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The impact of top management team characteristics on a firm's default risk: Evidence from the United Kingdom SMEs

Master Thesis

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Abstract

Top management team (TMT) as the coalition of powerful actors in an organization with their own particular characteristics has a great influence in any decision-making processes and may affects the organizational outcomes accordingly. A number of researches has indicated that TMT characteristics do have influences on a firm's strategic outcomes and its performance. Yet, none of the literature – in the making of this study – explored the influence of TMT characteristics on a firm's default risk. Against the backdrop, this study investigates the impact of TMT characteristics on a firm's default risk, specifically the age, tenure, and size of the TMT and the presence of female top managers in the team, of small and medium-sized enterprises (SMEs). By treating the TMT characteristics as predictors and the existing financial-based default risk measure as the dependent variable, this study shows promising results. Based on the sample consisting of 7151 observations of SMEs across United Kingdom from the year 2013-2016, the results show that the average age and tenure of a TMT and the presence of female top managers in the team have a negative impact on a firm's default risk. This study contributes in two ways. For the literature, this study acts as the preliminary attempt to explore the impact of TMT characteristics on a firm's default risk. As for more practical application, this study gives an insight and helps the practitioners in assessing firm's default risk by taking into account the TMT characteristics in the process.

Keywords: Top management team characteristics, default risk, SMEs, United Kingdom.

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1. Introduction

1.1. Problem statement

As reported in the annual report on European Small and Medium Enterprises (SMEs) (Muller, et al., 2017), in the EU-28 countries, more than 99% of non-financial business operating enterprises in 2016 were SMEs. These SMEs employed 93 million people, accounting for 67% of total employment and generating 57% of value added in the EU-28 countries non-financial business sector. Similar to this, in the United Kingdom (UK) alone, SMEs represent more than 99% of all business in 2017, employed more than 16 million people, which accounted for 60% of total employment, and generating 51% of total value added. However, this numbers could not hide the fact that SMEs are inherently risky businesses. This argument is supported by an evidence which shows that SMEs in the UK are suffering from an arguably high bankruptcy rate. From 2001 to 2016, while on average there are 288 thousand new firms annually, 242 thousand firms filed for bankruptcy annually at the same period (Rhodes, 2017). In the other words, for every ten new firms, roughly, only less than two firms will survive on average. This is rather unfortunate since SMEs are accounted for more than half the total employment in the UK. Not only the bankruptcy of a firm results in the loss of millions of jobs annually and greatly harm the business owner(s) themselves, it also vastly affects the rest of the stakeholders, e.g. customers, suppliers, government, and creditors. Hence, understanding the cause of bankruptcy, thus default risk, is of considerable relevance for SMEs.

Regardless, SME bankruptcies are difficult to track and measure, as failed firms are often difficult to locate and if located it is difficult to determine the reason for their failure (Gupta, Gregoriou, & Healy, 2015). Due to this, recent literature was trying to understand the rate and cause of such failures. Carter and Auken (2006) reported that the principal reasons among firms can be categorized into lack of knowledge, constraints to debt financing, and the economic climate. Among other causes of small business failures, empirical literature suggests that financial constraints are the strongest (Hutchinson & Xavier, 2006). Furthermore, some studies also suggest that the poor management skills as one of the potential factors for small firm's failure (Gupta, Gregoriou, & Healy, 2015).

Currently, both practitioners and academics focus heavily on the use of financial factors in assessing firm's default risk. In practice, it is true that both financial and non-financial factors, with TMT characteristics is being one of them, are used by financial institutions in assessing borrowers' credit risk. However, these two factors are not treated equally. There is a tendency among practitioners to rely heavily on the firm's financial factors when it comes to assessing their default risk. An overview of international best practice rating standards in the banking sector identified three main categories of rating processes: Statistical-based processes, constrained expert judgement-based processes, and expert judgement-based processes (Basel Committee of Banking Supervision, 2000a). However, the weighing schemes of these risk factors differ considerably across banks. While the used of financial-based methods are relatively uniform across banks, the differences in opinion on borrower default risk result from a different evaluation of non-financial factors (Grunert, Norden, & Weber, 2005).

Similar to the aforementioned practices, academics also have been developing and perfecting various default risk prediction methods which are based on financial factors for at least half a century, without giving much attention to the potential of non-financial factors. For instance, Altman (1968) in his seminal paper successfully convinced the academics that one could predict borrower's one-year insolvency by using only five financial ratios and claimed that his method has a 95% accuracy in doing so. Merton (1974) also developed the widely regarded distance to default model which implies that a company is worth nothing (bankrupt) when the market value of its assets drops below the book value of the liabilities. Their nature of being able to be reduced to a series of numbers, makes financial factor variables are easier to be obtained, transferred, stored, and interpreted, thus, it is more convenient in practice.

One of the interesting non-financial factors which is suspected to influence firm's default risk is the top management team (TMT) characteristics (Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009; Grunert, Norden, & Weber, 2005). Top management team is defined by Hambrick and Mason (1984) as the 'dominant coalition' of individuals responsible for setting firm direction, hence, top managers. In more practical definition, Ang, Lauterbach, and Schreiber (2002) considered the top four or five top executives in each firm (banks in their particular study) as the top management team. The number of studies on the relevance of TMT on firm's organizational outcomes and performance have largely increased, based on the premise that relatively straightforward demographic data on top managers may be potent predictors of strategies and performance levels (Hambrick & Mason, 1984). Despite the evidence that firms' organizational outcomes and performance are affected heavily by the top managers, academics and practitioners have not paid enough attention on the effect of TMT characteristics on firm's default risk. On one hand, at the time of this thesis is being written, there is no known study that observes the influence of TMT characteristics on firm's default risk. On the other hand, in practice, even though the TMT characteristics variable are indeed included in the process of assessing firm's default risk, their relevance is still predominantly considered in a holistic manner, subsequently, has a small effect on creditors' consideration. Based on the fact that SMEs suffers from high bankruptcy rate, which suggest the need of a better default risk assessment, and the premise that TMT characteristics do influence firm's organizational outcomes and performance, this thesis will try to explore the influence of TMT characteristics on firm's default risk.

1.2. Research proposition

Being the focal point of this thesis, previous literature broadly agrees that top management (TMT) characteristics do influence the organizational outcomes and the performance of a firm. For instance, Cheng, Chan, and Leung (2010) showed an evidence that the education level, age, and tenure of the firm's top executives reflect human and social capital of the upper echelons, and they exert influences on corporate performance. Escribá-Esteve, Sánchez-Peinado, and Sánchez-Peinado (2009) examined the influence of TMT characteristics on the performance of small and medium-sized enterprises (SMEs) by using strategic orientation as the mediating variable. They found that firms with younger and more experience TMT member are more likely to adopt a more proactive strategic orientation which eventually leads to a better firm's performance. Barker and Mueller (2002) found that firms with younger CEO have a higher spending in R&D and suggest that younger CEOs are more innovative. Li (2018) reported that there is an inverted U-shaped relationship between TMT tenure and firm internationalization. He argued that top managers with longer tenure have better capabilities in evaluating and allocating organizational resources effectively when entering a foreign market. However, over time, top managers tend to avoid risk and take a more conservative decision toward internationalization, thus withdrawing from investment opportunities in foreign markets. Given the examples, and the advantages of the objectivity and the data availability of TMT demographic information, there is no known literature in the making of this thesis explores the influence of TMT characteristics on firm's credit risk. This context motivates the needs to examine the effect of TMT characteristics on the default risk of SMEs.

Closely follows the aforementioned literature on TMT characteristics subject, this thesis draws on two strategic management concepts, upper echelons theory and the resource-based view (RBV) to explore the possible relationship between TMT characteristics and firm's default risk. Upper echelons theory posits that the TMT can influence organizational outcomes such as corporate strategies and performance. It further suggests that the characteristics of the top executives serve as valid proxies of their cognitive frames and strategic actions (Hambrick & Mason, 1984). If the top executives are viewed as the firm's essential human resources, upper echelons theory also well echoes RBV, which advocates the importance of human resources to achieve organizational effectiveness (Hitt, Bierman, Shimizu, & Kochhar, 2001).

In addition to the aforementioned concepts, this study focuses on the role of TMT in SMEs setting as the role of TMT is more important and apparent in small businesses than in large corporations. Escribá-Esteve, Sánchez-Peinado, and Sánchez-Peinado (2009) argued that SMEs provide a more direct setting to empirically test the effects of TMT characteristics on firms' attitudes and performance than larger companies. SMEs usually lack the amount of slack resources and the kind of hierarchical administrative systems which help larger companies in their decision-making process (Lubatkin, Simsek, Ling, & Veiga, 2006). In particular, due to its fewer hierarchical levels, the SMEs' top managers are more likely to play both strategic and operational roles, consequently, Lubatkin et al. (2006) argued that SMEs have to rely more on the abilities of their top managers to attain ambidexterity.

Based on the aforementioned literature which suggest that the TMT characteristics do influence the firm's organizational outcomes and performance (e.g. Barker & Mueller, 2002; Cheng, Chan, & Leung, 2010; Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009), this study acts as a preliminary attempt to examine the influence of TMT characteristics on firm's default risk. Furthermore, SME setting will be used in this study since SMEs provide a more direct setting to empirically test the effect of TMT characteristics on firm's attitude (Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009; Lubatkin, Simsek, Ling, & Veiga, 2006), hence default risk. This leads to the following research question:

"Do top management team characteristics influence default risk – especially – of Small and Medium Enterprises?"

The firms' dataset from UK is chosen in this study for two reasons. First, of all European countries firms' dataset available in ORBIS database, UK has the most complete information of its firms regarding both administrative information (e.g. Top management team and the board) and financial data (e.g. income statement and balance sheet). Second, the firms' bankruptcy rate in UK is relatively high, as for every ten new firms, roughly, only less than two firms will survive on average annually (Rhodes, 2017), resulting in the loss of millions of jobs annually, greatly harm the business owner(s) themselves and all the stakeholders. This suggests that there is a need of study in understanding on what factors may affect firms default risk in UK.

This study contributes to the both practical field and the existing literature. In the practical field, this study will have implications for both financial institutions and SMEs. By understanding the impacts of top management team characteristics on firm's default risk, financial institutions will be able to assess their borrower creditworthiness better and hence they would have a more accurate prediction eventually. By doing this, banks as one of the major financial institutions, could reduce their monitoring cost in the process to the minimum. Moreover, bank loan officers could have an insight on how to measure and judge their clients' TMT characteristics, which will be taken into consideration in giving credit, without being fully dependent on their experience. Furthermore, since the TMT characteristics are treated as a quantitative data, the credit assessment process could be automated, hence, increasing the efficiency in the process. As for the SMEs, since their default risk is better understood, the chance of their credit proposal will be granted is higher, and at the same, the cost of the credit could be lower. While for the academics, this study could give a preliminary insight on how TMT characteristics influence the firm's default risk since as far as it is observed there is no know literature examining this particular topic.

This thesis is organized as follows. Chapter 2 provides an overview of related literature regarding the impacts of top management team characteristics in assessing firm's credit risk. Chapter 3 provides the hypotheses of this thesis based on the literature review. Chapter 4 presents the methodology which will be used in this study to test the hypotheses. Chapter 5 describes the dataset which will be used for the purpose of this thesis. Chapter 6 discusses the result of this study. Finally, chapter 7 gives conclusions and the limitations of this study, followed by recommendations for future research.

2. Literature review

2.1. Default risk

Debt instruments, by definition, are contracts containing a promise to pay a future stream of cash to investors who hold the contracts. In addition to promises of future cash, a debt contract also establishes: the financial requirements and restrictions that the borrower must meet, and the rights of the holder of the debt instrument if the borrower defaults. Meanwhile, default is most simply defined as the failure to pay interest or principal on a debt instrument when due, and it occurs when the debtor is unable to meet/pay the obligations given by the creditor at the first place. Basel Committee on Banking Supervision (2000b) defined default precisely as 90 days overdue on credit agreement payments, and it has become the operational definition for major lenders (Altman, Sabato, & Wilson, 2010). In the ideal case, the borrower will comply with the debt contract and fulfill their obligations. However, in reality, numerous firms are not able to generate enough cash flows to cover its debt and principal payments and cause them to default. This probability of not fulfilling its obligation in debt contract is called default risk or default probability. Default risk refers to the likelihood that a firm will lack the ability to repay the principal and interest for its debt obligations as stipulated (Bakshi, Madan, & Zhang, 2006; Vassalou & Xing, 2004). Moreover, the definition of default risk could be derived from the definition of credit risk, since according to Basel Committee (2000c), "Credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms". The terms "default risk" and "credit risk" themselves are often used interchangeably in literature (see e.g. Gupta, Wilson, Gregoriou, and Healy, 2014).

Debt holders are not the only stakeholders that assess firm default risk. Debtor risk evaluation is usually involved in firm valuation process and assessment of liquidity (Brealey, Myers, & Allen, 2008). Hence, along with debt holders, default risk should be one of the main concerns of shareholders as well. Internally, top managers are most likely interested in reducing default risk since it is likely to cause higher cost of capital and operations difficulties (Sun & Cui, 2014). Also, debt is the single largest source of external financing for SMEs (Scherr, Sugrue, & Ward, 1993), so the top managers are motivated to reduce their default risk in order to ensure sufficient future support.

2.1.1. Determinants of default risk

The next question is, which factors can affect default risk at the first place, since understanding the factors which may affect firm's credit risk is crucial not only for the firm itself, but also for all the stakeholders (e.g. employees, customers, creditors). Even though the principal determinant of default risk is the likelihood of a firm will not repay its principal and interest, there are underlying factors which may affect this likelihood. Firm characteristics, corporate governance, and TMT characteristics are suspected to affect firm's default risk. In the following section, both firm characteristics and corporate governance and their effects on firm's default risk will be discussed. As for TMT characteristics, their influence on firm's default risk will be discussed in the chapter 2.2. since they are the main topic of this thesis.

2.1.1.1. Firm characteristics

First firm characteristics in relevance to the default risk which will be discussed is the firm age. There is a theory called "liability of newness" by Stinchcombe (1965) which generally stated that a company's risk of exit is highest at the time of start-up and decreases with the age of the company. This is because the new firm depends on the cooperation of strangers, have low levels of legitimacy, and hence are unable to compete effectively against more established organizations. As a firm grows, its organization structures would be stabilized and ties with environments become durable, causing the failing rate to fall (Stinchcombe, 1965). On the other hand, Hudson (1987) suggests that new firm is most likely to have a "honeymoon period" before being at real risk of failure. The argumentation behind this is that it takes time to build up problems and for creditors to get organized into formal insolvency proceedings (Hudson, 1987). He conducted a survey where the sample 1,830 liquidated companies are used from the period between 1978 and 1981 in the UK to understand the effect of age on liquidated companies. From this survey, he suggests that the majority of the liquidated companies were formed by young companies. Furthermore, he also suggests that company needs at least nine years to be regarded as established firm. However, he also found evidence that for the first two years of its lifetime, a firm will have their "honeymoon period". Align with Stinchcombe (1965), Altman et al. (2010) found that, as expected, the age of a company is negatively correlated to failure probability, suggesting that the longer a company survives the less likely it is to fail. Furthermore, following

Hudson (1987), Altman et al. (2010) also used an age dummy variable of 3-9 years bracket and found that companies within this bracket are more vulnerable to failure.

The second firm's characteristic factor is its size. On the one hand, it is suggested that larger firms tend to fail less often than smaller ones since larger firms are more diversified and have more stable cash flow (Gill, Biger, Chenping, & Bhutani, 2009; Psillaki, Tsolas, & Margaritis, 2010). Moreover, larger firms more likely to be better managed and have a better organizational and financial structures in place. Unlike smaller firms, large firms typically have fewer difficulties in raising external finance and hence generally less vulnerable to business hazards or to economic downturns (Psillaki, Tsolas, & Margaritis, 2010). On the other hand, Altman et al. (2010) found a non-linear relationship between default risk and size, as measured by asset values. Their result shows an increasing and decreasing relationship between asset and default risk. They argued that businesses with low asset value are less likely to be pursued through legal process of insolvency as the creditors would have a little gain from it. After modelling the size-default risk relationship, Altman et al. (2010) suggest an asset level threshold (£350,000) where the "legal insolvency" becomes attractive for creditors.

Further studies even distinguish the difference in capital structure among SMEs themselves which resulted in different default risk characteristics. Mateev et al. (2013) argued that, due to information asymmetries, micro, small, and medium firms will have a different capital structure. Specifically, micro and small firms are primarily dependent on short-term debt and trade credits, while medium-sized firms tend to use long-term bank loans as their external source of finance (Mateev, Poutziouris, & Ivanov, 2013). Based on this finding and the work by Altman and Sabato (2007), Gupta et al. (2015) examined the difference of modeling credit risk between micro firms and SMEs. They found that three of the financial ratios which are reported to be significant in Altman and Sabato (2007) are insignificant in their micro model but significant in their SMEs model, suggesting that micro and SMEs need to be considered separately while modelling credit risk. Furthermore, the difference in significance of the three financial ratios both highlights the importance of internal sources of finance and liquidity for micro firms' survival and support the view that difficulty in access to externa finance decreases as the firm gets larger.

The third firm characteristics factor is industry effects. Under the idea that industry conditions affect the marginal product of capital, Maksimovic and Phillips (1998) argued that if bankruptcy function sees as a facility to redeploy asset into more productive uses, its incidence should also differ systematically with industry conditions. The main finding from their study is that the frequency of bankruptcy indeed lowest in high-growth industries. The proportion of the frequency of bankruptcy is more than three times in declining industries that in high-growth industries (Maksimovic & Phillips, 1998). Align with the previous finding, work by Chava and Jarrow (2004) shows that industry groupings significantly affect both the intercept and slope coefficients in the bankruptcy forecasting equations. Moreover, based on their classification, the result reveals that the miscellaneous grouping industries (agriculture, construction, wholesale & retail, and service industries) have the highest default probabilities, follows by manufacturing and minerals, and the transportation, communications and utilities being the lowest in default probabilities (Chava & Jarrow, 2004). They argued that there are two reasons on why industry effects should be an integral part in bankruptcy prediction. First, different industries face different environment of competition and, hence, the bankruptcy probability may differ for firms in different industries. Second, different industries may have different accounting conventions, hence, implying that the bankruptcy probability may differ for firms in different industries with otherwise identical balance sheet.

Another possible firm characteristics factors are innovation and internationalization. Hsu, Lee, Liu, and Zhang (2015) proposed that outsider investors consider more innovative firms to have a lower default probability, as firms with more and higher-quality patents are more likely to earn first-mover advantages and become market leaders. This is because they are equipped with both more recent and influential technologies. Furthermore, patents raise entry cost for newcomers and help prevent competitors from using familiar technologies. Based on this, Hsu et al (2015) suggested that firm with such competitive advantages in innovation will have more financial stability and decrease default risk. Regarding the effect of internationalization, based on the previous finding that internationalization has a positive influence on firm's performance, Gupta et al (2014) examined the effect of internationalization on the default risk of SMEs. They argued that international firms enjoy less volatility in their revenue due to their diversified revenue streams and face lower business risk due to integrated international markets. However, on the other hand, international firms may have more exposure to multiple political environments and variability of exchange rates which in turn may result in higher credit risk. Despite their argumentation behind it, their findings show that almost the same set of factors affect the default probability of both domestic and international firms. Hence, they suggested that there is no potential need to treat domestic and international SMEs separately while modelling credit risk.

2.1.1.2. Corporate governance

In addition to firm characteristics, corporate governance also suspected to play a critical role in determining firm’s default risk. Agency theory posit that the two main parties involved in corporate activity (managers and owners) often behave in their own self-interest which may often resulted in conflict between the two, hence agency problems. Corporate governance is conceived as a mechanism to mitigate and/or restrain managerial self-interest to enable the firm to optimally create wealth for shareholders (Platt & Platt, 2012). Platt and Platt (2012) stated that the evidence on the relationship between corporate governance factors and corporate bankruptcy has been mixed. For instance, they said that some studies found that bankrupt firms are more likely to have small boards of directors or lose directors as the firm in the near bankruptcy, while others found just the opposite. Furthermore, they added that some studies found that the CEO duality as board chairman is an important predictor of bankruptcy while other studies did not find this relationship to be predictive. Based on the mixed previous findings, Platt and Platt (2012) conducted an elementary study regarding the corporate governance and bankruptcy by comparing the corporate board attributes between bankrupt and non-bankrupt firms. The most notable finding is that the number of independent directors in the boards positively relates to the firm’s financial health, and healthy firms on average have larger boards than bankrupt firms.

Regardless the finding, the work by Platt and Platt (2012) has been criticized by Schultz et al. (2017) for studying the governance mechanisms of firms that actually failed instead of the likelihood of failure of all firms, and hence the study by Platt and Platt (2012) is claimed to suffer from a sample selection bias. Against this backdrop, Schultz et al. (2017) examined the influence of corporate governance on the probability of default. At first, by using pooled OLS and fixed effects approaches, their findings suggest that the likelihood of firm failure decreases as inside ownership increases. However, after both dynamic difference and dynamic panel generalized method of moments (GMM) are employed, they did not find a significant relationship between default probability and corporate governance mechanisms. Eventually, their findings suggest that corporate governance variables are correlated with the probability of default, even though not causally related.

2.1.2. Default risk models

Arguably, four decades ago, most financial institutions (FIs) relied virtually exclusively on subjective analysis or so-called banker "expert" systems to assess firm's credit risk (Altman & Saunders, 1998). In this era, bankers essentially used the well-known 4 "Cs" of credit: Character, capital, capacity, and collateral. However, Somerville and Taffler (1995) shows that the subjective banker judgments are shown to be biased, and tend to be overly pessimistic, even though they suggest that the multivariate modelling approach is not necessarily superior. Unsurprisingly, over the past decades, FIs have moved towards more objectively based approach from subjective/expert systems. There are three major default risk models which will be discussed in this section: Multivariate accounting based, "risk of ruin" models, and neural network analysis.

2.1.2.1. Multivariate accounting-based models

There are at least four methodological approaches in multivariate default risk systems: Linear probability model, logit model, probit model, and discriminant analysis model, which by far, discriminant analysis model has become the dominant followed by logit analysis (Altman & Saunders, 1998). Essentially, MDA statistical technique used to classify an observation into one of several a priori groupings dependent upon the observation's individual characteristics. Variate's, also known as the discriminant function, weights for each independent variable is calculated to maximize the differences between the groups and to achieve the discrimination (Hair, Black, Babin, & Anderson, 2014). Discriminant analysis is the appropriate statistical technique for testing the hypothesis that the group means of a set of independent variables for two or more groups are equal, hence, it is used primarily in classifying and/or make predictions in problems, where the dependent variable is in qualitative form, e.g. default or non-default. When applied to finance field, the common form of discriminant analysis seeks to find a linear function of accounting and market variables that best distinguishes in classifying the repayment and non-repayment groups. An analysis of a set of variables is needed, including the interaction among variables, to maximize the between group variance while minimizing within group variance (Altman & Saunders, 1998). Following the almost exact process, logit analysis assumes the probability of default is logistically distributed, by definition, constrained to fall between 0 and 1, default and non-default.

One of the first academic who used multiple discriminant analysis (MDA) in predicting firm's default, and widely regarded, is Altman (1968). He pointed out that there are two advantages of using MDA technique in predicting firm bankruptcy, which are become the reason on why the MDA technique was selected. Unlike univariate study where one can only consider the measurements used for group assignments one at a time, by using MDA technique, one can consider an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties (Altman, 1968). He used 33 bankrupt and 33 non-bankrupt manufacturing firms in the US as the sample data, and used 5 financial ratios in the discriminant function, namely: Working capital/total assets, retained earnings/total assets, EBIT/total assets, market value equity/book value of total debt, sales/total assets. The results show that the discriminant function developed by Altman (1968) has 95% accuracy in the initial sample dataset. Moreover, the results also show that the model has 96% and 79% accuracy in prediction of the secondary sample of bankrupt and non-bankrupt firms respectively.

As for the logit analysis, Smith and Lawrence (1995) comparing the predictive power of ordinary least square technique with logit model in their research to produce a parsimonious model that will accurately forecast aggregate losses on the loan portfolio over its remaining life. The results suggest that both OLS regression and logit model are virtually identical, both by using initial and holdout sample.

2.1.2.2. "Risk of ruin" models

At its core conception, a firm goes bankrupt when the market value of its assets falls below its debt obligations to outside creditors. One of the most highly regarded risk and ruin model is by Merton (1974) which is based on options. There are several assumptions which need to be fulfilled in using Merton's (1974) model. It assumes that there is continuous trading of securities in financial markets where there are no transactions costs and taxes, while the market movements are unpredictable, hence, efficient market. It also assumes that a firm's equity is considered to be a call option on the value of the firm's assets, where the strike price of a firm's equity is equal to some proportion of its liabilities (Merton, 1974). Based on the aforementioned assumptions, the Merton's (1974) default probability model depends crucially on the beginning period market value of that firm's assets relative to its outside debt, as well as the volatility of the market value of firm's assets.

The Merton (1974) model is a rather unusual forecasting model. While most of the forecasting model posing a model and then estimating the model with maximum likelihood techniques, Merton (1974) model actually involves very little estimation. Instead, the model uses something more like calibration-solving for implied parameter (Bharath & Shumway, 2008). Consequently, it is unclear how the model can be extended, nor how the standard errors for forecasts can be calculated. Regardless, Bharath and Shumway (2008) employed a Cox proportional hazard model to assess the Merton (1974) model's accuracy, and test whether the model could be improved. The out-of-sample result shows that the Merton (1974) model is able to classify 64.9% of defaulting firms correctly, while the naïve model which is developed by Bharath and Shumway (2008) is able to classify 65.8% of defaulting firms correctly. Based on this out-of-sample forecasting result, they suggest that it is fairly simple to construct a model that outperforms the Merton (1974) model without using the Merton (1975) probability as an explanatory variable. Duffie, Saita, and Wang (2007) also showed that Merton (1974) model has a significant predictive power in a model of default probabilities over time.

There are quite some critics in the finance world on Merton's (1974) model, though. The major one is on how realistic its assumptions are since a number of assumptions are required to make the model works as mentioned earlier. Altman and Saunders (1998) suggest that there are two major concerns regarding the option-based model default prediction models. First, whether the firm's stock price volatility can be used as an accurate proxy of the variability in asset values at the first place. Second, the application feasibility for non-publicly traded equity companies.

The major drawback on using Merton (1974) model to predict firm's distance to default in this thesis is due to the need of market valuation in the method itself. This method will work almost perfectly well in the cases of large corporations where the market value is well established. However, since the focus of this thesis is on the SMEs cases, where the data is limited to only on financial statements, it is almost impossible to obtain the market valuation on the firms, hence, it is virtually impossible to deploy Merton (1974) model in this thesis framework. Instead, this thesis will utilize the default prediction model which is based on the historical accounting data, thus financial ratios, e.g. model by Altman and Sabato (2007) which will be further discussed in the following section.

2.1.2.3. Neural network analysis model

Essentially, neural network analysis is similar to non-linear discriminant analysis, where it drops the assumption that variables included in the bankruptcy prediction function are linearly and independently related. At the core of traditional neural network default risk models, they are designed to capture complex non-linear relationships and interactions among variables to calculate the default risk (Jones, Johnstone, & Wilson, 2017). However, Jones, Johnstone, and Wilson (2017) criticized that the way of neural network capture the relationships are largely hidden in the internal mathematical of the model system. Thus, even if the models can predict very well, their practical usefulness could be limited if they are too difficult to implement on interpret in practice (Jones, Johnstone, & Wilson, 2017).

The study of neural network could be traced back to the work by Altman, Marco, and Varetto (1994) where the dataset of 900 healthy and 900 vulnerable Italian companies was used to test the performance of neural network model. From this initial sample and after slightly greater than 2000 learning cycles by using a three-layer network, the neural network analysis was able to recognize correctly 97.7% of healthy and 97% of unsound companies. Moreover, the result shows that from the hold-out sample of 302 companies, the neural network model achieved correct classification rates of 93.6% for the healthy companies and 89.1% for unsound companies.

More than two decades after the work by Altman et al. (1994), Jones, Johnstone, and Wilson (2017) did a performance evaluation on the existing classifiers in predicting corporate bankruptcy, with neural network being one of them. A sample of 3,960 firm-year observations for the bankrupt sample and 26,169 firm-year observations for the healthy company was used for the learning process. Subsequent to the learning process, the 16 classifiers were put into a test by using the bankrupt companies' dataset. The result shows that for 1-year prior to bankruptcy, neural network analysis has an accuracy of 85%, well above 79% of that linear discriminant analysis. Yet, the performance of neural network analysis is still far below the "new age" classifiers which are high dimensional models, meaning they can handle very large numbers of input variables but largely immune to irrelevant inputs (Jones, Johnstone, & Wilson, 2017). These "new age" classifiers include Generalized Boosting, AdaBoost, and Random Forests reach an accuracy of around 94% in the 1-year prior to bankruptcy test.

2.2. Top management team characteristics

2.2.1. Top management team

The definition of top management team in this thesis will closely follow the work by Wiersema and Bantel (1992) where they defined top management team as the 'dominant coalition' of individuals responsible for setting firm direction. In more practical definition, Ang, Lauterbach, and Schreiber (2002) considered the top four or five top executives in each firm (banks in their particular study) as the top management team. In this study, the definition of top management team will be the chief executive him/herself and the executives that are directly one rank below.

According to the upper-echelons theory, firms' actions are the reflections of their top-level managers, and the demographic characteristics or personal attributes of top executives are the dominant factors shaping organizational outcomes (Hambrick & Mason, 1984). When examined more closely, upper echelons theory is aligned with RBV theory. From the RBV perspective, the sustainability of a firm's competitive advantages depends on how it utilizes its unique resources (both tangible and intangible assets) to achieve organizational effectiveness (Barney, 1991). This argument is latter supported by Hitt et al. (2001) who suggested that human capital is an essential intangible asset for firm operations.

The interest in the role of top management teams, rather than individual leaders, is based on the argumentation that at a more practical level, by examining the entire top management team rather than individuals will increase the potential strength of the study, as to some extent, chief executive shares tasks and power with other members (Hambrick & Mason, 1984). This argument is supported by Wiersema and Bantel (1992) who suggested that managerial responsibilities are unlikely to be the exclusive domain of just one individual (Wiersema & Bantel, 1992). Top managers as decision makers should make strategic choices which are made formally and informally, indecision as well as decision, major administrative choices (e.g., reward systems and structure) as well as the domain and competitive choices more generally associated with the term "strategy". If strategic choices have a large behavioral component, then to some extent they reflect the idiosyncrasies of decision makers (Hambrick & Mason, 1984). The view taken here is that top management team matters, as they have discretion in the firm to engage the strategic decisions.

2.2.2. The influences of top management team decisions

The seminal work of Hambrick and Mason (1984), has opened a new stream of research on exploring the impact of TMT characteristics and composition on strategy and firm's performance, and consequently, a significant amount of works has been devoted in the past on that matter (Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009). Barker and Mueller (2002) for instance, suggested that firm's relative R&D spending varies significantly with its CEO's characteristics. They assumed, based on the upper echelons theory, that CEOs have the greatest organizational power to influence R&D spending, and expected that CEO's will monitor R&D spending closely and adjust its level based on their preferences accordingly. In their work, Barker and Mueller (2002) found that both CEO tenure and age have a negative impact on R&D spending, even though the relationship between CEO tenure and R&D spending was not significant. Unlike the work by Barker and Mueller (2002), Kor (2006) examined the impact of the whole TMT rather than individual CEO and found an evidence that managers' tenure has a significant negative effect on the R&D spending. Also, she argued that the role of top-level managers in taking strategic choice on R&D investments can be relevant particularly in young, entrepreneurial firms. This is because of the simplicity of the organization structure and communication channels in such setting, which allows the top-level managers to interact with each other and with firm's resources to influence R&D strategy.

Another research domain on the influence of TMT characteristics is on the firm's performance. Cheng et al (2010) examined if there exists a systematic relationship between top executives' demographic characteristics and corporate performance, by using Chinese firms as the dataset. Their main finding is that the TMT demographic characteristics do have an impact on firm performance, which is measured by Earning Per Share, Return on Assets, Stock returns, and Abnormal stock returns. They found that firms perform better when the chairpersons have higher education level, older, and have shorter tenure. Still within the domain of firm performance, Acar (2015) investigated the impact of top management team composition on the SME export performance by using the SMEs dataset from Turkey. She argued that SMEs provide a more direct setting to empirically test the effects of TMT characteristics on firms' performance than do larger companies. This is because SMEs have much limited resources and lack of administrative systems that help with the decision-making process. Hence, SMEs have to rely more on their managers (Acar, 2016). This argumentation is supported by Zhang (2017) where she empirically examined the moderating role of top manager characteristics on the agglomeration economies-firm performance relationship. Her study shows that the interaction coefficient between chairman age and firm performance is more significant in SMEs compared to larger firms. These results suggest that SMEs rely more to the top managers.

2.2.3. How do top management team characteristics affect firm's credit risk?

One way to explain the impact of top management team characteristics on firm credit risk is through the evidence that top management team as the decisions maker does have an impact in firm strategic change. A work by Wiersema and Bantel (1992) decomposed factors which affect the strategic change in a firm into four tendencies: receptivity to change, willingness to take risk, diversity of information sources and perspectives, and creative-innovative decision making. These four tendencies are suspected to have an impact on firm credit risk subsequently by influencing the initiation of strategic change. Receptivity to change suggests an openness to pursuing business approaches. Managers which have this tendency are willing to adjust the firm strategy based on the changing environment to ensure the stability and the continuity of the business, and thus, lowering its probability of default. Willingness to take risk is important since changing firm strategy involves risks, and the payoffs of the new strategy are not guaranteed. Managers should have a willingness to take risk at a certain justifiable degree that they would take risky decisions in which they think have the best payoff, yet, not to be overconfident that they put the company into an unaffordable risk. The managers' diversity in information sources and perspectives, and creativity and innovativeness, suggest a differentiation in an organization's belief which affect the perception of the feasibility and novelty of changes in strategy, which in turn, may affect the firm credit risk. These four tendencies are aligned with the recommendation by Basel Committee on Banking Supervision (2001). One of the suggested criteria on risk assessment of a borrower is the "depth and skill of management to effectively respond to changing conditions and deploy resources, and its degree of aggressiveness vs. conservatism" (Basel Committee on Banking Supervision, 2001, p. 50, No. 265). In practice, these for tendencies may affect firm credit risk in the following manners: First, proficient managers tend to choose a better project which has a higher NPV, which implies the higher probability in paying the debt before the maturity date expired. Second, the top managers have more knowledge on how to run a company and how to deal with the finance market due to their information resources and perspectives. Third, the top management team might prefer less risky investments, so they can reduce their uncertainty of their undiversifiable "human capital" investment in their firm (Amihud & Lev, 1981) which in turn may lower firm's credit risk.

The next logical matter which should be explored is what characteristics among top management team that may be involved in the aforementioned tendencies. Both works by Wiersema and Bantel (1992) and Cheng, Chan, Leung (2010) argued that the top management team demographic characteristics or personal attributes are not only the dominant factors but also might explain more variance in the strategic change and organizational outcomes than would the presumed intervening constructs. From the upper echelons perspective, a couple of top management team characteristics variable will be used as measures: age, tenure, gender, and the top management team size. These measures are likely to have a significant bearing on organizational outcomes. The evidence of aforementioned variables in the following will be closely related to the firm's financial performance. This is due to the fact that both firm's financial performance and credit risk are almost indivisible since the measure for both attributes is practically similar.

Many studies show that age and tenure of managers are closely related to their tendency to take risks and take initiate innovative strategies (Barker & Mueller, 2002). Stevens, Beyer, and Trice (1978), and Hambrick and Mason (1994) suggested that older top managers tend to be more conservative, while younger top managers are more likely to have better ability to develop new ideas, lower commitment to organization status quo and more interested in progression than career stability. Furthermore, studies by Kosnik (1987), and Brown and Maloney (1999) suggested that the older executives, the better their understanding on firm and its industry, hence, the better the performance of the firm. Study by Hambrick and Fukutomi (1991) found that the longer top managers' tenure in a firm, the greater commitment they have to the original routine of business operations. Additionally, they may also lose their interest in their firms over time. On the other hand, organization learning theory together with resource-based view suggest that age and tenure may be valuable intangibles as knowledge and experience can enrich and add value to human capital (Cheng, Chan, & Leung, 2010).

The relationship between gender and firm performance in the finance and management literature are remain ambiguous (Carter, Simkins, & Simpson, 2003; Dwyer, Richard, & Chadwick, 2003). For instance, Kalleberg and Leicht (1991) hypothesized that male top managers are likely to manage a firm in a better way due to their tendency to initiate in innovative business strategies. However, they did not find any empirical evidence to support the aforementioned hypothesis. On the other hand, Carter et al. (2003) found a statistically significant positive relationship between the presence of women on the board and firm value. Regarding the risk-taking behavior, Khan and Vieito (2013) argued that women are more risk-averse, worry more about the way the company capital is spent, and normally extract less personal benefits from the company than men. Furthermore, women who manage mutual funds take less unsystematic risks and prefer to take more stable investments than men.

The impact of top management team size on firm performance is often examined in the finance and management literature as well with various disagreement regarding the result. Wiersema and Bantel (1992), for instance, argued that large top management team have more potential for dissimilarity. On the other hand, as the number of members on top management team increases, there will be more structural elaboration (Meyer, 1972), including a differentiation in perspectives (Dearborn & Simon, 1958), specialization of skills, and diversity of opinion (Bales & Borgatta, 1995). Furthermore, Haleblian and Finkelstein (1993) found that firms with a larger top management team are performed better than their fellow firms with smaller top management team in complex environments.

2.3. Small and Medium-sized Enterprises (SMEs)

The focus of this thesis will be on the scope of SMEs due to their characteristics since SMEs are not just larger firms scaled down. First, small businesses are inherently riskier due to several reasons. The owner/manager may be less risk-averse than top managers of larger firms, and consequently may select riskier projects. Furthermore, the owner/manager is generally a specialist in one facet of the firms, with less interest and ability in other critical areas. Lastly, small firms, particularly those in high-tech domain, serve in a limited number of products or services for which there may be no accepted market niche (Scherr, Sugrue, & Ward, 1993).

Second, it is well-known that SMEs have a higher degree of information opacity compare to larger firms. The value of the human capital, which is critical in determining small business success, is not easily observed. Moreover, the audited reports and data from commercial reporting agencies on small businesses are often limited or unavailable at all (Scherr, Sugrue, & Ward, 1993). Consequently, information opacity among SMEs leads to its third characteristic, lower earnings quality. Ball and Shivakumar (2005) argued that private companies tend to resolve information asymmetry by an “insider access” model. It is less likely for them to use public financial statements in contracting the lenders and other parties. Correspondingly, their financial reporting is more likely to be influenced by taxation, dividend, and other policies. These differences imply a demand for a lower quality financial reporting. In their work, Ball and Shivakumar (2005) interpreted the reporting quality in abstract terms, as the usefulness of financial statements to investors, creditors, managers, and all other parties contracting with the firm. They found a consistent evidence that private-companies' earnings indeed are lower in quality on average, compare to their public firms' counterpart, despite of being prepared under the same regulations.

These three aforementioned characteristics of SMEs make them have more limited external financing alternatives compare to larger firms, which is the fourth characteristics of SMEs. According to Myers' (1984) Pecking Order Theory, due to information asymmetries between firms and their (potential) investors regarding the firms' current operations and future prospects, the investors will ask a return on the capital that is lent – in case of debt finance or invested – in case of equity finance. Consequently, external financing, both debt and equity, are less attractive than internal financing. As a result, firms tend to finance their needs in hierarchical fashion. First, they will use internal equity, followed by debt, and finally external equity. This theory holds for all firms regardless their size. However, asymmetric information problems between firms and outside investors are more acute in the case of SMEs than for larger firms, and consequently making the differences in costs between internal equity, debt, and external equity greater. Hence, the Pecking Order Theory approach should have even more appeal to SMEs than to large firms. Based on this theory, external equity will be extremely costly, and debt will be much preferred as the financing method for small firms (Scherr, Sugrue, & Ward, 1993).

Not only the aforementioned literature suggests the high dependency of SME on debt financing because of it is relatively lower in cost, but also show the intricate relationship between SME and the debt provider itself. SMEs on one hand, need debt to finance or expand their business activity, in the other words, not to be default or even bankrupt. However, due to the nature of SMEs of being risky (high default risk) and having an acute level of information opacity, the debt providers are reluctant to give credit to SMEs at the first place. The lack of external financing, in turn, will even leverage the SMEs' risk further to go default. Hence there is a need of exploring the determinants which may affect SMEs default risk, which may lower the information opacity, the uncertainty for the debt provider, and SMEs default risk itself.

3. Hypothesis development

Four variables were chosen for this study: age, tenure, gender, and the size of top management team. Based on the previously discussed literature, these variables are indicators of the top management team characteristics on risk-taking behavior. Moreover, the selected variables also serve as indicators of top management team characteristics in determining firm performance in another study. Hence, the selected variables also may affect the firm credit risk subsequently, and thus relevant to the following hypotheses.

3.1. Age

To older top managers, security, both financial and career, may become very important (Wiersema & Bantel, 1992). Hambrick and Mason (1984) found that older top managers tend to be more conservative and risk-averse in comparison to their younger counterparts. This finding is supported by Barker and Mueller (2002) who found that younger CEOs are more likely to spend more on R&D which supported their argument that top management team's age is negatively correlated with the tendency to initiate innovative strategic endeavors. However, the risk-taking behavior of younger top managers may lead them to take negligent strategic decisions. On the other hand, older top managers may consider more factors before taking the strategic decisions. This argument is supported by the evidence that younger managers have been associated with both corporate growth and volatility of sales and earnings (Child, 1974; Hart & Mellons, 1970). As a result, younger top managers may lead the firm into a higher risk:

Hypothesis 1a: As top management team age increase, a firm's default risk decreases.

3.2. Tenure

The longer the top time the top managers stays in a firm, the more experience and greater task knowledge they will have with the firm (Cheng, Chan, & Leung, 2010). Consequently, they will have better ability, and more confidence in managing the firm and less likely to take higher risk decisions (Miller, 1991). At the same time, due to their reluctance in taking higher risk decisions, as the top managers' tenure increases, they tend to make fewer changes in corporate strategy (Hambrick & Fukutomi, 1991). Moreover, top managers' tenure in the industry is associated with commitment to the industry they are dealing with. Due to this, top managers have established ways of doing business within the industry which resulted in risk-aversion behavior, hence, less willing to go out from their comfort zones (Acar, 2016; Bantel & Jackson, 1989; Datta, Rajagopalan, & Zhang, 2003; Wiersema & Bantel, 1992; May, 1995). Consequently, top managers with a longer average tenure will have more understanding of the firm's internal conditions and the operating environment in which it operates. At the same time, they will have more commitment to the firm which resulted in a risk-aversion behavior. On the other hand, the longer the top managers' tenure may lead them to the increase of isolation from outside sources of information (Pelz & Andrews, 1966). The lack of information sources may reduce the innovativeness; hence, less strategic change will be taken. This, in turn, may reduce the firm overall performance (Li & Calantone, 1998). However, this also may suggest a less volatility in sales and earnings, and together with risk avoidance behavior of longer tenure managers, it may be translated into more certainty and lower credit risk:

Hypothesis 1b: As top management team tenure increases, a firm's default risk decreases.

3.3. Gender

The number of female in the top management team has increased in the past decades. This is might due to the response from the firms to both external and internal pressure for top management team diversity (Farrel & Hersch, 2005). As male top managers are, in general, more innovative than the female counterparts (Kalleberg & Leicht, 1991), and innovation is a major driver of firm performance (Li & Calantone, 1998), there is a tendency that company which is led by male top managers outperforms those which is led by female top managers. However, Carter et al. (2003) provided an evidence that the number of women in the top management team has a positive impact on firm value. Regarding the risk-taking behavior, Khan and Vieito (2013) argued that women are more risk-averse, worry more about the way the company capital is spent, and normally extract less personal benefits from the company than men. Furthermore, women who manage mutual funds take less unsystematic risks and prefer to take more stable investments than men. In their work, Khan and Vieito (2013) showed that firm risk level is smaller when they have a woman as a CEO. Based on these evidence and literature:

Hypothesis 1c: Higher percentage of female in TMT will lower a firm's default risk.

3.4. Size

As the top management team size increases, group cohesion and communication intensity become strained (Shaw, 1976). However, at the same time, based on the resource-based view, the sustainable competitive advantages of a firm depend on how it utilizes its unique bundle of resources (both tangible and intangible assets) to achieve organizational effectiveness (Barney, 1991). Top management team as the firm's human capital is an essential intangible asset for firm operations (Hitt, Bierman, Shimizu, & Kochhar, 2001). In a larger number of members on the top management team, structural elaboration is expected (Meyer, 1972), including the differentiation in perspective (Dearborn & Simon, 1958), specialization of skills, and diversity of opinion (Bales & Borgatta, 1995). These literatures imply that the increase of top management team in size may give them a better ability in taking better strategic decisions, hence, increasing the firm performance and lowering credit risk at the same time. In addition, Haleblian et al. (1993) found that in a more complex situation, the size of top management team has a positive impact on firm performance. Hence:

Hypothesis 1d: Firms with larger top management team size, will have a lower default risk.

4. Methodology

4.1. Statistical method

This thesis closely follows the model of previous studies on default risk (e.g. Broogard, Li, and Xia, 2017; Hsu, Lee, Liu, & Zhang 2015; Schultz, Tan, & Walsh. 2017) by using ordinary least square (OLS) regression technique where the default risk measure by Altman and Sabato (2007) is treated as the dependent variable. This technique is chosen because OLS regression is not only used in bankruptcy studies, but also widely used in the TMT characteristics studies (e.g. Barker & Mueller, 2002; Zhang, 2017; Cheng, Chan, & Leung, 2010). OLS approach assumes all predictors are strictly exogeneous, and it is appropriate when the dependent variable is metric as an interval or ratio scale. OLS uses t-test to measure the effect magnitude of each independent variable on the dependent variable and determine whether the effect is significant or not. However, in some cases, there are concerns over firm-level omitted variables which may influence the predictors to a great extent, hence there is a probability that there is a correlation among the independent variables and the error term, which leads to the endogeneity problem. To overcome this problem, 2SLS regressions are commonly used by using one or more instrumental variables (IVs), where the IVs are assumed to be exclusively uncorrelated with dependent variables of interest, except working through the influenced variables (e.g. Hsu, Lee, Liu, & Zhang, 2015). However, since the independent variables in in this thesis are the TMT characteristics, the independent variables are assumed to be strictly exogeneous. Which means it assumes that, in this particular case, TMT characteristics are determined independently from the firm's default risk.

Unlike the works by Gupta et al. (2014) and Gupta et al. (2015) where the financial ratios from Altman and Sabato (2007) model are treated as the predictors of default events, this thesis will closely follow the model of previous studies on default risk (e.g. Broogard, Li, and Xia, 2017; Hsu, Lee, Liu, & Zhang 2015; Schultz, Tan, & Walsh. 2017) where the default risk measure variable is solely treated as the dependent variable. However, instead of using the Merton (1974) model as the default prediction model, the Altman and Sabato (2007) Z-score will be used. The justification on this choice is based on the fact that Altman and Sabato (2007) Z-score has been proven to be robust in two separated datasets, where they initially developed the model by using U.S. SMEs dataset in the original work (Altman & Sabato, 2007) and later when they test the model for the second time by using U.K. SMEs dataset (Altman, Sabato, & Wilson, 2010). Based on this, it is assumed that the Altman and Sabato (2007) Z-score can be utilized as a standalone firm default predictor.

4.2. Model

Based on the previous discussion, an OLS regression will be conducted that has commonly been used in previous studies of default risk (Brogaard, Li, & Xia, 2017; Hsu, Lee, Liu, & Zhang, 2015; Schultz, Tan, & Walsh, 2017). The impact of top management team characteristics will be examined using the following regression:

$$\begin{aligned} DefRisk_{it} = \alpha_0 + \beta_1 TMT\_Age_{it} + \beta_2 TMT\_Tenure_{it} + \beta_3 TMT\_Gender_{it} + \beta_4 TMT\_Size_{it} \\ + \beta_5 F\_Age_{it} + \beta_6 LnAssets_{it} + \beta_7 Leverage_{it} + Industry_i + Year_t \quad (1) \\ + \varepsilon_{it} \end{aligned}$$

The default risk variable ($DefRisk_{it}$) itself is measured by two different equations based on the work by Altman and Sabato (2007) which will be further explained in the following section.

4.3. Variables

4.3.1. Dependent variables

The measurement of default risk in this study will utilize the Altman and Sabato (2007) default models total score. Thirty-nine years after his seminal paper on corporate bankruptcy prediction model (Altman, 1968), as widely known as Altman Z-score, Altman and Sabato (2007) had been developing a newer version of the model by using U.S. and later tested the new model by applying it to U.K. SMEs using both the U.S. coefficients and re-estimations based on the U.K. sample (Altman, Sabato, & Wilson, 2010). This new model eventually introduced the new model in 2012, widely known as Altman Z-score plus. Unlike the Z-score, the new Z-score plus is tailored for SMEs credit risk application. There are two major improvements in this new model. Firstly, unlike its predecessor, which using the MDA technique, the new model was developed by using logistic regression analysis technique. Altman and Sabato (2007) said that, in the past, authors who worked with MDA pointed out that two basic assumptions of MDA are often violated when applied to the default prediction problems[1]. Moreover, in MDA models, the standardized coefficients cannot be interpreted in the same manner as the slopes of a regression equation, hence do not indicate the relative importance of the different variables (Altman & Sabato, 2007). According to them, from a statistical point of view, logit regression is fit well the characteristics of the default prediction problem. The reason for this is that the dependent variable is binary (default/non-default) and with the groups being discrete, non-overlapping, and identifiable

Secondly, instead of using listed corporations' data, Altman and Sabato (2007) used the U.S. based SMEs in developing their new default prediction model. They said that governments and SME associations have criticized that high capital charges for SMEs could lead to credit rationing of small firms and reduce economic growth, given that the importance of these firms in the economy. However, at the same time, lending to SMEs is riskier than to large corporates (Altman & Sabato, 2007). Hence, as a consequence, they demonstrated that banks should have developed credit risk models specifically addressed to SMEs in order to minimize their expected and unexpected losses.

Similar as the original Z-score (Altman, 1968), Altman and Sabato (2007) chose five accounting ratio categories, as their independent variables, describing the main aspects of a company's financial profile: liquidity, profitability, leverage, coverage, and activity. Initially there were 17 variables examined to measure the 5-company's financial profile. After manually selecting the variables and applying a statistical forward stepwise selection procedure, they ended up with 5 variables which did the best overall job together in the prediction of the SME default, as follows:

- X_1 = Leverage, measured by Short term debt/Equity book value,
- X_2 = Liquidity, measured by Cash/Total assets,
- X_3 = Profitability, measured by EBITDA/Total assets,
- X_4 = Coverage, measured by Retained earnings/Total assets, and
- X_5 = Activity, measured by EBITDA/Interest expenses.

[1] (a) the independent variables included in the model are multivariate normally distributed; (b) the group dispersion matrices (or variance-covariance matrices) are equal across the failing and the non-failing group (Altman & Sabato, 2007).

As for observing the default event, they constructed the dependent variable as binary (0 = default / 1 = non-default). The results of the new model are accurate, 75% in accuracy ratio. Moreover, they improved the prediction accuracy even more by taking the logarithmic value of the predictors and ended up in a jump of accuracy ratio from 75% to 87%.

Since its early introduction in 2007, only a handful academics have implemented the new Altman model in their works. One of them is Gupta et al. (2014) where they examined the effect of internationalization on modelling risk for SMEs by using U.K. dataset. They selected financial ratios which are successful in prior default prediction study, and particularly employed most of the covariates which are found to be significant in the Altman et al. (2010) study, which is also based on a sample of U.K. firms. They argued that the financial ratios used in Altman et al. (2010) have a well justified and non-overlapping selection of explanatory variables. However, they had to remove the EBITDA/Total assets variable from the Altman model since it exhibited a strong correlation with other covariates. Similar to this, Gupta et al. (2015), where they studied the role of SMEs' size in forecasting bankruptcy in U.K., also removed the EBITDA/Total assets variable as it showed strong positive correlation with Retained earnings/Total assets variable. They argued that this high correlation supported the view that SMEs face difficulty in accessing external finance and are primarily dependent on internal sources of finance like retained earnings (Gupta, Gregoriou, & Healy, 2015).

Two models were developed in the aforementioned work. Both models use the five financial ratios. As for the first model, the total default risk score is measured by the following equation:

$$ALT\_Z = 4.28 - 0.01X_1 + 0.02X_2 + 0.18X_3 + 0.08X_4 + 0.19X_5 \tag{2}$$

Where Z is the total score. The higher the total score, the lower the probability of the firm will go default. As for the second model, Altman and Sabato (2007) utilized the natural logarithmic transformed predictors in their attempt to increase the accuracy of the model. By transforming the predictors, Altman and Sabato (2007) claimed that the accuracy ratio of their model jumped from 75% to 87%. The total default risk score for the log-transformed model is measured by the following equation:

$$LogALT\_Z = 53.48 - 1.13\left(Log(X_1)\right) + 1.84\left(Log(X_2)\right) + 4.09\left(-Log(1-X_3)\right) + 4.32\left(-Log(1-X_4)\right) + 1.97\left(Log(X_5)\right) \quad (3)$$

4.3.2. Independent variables

To test the hypotheses, four key top management team characteristics variables are used. First, the age of TMT members (TMT_Age) variable is measured as the average age of the TMT members. Second, the TMT members tenure (TMT_Tenure) is measured by the number of years the average top managers have stayed in the firm. Third, the gender diversity among TMT members (TMT_Gender) is measured as the percentage of female top managers in the TMT. Lastly, the size of TMT (TMT_Size) is measured as the number of people in the TMT.

4.3.3. Control variables

Following the extant literature (see, e.g. Cheng, Chan, & Leung, 2010; Hsu, Lee, Liu, & Zhang, 2015; Schultz, Tan, & Walsh, 2017), three firm-specific control variables will be incorporated in the model. Firm age (F_Age) which is the number of years the firm has been operating. Unlike the larger and older firms, small and young firms are inherently riskier and they are on average expected to have a higher probability of default (Psillaki, Tsolas, & Margaritis, 2010; Ortiz-Molina & Penas, 2008; Van Caneghem & Van Campenhout, 2012). One of the reason for this the fact that older and more mature firms as an organization have a more experience in the industry and already have established a set of know-how in doing business. Firm size (Assets) which is the value of firm's total assets. A larger firm is argued to be more closely scrutinized by analysts and the market, thus, it is argued that larger firm has more pressure to perform better and hence lowering its credit risk (Cheng, Chan, & Leung, 2010). The firm's leverage level (Leverage) which is the ratio of the firm's total debt to the book value of its assets. Based on the evidence by Chava and Jarrow (2004) which shows that industry groupings significantly affect both the intercept and slope coefficients in the bankruptcy forecasting equations, industry dummy variable (Industry) will be included in regression to further control any industry-specific effect. Lastly, year dummy variable is included in regression to control any effect of aggregate trends. Table 4.1. presents an overview of the description of variables.

Table 4.1. Description of variables

Variable	Description	Source(s)
Default risk variables		
ALT_Z	The total score of Altman and Sabato (2007) default risk model (Eq. 4)	(Altman & Sabato, 2007)
LogALT_Z	The logarithmic transformed predictors of the Altman and Sabato (2007) default risk model (Eq. 5)	(Altman & Sabato, 2007)
Top management team characteristics variables		
TMT_Age	Average age of top management team	(Barker & Mueller, 2002; Hambrick & Mason, 1984)
TMT_Tenure	Average tenure of top management team	(Acar, 2016; Hambrick & Fukutomi, 1991)
TMT_Gender	Percentage of female top managers in top management team	(Khan & Vieito, 2013)
TMT_Size	Number of people in top management team	(Haleblian & Finkelstein, 1993; Hitt, Bierman, Shimizu, & Kochhar, 2001)
Firm-specific control variables		
F_Age	Age of the firm	(Hudson, 1987; Stinchcombe, 1965)
Assets	Firm's total assets	(Altman, Sabato, & Wilson, 2010; Gill, Biger, Chenping, & Bhutani, 2009; Psillaki, Tsolas, & Margaritis, 2010)
Leverage	Ratio of the firm's total debt to the book value of its assets	(Altman & Sabato, 2007; Gupta, Gregoriou, & Healy, 2015)
Industry and year control variables		
Industry	Dummy variables, equal to 1 if the firm belong to one industry and zero otherwise	(Maksimovic & Phillips, 1998; Chava & Jarrow, 2004)
Year	Dummy variables, equal to 1 if the firm belong to one year and zero otherwise	(Cheng, Chan, & Leung, 2010; Schultz, Tan, & Walsh, 2017; Hsu, Lee, Liu, & Zhang, 2015)

4.4. Multicollinearity problem

In the study of top management team characteristics, multicollinearity problem should be taken into account in the process. There is a probability where one predictor variable is correlated with others in a substantial degree. For example, there is a probability where the top managers with longer tenure are also older in age. Eventually, multicollinearity reduces any single independent variable's predictive power by the extent to which it is associated with other independent variables (Hair, Black, Babin, & Anderson, 2014). The elementary and obvious way to identify multicollinearity is by examining the correlation matrix of the independent variables. The first indication of the substantial multicollinearity existence is the presence of high correlations (0.9 and higher generally) among independent variables (Hair, Black, Babin, & Anderson, 2014). The next step is to check the value of Variance Inflation Factor (VIF). Following the rule of thumb by Belsley, Kuh, and Welsch (1980), a value of VIF below 10 indicates no multicollinearity problem. The same rule of thumb is used by Cheng et al. (2010) as they check the multicollinearity for the management demography independent variables in their study. Acar (2016) in her study where one of the independent variables is the TMT tenure variety diversity, centred the variable which is prone to multicollinearity problem by subtracting its means from its observed value before it was squared, to reduce the likelihood of multicollinearity problem. This technique resulted in the value of VIF below 10, which is acceptable. In another study, Barker and Mueller (2002) examined the effect of their two highly correlated independent variables in two separate regressions to avoid multicollinearity problems. Altman et al. (2010) also had a multicollinearity problem when choosing the accounting-based variables for their model, due to a large degree of overlap between variables. After taking multicollinearity into the consideration, Altman et al. (2010) eventually used the same accounting-based variables which are also used in Altman and Sabato (2007).

4.5. Robustness tests

Following the regression models which are conducted to test the hypotheses, two robustness tests will be done to examine whether the results hold under different settings. The first robustness test will be done by conducting a regression analysis by using a subsample consisting of firms which belong to different industries, while the second robustness test will be done for different years. Three different industries are chosen for the subsample analysis, wholesale & retail, manufacturing, and construction. These industries are chosen since each of them has different levels of competition and, therefore, the degree in which the TMT affecting a firm's default risk is expected to be different as well. In the wholesale & retail industry, the role of TMT members is expected to be more crucial since the competition level among companies is considerably high due to the relatively saturated market and the existence of disruptive newcomers. As for the manufacturing and construction industries, the role of TMT is expected to be less crucial, since the level of competition is relatively low. The second robustness test will be done by using a dataset with different years to see whether the models hold for different time settings. The time settings which will be used in this robustness tests are from 2015 and 2016 data.

5. Sample

In this thesis, a dataset consists of SMEs in the United Kingdom during the period of 2013 through 2016 is used and the data is extracted from the ORBIS databases of Bureau van Dijk (BvD). Both administrative information (e.g. Top management team information and firm age) and financial data (e.g. income statement and balance sheet) are available in this database. The ORBIS formats have been derived from the word's most commonly used formats for the presentation of business accounts (Riberio, Menghinello, & De Backer, 2010). Regarding the administrative data, ORBIS is less harmonized for cross-country data. However, it is not a problem since only data from the UK are used in this study and the data within a country is uniform. Furthermore, regarding the financial data format, ORBIS database is adhered to international standards.

5.1. Sample classification and size

Several requirements are set for the statistical sampling of the empirical data. The foremost requirements are regarding the classification of SMEs. The definition of SME in this thesis will be based on the European Commission guidelines (European Commission, 2015) which are as follows:

- Number of employees between 10 and 250, and
- Annual turnover between EUR 2 million and 50 million, or
- Annual balance sheet total between EUR 2 million and 43 million.

The annual balance sheet-based definition will be used instead of the annual turnover-based. The reason behind it is that enterprises in the trade and distribution sectors have higher turnover figures than those in the manufacturing sector by nature (European Commission, 2015). Thus, by using the balance sheet-based criteria, these industries might be included as well. Moreover, to further support the framework, only unlisted firms are included in the dataset and the firms should be the Global Ultimate Owners (GUO). It means that the firms are the highest parent company. The justification on this choice is the fact that there are some firms that may have access to significant additional resources (e.g. because it is owned by, linked to or partnered with a larger enterprise which is not an SME), which make these firms might not be eligible for SME status (European Commission, 2015). Lastly, only non-financial companies will be included in the dataset.

Based on the specifications, there are 3692 firms in the initial sample which have data from 2013-2016, with the total of 12580 year-observations. However, there are many companies in the initial dataset which do not have a complete information regarding either/both TMT characteristics and/or accounting data. Consequently, these firms have to be filtered out, and 7945 observations remain. Finally, to mitigate the impact of outliers, the Altman Z-scores (ALT_Z) variables are truncated at the 5th and 95th percentiles and resulting the value of Altman Z-scores range between 4.83 and 304.84. Consequently, 7151 observations remain. Table 5.1. represents the sample selection steps and the number of observations from each step.

Table 5.1. Firms sample size

Number of observations	Description
12580	Initial sample of UK's non-financial unlisted SMEs.
7945	After firms with missing information (no TMT data and/or accounting data) are excluded.
7151	Final sample size, after excluding the outliers.

5.2. Industry classification

The industry classification of the dataset in this thesis is based on the North American Industry Classification System (NAICS). Nine industry categories are created to control the industry effect. The categorization is based on the work by Altman et al. (2017) which classify the industies into: Agriculture (NAICS code 11), utilities (NAICS code 22), construction (NAICS code 23), manufacturing (NAICS code 31, 32, and 33), wholesale and reatail (NAICS code 42, 44, and 45), information (NAICS code 51), accommodation and food services (NAICS code 72), service (NAICS code 81) and others. Figure 5.1. shows an overview of the firms of this study are distributed based on their industry categories. Almost half of the firm observations (2918) in this study are belong to the "other", which are not belong to other eight industry categories. Meanwhile, firms belong to "wholesale & retail", "Manufacturing", and "Construction" represent the other half of the total observations in this study, with the value of 1473, 1302, and 725 respectively.

Figure 5.1. Firms industry classification

6. Results

The results of this study are discussed in this chapter. First, the descriptive statistics of the variables will be shown and discussed to give the big picture of the sample firms. Subsequently, the correlation matrix among the variables will be shown and examined (e.g. to see whether there is a multicollinearity problem in the sample). Finally, the regression analysis results will be discussed in the last section.

6.1. Descriptive statistics

The descriptive statistics, mean, minimum, percentiles (25, 50, 75), maximum, and standard deviation of the TMT characteristics, default risk measures, and control variables are summarized in table 6.1. All the data presented in this table is from year period of 2013-2016, consisting 3692 firms with 7151 observations. The average age of TMT members (TMT_Age) in this study is 54.19 years old while the youngest and oldest average age of the TMT members are 21.50 and 85.50 years old, respectively. Furthermore, the 25th percentile of the top managers' age is 49.33 years old, suggesting that most of the top managers (almost 75% of them) are in their middle age. This average age of TMT members among UK's SMEs is significantly higher than the average age of TMT members of those Spain's SMEs in the study by Escribá-Esteve et al. (2009) which have the average age of 41.9 years old. On average, these top managers have held their position (TMT_Tenure) in their firm for 9.85 years, with the shortest and longest tenure period of 0.13 and 44 years. The firms with the lowest average tenure might be a new firm (one or two years old) with new recruited top managers, or firms that just replace all of its managers which resulted in the drop of the average tenure of the TMT members. Regarding the role of women in the top management team in this study (TMT_Gender), in overall, only 16% of all firms' TMT members are women. Furthermore, at most, less than half of the SMEs in this thesis sample have women in their top management team (median of 0% woman in the top management team), even though there are couple of firms which have a top management team which the members consist only of women. Lastly, the average TMT size (TMT_Size) is 3.62 with the median of 3 members, while the smallest TMT consisting of only one member and the largest consisting of 19 members. The average number of TMT member in UK's SMEs is similar to those Spain's SMEs in the work by Escribá-Esteve et al. (2009). This study found that the average number of

TMT member in Spain's SMEs is 4, slightly higher than the average number of TMT member in this study

Table 6. 1 Descriptive statistics

Variable	N	Mean	Std. Deviation	Minimum	Percentiles			Maximum
					25	50	75	
Top management team characteristics								
TMT_Age	7151	54.19	7.83	21.50	49.33	53.80	59.00	85.50
TMT_Tenure	7151	9.85	6.59	0.13	4.33	9.00	14.00	44.00
TMT_Gender	7151	0.16	0.21	0.00	0.00	0.00	0.33	1.00
TMT_Size	7151	3.62	2.00	1.00	2.00	3.00	4.00	19.00
Default risk measures								
ALT_Z	7151	20.13	34.97	4.83	6.53	8.99	16.07	304.84
LogALT_Z	7151	52.98	4.03	38.06	50.24	53.36	55.79	64.87
Leverage (X1)	7151	3.06	17.52	0.01	0.54	1.12	2.35	839.88
Liquidity (X2)	7151	0.12	0.13	0.00	0.02	0.08	0.18	0.82
Profitability (X3)	7151	0.14	0.09	0.00	0.07	0.12	0.19	0.94
Coverage (X4)	7151	0.37	0.23	-1.51	0.21	0.37	0.53	0.97
Activity (X5)	7151	77.61	183.31	0.17	7.95	18.01	53.41	1571.08
Control variables								
F_Age	7151	19.19	19.76	1.00	6.00	13.00	25.00	116.00
Assets	7151	14.69	8.92	2.08	7.95	12.13	19.26	42.96
Leverage	7151	0.60	0.21	0.03	0.44	0.61	0.76	1.00

Notes: All the data is from UK SMEs with the year period of 2013-2016. All variables are as explained in table 4.1. LogALT_Z is the logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. Assets is the value of firm's total assets in million euro.

As for the default risk measures, the average total score of Altman and Sabato (2007) Z-score (ALT_Z) is 20.13, with the minimum and the maximum score of 4.83 and 304.84 respectively. Furthermore, the median for the Z-score is lower (8.99) than the average, with the 25th and the 75th percentiles of 6.53 and 16.07 respectively. As for the logarithmic transformed predictors default risk score (LogALT_Z), the average score is 52.98 with the minimum and maximum score of 38.06 and 64.87 respectively. Regardless, there is no exact manner for this average Z-score to tell relatively whether the firms are in low or high default risk since there is no exact benchmark in the work by Altman and Sabato (2007) which tells what the thresholds of score are where the firm have a low or high default risk. The only evidence which is presented in their work is the fact that the higher the total Z-score of a firm, the lower the probability that the firm will go default, and vice versa.

In the control variables part, it can be seen that the average age of the firms (F_Age) is 19.19 years old, with the youngest and the oldest firms of 1 and 116 years old. Furthermore, the median age of the firm is 13 years old while the standard deviation is 19.76. The fact that the average age of the firms is significantly higher than its median, and the standard deviation is substantially high, indicates that the overall data for the firm's age is skewed to the right. Consequently, instead of using the raw data of the firm's age, the natural logarithm value of the firm's age will be used in the later correlation matrix and regression analysis.

The average size of firm's assets (Assets) is 14.69 million euro, with the minimum and maximum value of 2.08 and 42.96 million euro respectively. Furthermore, the median size of the firm is 12.13 million euro while the standard deviation is 8.92 million euro. Since the average size of the firms is significantly higher than its median, and the standard deviation is substantially high, it can be concluded that the overall data for the firm's size is skewed to the right. Consequently, instead of using the raw data of the firm's assets, the natural logarithm value of the firm's assets will be used in the later correlation matrix and regression analysis.

Lastly, the average leverage level (Leverage) of the firms is 0.6, with the lowest and highest leverage level are 0.03 and 1 respectively. At a leverage level of exactly 1, some firms in the sample are fully financed by debt. Furthermore, the median of firm's leverage level is 0.61, suggesting that more than half of the firms' observations in the sample are financing more than half of their business with debt rather than equity.

6.2. Correlation matrix

Table 6.2 lists the correlation matrix for the variables included in the study. The first notable information from the table is the high correlation between average tenure (TMT_Tenure) and the average age of TMT members (TMT_Age) ($r = .399^{**}$). This is expected, since top managers who have served for a longer time in TMT, are expected to be older as well, even though it is not necessarily for older top managers to have a long tenure. Furthermore, there is a negative correlation between TMT members' average tenure and TMT size (TMT_Size) (r = -0.120**), suggesting that a firm's TMT with a longer tenure more likely to be smaller in size. Regarding the gender diversity in the TMT, the percentage of female top managers in the TMT is positively correlated with the size of TMT (r = 0.121**), suggesting that there is a higher probability to find a woman top manager in a bigger TMT. Furthermore, there is a negative correlation between TMT members' average tenure an TMT size (r = -.120**), suggesting that TMT with longer tenure is more likely to be smaller in size.

Table 6.2. Pearson correlation matric

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) TMT_Age	1								
(2) TMT_Tenure	.399**	1							
(3) TMT_Gender	.085**	.040**	1						
(4) TMT_Size	0.001	-.120**	.121**	1					
(5) ALT_Z	-.029*	-0.009	-.029*	0.006	1				
(6) LogALT_Z	.076**	.068**	0.003	0.013	.401**	1			
(7) LnF_Age	.260**	.755**	.071**	.148**	0.005	.040**	1		
(8) LnAssets	.094**	.056**	.059**	.136**	-.061**	.046**	.106**	1	
(9) Leverage	-.235**	-.235**	-.088**	-.067**	-.168**	-.487**	-.277**	-.225**	1

*Notes: All the data is from UK SMEs with the year period of 2013-2016. All variables are as explained in table 4.1. LogALT_Z is the logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. LnF_Age and LnAssets are natural logarithmic transformed variables. **. Correlation is significant at 0.01 level. *. Correlation is significant at 0.05 level.*

On the default risk measure (ALT_Z), both TMT members' average age (TMT_Age) and female top managers percentage (TMT_Gender) are negatively correlated with it (r = -0.029* & r = -0.029*). These correlations are on the contrary of the hypothesis 1a and 1b which stated that as top management team age increase, a firm's default risk decreases and higher percentage of female in TMT will lower a firm's default risk. More on the default risk measure, both TMT members' average age and TMT members' average tenure are positively correlated with the logarithmic transformed predictors of the default risk measure (LogALT_Z) (r = 0.076** & r = 0.068**).

As for the control variables, the age of a firm (LnF_Age) is positively correlated with the default risk measures as measured by the logarithmic transformed predictors (r = 0.040**). It also positively correlated with the default risk as measured by the unlogged transformed predictors even though it is not significant (r = 0.005). This is in line with the literature which argued that as a firm grows, its organization structures would be stabilized and ties with environments become durable, causing the failing rate to fall. Furthermore, the firm's age also positively and significantly correlated with all the TMT characteristics (r = 0.260**; r = 0.755**; r = 0.071**; r = 0.148**). The positive correlations between firm's age and TMT member's average age and average tenure are expected, since older firm is more likely to have older and higher tenure top managers. Meanwhile, the firm size control variable (LnAssets) is both negatively and significantly correlated with the default risk measure as measured by the unlogged predictors default risk (r = -.092**). This is in line with the evidence in the literature which shows that as a firm gets bigger (bigger assets) legal insolvency becomes attractive for creditors, hence increase the default probability. However, the firm size control variable (LnAssets) is both positively and significantly correlated with the logarithmic transformed predictors default risk (r = 0.046**). Finally, the leverage level (Leverage) of a firm is both negatively and significantly correlated with all the default risk measures (r = -.168** and r = -0.487**). This is very logical since one of the variables included in the default risk measures in this study is the leverage level of a firm.

To test the presence of multicollinearity, variance inflation factor (VIF) is calculated. Multicollinearity problem arises when two or more independent variables are correlated at a certain level in a regression model. The threshold for the VIF value to be considered as too high is 10, following the widely used the rule of thumb (Besley, Kuh, & Welsch, 1980). It means that one of any variables which have VIF value above 10 needs to be removed from the regression analysis. In this study sample, none of the variable has the VIF value above 10. An overview of the VIF table can be found in Appendix A

6.3. Regression results

The OLS regression results are presented in five models in Table 6.3. The first four models consist of only one TMT characteristics in each model. Model 5 represents the combination of TMT members' average tenure, percentage of female in the TMT and TMT size. Model 6 represents the combination of TMT members' average age, percentage of female in the TMT and TMT size. Model 7 represents the combination of TMT members' average age, TMT members' average tenure, and TMT size. Model 8 represents the combination of TMT members' average age, TMT members' average tenure, and percentage of female in the TMT. Lastly, model 9 represents the whole model where all TMT characteristics are included

Each of the model is regressed with two different default risk measure dependent variables, the unlogged Altman and Sabato (2007) Z-score and the natural logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. The results of the regression analyses are further discussed in detail in the following sections.

6.3.1. The effect of TMT age on firm's default risk

Start with the TMT members' average age, hypothesis 1a states that as top management team age increase, a firm's default risk decreases. The results of regression analysis presented in Table 6.3 show that the effect of TMT members average age on a firm's default risk is significantly negative in all the models where the TMT age variable is included (model 1, b = -0.25*** & b = -0.04***; model 6, b = -0.24*** & b = -0.04***; model 7, b = -0.23*** & b = -0.03***; model 8, b = -0.22*** & b = -0.03***; and model 9, b = -0.22*** & b = -0.03***). This is the opposite to what was expected in hypothesis 1a. The possible explanation for this significant negative effect is due to the creativity and innovativeness of younger top managers and their risk-taking behavior. Based on the work by Barker and Mueller (2002), younger top managers may select projects which have higher net present value due to their creativity and innovativeness and the fact that their career and financial security concerns have a longer time horizon than those older top managers, even though the project may be considered as high risk. Nevertheless, based on this result, even though hypothesis 1a cannot be confirmed, the fact that the average age of the TMT members does have a significant effect on a firm's default risk is in line with upper echelon theory which stated that the TMT characteristics can influence organizational outcomes.

Table 6.3. OLS regression of TMT characteristics on firm's default risk

	Model 1		Model 2		Model 3		Model 4	
Variables	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z
Intercept	115.50 ***	70.15 ***	103.31 ***	68.39 ***	102.90 ***	68.33 ***	102.74 ***	68.33 ***
	(15.28)	(125.86)	(14.69)	(131.41)	(14.64)	(131.31)	(14.61)	(131.24)
Top management team characteristics								
TMT_Age	-0.25 ***	-0.04 ***						
	(-4.59)	(-8.93)						
TMT_Tenure			-0.23 **	-0.03 ***				
			(-2.41)	(-3.92)				
TMT_Gender					-5.52 ***	-0.38 ***		
					(-2.91)	(-2.71)		
TMT_Size							0.15	0.02
							(0.71)	(1.60)
Control variables								
LnF_Age	-0.46	-0.18 ***	0.21	-0.11 **	-0.78 *	-0.23 ***	-0.88 **	-0.24 ***
	(-1.12)	(-5.84)	(0.35)	(-2.41)	(-1.93)	(-7.61)	(-2.15)	(-7.89)
LnAssets	-5.96 ***	-0.64 ***	-6.14 ***	-0.66 ***	-5.99 ***	-0.65 ***	-6.12 ***	-0.66 ***
	(-8.57)	(-12.42)	(-8.81)	(-12.82)	(-8.60)	(-12.53)	(-8.73)	(-12.73)
Leverage	-36.90 ***	-10.56 ***	-35.64 ***	-10.38 ***	-35.79 ***	-10.37 ***	-35.40 ***	-10.35 ***
	(-17.54)	(-68.09)	(-17.11)	(-67.32)	(-17.17)	(-67.22)	(-17.01)	(-67.14)
Adjusted R^2	0.053	0.611	0.051	0.608	0.051	0.607	0.05	0.607
F-statistic	27.448	750.631	23.373	739.68	26.561	738.323	26	737.509
P-value	0	0	0	0	0	0	0	0
N	7151	7151	7151	7151	7151	7151	7151	7151

Table 6.3. (Continued)

	Model 5		Model 6		Model 7		Model 8		Model 9	
Variables	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z	ALT_Z	LogALT_Z
Intercept	103.62 ***	68.41 ***	115.35 ***	70.15 ***	114.90 ***	70.11 ***	114.62 ***	70.08 ***	114.73 ***	70.10 ***
	(14.74)	(131.49)	(15.27)	(125.88)	(15.14)	(125.30)	(15.12)	(125.35)	(15.13)	(125.32)
Top management team characteristics										
TMT_Age			-0.24 ***	-0.04 ***	-0.23 ***	-0.03 ***	-0.22 ***	-0.03 ***	-0.22 ***	-0.03 ***
			(-4.40)	(-8.72)	(-4.05)	(-8.15)	(-3.86)	(-7.95)	(-3.88)	(-8.00)
TMT_Tenure	-0.23 **	-0.03 ***			-0.10	-0.01	-0.11	-0.01	-0.10	-0.01
	(-2.26)	(-3.54)			(-0.92)	(-0.85)	(-1.16)	(-1.33)	(-0.93)	(-0.86)
TMT_Gender	-5.66 ***	-0.40 ***	-5.22 ***	-0.34 **			-5.15 ***	-0.32 **	-5.23 ***	-0.34 **
	(-2.97)	(-2.84)	(-2.74)	(-2.38)			(-2.71)	(-2.29)	(-2.74)	(-2.39)
TMT_Size	0.03	0.01	0.17	0.02	0.03	0.01			0.09	0.02
	(0.16)	(0.53)	(0.81)	(1.48)	(0.15)	(0.85)			(0.42)	(1.08)
Control variables										
LnF_Age	0.26	-0.11 **	-0.47	-0.18 ***	-0.05	-0.15 ***	0.08	-0.13 ***	-0.02	-0.15 ***
	(0.41)	(-2.31)	(-1.12)	(-5.91)	(-0.07)	(-3.24)	(0.13)	(-3.02)	(-0.03)	(-3.21)
LnAssets	-6.08 ***	-0.66 ***	-5.96 ***	-0.64 ***	-6.02 ***	-0.65 ***	-5.95 ***	-0.64 ***	-5.98 ***	-0.64 ***
	(-8.68)	(-12.70)	(-8.51)	(-12.43)	(-8.59)	(-12.49)	(-8.53)	(-12.39)	(-8.53)	(-12.44)
Leverage	-36.03 ***	-10.40 ***	-37.18 ***	-10.58 ***	-36.89 ***	-10.56 ***	-37.20 ***	-10.58 ***	-37.19 ***	-10.58 ***
	(-17.27)	(-67.37)	(-17.66)	(-68.12)	(-17.53)	(-68.06)	(-17.67)	(-68.13)	(-17.66)	(-68.12)
Adjusted R^2	0.051	0.608	0.053	0.612	0.052	0.611	0.053	0.612	0.053	0.612
F-statistic	23.812	653.698	24.695	663.227	21.281	662.476	24.738	663.163	23.371	626.399
P-value	0	0	0	0	0	0	0	0	0	0
N	7151	7151	7151	7151	7151	7151	7151	7151	7151	7151

*Notes: Table reports the unstandardized coefficients. Figures in parentheses represent the t-statistics. All the data is from UK SMEs with the year period of 2013-2016. All variables are as explained in table 4.1. LogALT_Z is the logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. LnF_Age and LnAssets are natural logarithmic transformed variables. Industry dummy variables ($Industry_j$) and year dummy variables ($Year_t$) are included in the regressions. ***. Significant at 0.01 level. **. Significant at 0.05 level. *. Significant at 0.1 level.*

6.3.2. The effect of TMT tenure on firm's default risk

As for the TMT members' average tenure, hypothesis 1b states that as top management team tenure increases, a firm's default risk decreases. As can be seen in Table 6.3 (models 2, 5, 6, 8, and 9), TMT members' average tenure have a negative effect on a firm's default risk which is opposite to what was expected in hypothesis 1b and similar to the effect of TMT age. However, the effect is only significant when TMT members' average age variable is removed from the model (model 2, b = -0.23*** & b = -0.03***; model 5, b = -0.23*** & b = -0.03***). The reason behind this significance diminishment is because the TMT members' average tenure variable is positively and significantly correlated with the TMT members' average age variable (r = .399**, see table 6.2). Furthermore, the TMT members' average tenure variable has a relatively high degree of multicollinearity in comparison with the other variables (VIF = 3.025, see appendix A). Hence, the effect of TMT members' average tenure on a firms' default risk only can be captured properly in a model where the TMT members' average age variable is absent.

Apart from the multicollinearity issue, the reason on negative and significant effect of TMT members' average tenure on a firm's default risk is that top managers with longer tenure may become more strongly committed to implement their own paradigm on how the organization should be run. They may have little interest in pursuing strategies of innovation to keep the firm evolving over time and instead preferring to emphasize stability and efficiency (Barker & Mueller, 2002). Consequently, the firm may lose opportunities along the way which may increase firm's profitability and value which in return may decrease the firm's default risk eventually.

6.3.3. The effect of female TMT members on firm's default risk

Regarding the presence of female in TMT, hypothesis 1c states that the higher percentage of female in TMT will lower a firm's default risk. Opposite to the hypothesis 1c, the regression results in table 6.3 show that the presence of female top managers in a TMT has a significantly negative effect on firm's default risk (model 3, b = -5.52*** & b = -0.38***; model 5, b = -5.66*** & b = -0.40***; model 6, b = -5.22*** & b = -0.34**; model 8, b = -5.15*** & b = -0.32**; and model 9, b = -5.23*** & b = -0.34**). The results suggest that the risk-averse behavior of female top managers does not necessarily lower a firm's default risk as the consequent. Therefore, hypothesis 1c is not supported. The possible explanation for this negative result may be due to the innovativeness of the male top managers. Similar to the argumentation on effect of TMT member's average age, male top managers may select projects which have higher net present value due to their innovativeness (Kalleberg & Leicht, 1991) which in turn will lower the firm's default risk.

6.3.4. The effect of TMT size on firm's default risk

Finally, regarding the TMT size, hypothesis 1d states that firms with larger top management team size, will have a lower default risk. As can be seen in table 6.3 (model 4, 5, 6, 7, and 9) the results of regression analysis, show that TMT size does not have any significant effect on a firm's default risk. The possible explanation for this insignificant effect is that as the TMT size gets larger, they have more potential for dissimilarity (Wiersema & Bantel, 1992). Furthermore, as the team size increases, group cohesion and communication intensity become strained (Shaw, 1976). Thus, it is expected that TMT size and firm's default risk have a non-linear relationship. Consequently, the correlation between TMT size and firm's default risk cannot be captured properly in a linear manner which is been done in this study.

6.3.5. The control variables

Even though control variables are not the main interest of this study, the present findings reveal that they also affect a firm's default risk. Regarding the firm's size, Altman et al. (2010) argued that businesses with low asset value are less likely to be pursued through legal process of insolvency as the creditors would have a little gain from it. Meanwhile, as the firm's assets get higher, legal insolvency becomes attractive for creditors. This argumentation is supported by the results in table 6.3 in all models, where the assets of a firm have a significantly negative effect on a firm's default risk. As for the firm age, it has a significantly negative effect on a firm's default risk, as measured by the logarithmic transformed predictors default risk model, in all models. Furthermore, in the regressions where the default risk is measured by the unlogged transformed predictors, only in the models where TMT members' average age and tenure are excluded that the firm's age has a significantly negative effect on a firm's default risk (model 3, $b = -0.78^{*}$; and model 4, $b = -0.88^{**}$). These results are not in line with the argumentation that small and young firms are inherently riskier and they are on average expected to have a higher probability of default (Psillaki, Tsolas, & Margaritis, 2010; Ortiz-Molina & Penas, 2008; Van Caneghem & Van Campenhout, 2012).

6.4. Robustness tests

Two robustness tests will be performed in this section to examine whether the results of the models hold under different settings. The TMT size variable is excluded in both robustness tests since it does not have and significant effect on a firm's default risk as shown in table 6.3. All models in the robustness tests are regressed on the logarithmic transformed default risk model since it has more statistical power than the unlogged model.

6.4.1. Subsample analysis on different industry classifications

The first robustness test in this study is a subsample analysis based on different industry classifications. Started with the wholesale & retail industry, it is expected that the effect of TMT characteristic will be more pronounce in this setting. The results in table 6.4 show that the only TMT characteristics variables which have significantly negative effect on a firm's default risk are TMT members' average age and tenure (model 1, b = -0.03^{***}; and model 2, b = -0.06^{***}), while the presence of female in the TMT does not have any significant effect in the wholesale and retail industry. As for the manufacturing industry, it is expected that the role of TMT is not as crucial as to the other industries. As shown in table 6.4 (model 4, 5, and 6), all of the TMT characteristics variable do not have any significant effect on a firm's default risk, aligned with the expectation. Lastly, for the construction industry, it is also expected that the role of TMT is not as crucial compare to the other industries. However, as can be seen in table 6.4, both TMT members' average age and the presence of female in the TMT have a significantly negative effect on a firm's default risk (model 7, b = -0.04^{***}; and model 9, b = -1.10^{**}). The effect of the presence of female in the TMT is even more pronounce in this industry in comparison to the main results as shown in table 6.3 where all the industries are included.

Table 6.4. OLS regression subsample of different industries

	Panel A: Wholesale & retail industry			Panel B: Manufacturing industry			Panel C: Construction industry		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z
Intercept	(67.50***	65.73***	65.54***	65.66***	65.13***	65.12***	73.59***	71.72***	71.58***
	(51.33)	(55.02)	(54.66)	(46.70)	(49.53)	(49.65)	(44.22)	(46.24)	(46.42)
TMT_Age	-0.03***			-0.01			-0.04***		
	(-3.52)			(-1.04)			(-2.96)		
TMT_Tenure		-0.06***			0.00			0.00	
		(-3.55)			(-0.05)			(-0.12)	
TMT_Gender			0.17			0.15			-1.10**
			(0.55)			(0.46)			(-2.19)
LnF_Age	-0.42***	-0.19*	-0.47***	-0.12*	-0.13	-0.13**	-0.40***	-0.49***	-0.48***
	(-6.05)	(-1.88)	(-6.91)	(-1.86)	(-1.38)	(-2.01)	(-3.33)	(-3.19)	(-4.20)
LnAssets	-0.34***	-0.34***	-0.32***	-0.28**	-0.28**	-0.28**	-0.90***	-0.94***	-0.92***
	(-2.90)	(-2.86)	(-2.69)	(-2.19)	(-2.17)	(-2.18)	(-5.82)	(-5.99)	(-5.88)
Leverage	-11.43***	-11.27***	-11.21***	-12.33***	-12.30***	-12.29***	-9.98***	-9.73***	-9.72***
	(-32.36)	(-32.31)	(-31.94)	(-34.74)	(-34.72)	(-34.63)	(-19.60)	(-19.15)	(-19.32)
Adjusted R^2	0.624	0.624	0.621	0.667	0.667	0.667	0.606	0.601	0.603
F-statistic	349.462	349.562	344.899	373.631	373.65	373.255	159.799	156.646	158.373
P-value	0	0	0	0	0	0	0	0	0
N	1473	1473	1473	1302	1302	1302	725	725	725

*Notes: Table reports the unstandardized coefficients. Figures in parentheses represent the t-statistics. All variables are as explained in table 4.1. LogALT_Z is the logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. LnF_Age and LnAssets are natural logarithmic transformed variables. Year dummy variables ($Year_t$) is included in the regressions. ***. Significant at 0.01 level. **. Significant at 0.05 level. *. Significant at 0.1 level.*

6.4.2. Subsample analysis on different years

The second robustness test in this study is a subsample analysis based on different years. To test whether the result is still hold in different time settings, a robustness test is done by running the regression model with the data from year 2015 and 2016. Hsu et al (2015) and Schultz et al. (2017) acknowledged that default risk is persistent over time and included the lagged default risk variable as predictor in their model accordingly. Based on this, if default risk is persistent, hence the effect of TMT characteristics on a firm's default risk would be persistent over time as well.

The results of the subsample analysis based on different years are presented in Table 6.5. Panel A represents the results of the 2016 data, while Panel B represents the results of the 2015 data. In both panels, each model only consists of one TMT characteristics variable since the effect of TMT members' average age is diminished as the TMT members' average age variable is included. TMT size variable is not included since it does not show any significant effect on a firm's default risk. All models are regressed on the logarithmic transformed predictors default risk Z-score.

As can be seen in Table 6.5, TMT members' average age (model 1, $b = -0.03^{***}$; and model 4, $b = -0.03^{***}$), TMT members' average tenure (model 2, $b = -0.03^{**}$; and model 5, $b = -0.03^{***}$), and the presence of woman in the TMT (model 3, $b = -0.63^{***}$; and model 6, $b = -0.49^{**}$) have significantly negative effects on a firm's default risk, aligned with the main results in table 6.3. Several other subsample analyses on different year are conducted and show a relatively similar results with an exception for the percentage of female on TMT, which does not show any significant effect on a firm's default risk specifically in the year 2014.

Table 6. 5. OLS regression analyses subsample of 2016 and 2015

	Panel A: Year 2016			Panel B: Year 2015		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z	LogALT_Z
Intercept	67.49 ***	66.01 ***	66.02 ***	67.97 ***	66.52 ***	66.49 ***
	(75.68)	(79.21)	(79.25)	(68.71)	(71.16)	(71.08)
Top management characteristics variables						
TMT_Age	-0.03 ***			-0.03 ***		
	(-4.67)			(-4.50)		
TMT_Tenure		-0.03 **			-0.03 ***	
		(-2.40)			(-2.68)	
TMT_Gender			-0.63 ***			-0.49 **
			(-2.77)			(-2.00)
Control variables						
LnF_Age	-0.11 **	-0.02	-0.15 ***	-0.10 *	0.01	-0.14 ***
	(-2.15)	(-0.28)	(-3.09)	(-1.93)	(0.08)	(-2.77)
LnAssets	-0.46 ***	-0.48 ***	-0.46 ***	-0.49 ***	-0.52 ***	-0.50 ***
	(-5.53)	(-5.74)	(-5.57)	(-5.23)	(-5.54)	(-5.37)
Leverage	-9.96 ***	-9.81 ***	-9.84 ***	-10.12 ***	-9.97 ***	-9.97 ***
	(-39.93)	(-39.58)	(-39.64)	(-36.68)	(-36.37)	(-36.31)
Adjusted R^2	0.449	0.444	0.445	0.433	0.429	0.428
F-statistic	139.345	136.931	137.218	118.519	116.604	116.138
P-value	0	0	0	0	0	0
N	2041	2041	2041	1843	1843	1843

*Notes: Table reports the unstandardized coefficients. Figures in parentheses represent the t-statistics. All variables are as explained in table 4.1. LogALT_Z is the logarithmic transformed predictors of the Altman and Sabato (2007) Z-score. LnF_Age and LnAssets are natural logarithmic transformed variables. Industry dummy variables ($Industry_j$) is included in the regressions. ***. Significant at 0.01 level. **. Significant at 0.05 level. *. Significant at 0.1 level.*

7. Conclusion

The whole study is summarized in this chapter. Conclusion are drawn based on the results of the study at first. Subsequently, limitations and recommendations are presented and discussed.

7.1. Conclusions

This thesis represents an attempt to explore the impact of top management team on a firm's default risk, especially in the SME cases. Over the past decades, since the seminal work by Hambrick and Mason (1984) on the upper-echelon theory, there has been a surge of interest in top executives, under the premise that the dominant coalition of the organization – top managers – play a pivotal role in shaping major organizational outcomes. The core ideas of the aforementioned work have become the cornerstone of many mainstream management and economic works, where they found that TMT characteristics do influence the outcomes of a company as an organization (e.g., Acar, 2016; Barker & Mueller, 2002; Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009). Notwithstanding the importance of top manages in determining firm's output as an organization, no study was found – in the making of this thesis – that investigate the role of TMT on a firm's default risk. Instead, the literature on the modelling of default risk gravitates toward the financial information to predict insolvency. Combining both upper-echelon theory, where it is assumed that top managers have a pivotal role in determining firms' outcomes as an organization, and finance-based default risk model, this thesis attempts to explore the impact of TMT characteristics on a firm's default risk. Four hypotheses are formulated which propose that the age, tenure, gender composition, and size of the TMT are important elements of TMT characteristics which may influence a firm's default risk.

The regression results confirmed the aforementioned literature in which the TMT characteristics do have influence on determining firm's default risk. Regarding the age of the TMT members, the evidences show that TMT members' average age has a negative effect on a firm's default risk. The possible explanation on this opposite result is that younger top managers are more likely to be more creative and innovative. Subsequently, they may select projects which have higher net present value regardless their higher risk. Consequently, the firm may generate more profit which in turn may reduce their default risk all together. As for the TMT members' tenure, the evidences show that TMT members' average tenure has a negative effect on a firm's default risk. The possible reason behind it is that top managers with longer tenure may become more strongly committed to implement their own paradigm on how the organization should be run. They may have little interest in pursuing strategies of innovation to keep the firm evolving over time. Consequently, the firm may lose opportunities along the way which may increase firm's profitability and value which in return may decrease the firm's default risk all together. On the presence of female top managers, the evidences show that the presence of female on the TMT has a negative effect on a firm's default risk. The possible explanation for this negative result may be due to the innovativeness of the male top managers. Similar to the argumentation on effect of TMT member's average age, male top managers may select projects which have higher net present value due to their innovativeness which in turn may increase the firm's profitability and lower the firm's default risk. Lastly, regarding the TMT size, the evidences show inconclusive results, where there is no significant effect of TMT size on a firm' s default risk in any models. This is might due to the argumentation that even though the addition of one person in a group may increase the group overall performance, as the group getting larger, group cohesion and communication intensity become strained. Hence, the correlation of TMT size and a firm's default risk may not be captured properly by using linear regression which is been done in this study.

In conclusion, this study found some evidences that TMT characteristics do have an important role in determining firm's default risk, even though as on the manner as it was not expected. Any limitations and recommendations will be further discussed in the following section.

7.2. Limitations and recommendations

The main limitation of this study is the extensiveness of the data source. It is true that ORBIS is able to provide firms' information regarding its TMT members. However, it does not clearly mention the exact function nor position of each top executives besides calls them "senior management". Only a handful firms in the dataset that have a specific function and position for each top manager (e.g., CEO, COO). Furthermore, the sample only consists of UK SMEs, which may influence the blurry position in the upper echelon level between top management team and board of directors' members. In the particular dataset in which is used in this study, all of TMT members are also board of directors' members as well. The impact of TMT characteristics on a firm's default risk may not be captured properly due to this duality phenomenon among UK SMEs.

The second limitation of this study is that the TMT characteristics may not be measured appropriately. As mentioned earlier, the average tenure and age of the TMT members are used in measuring TMT members tenure and age. In result, there might be a possibility that the older or longer tenure top managers have more influences in decisions making over the younger or shorter tenure top managers. Consequently, the effect of these two variables might not be captured properly.

Based on the results and limitations of this study, several recommendations for future studies are discussed. In the interest of generalizability of the research, it is recommended to conduct similar study in different countries and different settings (e.g., large corporations). It is safe to say that this study is very specific regarding the dataset which are used, UK SMEs. Hence, even if the results are in line with what were expected beforehand, the results may not be generalizable in a wider perspective. Further research might examine the impact of TMT characteristics on a firm's default better by using different firms' settings and countries.

Similar to the aforementioned recommendation, with regard to explore deeper on the impact of TMT characteristics on a firm's default risk, a couple of different TMT characteristics measures could be utilized. TMT members education would be an interesting characteristic to be explored on. Several studies have done in the past to explore the impact of TMT members education level on a firm's outcomes (Acar, 2016; Escribá-Esteve, Sánchez-Peinado, & Sánchez-Peinado, 2009) and some of the studies did find that TMT members' level of education have a significant impact on a firm's outcomes (Barker & Mueller, 2002; Cheng, Chan, & Leung, 2010). The aforementioned studies also explored the impact of TMT members experience in a particular field on a firm's outcomes, which might be interesting to be explored on as well. These two TMT characteristics are not available during the making of this thesis to be explored on, which would be strongly recommended in the future study.

Lastly, regarding the manner in which the research is conducted, future research could examine this study's topic with different approach. As mentioned earlier, this study utilizes OLS regression analysis with Altman and Sabato (2007) Z-score as the dependent variable while TMT characteristics as the independent variables, by using non-bankrupt firms as the sample. Different approach could have been taken by utilizing different and more rigorous statistical method (e.g., logistic regression), by using both bankrupt and non-bankrupt firms as the sample. Consequently, the results might have a more statistical power to differentiate between firms.

8. References

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9. Appendices

Appendix A: Variance inflation factor (VIF)

Model	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
TMT_Age	0.788	1.270
TMT_Tenure	0.331	3.025
TMT_Gender	0.964	1.038
TMT_Size	0.825	1.213
LnF_Age	0.351	2.852
LnAssets	0.913	1.095
Leverage	0.848	1.179
Agriculture	0.957	1.045
Utilities	0.992	1.008
Construction	0.869	1.151
Manufacturing	0.812	1.232
Wholesale & retail	0.795	1.258
Information	0.964	1.037
Accommodation & food	0.950	1.053
Service	0.950	1.052
2015	0.705	1.418
2014	0.701	1.427
2013	0.713	1.403