level of CCC, which averages 100,157 (77,103), indicates that there is

Table 4 Descriptive statistics

Variable	Mean	Median	Standard deviation	Minimum	Maximum	N
Dependent variables						
Interest coverage ratio (ICR)	122,678	3,732	1184,982	-2917,80	40853,04	13642
Altman's Z-score (Z-score)	3,042	2,626	2,596	-12,93	29,55	13185
Independent variables						
Cash Conversion Cycle (CCC)	100,1569	77,103	166,335	-862,22	1921,57	8114
• Days' Inventory Outstanding (DIO)	84,957	49,543	188,510	0	3726,08	10328
• Days' Sales Outstanding (DSO)	95,244	61,941	159,037	0,01	3136,98	13215
• Days' Payables Outstanding (DPO)	72,831	36,389	166,960	0	2373,87	8609
Age-Size-Cash-flow-Leverage (ASCL)	1,707	2,000	0,919	0	4,00	20050
Industry growth (INDG) (%)	2,326	3,425	12,928	-47,10	43,23	10091
Industry competition (COMP) (%)	3,307	4,050	6,049	-46,00	30,00	10093
Industry sales price (Price) (%)	4,374	4,200	5,722	-29,60	32,80	10091
Industry Barriers (Barriers) (%)	56,931	56,150	9,210	2,68	98,50	10092
• Demand risk (DEM) (%)	27,229	27,050	7,234	0,73	64,70	10089
• Labour market risk (Labour) (%)	3,312	2,650	1,975	0	21,40	10087
• Materials risk (MAT) (%)	2,451	1,975	2,148	0	21,72	10081
• Financial risk (FIN) (%)	12,200	11,625	5,379	0	46,05	10091
• Weather risk (Weather) (%)	5,183	4,100	4,386	0	31,90	10093
Control variables						
Firm age (AGE)	24,945	17,000	25,322	0	185,00	19518
Log growth (Growth) (Thousands of Euros)	2,891	2,946	0,941	-1,37	6,29	5270

a high variety in liquidity management between Dutch companies. The relatively high average number may lead to companies, on average, encountering liquidity issues, which may increase their chance of going into bankruptcy or financial distress. The average days' inventory outstanding is 84,957 (49,543), which means that it takes the firms in this sample on average 84,957 days to collect the cash from the inventory. The same is the case for day's sales outstanding, which averages 95,244 (61,941). This indicates that a company collect the funds from sales in average in 95 days, which seems rather long. Therefore, the median is in this instance probably a better indicator, as approximately 62 days is a more realistic payment term. On average, companies have 72,831 (36,389) days of payables outstanding. Again, the median of approximately 36 days is more realistic in this case. The SME sample shows a higher level of cash conversion cycle.

In order to measure firm's access to financing, the age-size-cash-flow-leverage measure comes into play. Recalling from the previous chapter, a company that has a below median age, size and cash-flow, and an above-median level of leverage will have a lower access to financing. In this case, a zero has been assigned to companies with a low access of financing, and a four has been assigned to companies with a high access to financing. Following from this logic, the median value of the ASCL-index pertains to 2,00, whereas the mean is slightly lower (1,707). As expected, SMEs have a lower ASCL-index, and thus have more trouble in acquiring external financing according to this index.

Regarding the industry variables, the average industry growth over a year relates to 2,326 (3.425) percent. However, there is a large dispersion as the minimum and maximum are respectively -47,10 percent and 43,23 percent. Furthermore, the average competition has been risen by 3,307 (4,050) percent over the last four years over all included industries. In addition, the sales price has been risen by 4,374 (4,2) percent as well over the last four years, but there is a high variety between industries as the minimum and maximum are respectively -29,60 percent and 32,80 percent. The level of industry barriers is prevalent among many industries, as the average level of barriers faced pertains to 56,931 (56,150) percent. These barriers could include demand risk, labour market risk, materials risk, financial risk, and weather risk. As can be seen in the table, the level of demand risk (27,229 (27,050) percent) and the financial risk (12,200 (11,625) percent) are mostly encountered by firms in this sample. What is striking is that in the SME sample, industry growth is less, as well as industry competition. It might therefore be the case that SMEs prefer to operate in less risky environments.

Furthermore, it can be noticed that the average age of firms in this sample is 24,945 (17,000) years, with a large standard deviation of 25,322 years. The log of growth averages 2,891 (2,946), which indicates that firms are on average investing money in order to facilitate firm growth. The SME firms are slightly younger on average and have a lower growth in terms of tangible assets.

4.2 Univariate tests

Table 5 reports the Pearson correlations that are present among the variables included in this study. The highest correlations, i.e. with a significance level of 1%, are made bold. As expected, there is a high correlation between the dependent variables (1) interest coverage ratio and the (2) Altman's Z-score (,378). This indicates that both measure the same construct and are probably both good indicators of financial distress. In addition, it can be noted that both dependent variables have relatively high correlations, i.e. significant at the 1%-level, with the independent and control variables. This might mean that there will be statistically significant relationships between the variables. In this section, only the correlations higher than .300 will be discussed.

As can be seen in Table 5, there is a high negative correlation between Altman's Z-score and days' payables outstanding (-,345), which indicates that companies that have high payables outstanding, the probability of financial distress will be higher. It could also be the other way around: if firms have a high probability of financial distress, they are unable to pay their obligations and thus will have a high level of payables outstanding. The cash conversion cycle logically correlates highly with days' inventory outstanding (,349) and days' sales outstanding (,450), as it is composed of these factors. The industry's growth rate is highly correlated with the level of perceived position of a company versus its competitors (,311), the level of barriers (-,516), demand risk (-,589) and materials risk (,393). This might indicate that a growing industry facilitates incumbents to expand. Furthermore, a high growth industry might be linked to a favorable industry climate as it is negatively associated with the percentage of barriers in an industry. In line with this, a high-growth industry has no problems in terms of customer's demand, but might have problems with acquiring materials. As the level of barriers is composed of, among others, demand risk (,456), materials risk (-,323) and financial risk (,520), it is logical that these have high correlations among each other. However, it is counterintuitive that the level of materials risk is negatively associated with the total barriers in the industry, but it might be that encountering production materials risk will lead to less other risks or that due to the resource-based view, companies have established

Table 5 Correlation table

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
[1]																		
[2]	**,378**																	
[3]	-,014	**-,096**																
[4]	**-,096**	**-,261**	**,349**															
[5]	,012	**-,291**	**,450**	**,037**														
[6]	**-,120**	**-,345**	**-,168**	**,208**	**,206**													
[7]	**,233**	**,174**	**,032**	,011	-,007	**-,098**												
[8]	**,041**	**,052**	,036	**,043**	-,001	**-,063**	**-,031**											
[9]	-,016	,028	-,034	**-,050**	-,023	-,013	-,008	**,192**										
[10]	,027	**,109**	**,050**	**,054**	**-,042**	**-,192**	,001	**,311**	**,233**									
[11]	**-,110**	-,023	**-,089**	**-,041**	**-,117**	**,083**	-,002	**-,516**	**-,070**	**-,168**								
[12]	-,015	**-,032**	-,032	**-,042**	,016	**,046**	,000	**-,589**	**-,397**	**-,259**	**,456**							
[13]	,003	**-,082**	,010	**-,035**	**,099**	**,064**	-,008	**-,029**	**,185**	**,120**	,011	,013						
[14]	**,078**	**,044**	**,079**	**,046**	**,038**	**-,079**	**,059**	**,393**	**,075**	**,094**	**-,323**	**-,413**	-,025					
[15]	**-,096**	**-,043**	**-,055**	**,042**	**-,088**	**,108**	,016	**-,069**	**,154**	**-,086**	**,520**	**-,231**	,001	**-,141**				
[16]	-,015	**,132**	-,031	,017	**-,161**	**-,142**	,020	-,020	**,034**	**,241**	**,210**	**-,086**	**-,389**	**,076**	-,015			
[17]	**,093**	**,048**	**,033**	,017	,010	**-,054**	**,419**	**,059**	-,007	-,007	**-,089**	**-,056**	**-,053**	**,143**	**-,030**	**,031**		
[18]	**-,173**	**-,207**	**-,091**	,023	-,014	**,138**	**,273**	,000	**,056**	**-,062**	,016	-,042	**,110**	,003	**,087**	**-,114**	**,041**	

Significant correlations (P < 0.01) are made bold.

[1] Interest Coverage Ratio, [2] Z-score, [3] Cash conversion cycle, [4] Days' inventories outstanding, [5] Days' sales outstanding, [6] Days' payables outstanding, [7] ASCL-index, [8] Industry growth, [9] Industry sales price, [10] Industry competition, [11] Industry barriers, [12] Low demand, [13] Labor shortage, [14] Material shortage, [15] Financial barriers, [16] Weather risk, [17] Age, [18] Growth

relationships with suppliers so that production materials can be acquired. The negative relationship is also indicated by the high correlation between demand risk and materials risk (-,413). In addition, labor market risk and weather risk also have a significant negative correlation with one another (-,389).

4.3 Multivariate tests

In this section, first the assumptions that need to be fulfilled in order to conduct OLS regression will be tested. Afterwards, the regression results for Panel A are provided, as well as a short interpretation of the numbers found. Then, the regression analyses will be conducted with Panel B. The section will end with some robustness checks.

4.3.1 Assumptions tests

One of the aims of this research is to find out which risk factors have a significant relationship and are therefore able to explain the differences in the levels of financial distress, proxied by the interest coverage ratio and Altman's Z-score. Therefore, it has been chosen to conduct ordinary least squares regressions. In the methodology chapter, an introduction to this method has already been given, but before one can conduct ordinary least squares regression, the data must meet certain requirements. These requirements include normality, heteroscedasticity, linearity, multicollinearity and autocorrelation. Firstly, it is important to find out whether the variables included in the model have a close-to-normal distribution. If the model is skewed or if many outliers are present, ordinary least squares regression could yield different results or may provide no statistically significant relationships. Normality can be checked for by using histograms and Normal Q-Q plots of the variables. After re-expressing some variables, i.e. interest coverage ratio, days' inventory outstanding, days' sales outstanding, days' payables outstanding, labor market risk, weather risk, and firm growth, due to these having a high skewness to the right, all variables show a close-to-normal distribution, which leads to the fulfilment of this requirement.

Furthermore, the requirement of heteroscedasticity relates to the standardized residuals being normally distributed and scattered in a random pattern. If no clear pattern can be identified by looking at the histograms, P-P plots and scatterplots of the standardized residuals, heteroscedasticity is no problem and the variables are safe to use. In this case, heteroscedasticity did not appear to be a problem as no pattern could be identified in the standardized residual plots.

In addition, linearity can be checked for by plotting the variables in scatterplots by which a linear pattern should be identified. After re-expressing the variables that had a high level of skewness, all variables are close to linear and are safe to include in the regression models. Next, it is important to check for multicollinearity, which appears if variables exert influence on each other, which in turn will make the regression results less reliable. Multicollinearity can be measured by the variance inflation factor (VIF) and by looking at the correlation matrix, which indicated a few very high correlations among the variables (>0,300). It appears that multicollinearity is no issue as all VIF have remained under 5 during the analyses. Furthermore, when including the industry dummies together with the industry variables, it followed logically that the correlations among the variables were too high. Therefore, it has been chosen not to include the industry dummies in the models that include industry variables. The level of autocorrelation among variables can be measured by applying the Durbin-Watson test, of which the outcomes are depicted in Table 5 till 10. In case of no autocorrelation, the Durbin-Watson test equals 2. Values nearby 0 indicate a high positive autocorrelation, whereas values nearby 4 indicate a highly negative autocorrelation. As can be seen in the regression tables, all regression analyses do not have strong autocorrelations, so this does not appear to be a problem.

4.3.2 Regression analyses Panel A

In Tables 6 and 7, the regression results for the full sample, including both large and SME firms, have been depicted. Here, it has been chosen not to include the industry dummies due to the high multicollinearity that has been caused by inclusion of these variables. Overall, the models differ in their level of R Squared, or explained variance. The best explanatory model is the one including the ASCL-index for the interest coverage ratio (i.e. R Square of 14,1%) and for the Altman's Z-score, the best model includes DIO, DSO, and DPO with an explained variance of 25,7 percent. As can also be seen is that, contrary to what literature indicated, models including industry variables do not consistently perform better than models excluding industry variables in terms of explained variance.

Table 6 Regression results Dependent variable: Interest Coverage Ratio - Panel A

CCC		-,022 (-1,018)	,013 (,433)						-,080 (-2,013**)
CCC^2			-,051 (-1,730*)						-,049 (-1,278)
DIO				-,101 (-4,719***)					
DSO				,049 (2,298**)					
DPO				-,068 (-2,998***)					
ASCL					,367 (19,531***)				,358 (11,587***)
CCC*ASCL						,014 (,633)			,071 (2,022**)
INDG							,005 (,145)		-,010 (-,250)
COMP							-,010 (-,464)		-,020 (-,772)
Price							-,049 (-2,101**)		-,049 (-1,722*)
Barriers							-,135 (-5,159***)		-,142 (-4,316***)
DEM								-,037 (-1,197)	
Labour								,007 (,306)	
MAT								,040 (1,577)	
FIN								-,090 (-3,651***)	
Weather								-,082 (-3,235***)	
Age	,095 (5,668***)	,093 (4,350***)	,093 (4,357***)	,101 (4,764***)	-,049 (-2,827***)	,090 (4,224***)	,050 (2,317**)	,050 (2,273**)	-,083 (-2,965***)
Growth	-,213 (-11,692***)	-,194 (-8,266***)	-,190 (-8,043***)	-,170 (-7,127***)	-,291 (-16,388***)	-,191 (-8,173***)	-,130 (-5,488***)	-,137 (-5,583***)	-,213 (-7,018***)
Adjusted R^2	,046	,040	,041	,059	,141	,040	,031	,029	,121
Size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No	No	No	No
Durbin-Watson	1,409	1,416	1,925	1,424	1,439	1,416	1,434	1,427	1,879
N	3442	2122	2122	2139	3442	2122	2198	2106	1373

Notation: b(t) * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Cash conversion cycle

It has been hypothesized that the cash conversion cycle follows a quadratic relationship with firm performance, as it has been argued that there is an optimal level of working capital (Baños-Caballero et al., 2014). In this study, the authors have found a positive relationship between CCC and firm performance, and a negative relationship between CCC^2 and firm performance, indicating the existence of an inflection point at $-\beta^1/2\beta^2$. However, in this sample it has been found that there is a negative relationship between both CCC and Altman's Z-score (*t* = -6,876, *P* < 0.01) and

Table 7 Regression results Dependent variable: Z-score - Panel A

CCC		-,146	-,152						-,287
		(-8,545***)	(-6,876***)						(-9,825***)
CCC^2			,010						,061
			(,444)						(2,061**)
DIO				-,217					
				(-13,604***)					
DSO				-,228					
				(-14,391***)					
DPO				-,164					
				(-9,813***)					
ASCL					,208				,256
					(12,339***)				(10,212***)
CCC*ASCL						-,006			,069
						(-,360)			(2,864***)
INDG							,037		,018
							(1,300)		(,554)
COMP							,061		,096
							(3,163***)		(4,503***)
Price							,000		,012
							(,013)		(,489)
Barriers							,017		-,015
							(,751)		(-,551)
DEM								-,008	
								(-,298)	
Labour								-,014	
								(-,696)	
MAT								,027	
								(1,223)	
FIN								-,024	
								(-1,129)	
Weather								,076	
								(3,552***)	
AGE	,040	,036	,036	,040	-,044	,028	,029	,019	-,054
	(2,790***)	(2,134**)	(2,136**)	(2,561***)	(-2,774***)	(1,603)	(1,598)	(,994)	(-2,418**)
Growth	-,314	-,342	-,343	-,264	-,350	-,332	-,279	-,262	-,351
	(-19,954***)	(-18,303***)	(-18,276***)	(-15,003***)	(-22,233***)	(-17,583***)	(-13,575***)	(-12,313***)	(-14,526***)
Adjusted R^2	,103	,127	,127	,257	,133	,106	,086	,088	,171
Size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No	No	No	No
Durbin-Watson	1,428	1,373	1,896	1,429	1,415	1,362	1,494	1,497	1,733
N	4334	3037	3037	3061	4334	3037	2780	2668	1969

Notation: b(t) * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

between CCC^2 and interest coverage ratio (t = -1,730, $P < 0.10$). When including CCC and CCC^2 in the full regression model with Altman's Z-score begin the dependent variable, both CCC (t = -9,825, $P < 0.01$) and CCC^2 (t = 2,061, $P < 0.05$) are statistically significant. When interest coverage ratio is the dependent variable in the full regression model, only CCC is statistically significant (t = -2,013, $P < 0.05$).

The results found in the regression results including the interest coverage ratio are partially as expected: the cash conversion cycle follows a quadratic relationship with the probability of bankruptcy in the individual model. The same holds true for Altman's Z-score regarding the full regression model. This is probably due to the costs of not investing the locked-up money elsewhere and is in line with results found in previous studies, e.g. Baños-Caballero et al. (2014) and Zeidan and Shapir (2017). In addition, it has been chosen to plot the variable CCC and the interest coverage ratio independently (not reported) and look at the *F*-statistics of both a plotted linear relationship and a quadratic relationship. Although both have a very low level of R Squared, i.e. respectively 0.000 and 0.003, the plotted quadratic relationship is statistically significant ($P < 0.01$) and yields a higher *F*-statistic, respectively 9.192 and 1.048. This is in line with the results found in the regression analyses with the dependent variable being interest coverage ratio. Applying the computation for the inflection point, i.e. $\beta^1/2\beta^2$ shows that the optimal cash conversion cycle yields 82,97 days. This provides support for Hypothesis 1.

When plotting the relationship between CCC and Altman's Z-score, different results as compared to the interest coverage ratio have been found as both the linear and the quadratic relationship have an R Squared of 0,009, which is significant ($P < 0.01$). However, the *F*-statistic of the linear relationship is higher than the *F*-statistic of the quadratic relationship, respectively 75,532 and 37,807, thereby providing evidence for there being a linear relationship between CCC and Altman's *Z*-score. This would indicate that the relationship between the cash conversion cycle and Altman's Z-score is negative, and that the longer it takes to collect cash, the higher the probability of financial distress. This has also been found by Eljelly (2004) and García-Teruel and Martínez-Solano (2007). It is difficult to find conclusive support for Hypothesis 1, as there is only partial support. However, what can definitely be taken from these analyses is that having a high level of CCC, and thus a high level of working capital leads to firms being more susceptible for financial distress.

Regarding the components of the cash conversion cycle, both analyses show that days' inventory outstanding, days' sales outstanding and days' payables outstanding all have a statistically significant relationship with the probability of financial distress. Generally, it can be concluded that high numbers for all of these indicators means a higher probability of financial distress, as all are highly negatively related to both the interest coverage ratio and Altman's Z-score, except for DSO and the interest coverage ratio ($t = 2{,}298$, $P < 0.05$). This may indicate that having many days' sales outstanding is positively related to business performance as it shows that the company has a high revenue and just still needs to collect the money from it. However, overall it indicates that having a high level of receivables and inventory has a negative influence on firm performance. In addition, having many payables outstanding follows the same relationship, as it may indicate that a firm has liquidity problems, which may lead to them having less access to financing or problems in general.

ASCL-index

The age-size-cash-flow-leverage index indicates the level of access to financing, of which a 4 indicates a high access to financing (i.e. above-median age, size, cash-flow and below-median leverage), whereas a 0 indicates a low access to financing (i.e. below-median age, size, cash-flow and above-median leverage). The ASCL-index has been found to relate positively with the interest coverage ratio (t = 19,531, P < 0.01) and Altman's Z-score (t = 12,339, P < 0.01). This indeed indicates that firms having a better access to financing have a lower probability of financial distress. This might be due to the pecking order theory, which describes that if a firm does not generate enough internal funds, it has to reside to outside capital, preferably debt. If a firm is not able to collect outside financing, it will have a negative impact on the business, as a firm is then not able to expand or may run into liquidity problems. Therefore, the relationship between ASCL and financial distress behaves as expected in Hypothesis 2.

Interaction CCC and ASCL

In addition, we are interested in finding evidence for access to financing moderating the relationship between CCC and the level of financial distress. This has been included on the basis of agency problems, which increases the wedge between the costs of internal and external financing due to credit rationing (Baños-Caballero et al., 2014). It was argued that a higher level of working capital requires more financing, and thus it is argued that firms having lower levels of access to financing will have a lower level of working capital, and thus a lower cash conversion cycle. When including only the interaction variable CCC*ASCL, of which both variables were firstly centered, and the control variables, both individual regressions do not yield statistically significant results, but in the full models there has been found evidence of the interaction variable being statistically significant related to the interest coverage ratio (t = 2,022, P < 0.05) and Altman's Z-score (t = 2,864, P < 0.01). This provides evidence for Hypothesis 3 and indicates that access to external financing moderates the relationship between the cash conversion cycle and the probability of bankruptcy.

When testing the interaction variable by looking at the *F*-change in both models, the results indicate that there is evidence for an interaction effect with the interest coverage ratio (*R Square change* = ,003, *Sig. F change* = ,043) and Altman's Z-score (*R Square change* = ,003, *Sig. F change* = ,004). This provides additional evidence for Hypothesis 3.

Industry barriers

Operating in an industry with many risks, will lead to a higher probability of default according to industry organization economics theory (Miloud et al., 2012). Therefore, a variable has been tested that identifies that overall percentage of barriers perceived in a certain industry in a specific province. The kind of barriers included in this research are demand risk, labour market risk, materials risk, financial risk and weather risk. The overall barrier-variable has a statistically significant negative relationship with the interest coverage ratio (t = -5,159, $P < 0.01$). The relationship between the percentage of barriers and Altman's Z-score is insignificant (t = ,751, $P > 0.1$). This provides some evidence for industry organization economics theory and therefore it can be concluded that Hypothesis 4 is somewhat supported.

When taking a closer look at the types of risks an industry is subjected to, it becomes clear that only financial risk and weather risk are significantly related to the dependent variables. The level of financial risk, and more specifically firm access to financing, is positively related to the probability of default as measured by interest coverage ratio (t = -3,651, $P < 0.01$). This has also been found by the variable "ASCL" which indicated that having a lower access to financing will have a positive influence on the probability of default. If a firm cannot obtain bank financing when internal funds do not suffice, a firm cannot grow or even be unable to pay its obligations, which will have a negative influence on firm performance. Furthermore, weather influences are statistically significant and positively related to the interest coverage ratio (t = -3,235, $P < 0.01$) and significantly positively related to Altman's Z-score (t = 3,552, $P < 0.01$), which seems counterintuitive. A possible explanation for the latter result found is that some firms are better able to deal with weather circumstances than others due to the resource-based view (Peteraf, 1993).

Industry growth

The literature and empirical evidence have not found conclusive evidence of the relationship between the industry growth rate and the level of financial distress a firm encounters. It has been argued that operating in a high-growth industry leads to firms striving for innovations (McDermott, 2014) and higher demand (Karuna, 2007) due to reduced further entry into the industry. However, such an industry will also be attractive for new entrants and may lead to a loss of market share and a higher price competition (Karuna, 2007). This inconclusive evidence is also reflected in the regression results. The relationships between industry growth and the interest coverage ratio (t = ,145, $P > 0.1$) and Altman's Z-score (t = 1,300, $P > 0.1$) are insignificant. Therefore, no evidence has been found for Hypothesis 5, and it still remains the question whether industry growth influences the level of financial distress and if so, in what direction.

Industry competition

Regarding the level of industry competition and its influence on firm's probability of default, the literature and empirical evidence were also inconclusive. On the one hand, it was argued that a high degree of competition should stimulate managers to perform better and thus a high degree of competition can have a positive influence on firm performance (Schmidt, 1997; Karuna, 2007). However, according to Sutton (1990), intense competition could also lead to bankruptcy as firms cannot compete efficiently. As the conventional view and literature supported that competition leads to a higher probability of default due to lower price margins, this has also been hypothesized. The relationship between competition and the interest coverage ratio is insignificant (t = -,464, $P > 0.1$), but the relationship between competition and Altman's Z-score is significant (t = 3,163, $P < 0.01$). This provides evidence for Hypothesis 6, as firms that operate in an industry where the competition gets less, or where their own competitive position within the industry gets better, have a lower probability of default. This probably means that firms are able to attain market share and charge higher prices, so they do not have to compete on lower prices and become more efficient (Karuna, 2007). This is also in line with the univariate statistics performed as the correlation between a better position in the market and a higher sales price is significant at the 1%-level with a correlation of ,233.

Industry sales price

The sales price is linked to the level of competition present in the industry (Karuna, 2007). The prevailing argument is that higher levels of competition lead to lower sales prices and thus lower margins for firms. Therefore, it has been hypothesized that having lower industry prices leads to a higher probability of default. However, the opposite has been found regarding the relationship between industry sales price and the interest coverage ratio (t = -2,101, $P < 0.05$). The relationship between industry sales price and Altman's Z-score has been found to be insignificant (t = -,013, $P > 0.1$). These findings indicate that a lower industry sales price leads to a lower probability of default, thereby not supporting Hypothesis 7. This might be due to firms operating in industries with decreasing sales prices having more efficient operations and are able to compete on price (Sutton, 1990).

Control variables

In the baseline model, it can be seen that the control variables all yield statistically significant relationships with both the interest coverage ratio and Altman's Z-score. The variable "Age" is significantly and positively related to both the interest coverage ratio (t = 5,668, $P < 0.01$) and Altman's Z-score (t = 2,790, $P < 0.01$), which was also expected. Older companies have oftentimes easier access to capital and have more knowledge built up, so that agency problems are oftentimes alleviated, which enhances firm performance (Mulier et al., 2016). The variable "Growth" follows a significantly negative relationship with the interest coverage ratio (t = -11,692, $P < 0.01$) and with Altman's Z-score (-19,954, $P < 0.01$). This may be due to companies not having the necessary knowledge in-house to support the growth, which in turn may harm firm performance and cause financial distress (Marcelino-Sádaba et al., 2014).

4.3.3 Regression analyses Panel B: Dutch SMEs

The descriptive statistics in Table 4 and Appendix 2 already showed some differences between the full sample and the SME sample, so there is a need to distinguish between both. This section only included the sample with micro-, small-, and medium-sized businesses. The results can be found in Tables 8, 9 and 10 of which the latter also includes industry dummies for the credit/liquidity risk measures. Only the results that are deviating from the aforementioned results will be described in-depth.

Credit/liquidity risk

In line with the results of Panel A, there is no clear consensus on the cash conversion cycle and its relationship with financial distress. In line with previous results, the relationship between CCC^2

Table 8 Regression results Dependent variable: Interest Coverage Ratio - Panel B

CCC		-,036	,030						-,026
		(-1,055)	(,579)						(-,397)
CCC^2			-,087						-,141
			(-1,707*)						(-2,080**)
DIO				-,072					
				(-2,126**)					
DSO				,075					
				(2,252**)					
DPO				-,090					
				(-2,559**)					
ASCL					,347				,331
					(13,295***)				(6,938***)
CCC*ASCL						,051			,113
						(1,516)			(2,133**)
INDG							-,028		-,063
							(-,669)		(-1,151)
COMP							-,025		-,064
							(-,807)		(-1,552)
Price							-,042		-,022
							(-1,228)		(-,483)
Barriers							-,146		-,184
							(-3,931***)		(-3,580***)
DEM								-,033	
								(-,729)	
Labour								,038	
								(1,123)	
MAT								,040	
								(1,102)	
FIN								-,065	
								(-1,834*)	
Weather								-,089	
								(-2,527**)	
AGE	,069	,062	,063	,066	-,070	,050	,045	,053	-,104
	(2,896***)	(1,830*)	(1,844*)	(1,996**)	(-2,794***)	(1,485)	(1,500)	(1,694)	(-2,374**)
Growth	-,207	-,193	-,184	-,173	-,301	-,188	-,138	-,149	-,238
	(-8,656***)	(-5,700***)	(-5,400***)	(-5,104***)	(-12,664***)	(-5,600***)	(-4,562***)	(-4,677***)	(-5,339***)
Adjusted R^2	,047	,042	,045	,062	,137	,044	,033	,030	,125
Size dummies	No	No	No	No	No	No	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No	No	No	No
Durbin-Watson	1,390	1,507	1,839	1,450	1,430	1,505	1,463	1,453	1,797
N	1674	847	847	861	1674	847	1101	1038	573

Notation: b(t) * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

and the interest coverage ratio is significantly negative (t = -1,707, P < 0.1), whereas the relationship between CCC and the interest coverage ratio is again insignificant (t = -1,055, P > 0.1). Again, only the quadratic relationship was found to be significant (F = 6,903, P < 0.01). The inflection point found in this case pertains to 78,90 days, assuming the coefficient of the linear relationship *(β_1)* has remained the same. The relationship between CCC and Altman's Z-score is significant (t = -5,057, P < 0.01) in contrast to the influence of CCC^2 on Altman's Z-score (t = ,334 P > 0.01). These last results do not provide additional evidence for Hypothesis 1.

Table 9 Regression results Dependent variable: Z-score - Panel B

CCC		-,132	-,140						-,249
		(-5,057***)	(-3,981***)						(-5,467***)
CCC^2			,012						-,034
			(,334)						(-,701)
DIO				-,134					
				(-5,207***)					
DSO				-,178					
				(-7,061***)					
DPO				-,124					
				(-4,722***)					
ASCL					,268				,311
					(11,249***)				(8,699***)
CCC*ASCL						,070			,094
						(2,677***)			(2,612***)
INDG							,014		-,019
							(,353)		(-,438)
COMP							,003		,053
							(,099)		(1,654*)
Price							,045		,058
							(1,409)		(1,597)
Barriers							-,023		-,054
							(-,657)		(-1,370)
DEM								-,028	
								(-,673)	
Labour								,016	
								(,510)	
MAT								,050	
								(1,550)	
FIN								-,009	
								(-,267)	
Weather								,040	
								(1,274)	
AGE	,079	,083	,083	,084	-,033	,067	,078	,067	-,037
	(3,639***)	(3,175***)	(3,174***)	(3,347***)	(-1,414)	(2,535**)	(2,895***)	(2,371**)	(-1,105)
Growth	-,213	-,264	-,265	-,220	-,274	-,253	-,178	-,160	-,285
	(-9,828***)	(-10,112***)	(-10,093***)	(-8,643***)	(-12,621***)	(-9,644***)	(-6,589***)	(-5,626***)	(-8,709***)
Adjusted R^2	,049	,084	,083	,142	,105	,071	,031	,029	,153
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No	No	No	No
Durbin-Watson	1,651	1,661	1,984	1,658	1,651	1,644	1,687	1,698	1,701
N	2035	1353	1353	1371	2035	1353	1360	1285	909

Notation: b(t) * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Furthermore, the relationship between ASCL and both dependent variables provides the same evidence as in the full sample: the ASCL is significantly and negatively related to the probability of bankruptcy, which provides additional evidence for Hypothesis 2.

Again in this sample, support has been found for the interaction variable CCC*ASCL, as it is positively related to the interest coverage ratio (t = 2,133, $P < 0.05$), Altman's Z-score excluding industry dummies (t = 2,677, $P < 0.01$) and including industry dummies (t = 2,649, $P < 0.01$). This

Table 10 Regression results Liquidity risk - Panel B (including industry dummies)

	ICR	ICR	ICR	ICR	ICR	Z-score	Z-score	Z-score	Z-score	Z-score
CCC	-,047	,031				-,145	-,157			
	(-1,374)	(,579)				(-5,407***)	(-4,314***)			
CCC²		-,099					,017			
		(-1,927*)					(-,491)			
DIO			-,078					-,129		
			(-2,192**)					(-4,747***)		
DSO			,058					-,190		
			(1,737*)					(-7,362***)		
DPO			-,105					-,115		
			(-2,831***)					(-4,008***)		
ASCL				,337					,268	
				(13,111***)					(11,282***)	
CCC*ASCL					,032					,070
					(,936)					(2,649***)
AGE	,032	,032	,032	-,097	,023	,068	,068	,069	-,050	,056
	(,944)	(,929)	(,938)	(-3,846***)	(,659)	(2,521**)	(2,521**)	(2,663***)	(-2,090**)	(2,052**)
Growth	-,142	-,133	-,121	-,253	-,138	-,242	-,243	-,211	-,245	-,232
	(-3,910***)	(-3,612***)	(-3,345***)	(-10,109***)	(-3,796***)	(-8,564***)	(-8,572***)	(-7,698***)	(-10,561***)	(-8,140***)
Adjusted R²	,090	,093	,112	,172	,088	,096	,096	,152	,114	,081
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Durbin-Watson	1,527	1,923	1,475	1,457	1,527	1,655	1,967	1,656	1,656	1,645
N	847	847	861	1674	847	1353	1353	1371	2035	1353

Notation: b(t) * Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

has also been tested by checking the change in the *F*-statistic in the full model with and without the interaction variable. The model with the dependent variable being the interest coverage ratio showed a significant change in R Square of 0.007, of which the significance of the *F*-change pertains to 0.033. The same results have been found with Altman's Z-score being the dependent variable (*R Square change* = 0,006, *Sig. F change* = 0,009). This provides additional support for Hypothesis 3. Firms that do not have the possibility for outside funding should make cash conversion cycle management priority (Zeidan & Shapir, 2017). The opposite holds also true, as firms being able to get sufficient financing have less of a need to improve their cash conversion cycle (Kling et al., 2014).

Business/industry risk

In Panel A, industry barriers were found to have a positive effect on the probability of financial distress in terms of the interest coverage ratio, providing evidence for Hypothesis 4. In line with this, the level of industry barriers still has a negative and statistically significant effect on the interest coverage ratio (t = -3,931, P < 0.01), but the relationship between the level of industry barriers and Altman's Z-score remains insignificant (t = -,657, P > 0.1). What is striking, is that even the individual industry risk factors are insignificantly related to Altman's Z-score, i.e. the relationship financial risk and Altman's Z-score (t = -,267, P > 0.1) and weather risk and Altman's Z-score (t = 1,274, P > 0.1). The relationship between financial risk and the interest coverage ratio still remains significant and negative (t = -1,834, P < 0.1) and the relationship between weather risk and the interest coverage ratio is significant and negative (t = -2,527, P < 0.05). This is as hypothesized due to industry organization economics predicting that industry barriers will exert a positive influence on firm's probability of financial distress. The relationship between industry growth and the interest coverage ratio (t = -,669, P > 0.1) and Altman's Z-score (t = ,353, P > 0.1) still remain insignificant, thereby providing evidence for there not being any effect of industry growth on the probability of financial distress. In line with the result found in the full sample regarding competition, there has been found evidence that competition does also have a significant influence on the probability of bankruptcy in SME firms in terms of Altman's Z-score (t = 1,654, P < 0.1). This provides additional evidence for Hypothesis 6. No evidence has been found for there being an influence of industry sales prices on the probability of bankruptcy in the SME setting, which provides less evidence for Hypothesis 7.

4.3.4 Robustness checks

When performing research on panel-data, there is a risk of survivorship bias, as some companies have gone bankrupt during the timespan of this research (i.e. 2011 till 2015) (Kling et al., 2014). In total, 219 companies have gone bankrupt over this time, which may lead to other companies exerting a relatively larger influence on the regression results than the firms that have gone bankrupt. It might be that the changing number of these units has an influence on the final empirical outcome (Kling et al., 2014). Therefore, it has been chosen to perform the full regression analyses in the full sample again with only the firms that did not go bankrupt in the period spanning from 2011 until 2015. Regarding the interest coverage ratio, the results only changed slightly, i.e. the significance level of CCC^2 changed from 5% to 1%. In the analyses conducted with Altman's Z-score, the significance level of the interaction variable changed from 5% to 10%. This indicates that survivorship bias is probably not an issue within this research.

In addition, a logistic regression has been performed on whether the dependent variables interest coverage ratio and Altman's Z-score are able to explain bankruptcy as a binary variable. The unreported results indicate that Altman's Z-score is significantly and directly related to bankruptcy at the 5 percent level (*Wald* = 4,915, $P < 0.05$). The interest coverage ratio is not significantly related to bankruptcy (*Wald* = ,596, $P > 0.1$), but it might be that the interest coverage ratio reflects the probability of financial distress better than the probability of bankruptcy (Tinoco & Wilson, 2013).

4.4 Survival analyses

In preparation for the survival analysis, cases have been identified in which firms have defaulted over the period spanning from 2011 until 2015. The firms that have defaulted have experienced a so-called 'event', which is a pre-requisite for conducting any survival analysis. In addition, it was important to identify the time-frame over which the firm has existed, or still exists, in this case the founding years until default or 2015, if the firms had not defaulted over that particular time period. The other data used in the survival analysis, the so-called predictor variables, have been matched to the year of default. If the firm still exists, the year taken was 2015. This has been done in order to make sure that the right predictor variables are linked to the event. The variables that have been included pertain to firm-specific variables, including the interest coverage ratio, Altman's Z-score, the cash conversion cycle and the ASCL-index. These have been found to explain the probability of financial distress in the regression analyses, so it is also interesting to find out whether they are able to predict actual bankruptcy over particular groups.

4.4.1 Full sample

The results of the first survival analysis can be found in Table 11. When including every variable in the Survival Analysis model, the model itself is significant (χ^2 = 24,246, $P < 0.01$), as well as the full ASCL variable (*Wald* = 16,913, $P < 0.01$). This indicates that the variables together are able to explain differences between the group that encountered the event, i.e. bankruptcy, and the group that did not. Figure 1 in Appendix 3 shows the exact survival probabilities for the groups divided based on the ASCL-index, the variable that has indicated to be the best predictor in this model. It becomes clear that groups that have trouble receiving financing, i.e. groups with an ASCL of 0 or 1, have a higher chance of going bankrupt than groups with an ASCL of 2, 3 or 4. As the differences between the groups among each other are not statistically different, it is difficult to determine the exact hazard rate. However, it is clear that different groups experience different survival rates over time. For example, a firm that has an ASCL of 0 and thus a low access to financing, has under the conditions included in the model, a survival probability of approximately 0.7 over 20 years, whereas a firm that has an average access to financing, i.e. an ASCL of 2, has a survival probability of approximately 0.95 over 20 years. These results indicate the importance of having a proper access to financing. However, as all other variables are insignificant under the circumstances of this model, each variable will be evaluated independently next as to find out which variables alone might be able to explain the survival probability of firms.

Table 11 Results Survival Analysis Full model

	Event (N)	Censor (N)	Total (N)	χ^2	Sig.	B	SE	Wald	df	Sig.	Exp. (B)
Full sample	39	428	467	24,246***	,001						
ICR						,033	,369	,008	1	,929	1,033
Z-score						-,534	,372	2,060	1	,151	,586
CCC						-,203	,332	,008	1	,540	,816
ASCL								16,913***	4	,002	
ASCL (1)						10,343	62,344	,028	1	,868	31049,538
ASCL (2)						9,663	62,340	,024	1	,877	15720,544
ASCL (3)						8,208	62,340	,017	1	,895	3671,651
ASCL (4)						7,850	62,341	,016	1	,900	2566,183

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

5.4.2 Individual variables

The results of the tests can be found in Table 12. Regarding the interest coverage ratio, the results indicate that the interest coverage ratio significantly predicts differences between the two groups (i.e. above-average and below-average interest coverage ratios) over the next years (*Wald* = 11,295, $P < 0.01$), of which Figure 2 can be found in Appendix 3. The most important outcome of the survival analysis is Exp. (B), which can be interpreted as the predicted change in a unit if the predictor variable changes by a unit. The value of Exp. (B) of the interest coverage ratio pertains to 1,740, which means that the bankruptcy hazard of a firm with a below-average interest coverage ratio is 1.740 times higher than the bankruptcy hazard of a firm with an above-average interest coverage ratio. Regarding Altman's Z-score, the survival analysis indicates that Altman's Z-score is not a significant predictor of differences between above-average Altman's Z-score and below-average Altman's Z-scores in relation with bankruptcy (*Wald* = 1,66, $P > 0.1$). This may even indicate that Altman's Z-score might not be a good predictor of bankruptcy, but in the logistic regression results in the robustness checks section, Altman’s Z-score was able to explain bankruptcy. The insignificant results can also be seen in Figure 3 in Appendix 3. Although the lines differ from each other and move in the expected direction, the lines are not significantly apart from each other to draw conclusions.

In addition, the cash conversion cycle is also an insignificant predictor of bankruptcy when dividing groups in above-average cash conversion cycles and below-average cash conversion cycles (*Wald* = ,730, *P* > 0.1). These results also become apparent Figure 4 in Appendix 3. The lines are not much deviating from each other and are following more or less the same trend. In line with what has been found earlier, the ASCL index is a good predictor of bankruptcy and differentiates between the different groups, ranging from 0 (worse access to financing) to 4 (best access to financing). The overall measure of ASCL is significant (χ^2 = 62,162, *P* < 0.01), as well as ASCL (2), which relates to the line ASCL = 1,00, which is significantly different from the other ASCL measures (*Wald* = 3,46, *P* < 0.1), which is also clearly visible in Figure 5 in Appendix 3. Again, Exp. (B) can be used to indicate the expected differences between the groups, and in this case between the group with an ASCL of 1,00 and the reference group, i.e. firms with an ASCL of 4,00. The Exp. (B) of 2,972 indicates that the bankruptcy hazard of the group with ASCL of 1,00 is 2,972 times higher than the bankruptcy hazard of the reference group with an ASCL of 4,00. To conclude, when analyzing all the variables separately, only the interest coverage ratio and the ASCL seem good predictors of bankruptcy. Therefore, these two have been combined in a survival analysis to find out whether the results change significantly.

Table 12 Results Survival Analysis Individual variables

	Event (N)	Censored (N)	Total (N)	χ^2	Sig.	B	SE	Wald	df	Sig.	Exp.(B)
ICR	153	1725	1878	11,585***	,001	,554	,165	11,295***	1	,001	1,740
Z-score	159	2320	2479	1,669	,196	,205	,159	1,66	1	,197	1,227
CCC	70	1036	1106	,732	,392	-,206	,241	,730	1	,393	,814
ASCL	218	3800	4018	62,162***	,000			64,527	4	,000	
ASCL (1)						,678	,664	1,043	1	,307	1,971
ASCL (2)						1,089	,588	3,46*	1	,064	2,972
ASCL (3)						-,042	,588	,005	1	,943	,959
ASCL (4)						-,183	,611	,090	1	,765	,833

* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

5.4.3 Optimal model

The results of the survival analysis including the variables interest coverage ratio and ASCL are depicted in Table 13. The full model is significant and is therefore able to distinguish different survival probabilities between groups (χ^2 = 91,585, *P* < 0.01). When taking a look at the individual variables, ASCL (2), i.e. the group with an ASCL of 1,00, is again significant in describing differences between this group and the groups with another ASCL (*Wald* = 4,015, *P* < 0.05), by which the interest coverage ratio serves as a control variable. The Exp. (B) equals 3,370, which means that firms with an ASCL of 1,00 have a 3,370 times higher chance of going bankrupt than firms in the reference group, i.e. with an ASCL of 4,00, when controlling for the interest coverage ratio. This becomes also visible in Figure 6 in Appendix 3. In addition, the interest coverage ratio is significant in describing differences between the groups with an above-average and a below-average interest coverage ratio (*Wald* = 4,056, $P < 0.05$), by controlling for the ASCL. The Exp. (B) equals 1,410, which means that firms with a below-average interest coverage ratio have a 1,410 times higher chance of going bankrupt than firms with an above-average interest coverage ratio, when controlling for the ASCL. This is depicted in Figure 7 in Appendix 3.

Table 13 Results Survival Analysis Optimal Model

	Event (N)	Censored (N)	Total (N)	χ^2	Sig.	B	SE	Wald	Sig.	Exp. (B)
Full model	153	1725	1878	91,585***	,000					
ICR						,344	,171	4,056**	,044	1,410
ASCL								68,291***	,000	
ASCL (1)						1,224	,751	2,653	,103	3,401
ASCL (2)						1,215	,606	4,015**	,045	3,370
ASCL (3)						-,316	,597	,281	,596	,593
ASCL (4)						-,523	,623	,704	,401	,593

* Significant at the 10% level   ** Significant at the 5% level   *** Significant at the 1% level

5. Discussion

In this discussion, first a summary of the findings will be presented, as well as a summary of the acceptance or rejection of the hypotheses. After that, the scientific as well as the practical implications will be discussed. Furthermore, the limitations and directions for future research will discussed. The chapter ends with a conclusion in which the main aspects and findings of this research will be outlined. The goal of this research was to find out which risk factors have a high influence on the probability of bankruptcy for Dutch firms, and SMEs more specifically. It was hoped for to find a few risk factors that explain a relative portion of the probability of bankruptcy. The research question as stated at the beginning of this research is as follows: *"What are the most important risk factors, both firm-specific and industry-specific, that influence the probability of bankruptcy of Dutch firms, and more specifically of small and medium-sized enterprises?"*

Summary of findings

After conducting multiple regression and survival analyses, it is important to reflect on the findings in relationship with previous literature and empirical findings as to draw conclusions on the influence of several risk factors related to credit/liquidity risk and industry risks. In this section, I will make a distinction between SMEs and the full sample, as some variables were not significant in either one of the samples. Overall, the results regarding the hypotheses are the following:

Hypothesis	**Outcome**
Hypothesis 1: The cash conversion cycle follows a U-shaped relationship with bankruptcy risk.	Partially supported
Hypothesis 2: Firms with a better access to external financing have a lower bankruptcy risk than firms with worse access to external financing.	Supported
Hypothesis 3: Access to bank financing moderates the relationship between the cash conversion cycle and bankruptcy risk.	Supported
Hypothesis 4: Firms that operate in an industry with a high level of barriers have a higher bankruptcy risk than firms that operate in an industry with fewer barriers.	Partially supported
Hypothesis 5: Firms that operate in an industry with a higher growth rate have a lower bankruptcy risk than firms that operate in an industry with a lower growth rate.	Not supported
Hypothesis 6: Firms that operate in an industry with a stronger level of competition have a higher bankruptcy risk than firms that operate in an industry with a weaker level of competition.	Partially supported
Hypothesis 7: Firms that operate in an industry with lower sales prices, have a higher bankruptcy risk than firms that operate in an industry with higher sales prices.	Not supported

Regarding liquidity risk, the overarching variable taken, i.e. the cash conversion cycle, was hypothesized to follow a quadratic relationship with the probability of default. After conducting several analyses, the general conclusion is that in some cases the cash conversion cycle follows an inverted U-shaped relationship with the interest coverage ratio. This means that at some point, i.e. the inflection point, the opportunity cost-effect kicks in, which indicates that the firm has a too high level of working capital, which they could have invested elsewhere (Baños-Caballero et al., 2014; Zeidan & Shapir, 2017). This is in line with the results found by Baños-Caballero et al. (2014) and Zeidan and Shapir (2017). These inflection points pertained to 82,97 days for the full sample and 78,90 days for the SME-sample. In the study by Baños-Caballero et al. (2014), conducted on a UK-sample, the inflection point pertained to 66,95 days as firm performance was measured in terms of the Q-ratio. As the numbers found in this study do not deviate too much from the optimum found in the previously-mentioned study, the results are realistic. Many firms are fixated on increasing liquidity measures such as the current and quick ratio, but do not realise that too much money could be locked-up in working capital. Therefore, it is important that firms understand the practical side of this study and try to optimize their level of working capital. However, the results found were not fully conclusive as for Altman's Z-score being the dependent variable, a negative linear relationship with CCC has been found. This indicates that the more working capital a firm possess, the worse the firm performance in terms of Altman's Z-score. The same logic could be applied to this outcome, as the firm probably suffers from opportunity costs, financing problems (Deloof, 2003), and a higher cost of capital (Zeidan & Shapir, 2017). This is in line with the result found by Eljelly (2004) as additional working capital comes along with lost profits and additional costs from holding excessive liquidity. Hypothesis 1 is only partially supported, but the need of not having too much money locked-up in working capital is evident.

Access to financing has been shown to be consistently significantly related to both the interest coverage ratio and Altman's Z-score. The age-size-cash-flow-leverage index has shown that companies with a high ASCL, used as a proxy for access to external financing, perform better and have a lower chance of going bankrupt. This has also been argued by Mulier et al. (2016). The explanation for this lies in agency theory, as firms having lower levels of information asymmetry are better able to attract capital from outside capital markets. Many information is not present in the outside market which makes it more difficult to assess the firm (Chemla & Hennessy, 2014). However, especially the firms that do not generate enough internal funds, which may be equal to firms being smaller and younger, have to resort to outside financing, according to the pecking order theory (Frank & Goyal, 2003). The results also indicate this, as SMEs have a lower ASCL-index on average than larger companies, so they have more problems in obtaining external financing. This in turn also influences the probability of bankruptcy, which supports Hypothesis 2.

Based on the pecking order theory and signalling theory, it was argued that access to financing moderates the relationship between the cash conversion cycle and firm's probability of default. This is due to firms being able to get outside financing more easily, will less soon resort to another, more expensive, form of financing, for example trade credit (Bias & Gollier, 1997). In line with this, the signalling theory indicates that firms can substitute institutional loans for trade credit, which is especially the case if they cannot access the loan market (Wu et al., 2012). Firms that cannot easily borrow money, should make the optimalization of the cash conversion cycle priority (Zeidan & Shapir, 2017). In both panels, evidence for this interaction effect has been found. In addition, the full models have been tested by looking at the change in the F-statistic, and this is also significant in both panels. This means that being able to access external financing intervenes in the relationship between the cash conversion cycle and the probability of bankruptcy, concluding that firms that are financially constrained have a lower optimum of working capital. This result has also been found by Baños-Caballero et al. (2014), arguing that those firms have higher financing costs and greater capital rationing. If those firms try to optimize their level of working capital, the need for outside financing is less. Therefore, it can be concluded that Hypothesis 3 is supported.

Regarding the level of industry barriers, the results are often indicative of a negative influence of industry barriers on firm performance, which has also been predicted by industry organization economics theory (Miloud et al., 2012). The influence of industry barriers on the probability of financial distress is only statistically significant with the interest coverage ratio being the dependent variable. The insignificant results regarding Altman's Z-score might be due to the resource-based view, which describes why some firms might be able to perform well in unfavourable industries due to being able to access scarce resources (Peteraf, 1993). However, there is support for Hypothesis 4. When looking at the barriers more specifically, it appears that only the access to financing and weather risk are statistically significant, and as expected almost always negatively associated with the dependent variables. This again indicates the importance of being able to get financing in order to pay obligations, invest money in the business, and eventually grow.

Regarding industry growth, no significant results have been found. It was argued that operating in a growth industry might lead to firms striving for innovations (Prajogo & McDermott, 2014). In addition, further entry into the industry is less at some point due to incumbent firms' investments in cost reductions and quality improvements (Karuna, 2007). However, it might be that a rapid changing environment could be a threat as smaller firms might not be able to capture the resources necessary or through increased competition (Ju & Sohn, 2015). According to industry organization economics theory, a growing industry is attractive for outsiders, but incumbent firms are also enables to attain market share (Miloud et al., 2012). As this research does not show any significant results, we cannot accept Hypothesis 5, and it remains the question if, and in what direction, industry growth exerts influence on the firm. The insignificant results might be due to there being benefits and downsides of operating in a growth industry; it might depend on the firm whether they are able to benefit from it, based on the resource-based view (Peteraf, 1993).

There was no consensus in literature on whether competition can be viewed as a substitute for managerial incentives or not (Karuna, 2007) and thus, whether it can work as a corporate governance mechanism. In this research, competition has been found to be positively related to the probability of default in terms of Altman's Z-score, both for the full and the SME sample, which is in line with the view that competition can lead to firms being driven out of the market due to being less efficient (Sutton, 1990). This does not provide evidence for the results found by Karuna (2007), as Karuna (2007) has found evidence for there being a relationship between managerial incentives and the level of industry competition. In this research, therefore, there has not been found evidence that competition is an effective corporate governance mechanism that motivates managers to perform better. However, this result has only been found for Altman's Z-score, thus only providing partial support for Hypothesis 6.

The prevailing sales price in the industry is partially dependent on the level of competition, as Spanos et al. (2004) argue that a concentrated industry, and thus lower competition, allows for a higher sales price, which in turn leads to a higher level of profitability. In addition, Karuna (2007) has argued that lower prices lead to lower margins, which has a negative effect on firm's market share and expected profits. The results found in this study on the influence of sales price on the probability of financial distress are less clear-cut. Within the full sample and the dependent variable being interest coverage ratio, the influence of sales price is significantly negative, which does not provide evidence for Hypothesis 7. The results found might seem counterintuitive, but a possible explanation might be that having too high sales prices lead to less sales and thus a higher probability of default.

Overall, the models differ in terms of explained variance (i.e. Adjusted R^2). The best model included in this research is able to explain 25,7 percent of firm's probability of financial distress, in terms of Altman's Z-score. This model includes the variables days' inventory outstanding, days' sales outstanding, day's payables outstanding, age, growth, size- and year-dummies. All variables, except for age, are significantly and negatively related to Altman's Z-score. Being able to explain the portion of 25,7 percent without the inclusion of financial ratios, as well as qualitative variables on management and employee performance is rather high and explains the importance of including liquidity measures in default prediction models.

Within the field of default-prediction, researchers are attempting to integrate the time-aspect of variables, and thus they resort to models such as survival analysis in order to predict the probability of default. In this study, it appears that both the interest coverage ratio and the ASCL-index are good predictors of default. When including both variables separately, the survival model indicates that having a below-average interest coverage ratio will lead to a 1,740 times higher chance of going bankrupt than firms having an above-average interest coverage ratio. This indicates the importance of including the interest coverage ratio in default-prediction models and its ability to distinguish between firms that have a higher probability of going bankrupt and those that have not (Tinoco & Wilson, 2013). Furthermore, the results indicate that having an ASCL-index of 1,00 makes the firm 2,972 times more likely to go bankrupt than firms having an ASCL-index of 4,00 and thus a good access to financing. The firms having a high ASCL are on average older, larger, have a higher cash flow, and lower leverage. When including both variables in the model, both remain significant. When controlling for the ASCL-index, having a below-average interest coverage ratio now leads to a 1,410 times higher chance of going bankrupt. When controlling for the interest coverage ratio, having an ASCL of 1,00 now leads to a 3,370 higher chance of going bankrupt compared to the firms with an ASCL of 4,00. Again, the need for having proper access to financing and decreasing agency problems is profound, which is also argued by Mulier et al. (2016) as these authors argue that firms that are financially constrained might be less able to obtain external financing, but will also pay a higher interest rate.

The dependent variables used in these tests have shown that they perform well in explaining or predicting bankruptcy and are therefore considered to be good indicators. The interest coverage ratio is often applied in default studies as to proxy for financial distress (e.g. Tinoco & Wilson, 2013; Baños-Caballero et al., 2014). Altman's Z-score is oftentimes applied and improved upon, and has shown in the logistic regression in the robustness tests that it explains bankruptcy.

Scientific implications

Current research is still heavily tilted towards the use of financial ratios in default prediction studies, as well as a focus on larger firms due to information availability. It has, however, been argued that inclusion of non-financial data can improve bankruptcy prediction models. In addition, there is a need to distinguish between large firms and SMEs, especially when it comes to agency problems and more specifically information asymmetry. This study aimed to contribute to both due to the inclusion of liquidity measured beyond the financial ratios oftentimes included, i.e. current and/or quick ratio, access to financing, and industry data. In addition, two samples were used, of which one only included SME firms. I believe this research is a good starting point as it adds variables such as liquidity management and access to financing, and both have indicated their importance. It has, however, been found that inclusion of industry-specific variables did not improve the models significantly, but some individual variables might be worthwhile to consider in specific cases.

Practical implications

After conducting this research, the practical relevance is evident for firms, financial institutions, and SynnoFin.

Overall, it can be concluded that liquidity management should be a priority for companies. Zeidan and Shapir (2017) have found that working capital management leads to improved firm performance in terms of higher profitability and increased cash flow. Companies should not try to eliminate as much working capital as possible, as offering for example trade credit could lead to higher sales, or higher inventory could lead to less stock-outs (Baños-Caballero et al., 2014; Zeidan & Shapir, 2017). Optimizing the level of working capital in terms of the cash conversion cycle, a dynamic measure of liquidity management (Kling et al., 2014), will enhance firm performance and leads to a lower level of financial distress. Firms should acknowledge this and try to optimize their working capital management, e.g. by trying to produce just-in-time so that inventory can be decreased, or by offering less trade credit.

In addition, the variable ASCL, which is used as a proxy for access to external financing, is consistently related to the probability of bankruptcy, where firms having a high ASCL index have a lower probability of going bankrupt. However, these are oftentimes the firms that mostly need external financing, as these firms are on average younger, smaller in size and have acquired less cash flow. These findings indicate an important gap in the current lending process. The firms that need outside financing the most, based on the pecking order theory, have less of a possibility to resort to outside financing. This credit rationing process describes that banks and financial institutions are hesitant to provide loans to SMEs as they have a higher level of information asymmetry (Duarte et al., 2016). Credit information needs to be improved in order to solve this problem, but this can only be done by developing adequate risk models (Altman et al., 2010). This finding is especially important to both firms and financial institutions, as only by understanding these factors, firms can try to eliminate agency problems. As this research has found that the influence of the cash conversion cycle on the probability of financial distress is moderated by access to financing, the need is even higher for these firms, as it is a cheaper source of financing (Zeidan & Shapir, 2017).

The outcomes of this research are also relevant to SynnoFin, as it can optimize their software by providing insights to firms about their liquidity management, probability of bankruptcy, access to financing, and the implications of industry specific variables. Some variables in this research, e.g. days' inventory outstanding, days' sales outstanding, days' payables outstanding and ASCL, have been shown to explain a large portion of the probability of bankruptcy and are therefore important to include in credit risk models. Furthermore, the interest coverage ratio and Altman's Z-score have been able to explain bankruptcy in the different robustness checks performed and can therefore be used as proxies for bankruptcy risk.

Limitations

This research has several limitations of which some will be outlined here. One limitation is that the current ratio is part of Altman's Z-score, which might lead to biased results when including the cash conversion cycle as a liquidity risk measure. However, the difference between the current ratio and the cash conversion cycle has been widely acknowledged as the cash conversion cycle is a dynamic measure of liquidity management. In addition, the correlation coefficient between the two measures only pertains to -,096, which is the opposite of expectations and not too high, i.e. a correlation higher than ,300. Furthermore, the cash conversion cycle has also shown its ability to explain differences in the interest coverage ratio. Therefore, I believe that it is safe to include this variable, after these tests had been conducted. In line with this, two control variables have been decided to be deleted from the analyses and have not been reported, i.e. Assets and Return-on-Assets, as these were found to correlate too highly with Altman's Z-score.

Due to a limited scope and data availability, not all important risk factors as indicated in the literature review could be studied. Therefore, the different risk factors chosen might not yield the best results compared to other risk factors. However, this research still indicated a few important risk types, which should not be neglected.

Another limitation is that the data gathered has been used to construct the variables in this research, but this had to be done manually in some cases. Therefore, there is always a possibility that mistakes have been made in some cases. However, the large sample size should be able to correct for these mistakes and still provide evidence on the behavior of certain risk factors in explaining the probability of bankruptcy.

Future research

This research has a large sample size and the dependent variables used have shown their strength in either being able to explain or predict bankruptcy. However, within the scope of this master thesis, it was not possible to look at other risk factors. I would definitely suggest that further research focuses on for example operational risk factors, as these have been found to exert a profound influence on financial distress in previous studies. As this research has not focused on financial ratios, it would be a good idea for following research to construct a model with both financial ratios and (other) firm-specific risk factors as to find out whether both together are able to explain a larger portion of firm performance. In addition, more research should be conducted on management-specific components and their influence on financial distress. Only by doing this, more risk factors can be identified on which firms could focus in order to enhance their access to external financing. The research could also be extended by including other countries, as to being able to include country-specific variables.

Conclusion

This research has shown that the integration of liquidity risk measures is beneficial for credit scoring models. The cash conversion cycle and ASCL have shown to have practical relevance and are statistically significant related to the probability of bankruptcy. Firms should try to optimize the cash conversion cycle and try to eliminate agency problems as much as possible in order to obtain external financing. The inclusion of industry variables does not significantly add to the credit scoring model, but some of them might be important to take into consideration, especially industry barriers. In addition, it has been found that the interest coverage ratio and Altman's Z-score are good indicators of the probability of bankruptcy, and can therefore be of great importance to firms, financial institutions and researchers.

6. Acknowledgements

In this section I would like to, first of all, thank the whole finance department of the University of Twente for their useful feedback, tutorials and lectures throughout my Financial Management master. More specifically, I would like to thank Prof. Kabir and Dr. Ir. Van den Broek for their useful feedback during my master thesis specifically. In addition, I would like to thank Geert Haisma and SynnoFin for providing me with useful feedback, data, and the interesting research question.

Appendix

Appendix 1

Search category	Step result	Search result
Legal status: registered or deregistered	4.806.801	4.806.801
Total assets	868.659	869.659
Net sales	21.644	21.622
Trade creditors	39.881	13.078
Receivables	823.911	13.027
Stocks	170.609	8.312
Current assets	857.998	8.312
Current liabilities	838.190	8.312
Number of employees	419.277	7.219
Cash-flow	21.606	4.422
Total debts	853.186	4.422
Income after taxes	60.062	4.420
EBIT	58.523	4.420
Shareholders funds	877.195	4.419
Financial expenses	44.210	4.053
Tangible fixed assets	491.679	4.023
Depreciation on IFA and TFA	21.606	4.023

Appendix 2

Variable	Mean	Median	Standard deviation	Minimum	Maximum	N
Dependent variables						
Interest coverage ratio (ICR)	97,303	2,944	982,816	-2899,84	40853,04	7134
Altman's Z-score (Z-score)	2,751	2,450	2,606	-12,93	29,55	6356
Independent variables						
Cash Conversion Cycle (CCC)	107,262	79,670	196,489	-862,22	1921,57	3699
• Days' Inventory Outstanding (DIO)	97,472	54,574	207,474	,01	3613,48	4719
• Days' Sales Outstanding (DSO)	110,186	66,465	197,622	,01	3136,98	6371
• Days' Payables Outstanding (DPO)	90,866	41,737	200,867	0	2343,19	4067
Age-Size-Cash-flow-Leverage (ASCL)	1,532	2,000	,866	0	4,00	11570
Industry growth (INDG) (%)	1,970	2,850	13,201	-47,10	43,23	5968
Industry competition (COMP) (%)	2,878	3,900	6,269	-46,00	30,00	5970
Industry sales price (Price) (%)	4,366	4,200	5,996	-29,60	32,80	5968
Industry Barriers (Barriers) (%)	57,227	56,500	9,466	2,68	88,00	5969
• Demand risk (DEM) (%)	27,463	27,050	7,575	,73	64,70	5966
• Labour market risk (Labour) (%)	3,382	2,700	2,575	0	21,40	5964
• Materials risk (MAT) (%)	2,319	1,725	2,154	0	21,72	5962
• Financial risk (FIN) (%)	12,297	11,625	5,702	0	46,05	5970
• Weather risk (Weather) (%)	5,118	3,525	4,524	0	31,90	5970
Control variables						
Firm age (AGE)	23,261	16,000	23,835	0	185,00	11243
Log growth (Growth) (Thousands of Euros)	2,547	2,639	,862	-1,37	5,79	2831

Appendix 3

Figure 1

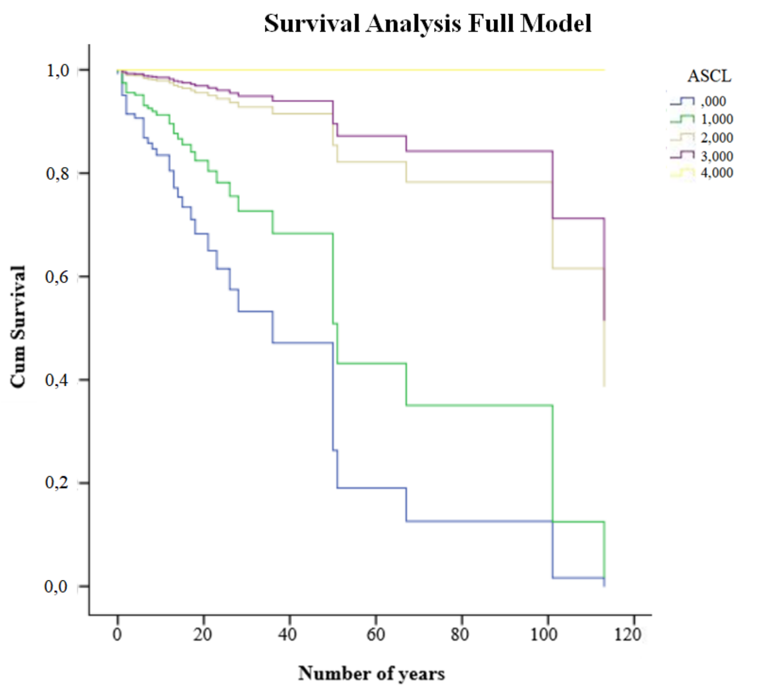


Figure 2

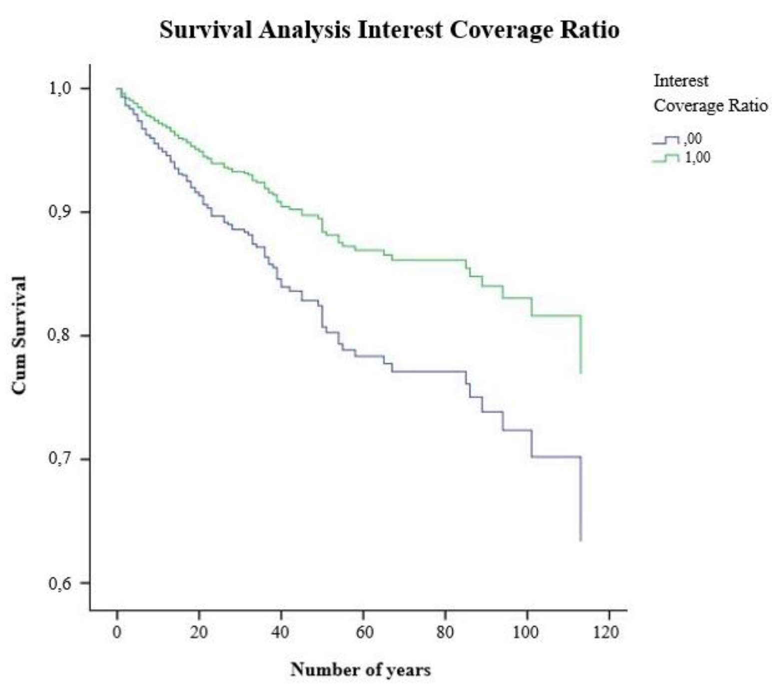


Figure 3

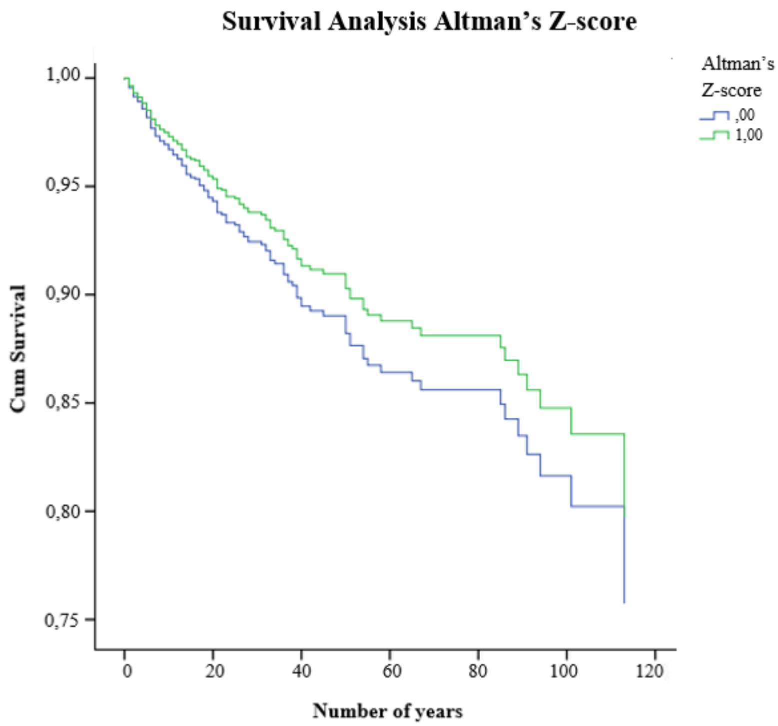


Figure 4

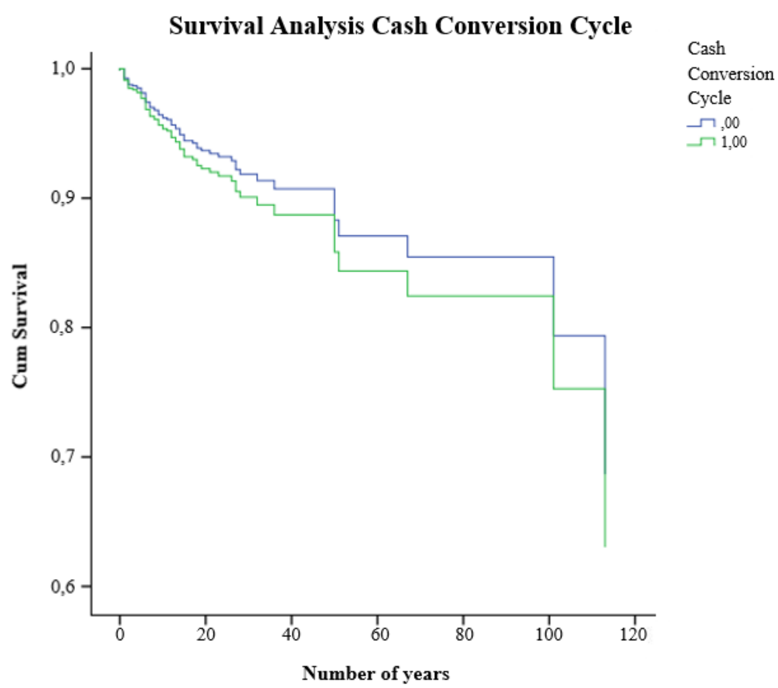


Figure 5

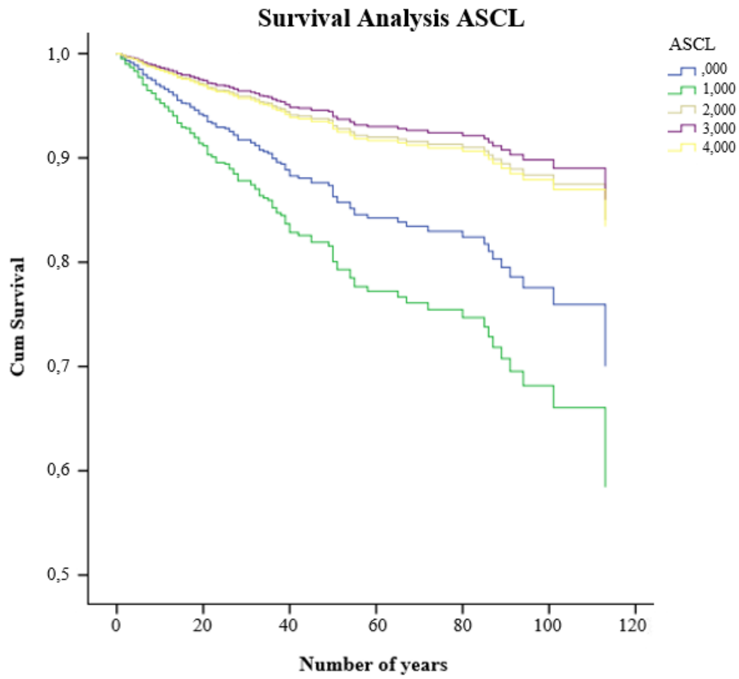


Figure 6

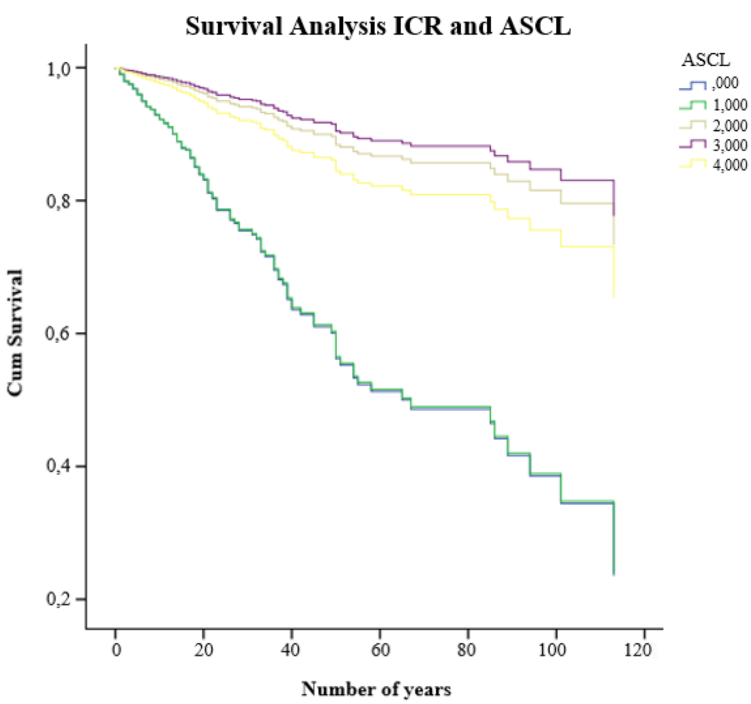
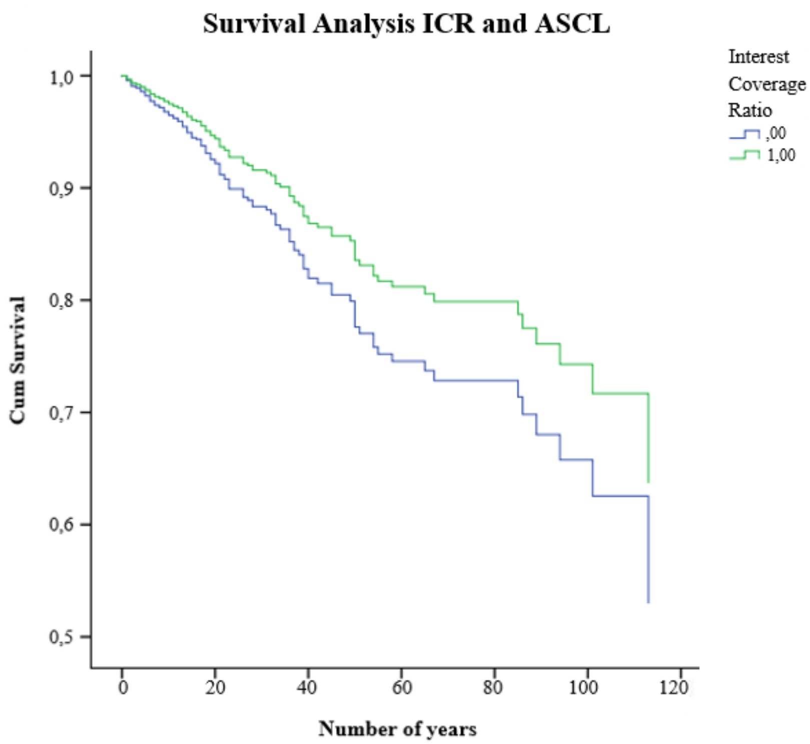


Figure 7


Survival Analysis ICR and ASCL
Interest
Coverage
Ratio
,00
1,00
1,0
0,9
0,8
0,7
0,6
0,5
Cum Survival
0
20
40
60
80
100
120
Number of years

References

Abellán, J. and J. G. Castellano, 2017, A comparative study on base classifiers in ensemble methods for credit scoring, Expert Systems with Applications, vol. 73, pp. 1-10.

Ahmed, A. S. and S. Duellman, 2011, Evidence on the role of accounting conservatism in monitoring managers' investment decisions, Accounting & Finance, vol. 51(3), pp. 609-633.

Ahmed, A. S. and S. Duellman, 2013, Managerial overconfidence and accounting conservatism, Journal of Accounting Research, vol. 51(1), pp. 1-30.

Ali, R., R. Lynch, T.C. Melewar and Z. Jin, 2015, The moderating influences on the relationship of corporate reputation with its antecedents and consequences: A meta-analytic review, Journal of Business Research, vol. 68, pp. 1105-1117.

Allen, L., G. DeLong and A. Saunders, 2004, Issues in the credit risk modeling of retail markets, Journal of Banking & Finance, vol. 28, pp. 727-752.

Altman, E. I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, The Journal of Finance, vol. 23(4), pp. 589-609.

Altman, E. I. and A. Saunders, 1998, Credit risk measurement: Developments over the last 20 years, Journal of Banking & Finance, vol. 21, pp. 1721-1742.

Altman, E. I., 2000, Predicting financial distress of companies: revisiting the Z-score and ZETA models.

Altman, E. I. and G. Sabato, 2007, Modelling credit risk for SMEs: Evidence from the U.S. market, Abacus, vol. 43(3), pp. 332-357.

Altman, E. I., G. Sabato & N. Wilson, 2010, The value of non-financial information in small and medium-sized enterprise risk management, The Journal of Credit Risk, vol. 6(2), pp. 1-33.

Anderson, R., 2007, The credit scoring toolkit: Theory and practice for retail credit risk management and decision automation, 1st Edition, Oxford University Press, New York.

Baños-Caballero, S., P. J. García-Teruel, P. Martínez-Solano, 2014, Working capital management, corporate performance, and financial constraints, vol. 67, pp. 332-338.

Barney, J., 1991, Firm resources and sustained competitive advantage, Journal of Management, vol. 17(1), pp. 99-120.

Bauer, J. and V. Agarwal, 2014, Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test, Journal of Banking & Finance, vol. 40, pp. 432-442.

Bias, B. and C. Gollier, 1997, Trade credit and credit rationing, The Review of Financial Studies, vol. 10(4), pp. 903-937.

Bikker, J. and K. Haaf, 2002, Competition, concentration and their relationship: An empirical analysis of the banking industry, vol. 26(11), pp. 2191-2214.

Brammer, S. J. and S. Pavelin, 2006, Corporate reputation and social performance: The importance of fit, Journal of Management Studies, vol. 43(3), pp. 435-455.

Brick, I. E. and W. K. H. Fung, 1984, Taxes and the theory of trade debt, The Journal of Finance, vol. 39(4), pp. 1169-1176.

Bromiley, P., D. Rau and Y. Zhang, 2017, Is R&D risky?, Strategic Management Journal, vol. 38, pp. 876-891.

CBS Statline, 2017, Conjunctuurenquëte Nederland, Retrieved 18th of June 2017,

Chemla, G. and C. A. Hennessy, 2014, Skin in the game and moral hazard, The Journal of Finance, vol. 69:4, pp. 1597-1641.

De Veaux, R., P. Velleman and D. Bock, 2014, Stats Data and Models (3rd ed.), Pearson Education Limited.

Dedman, E. and C. Lennox, 2009, Perceived competition, profitability and the withholding of information about sales and the cost of sales, Journal of Accounting and Economics, vol. 48(2&3), pp. 210-230.

Deloof, M., 2003, Does working capital management affect profitability of Belgian firms?, Journal of Business Finance and Accounting, vol. 30(3&4), pp. 573-587.

Dothan, M., 2006, Costs of financial distress and interest coverage ratios, The Journal of Financial Research, vol. 29(2), pp. 147-162.

Douma, S., R. Geoge and R. Kabir, 2006, Foreign and domestic ownership, business groups, and firm performance: Evidence from a large emerging market, Strategic Management Journal, vol. 27, pp. 637-657.

Duarte, F., A. P. M. Gama and J. P. Esperança, 2016, The role of collateral in the credit acquisition process: Evidence from SME lending, Journal of Business Finance & Accounting, vol. 43(5) & (6), pp. 693-728.

Edmister, R. O., 1972, An empirical test of financial ratio analysis for small business failure prediction, The Journal of Financial and Quantitative Analysis, vol. 7(2), pp. 1477-1493.

Eljelly, A., 2004, Liquidity-profitability tradeoff: An empirical investigation in an emerging market, International Journal of Commerce and Management, vol. 14(2), pp. 48-61.

Everett, J. and J. Watson, 1998, Small business failure and external risk factors, Small Business Economics, vol. 11, pp. 371-390.

Falkner, E. M. and M. R. W. Hiebl, 2015, Risk management in SMEs: a systematic review of available evidence, The Journal of Risk Finance, vol. 16(2), pp. 122-144.

Fernandes, G.B. and R. Artes, 2016, Spatial dependence in credit risk and its improvement in credit scoring, European Journal of Operational Research, vol. 249, pp. 517-524.

Ferreira Filipe, S., T. Grammatikos and D. Michala, 2016, Forecasting distress in European SME portfolios, Journal of Banking & Finance, vol. 64, pp. 112-135.

Fiordelisi, F., M. Soana and P. Schwizer, 2013, The determinants of reputational risk in the banking sector, Journal of Banking & Finance, vol. 37, pp. 1359-1371.

Fishman, R. and I. Love, 2003, Trade credit, financial intermediary development, and industry growth, Journal of Finance, vol. 58, pp. 353-374.

Frank, M. Z. and V. K. Goyal, 2003, Testing the pecking order theory of capital structure, Journal of Financial Economics, vol. 67(2), pp. 217-248.

Gormley, T. A. and D. A. Matsa, 2016, Playing it safe? Managerial preferences, risk and agency conflcits, Journal of Financial Economics, vol. 122, pp. 431-455.

Graetz, G. and D. M. Franks, 2016, Conceptualising social risk and business risk associated with private sector development projects, Journal of Risk Research, vol. 19(5), pp. 581-601.

Gupta, J., N. Wilson, A. Gregoriou, & J. Healy, 2014, The value of operating cash flow in modelling credit risk for SMEs, Applied Financial Economics, vol. 24:9, pp. 649-660.

Gupta, J., A. Gregoriou & J. Healy, 2015, Forecasting bankruptcy for SMEs using hazard function: To what extent does size matter?, Review of Quantitative Finance and Accounting, vol. 45(4), pp. 845-869.

Hair, J., W. Black, B. Babin and R. Anderson, 2013, Multivariate data analysis (7th ed.), Pearson.

Hansen, G. S. and B. Wernerfelt, 1989, Determinants of firm performance: The relative importance of economic and organizational factors, Strategic Management Journal, vol.10(5), pp. 399-411.

Huizingh, E., 2007, Applied statistics with SPSS, 1st Edition, London: SAGE

Jain, N., 2001, Monitoring costs and trade credit, Quarterly Review of Economics and Finance, vol. 41(1), pp. 89-110.

Ju, Y. and S. Y. Sohn, 2015, Stress test for a technology credit guarantee fund based on survival analysis, Journal of the Operational Research Society, vol. 66, pp. 463-475.

Kalak, I. E. and R. Hudson, 2016, The effect of size on the failure probabilities of SMEs: An empirical study on the US market using discrete hazard model, International Review of Financial Analysis, vol. 43, pp. 135-145.

Karuna, C., 2007, Industry product market competition and managerial incentives, Journal of Accounting and Economics, vol. 43(2&3), pp. 275-297.

Kim, M. H. and G. Partington, 2015, Dynamic forecasts of financial distress of Australian firms, Australian Journal of Management, vol. 40(1), pp. 135-160.

Kling, G., S. Y. Paul and E. Gonis, 2014, Cash holding, trade credit and access to short-term bank finance, International Review of Financial Analysis, vol. 32, pp. 123-131.

Kravet, T. D., 2014, Accounting conservatism and managerial risk-taking: Corporate acquisitions, Journal of Accounting and Economics, vol. 57, pp. 218-240.

Lambert, R. A., C. Leuz and R. E. Verrecchia, 2011, Information asymmetry, information precision, and the cost of capital, Review of Finance, vol. 16, pp. 1-29.

Li, K., J. Niskanen, M. Kolehmainen and M. Niskanen, 2016, Financial innovation: Credit default hybrid model for SME lending, Expert Systems with Applications, vol. 61, pp. 343-355.

Lofstrom, M., T. Bates and S. C. Parker, 2014, Why are some people more likely to become small-business owners than others: Entrepreneurship entry and industry-specific barriers, Journal of Business Venturing, vol. 29, pp. 232-251.

Marcelino- Sádaba, S., A. Pérez-Ezcurdia, A. M. Echeverria Lazcano and P. Villanueva, 2014, Project risk management methodology for small firms, International Journal of Project Management, vol. 32(2), pp. 327-340.

Meltzer, A. H., 1960, Mercantile credit, monetary policy, and size of firms, Review of Economics and Statistics, vol. 42(4), pp. 429-443.

Merton, R. C., 1974, On the pricing of corporate debt: The risk structure of interest rates, The Journal of Finance, vol. 29(2), pp. 449-470.

Miller, K. D., 1992, A framework for integrated risk management in international business, Journal of International Business Studies, vol. 23(2), pp. 311-331.

Miloud, T., A. Aspelund and M. Cabrol, 2012, Startup valuation by venture capitalists: an empirical study, Venture Capital, vol. 14 (2-3), pp. 151-174.

Modigliani, F. and M. H. Miller, 1958, The cost of capital, corporation finance and the theory of investment, The American Economic Review, vol. 48(3), pp. 261-297.

Mulier, K., K. Schoors and B. Merlevede, 2016, Investment-cash flow sensitivity and financial constraints: Evidence from unquoted European SMEs, Journal of Banking & Finance, vol. 73, pp. 182-197.

Olsson, C., 2002, Risk management in emerging markets, 1st Edition, Pearson Education Limited.

Peteraf, M. A., 1993, The cornerstones of competitive advantage: A resource-based view, Strategic Management Journal, vol. 14(3), pp. 179-191.

Prajogo, D. and C. M. McDermott, 2014, Antecedents of service innovation in SMEs: Comparing the effects of external and internal factors, Journal of Small Business Management, vol. 52(3), pp. 521-540.

Reach, 2017, Bureau van Dijk, Retrieved on 15th of June 2017

Schmidt, K. M., 1997, Managerial incentives and product market competition, The Review of Economic Studies, vol. 64(2), pp. 191-213.

Shumway, T., 2001, Forecasting bankruptcy more accurately: A simple hazard model, The Journal of Business, vol. 74(1), pp. 101-124.

Serrasqueiro, Z. S. and P. M. Nunes, 2008, Performance and size: empirical evidence from Portuguese SMEs, Small Business Economics, vol. 31, pp. 195-217.

SME Servicedesk (2017). Informatie over het MKB (midden- en kleinbedrijf) in Nederland | MKB Cijfers, definities en organisaties belangrijk voor marktonderzoek | MKB Servicedesk. Mkbservicedesk.nl. Retrieved 19 March 2017, from http://www.mkbservicedesk.nl/569/informatie-over-midden-kleinbedrijf-nederland.htm

Spanos, Y. E., G. Zaralis and S. Lioukas, Strategy and industry effects on profitability: evidence from Greece, vol. 25(2), pp. 139-165.

Sutton, J., 1990, Explaining everything, explaining nothing?, European Economic Review, vol. 34, pp. 505-512.

Tinoco, M. H. and N. Wilson, 2013, Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables, *International Review of Financial Analysis*, vol 30, pp. 394-419.

Tuzel, S. and M. B. Zhang, 2017, Local risk, local factors, and asset prices, The Journal of Finance, vol. 72(1), pp. 325-370.

Van Caneghem, T. and G. van Campenhout, 2012, Quantity and quality of information and SME financial structure, Small Business Economics, vol. 39(2), pp. 341-358.

Vander Bauwhede, H, M. De Meyere and P. Van Cauwenberge, 2015, Financial reporting quality and the cost of debt of SMEs, Small Business Economics, vol. 45, pp. 149-164.

Walker, K., 2010, A systematic review of the corporate reputation literature: Definition, measurement, and theory, Corporate Reputation Review, vol. 12(4), pp. 357-287.

Wu, W., O. M. Rui and C. Wu, 2012, Trade credit, cash holdings, and financial deepening: Evidence from a transitional economy, Journal of Banking & Finance, vol. 36(11), pp. 2868-2883.

Ylhäinen, I., 2017, Life-cycle effects in small business finance, Journal of Banking & Finance, vol. 77, pp. 176-196.

Zeidan, R. and O. M. Shapir, 2017, Cash conversion cycle and value-enhancing operations: Theory and evidence for a free-lunch, Journal of Corporate Finance, vol. 45, pp. 203-219.