On Eggs and Baskets: An Empirical Study of the Relation between Debt Capacity and Corporate Diversification [§]

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Abstract

Economic Theory suggests that corporate diversification has a positive impact on firm debt carrying capacity. The cash flows of a diversified firms segments result, when imperfectly correlated, in reduced volatility of total cash flows and increased debt carrying capacity. We empirically test the impact of corporate diversification on debt carrying capacity by using an established method based on Standard & Poor's long term credit ratings to estimate debt capacity and the Berry-Herfindahl index to estimate corporate diversification. Using the Compustat database, we measure both industry diversification and geographic diversification. We look at data between 1981-2013 and we study over 32,000 firm-year observations. The purpose of this paper is not only to shed a light on the relation between corporate diversification and debt capacity but also to improve current methods of assessing a firms debt capacity. In our sample, we find strong evidence for a positive association between diversification and debt capacity. Our findings are further confirmed using selected sub-samples.

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1 Introduction

"It is the part of a wise man to keep himself today for tomorrow, and not venture all his eggs in one basket." – Sancho Pancho
Don Quixote by Miguel de Cervantes

In the 80s, the conglomerate firm, a firm composed of several unrelated businesses, was a dominant corporate form in the United States. The common motive behind conglomerate mergers is that a merger generally leads, through diversification effects, to reduced risk for the combined entity. Other reasons to diversify are to reduce the dependence on a few products, realize opportunities, seek synergies in terms of markets or technology, grow aggressively or gain market power through market and capital access benefits. Today, most executives and boards realize how difficult it is to add value to businesses that are not connected to each other in some way, although a few talented people over time have proved capable of managing big conglomerates. As a result, conglomerates have mostly disappeared in the U.S and by the end of 2010 there were only 22 true conglomerates (**?**). Yet, many executives still believe that diversifying into unrelated industries reduces risk for investors and that diversified businesses can better allocate capital across businesses than the market.

Corporate diversification has become an integral part of the strategy of many companies. These diversification strategies may include both segment diversification and geographical diversification. However, the arguments that diversification benefits shareholders by reducing volatility is not persuasive. The rise of low-cost mutual funds underlines this point, since these funds made diversification accessible to even smaller investors.

The effects of corporate diversification have been well-documented in academic literature. Economic theory and research indicate both costs and benefits of diversification. Costs include better-performing segments subsidizing poor-performing segments and loss of management focus. The theoretical benefits of diversification result from the lower volatility of cash flows. These benefits include increased ability to do positive NPV investments as well as lower taxes due to higher debt carrying capacity. Research by **?** and **?** shows a lower market value of equity for diversified firms indicating costs outweighing benefits. This research is in line with historical developments, with the number of diversified conglomerates decreasing over the past decades.

In contrast, the effects of corporate diversification on the firms position in the debt markets is not documented extensively. More specifically, existing literature provides limited evidence on the impact of diversification on debt carrying capacity. In this study, we endeavor to provide empirical evidence on the relationship between diversification and debt carrying capacity. The results of this study provide insight on how diversification could impact firms through debt markets.

The underlying reason why debt and equity markets are pricing diversified firms differently can be explained through understanding the key differences between debt and equity. Briefly explained, debt is a contract to receive a fixed amount of future payments whereas equity is a right to receive a share in a ventures earnings. Equity holders have an unlimited upside at the risk of getting nothing whereas debt holders have a fixed return, with everything else equal a smaller risk of getting nothing. Debt is senior to equity in the capital structure. The question arises why holders of debt and equity price diversification differently. To illustrate with an example:

Consider two separate firms, Yin and Yang who are perfectly negatively correlated. Assume there are two different states of the world where Yin and Yang have pay-offs as defined in the table below.

	Yin	Yang	Combined Firm
Good	200	0	200
Bad	0	200	200

Debt holders have an outstanding loan of 100 to each one of these firms. Debt holders will prefer the combined firm over the two separate entities as they will get repaid in both the good and the bad state of the world. The combined debt of the both firms is 200, which equals the pay-off that is secured with certainty. Equity, on the other hand, will prefer the two firms to stay separate. Equity will receive the residual pay-off after the debt has been repaid. In case of the combined firm, the residual pay-off equals 0 in both states. When considering the separate firms, equity will get no pay-off in one of the states, but a pay-off equal to 100 in the other state.

This explains why equity holders generally will dislike decreased volatility as, everything else equal, it lowers their potential upside. Debt holders, on the other side, prefer lower volatility, as they do benefit from the potential upside. In theory, debt markets will therefore value the combined firm, with diversified cash flows, higher than a non-diversified firm.

There is a consensus in academic literature that equity markets discount and punish diversified firms. On the contrary, when investigating the diversification issue from a debt-holders perspective, several theories contradict each other. As illustrated by the example above, we expect debt markets to favour diversification and assign a premium to the diversified firm in accordance with **?**s theorem. Several studies, however, find that debt holders use a diversification-discount, mainly due to agency problems and inefficient internal capital markets. This study aims analyse whether the benefits of diversifications outweigh the costs or vice versa. In order to make conclusive statements, each of the effects ought to be quantified separately to account for potential mispricing in the market.

Theory suggests corporate diversification reduces credit risk and increases debt carrying capacity. Multiple geographical or industry segments reduce, in case of imperfect correlation, the volatility of firm cash flows. **?** has theoretically shown that conglomerate firms, due to the aforementioned imperfect correlation, have a lower default risk relative to a portfolio of standalone firms. Lewellen's co-insurance theorem will be tested in this study. In line with this theorem, research including **?** shows that diversified firms are more leveraged than their more focused counterparts.

When discussing diversification in this paper, we refer to industry or segment diversification unless specified otherwise. As a result of US accounting regulation SFAS 131 data on diversification across segments and industries is available for most listed US firms. Moreover, data regarding these segments is structured according to Standard Industry Classification codes (SIC-codes) used by the US Securities and Exchange Commisission (SEC). It has to be noted that restricting analysis by only including this one type of diversification decreases the accuracy of our diversification measure and analysis. The limitations of measuring diversification bases solely on different operating segments becomes apparent when considering those firms that operate in many different geographies.

An example of such a firm is the worlds largest chain of hamburger

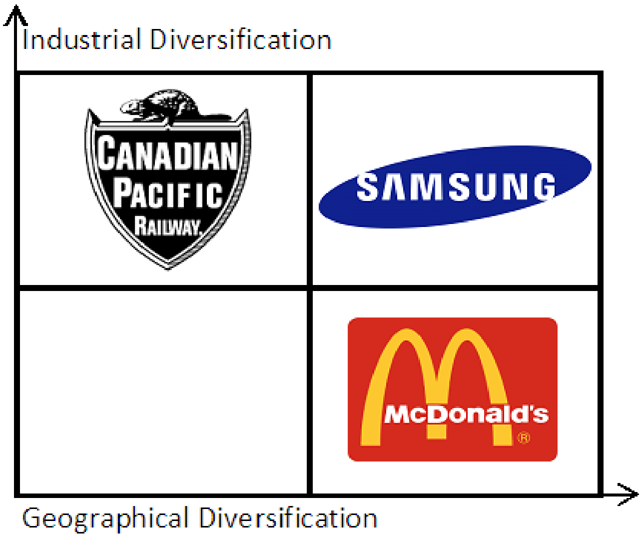


Figure 1: Different types of diversification

fast food restaurants, McDonalds. The company is headquartered in the U.S. but serves 68 million customers across 35,000 outlets in 119 countries each day. While McDonalds operates solely in the restaurant industry, the company can still be considered as diversified. Geographical diversification is a strategy that is considered to reduce risk exposure to events affecting one region. This allows firms to lower their risk exposure to political and economic changes and natural disasters by locating particular departments and/or resources in different parts of the world. If one of the firm's assets is located in a region vulnerable to geospecific risks such as tsunamis, earthquakes, revolutions, riots, economic crises, the parts located in other areas may compensate. In addition, business cycles are not perfectly aligned across the globe and different foreign markets seldom move in perfect correlation with each other. Therefore, a "boom" in one market can offset a "bust" in another market. It should however be noted that the effects of geographic diversification have decreased over the past decades as a result of globalization and the increased integration of international capital markets.

Limiting our analysis to segments and industries, the level of diversification is overestimated for certain firms. For example, Canadian Pacific Railway (CPR) is reporting 10 different segments while operating only in Canada. Firms operating in multiple segments but concentrated in one geographic area are exposed to location-related risks. If Canada were to suffer a natural disaster, CPR would affected across all its segments. Therefore, despite a high measure of diversification CPR is fully exposed to geospecific risks. In contrast, as Korean multinational conglomerate company headquartered in Seoul, Samsung comprises numerous subsidiaries and affiliated businesses. Samsung is diversified into several segments such as electronics, construction, shipbuilding, food processing, textiles, insurances, securities and retail and has production facilities in Korea, Vietnam, the United States and Germany.

In our analysis, we do not focus on geographical diversification. Limited data is available on the geographical diversification of firms. Moreover, as there is no regulation or generally accepted reporting standard data regarding different geographical regions is not reported consistently across firms. We do include geographical measures to further test our results, however they will not be a main focus in our study.

2 Thesis Statement

In this study we analyse the relation between industry diversification and debt capacity. We estimate debt capacity by using the credit rating regressions developed by Altman (1968) to estimate debt capacity following the procedure used by De Jong, Verbeek and Verwijmeren (2012). Diversification is measured using the Berry-Herfindahl index (Berry and Jacquemin, 1979) and the broad spectrum definition of diversification (Varadarajan and Ramanujam, 1987). Firstly, we apply both parametric and non-parametric tests to quantify the relationship between debt capacity and diversification, using the estimates generated by the debt capacity model. Secondly, we amend the debt capacity model to investigate if the inclusion of diversification increases the accuracy of the model. We further test the robustness of these results by considering several sub-samples, including sub-samples based on firm success, non-organic growth, business cycles and time period. Lastly, we test whether or not the findings in this study can be replicated when considering geographic rather than industry diversification.

Based on prevailing economic theory, we expect to find that more diversified firms have the ability to carry more debt. **?** developed the co-insurance theorem, stating that the imperfect correlation between cash flows in a diversified firm results in a lower volatility of the firm, decreasing default risk and hence increasing the maximum leverage. This, in turn, can be expected to lead to a credit worthiness of firms i.e. a superior credit rating. It can therefore be anticipated that diversification adds explanatory power to the assessment of the maximum leverage. We therefore define the hypotheses:

1. Diversification is positively associated with debt capacity
2. The inclusion of diversification when estimating debt capacity improves model accuracy.

In order to test the first hypothesis, we use an established model to estimate debt capacity. Using the estimations found using this model we use parametric and non-parametric tests to test for a relationship between diversification and maximum leverage.

The second hypothesis is tested by amending the model used to approximate maximum leverage. We compare the amended model, including diversification to the original model, to assess whether or not the inclusion of diversification increases model accuracy.

3 Existing literature

3.1 The co-insurance theorem

The idea of co-insurance effect for corporate debt was first developed by Lewellen (1971). It was argued that a merger of two or more firms whose revenue streams were not perfectly correlated would reduce the risk of default of the combined firm and thereby increase the ability to borrow of debt capacity of the merged firm (i.e. the co-insurance theorem). The conclusion of Lewellen's paper is that increased total borrowing capacity, combined with tax-deductible interest payments, provides an economic incentive for shareholder-wealth-maximizing firms to engage in conglomerate mergers. However, **?**s paper is incomplete as it does not take into consideration the impact of the co-insurance effect on the value of the already outstanding pre-merger debt in each firm. **?** and **?** extend the analysis to show that the co-insurance effect leads to an increase in the market value of the merging firms debt. Furthermore, they show a decline in the market capitalization of merged firm. These findings imply that the net financial result of non-synergistic merger is simply a wealth transfer from equity holders to debt holders. In our analysis, we estimate the maximum debt capacity of the firm expressed as the percentage of total firm value [1]. These estimates represent the maximum debt the firm would be able to issue starting from an all equity basis. Therefore the exclusion of the impact on outstanding debt in **?**s theory does not impair our research.

3.2 Other Costs and Benefits of Diversification

There is a lot of existing literature on both costs and benefits of diversification. The most commonly identified diversification benefits are economies of scope (Chandler 1977; Teece 1982), improved resource allocation through internal capital markets (Williamson 1975; Stein 1997) and the ability to use firm-specific resources to gain competitive advantage between different markets (Wernerfelt & Montgomery 1988). These benefits have to be weighed against the costs that occur with diversification. Costs can arise from agency problems afflicting diversification investments (Meyer et al. 1992) or inefficient resource allocation due to a malfunctioning of internal capital markets (Scharfstein 1998). Moreover, as pointed out by Harris et al. (1992) informational asymmetries between head office and divisional managers can result in additional costs for diversified firms. The majority of current research shows that from a shareholders perspective the cost of diversification outweighs the benefits. Berger and Ofek (1995) report that diversified US firms trade at an 8% to 15% equity discount compared to their more focused peers. Whited (2011) shows that studies regarding the diversification discount suffer from measurement errors. Furthermore, publications by Harris (1998) and Villalonga (2004) find data problems, while Graham et al. (2002) and Lins & Servaes (1999) find selection biases in terms firms, observation period or country. Moreover, several of the aforementioned papers fail to account for endogeneity of the decision to diversify i.e. variables that correlate with the decision to diversify.

[1]We estimate both the maximum book value leverage and the maximum market value leverage. In the section Approach and Data, these debt ratios are further defined.

3.3 Addition to current research

This paper aims to add to the current literature along several different dimensions. Firstly, we aim to evaluate the accuracy of the current prevailing models for estimating debt capacity. Secondly, we strive to analyse the relationship between diversification and debt capacity. Lastly, we aim to adapt this model to incorporate diversification. This amended model will be applied to determine whether the inclusion of diversification increases the accuracy of debt capacity estimates. The analysis presented in this paper provides insight in the role of diversification in debt markets and helps understand differences between equity and debt market in valuing diversification.

4 Approach and Data

In order to analyse the relationship between debt capacity and diversification this paper will follow a two step approach. Firstly, using a model based on credit ratings, we will estimate firm debt capacity. Secondly, using the debt capacity estimates found using this model we will analyse the relation between debt capacity. In the following section we will present the selection of the data-sample, the measures of diversification to be used and the model used to estimate debt capacity. After presenting these measures and models, we will discuss the tests used to determine the relationship between debt capacity and diversification.

4.1 Data Sample

Our analysis is based on Standard & Poors Compustat database, more specifically, the Compustat Industrial Segment Tapes. For our analysis we will use data starting in 1981, including all data available in the Compustat database. This data is combined with the Compustat North American database for firm-level data and Compustat's database on Standard&Poor's Long Term Credit Issuer ratings. Our data sample consists of approximately 32,000 observations between 1981 and 2013. These observations are further filtered to exclude incomplete data.

The firm-year observations with missing data are dropped and excluded from further analysis. Additionally, firms in the financial services industry and utilities industry (SIC codes 6000-6999 and 4900-4999) will be excluded from the dataset. These firms are dropped from the database due to their extraordinary financial structure, which is subject to regulation. For these firms, debt ratio can not be changed at the discretion of management. Therefore, debt ratios for financial services and utility firms, do not vary to the same extent as those of firms in other industries. As a result, any potential relationship between firm characteristics and capital structure decisions could be distorted. When these firms are included in the sample, their lack of variance in debt ratios creates noise. More simply put, any attempt to find variables explaining the firm's financing preferences would be impaired. The results of these preferences can not be observed accurately as government legislation may overrule them.

Furthermore, the SIC codes in the financial industry are far more granular than those in any of the other industries. This would result in an incorrect measure of diversification. We do not require a minimum amount of consecutive years of data, to avoid any survival biases.

The Compustat data is obtained on a segment level for all firms. Data is aggregated based on 2 digit SIC codes. For firms that report several segments with the same 2 digit SIC codes, these segments are combined and treated as one segment in further analysis. Based on these aggregated segments, we construct the Berry-Herfindahl index and other diversification measures on firm level. We match the segment-level data and diversification measures with firm-level data obtained from the Compustat North America Database. For each firm-year observation we obtain the monthly S&P credit rating from one month after the report date of the annual financial statements. Data from the next month is used, rather than data from the month of the financial statement to ensure that any information released in the statement is incorporated in the data.

4.1.1 Selection of unconstrained firms

In order to adequately estimate debt capacity, we require a sample of firms that are unconstrained in their access to financial markets. Debt capacity of firms that have limited access to financial markets may be affected by market entrance constraints and costs. In our analysis we will be using firms with an available Standard&Poors Long Term Credit Issuer rating. Additionally, we limit our data sample to those firms with available stock prices. Publicly traded firms with a credit rating can be assumed to have access to both the bond and stock market. The Compustat database contains observations for firms that have recently de-listed. These firms have available stock prices in the database but are excluded as they no longer have access to equity markets.

4.1.2 Sample Summary

The sample used in this paper consist of 30,400 firm-year observations. Table 1 provides summary statistics for several variables in the sample. We observe an average Berry-Herfindahl Index of 0.13, with a relatively high standard deviation of 0.21, indicating some variety of diversification levels in the sample. It can however be observed that the majority of firms in the sample are single-industry, with over 50% of the dataset consisting of firms with a BHI of 0.00. Our sample contains firms of various size, as is confirmed by the summary statistics for total assets and revenues. These statistics indicate a heterogeneous dataset, which allows for more powerful analysis.

Furthermore, we observe variance in both book debt ratio and market debt ratio. The exact definitions of these ratios can be found in the definition of debt ratio section. It should be noted that the average book debt ratio is higher than the market book ratio, indicating firms on average use prudent book values.

4.2 Diversification measures

We use the Berry-Herfindahl index (BHI) as our primary measure of revenue diversification. The BHI is a modification of the Herfindahl-Hirschman Index, a commonly accepted as a measure of market concentration. The Herfindahl-Hirschman index is calculated by squaring the market share of each firm competing in a market, and then summing the numbers up to get a number that ranges from close to zero up to 10.000. The mathematical

Table 1: Sample Summary Statistics Rating

	Berry-Herfindahl	Total Assets	Liabilities	Revenue	EBITDA	Net Income	Book Debt Ratio	Market Debt Ratio
N	32488	32488	32488	32488	32488	32488	30397	24691
mean	0.1306	7991	5157	5800	1862	299	0.6278	0.4953
sd	0.2090	24945	18003	15452	5209	1572	0.2858	0.2138
p25	0.0000	749	488	557	161	2	0.4665	0.3343
p50	0.0000	2094	1329	1576	458	55	0.5849	0.4881
p75	0.2502	6249	3963	4616	1343	230	0.7298	0.6420

Source:COMPUSTAT Database

expression is:

$$H = \sum_{\dot{L}=1}^{N} s_i^2 \tag{1}$$

$$H^* = \frac{(H-1)/N}{1-1/n} \tag{2}$$

Where s_i is the market share of a firm in the market and N is the number of total firms. Thus, in a market with only two firms, each have a 50% market share, the HHI equals $0.5^2 + 0.5^2 = 0.5$. The Herfindahl index ranges from 1/N to 1, where N is the number of firms in the market. If percentages are used as whole numbers, as in 50 instead of 0.5, the index can range up to 10.000.

The BHI is computed similarly to the Herfindahl-Hirschman index. As is shown in Table 2, the BHI is computed as the inverse of the Herfindahl-Hirschman, using the share of total firm revenues instead of market share.

Table 2: An Overview of Diversification Measures

Measure/ Authors	**Formula Description**	**Strengths**	**Weaknesses**
Modified Berry-Herfindahl index (Montgomery, 1982).	$Div. = 1 - \frac{\sum P_i^2 \cdot}{\sum (P_i)^2}$	Ease of computation	Does not measure relatedness between different groups at both 2- and 4-digit SIC-levels.
Entropy (Palepu, 1985)	$DT = DR + DU$ $DT = \sum_{j=1}^{m} DR_j p^j \sum_{j=1}^{m} P^j 1n(1/p^j)$ With: m is the number of industry groups $j = 1, ..., m$ p^j = share of total sales	Captures diversification across product groups (related) and within product groups (unrelated). Computes the amount of Total Diversification (DT), and its components. Related Diversification (DR) and Unrelated Diversification (DU).	Relies on accuracy of 10-K reports. Requires sales data at 4-digit level. Information available only for 10 largest product segments Computation is complex.
Rumelt's classification (Rumelt, 1974; Wrigley, 1970)	Based on: (i) specialization ratio (ii) direction of diversification (iii) vertical ratio a 4-category classification scheme^{2}1	Conceptual rigour. Relies on specific insight in the firm's history and behaviour.	Subjective. Reliability is questionable, tedious, time consuming, and requires extensive information on firm from various sources.
Broad and narrow spectrum diversity (Varadarajan and Ramanujam, 1987)	Absolute Number of 2-digit SIC segments and Number 4-digit SIC segments divided number of 2-digit SIC segments	Simplicity and ease of measurement and computation.	Validity and reliability is questionable.

[1]The classification consists(1)single business; (2) dominant business; (3) related business; (4) unrelated business.

4.2.1 Limitations of the Berry-Herfindahl Index

While the Berry-Herfindahl index provides several advantages over traditional measures of diversification, it also has several limitations. Most importantly, the BHI does not account for the correlation between different industries and SIC codes. This implies that the BHI for a firm that is diversified between uncorrelated industries and a firm that is diversified between correlated industries will be the same, given that the relative size of revenues in these industries is identical. It can be argued however that the latter firm is less diversified. The Berry-Herfindahl index is therefore an incomplete measure of diversification. The aforementioned exclusion of correlation measures can result in additional variation in the dataset. Moreover, since the BHI implicitly assumes no correlation between any of the different SIC codes, this results in an overestimation of diversification, creating a bias towards zero for any estimated relationship between diversification and debt capacity. As a result, the minimal detectable effect for any given size of the dataset, will be lower when using the Berry-Herfindahl index as a proxy for true diversification. This however, can be compensated by using a sufficiently large database. Due to the vast amount of firm level data available through the Compustat database, there is no reason to assume any issues resulting from the use of the BHI as a proxy. Secondly, by using 2 digit SIC codes, rather than the more granular 3 or 4 digit codes, the amount of different industries is narrowed down to 90. Albeit it is still likely that these industries have significant positive correlations, it can be assumed that most of these industries are not perfectly correlated. Therefore, there should be a benefit of diversification.

4.2.2 Additional Measures of Diversification

In addition to the Berry-Herfindahl index, a more traditional and simplistic measure of diversification will be used. Firstly, a dummy variable for diversification at the 2-digit SIC code level will be used. This variable will be 1 in case the firm reports revenues in segments in multiple SIC codes. As discussed above, using a binary variable as a measure of diversification does not correctly reflect a firms level of diversification. The use of a binary variable however does reflect a specific type of diversification. Due to the nature of US accounting standard, firms report revenues in all segments which represent more than 10% of the total revenues. The binary variable therefore indicates whether a firm has multiple segments that represent more than 10% of its revenues. This is not a proper measure of revenue diversification and does not reflect the sources of income that could potentially be used to cover the firms' costs. It does, however, measure the diversification of investment opportunities. A firm which operates in multiple segments will have the opportunity to invest in multiple segments in which it is already established. It therefore is spreading out its investment opportunities. A firm which has multiple segments can opt to invest in each of these segments. Given a certain critical mass, relative size of the segments is not of less importance. Considering the long term horizon of debt holders, investment opportunities and therefore long term stability of the firm could prove to be a significant factor. Therefore a binary variable is expected to add explanatory power to our analysis.

Secondly, we will be using broad spectrum diversity as defined by Varadarajan FIX REF as a third measure of diversification. This method has been used more extensively in existing literature and therefore provides a benchmark for the BHI. The broad spectrum is defined as the absolute number of 2-digit SIC codes in which the firm reports revenues. Table 2 provides a summary of all commonly used diversification measures as well as their relative strengths and weaknesses.

4.2.3 Potential issues with the use of segment data

The majority of studies that have reported a corporate diversification discount in the U.S. stock markets have used Compustat data. Research based on the data provided by Compustat dates back to the late 1970's and uses the segment tape data to breakdown a firm's activities by industry. Industry-level data is used to construct measures of diversification and estimate the effect of diversification on market capitalization or firm value. The use of Compustat segment data for the purpose of estimating diversification effects has several limitations. Firstly, these measures based on this data include noise, reducing the accuracy of the analysis. Moreover, due to several inaccuracies in the underlying data, the diversification measures used in these studies may contain a bias.

? reports that the extent of disaggregation in segment financial reporting is much lower that the true extent of a firms industrial diversification. Furthermore, Lichtenberg reports that the difference has increased over time. The Financial Accounting Standards Board (FASB) requires firms to report disaggregated information for segments that represent at least 10% of the total sales, assets or profits. This could lead to firms not reporting those segments that represent less than 10% of the total sales, leading to an underestimation of the diversification measure. If firms were to strictly adhere to these rules, the number of different industries in which the firm reports revenues is capped at 10. However, previous research does not observe such a limit in the Compustat data, nor is such a limit imposed. When considering the number of 4-digit SIC codes for which firms report disaggregated information, we find up to a 133 different segments per firm-year observation. According to **?** the number of firms reporting more than 10 segments may be as high as 17% of firms. The share of Fortune 500 firms reporting more than 10 segments is estimated to be as high as 56%.

In order to estimate diversification as accurately as possible, we include all segments for which firms report disaggregated information. When aggregating segments based on a 2-digit SIC code level we observe a maximum of 10 segments per firm in our sample. It should be noted that this maximum is not a result of the 10% threshold.

Despite the FASB regulation, managers have considerable discretion in disclosing segment-level information. As a result, the number of segments reported by some firms appears to have fallen below the threshold that FASB intended to establish through the accounting standards. This has triggered further regulation, such as SFAS 131 in 1997. This new regulation resulted in more strict recommended accounted standards, restricting management discretion. The implementation has resulted in a greater number of segments reported.

The use of segment data for a study of corporate diversification raises another concern due to the unclear definition of a segment. Officially, SFAF 14 defines a segment as a component of an enterprise engaged in providing a product or service or a group of related products and services primarily to unaffiliated customers (i.e. customers outside the enterprise) for a profit. Segment-level data is however self-reported and firms do not use a homogeneous definition of segments. As a result firms do not report segment level data based on the same standards, creating noise in the dataset.

The noise created by the self-reporting of firms is further exacerbated by the fact that segments are assigned a primary 4-digit SIC code by Compustat staff. David and Duhaime (1992) find that in 5-10% of cases, unrelated businesses were reported as a single segment. It can therefore be questioned whether or not segments across firms are comparable. Moreover, firms tend to change segments reported over time in absence of changes in operations. According to Denis, Denis, and Sarin (1997) and Hyland (1997) about 25% of the changes in the number of reported segments are changes in reporting method, as opposed to changes resulting from real operational diversification or refocusing. Their research indicates that inconsistencies in defining segments are not only occurring across firms, but also within firms.

Based on the aforementioned arguments it can be concluded that the use of segment data creates noise at various points in the estimation of the diversification effect. Firms present in multiple industries may be misclassified. Furthermore, segments might be misreported or aggregated incorrectly. As a result, segment data-based estimates of diversification are not an accurate measure of true diversification. The noise created by these inaccuracies reduces the minimal detectable effect of our analysis. This effect can be offset by maximizing the sample size.

While data inaccuracies that create noise can be offset by increasing sample size, a bias is cause for more serious concern. Those inaccuracies which can be assumed to be randomly distributed across the dataset, result in what is referred as noise. If data inaccuracies are correlated with our variables of interest, they may result in a "false positive". Errors of this type affect the validity of our analysis.

On one hand, the misallocation of firms to incorrect segments and the unintended aggregation of separate segments can be assumed to be random. As a result, the validity of our analysis will not be compromised. On the other hand, the issue resulting from differences in segment definition might result in a bias. Defining segments can be considered a management choice and is therefore the result of the preferences of management. These preferences are likely to also affect the strategic choices of management and hence overall firm characteristics.

Game-theoretic models suggest that high performing firms are less likely than low performers to disclose financial information (Darrough and Stoughton,1990; Feltham and Xie, 1992) and also to report segment data (Feltham, Gigler, and Hughes, 1990). Moreover, diversified firms tend to construct special segments for reporting purpose in order to avoid disclosing information to competitors about which of its operations are most lucrative. (Hayes and Lundholm, 1996). Assuming this is the case would result in a bias in high-performing industries as the segments of diversified firms would appear to be worse than what they actually are. The extent to which managers can change the definition of segments however is limited as their choices are subject to scrutinization by shareholders and third parties. Significant deviations of the generally accepted standards will therefore be punished by the market. It is reasonable to assume that the bias caused by management reporting decisions is limited.

Lastly, in our sample we are likely to overestimate diversification. Using the Berry-Herfindahl index we assume segments to be uncorrelated. According to the Fama French industry correlations, most segments are positively correlated. Therefore, we observe a larger diversification than if we were to correct for correlations. As a result any estimated relation between debt capacity and diversification will be biased. Given that correlations are mostly positive findings are not expected to affect the direction (i.e. a negative relation will not be estimated as positive or vice-versa).

4.3 Estimating Firm Debt Capacity

Firm debt capacity is estimated following Hess and Immenktter (2014) and de Jong, Verbeek and Verwijmeren (2011). The estimation model used in these papers, estimates debt capacity using the target credit ratings of firms. Graham and Harvey (2001) show using a survey that a primary concern of CFOs is maintaining target credit ratings. This indicates that firms do not have a target leverage level, but rather base their capital structure decisions on the potential effect on credit ratings. Additionally, Kisgen (2006) documents that financing decisions are closely related to credit ratings since a change in rating results to a shock in the costs of capital. Therefore Hess and Immenktter (2014) define debt capacity as the critical debt ratio that causes a firm to lose its target rating with a pre-defined probability.

4.3.1 Definition of Debt Ratio

In order to estimate the debt capacity of a firm, the current debt ratio needs to be measured appropriately. Our definition of the debt ratio in both market and book values follows Fama and French (2002) and Baker and Wurgler (2002). To calculate the debt ratio in book values we use book debt over book assets. Book debt is defined as total liabilities plus preferred stock less deferred taxes and convertible debt. The redemption value of preferred stock is used if preferred stock is missing. Book equity is then calculated by subtracting book debt from total assets.

When defining the debt ratio in market values, we use the common assumption that market value of debt equals book value. Market capitalization [3] is used as the market value of equity. To compute market capitalization, we use the share price and number of shares outstanding at the close of the fiscal year. Market value of assets is defined as book value of assets less book value of equity plus market value of equity. The debt ratio in market values is then computed as book liabilities over market value of assets. Following Hess and Immenktter (2012) we use total liabilities including both financial debt and non-financial liabilities, such as accounts payables. As we are interested in the maximum amount of liabilities a firm can bear, both types are included. Moreover, Welsh (2011) pointed out that excluding non-financial liabilities can result in biased implications.

Table 1 and 2 show the summary statistics for the Book Value and Market Value debt ratio in the sample. It is clearly observable that the majority of firms has either an A, a BBB or a BB rating. The average debt ratio is decreasing in the debt ratio. Moreover, the average Book Debt ratio is higher than the Market Debt ratio. It can further be observed that the average Book Debt ratio for firms with a CC rating or below is above 1, indicating that the book value of equity is negative (i.e. the firm is theoretically bankrupt). The Market Debt ratio however for these firms is, on average, below 1 indicating that equity markets still assign a positive value to those firms whose liabilities exceed the book value of their assets. Going forward, estimates using the market debt ratio will be referred to as market value based estimates, while those estimates using the book debt ratio will be referred to as book value based estimates

[3] Market capitalization is calculated as share price times number of shares outstanding

Table 3: Market Debt Ratios per Credit Rating

Credit Rating	**N**	**Mean**	**SD**	**p5**	**p95**
AAA	251	0.247	0.141	0.079	0.529
AA	1112	0.285	0.144	0.094	0.571
A	3770	0.354	0.149	0.124	0.610
BBB	5644	0.429	0.166	0.161	0.706
BB	5897	0.493	0.198	0.172	0.819
B	5164	0.598	0.226	0.188	0.932
CCC	493	0.772	0.211	0.336	0.990
CC	61	0.881	0.153	0.592	0.989
C	1	0.856	N/A	0.856	0.856
D	214	0.902	0.137	0.595	0.998
Total	22607	0.476	0.219	0.149	0.876

Source:COMPUSTAT Database

Table 4: Book Debt Ratios per Credit Rating

Credit Rating	**N**	**Mean**	**SD**	**p5**	**p95**
AAA	366	0.4724	0.1149	0.3050	0.6716
AA	1340	0.4747	0.1367	0.2543	0.7018
A	3734	0.5108	0.1526	0.2537	0.7619
BBB	5485	0.5397	0.1817	0.2605	0.8026
BB 6	6028	0.6015	0.2536	0.2327	1.0149
B 5	6625	0.7745	0.3712	0.2078	1.4312
CCC 4	650	0.9889	0.4611	0.3830	1.9323
CC 3	78	1.0782	0.5077	0.3603	2.1675
C 2	1	1.4304	.	1.4304	1.4304
D 1	223	1.2260	0.4993	0.5486	2.3155
Total	21640	0.606	0.296	0.271	1.008

Source:COMPUSTAT Database

4.3.2 Potential issues with the debt ratio

As mentioned previously, we assume that the market value of debt is equal to the book value of debt. For investment grade firms, the assumption that this ratio is one is generally accepted in literature. However, debt issued by firms with a non-investment grade credit rating often trades at a discount. These firms commonly report these debts at face value on their balance sheets. This results in the market value of debt being lower than the book value of debt. The assumption that debt and market value are equal therefore results in an overestimation of leverage for firms with non-investment grade credit ratings.

4.3.3 Credit Score Regression

Kisgen (2006) has shown that firms that are near a credit rating upgrade or downgrade are less likely to issue debt relative to equity than firms that are not near a change in ratings. This behavior is explained by the extra costs or benefits that are associated with a change but is not explained by traditional capital structure theory. Kisgen argues that managers' concern for a change in credit ratings is due to the indirect costs/benefits associated with different levels. Institutional investors have several regulations that are based on credit ratings and define if a bond can be held or not. Banks and pension funds might not be allowed to invest in firms with non-investment grade ratings. Additionally, investors groups such as insurance companies or brokers incur specific capital requirements for investing in a firms bond depending on the credit rating. A credit rating signals information about firm quality and the current state of the company. Kisgen concludes that managers are reluctant in adding on leverage if that implies a downgrade for their firm. Therefore, the debt capacity of a firm can be defined as the maximum amount of leverage a firm can take on without a downgrade. In this paper, we estimate debt capacity as the total amount of debt a firm can take on before it drops to below investment grade. We are aware that most AAA rated firms are not willing to accept a downgrade to the lowest investment grade rating. As we are interested in estimating the maximum leverage the firms operations can support rather than the target leverage. We model the amount of additional debt a firm can take on before it drops to BB rating. Using this method, we estimate the debt capacity for each firm based on the same constraints.

Using the concepts presented by Kisgen(2006), we use a credit score regression similar to Altman (1968), Kaplan and Urwitz (1979) and de Jong, Verbeek and Verwijmeren (2011) to estimate credit ratings for each firm-year observation. In this regression we estimate credit ratings as a function of the debt ratio and other firm characteristics using an ordered logit regression. This ordered logit regression, following Hess and Immenktter (2014) reads:

$$\begin{aligned} creditscore^*_{it} &= \alpha dr_{it} + \beta_1 x_{it} + \beta_2 z_{it} + \epsilon_{it} \qquad (3) \\ rating_{it} &= j, \text{if } \mu_{j-1} < creditscore^*_{it} < \mu_j, j = 1, ..., 10 \end{aligned}$$

In this ordered logit regression, $creditscore^*_{it}$ is the unobserved latent variable and μ_j , $j = 1, ..., 10$ denote the estimated thresholds between credit scores; $j = 10$ indicates a rating of AAA and j = 1 a rating of D. We do not distinguish between microratings (e.g. AA-, AA and AA+). The debt ratio is denoted by dr_{it}, while x_{it} refers to a vector of firm characteristics. According to Standard&Poors (2008) firm size, profitability, liquidity, age, asset characteristics and industry are key determinants of credit ratings. Following Hess and Immenktter (2012) we measure these factors using the following proxies.

$$\begin{aligned} FirmSize_{it} &= log(Revenue)_{it} \qquad (4) \\ Profitability_{it} &= EBITDA_{it}/Total\ Assets_{it} \\ Liquidity1_{it} &= Working\ Capital_{it}/Total\ Assets_{it} \\ Liquidity2_{it} &= Accounts\ Receivable_{it}/Total\ Assets_{it} \\ Tangibility_{it} &= Property,\ Plant\ \&\ Equipment_{it}/Total\ Assets_{it} \end{aligned}$$

In order to incorporate differences between industries in the credit score regression, dummy variables for each of the 49 Fama-French industries are included. Due to the exclusion of firms in the Financial Services and Utilities industry, our sample only includes firms covering 43 of the Fama and French industries.

4.3.4 Estimation of Debt Capacity

Using the credit regression above we can derive a measure of debt capacity. In doing this we once again follow **?**. For each *credit score*$_{it}$ larger than μ_j, we can define the probability of a downgrade to the rating j (or any lower rating) using the logit distribution:

$$P(rating_{it} \leq j) = \frac{1}{1 + \exp\left(-\mu_j + \alpha dr_{it} + \beta_1 x_{it} + \beta_2 z_{it} + \epsilon\right)} \tag{5}$$

Our primary debt capacity measure follows **?**, defining debt capacity by setting the debt ratio such that the probability of a downgrade to a below-investment-grade rating is equal to a constant probability p. We solve the equation for $j = 6$, as BB ($rating = 6$) is the lowest investment-grade rating. The resulting equation defines debt capacity as:

$$DC_t = \frac{log(1/p - 1) + \mu_6 - \beta_1 x_{it} - \beta_2 z_{it}}{\alpha} \tag{6}$$

The debt capacity, DC_{it} is defined as the debt ratio at which the probability of a downgrade equals p. For any debt ratio higher than DC_{it} the probability of a downgrade is higher than p. Therefore, assuming that the firm wants to avoid a downgrade, it has to keep its debt ratio below this threshold. These estimations of debt capacity, by definition, only hold for investment-grade firms. Moreover, we assume that all investment-grade firms are solely concerned with keeping an investment-grade rating and do not consider the potential loss of a more favourable rating.

4.4 Estimating the Impact of Diversification

Using the above model for the estimation of debt capacity, we analyse whether diversification is correlated with debt capacity. Furthermore, we can extend the above model to incorporate diversification to empirically test if the inclusion of a diversification measure increases the accuracy of the aforementioned credit score regression. In order to test for a correlation between diversification and debt capacity, various parametric and non-parametric tests are used. By initially testing for correlation, we check whether there is any relation between the estimates resulting from the currently used model. By amending the model we investigate if the inclusion of measures of diversification adds power to model. Through this method we analyse if diversification is related to debt capacity through another mechanism than the factors already included in the model (size, profitability, liquidity and tangibility).

4.4.1 Parametric Tests

In order to test for a relationship between diversification and debt capacity, we will be using both univariate and multivariate regression analysis as well as Pearson's product-moment correlation coefficient.

Pearson's coefficient is the most commonly used coefficient of correlation in both natural and social sciences. It is a parametric test which estimates the dependence between two variables as a coefficient between -1 and + 1.

Additionally, we will use simple univariate regression analysis using both the Berry-Herfindahl index and the broad definition of diversification [4]. In addition, both these measures will be used in a multivariate regression.

4.4.2 Non-Parametric Tests

In addition to the above parametric tests for diversification, we use several non-parametric tests. Non-parametric tests have the advantage that they do not depend on as many assumptions. Therefore, testing for a relation using non-parametric tests can give additional insights. We will be using the Mann-Whitney-U test, the Kendall tau rank correlation coefficient, Kolmogorov-Smirnov test, Mood's median test and Spearman's rank correlation coefficient.

In order to use the Mann-Whitney U test we will have to divide the sample into two groups. We define a control group and a treatment group. In the control group we include those firm who are fully undiversified or have a not significantly diversified, i.e. a BHI $<$ 0.25. In the treatment group we include only those firms with strong diversification, i.e. a BHI of 0.25 or higher. Using the Mann-Whitney U test, we test if the probability of the debt capacity of diversified firms being higher than that of single-industry firms is significantly different from 0.5. A significant deviation from 0.5 would indicate that there is a relation between both measures. Using a one-side test, the direction of this relation can be determined.

[4] number of 2 digit SIC segments

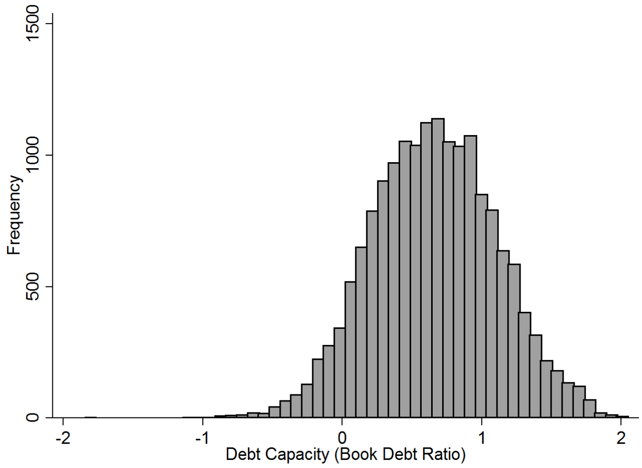
The Kendall rank correlation coefficient is a non-parametric test to measure association between two variables in sample. Kendall's tau, corrected for ties, can range from -1 to +1, indicating negative association and positive association respectively. Moreover, we can estimate the probability that Kendall's tau is normally distributed. For a perfectly unrelated sample, we expect Kendall's tau to be normally distributed. Therefore, the probability that Kendall's tau is normally distributed also shows the probability that both variables are independent.

Using the two-sample Kolmogorov-Smirnov test we can compare compare two different sample to test if these follow the same distribution. In order to use the Kolmogorov-Smirnov test we split our sample into two subsamples, using the same procedure used for the Mann-Whitney U test. The test quantifies the distance between the empirical distribution functions of both subsamples. The Kolmogorov-Smirnov test does not only consider the shape of the distribution but also the location. Therefore, we can estimate whether there is a difference between diversified and single-industry firms in either level of debt capacity or distribution of debt capacity.

Additionally, we will be using Mood's median test, a special case of the Pearson's chi-squared test. This non-parametric test estimates the probability that the medians of the two populations are equal. For this procedure we will again use the same subsamples as used for the Kolmogorov-Smirnov and Mann-Whitney U tests. The median test relies on few assumptions and only tests whether or not the medians of two populations are different. Using this test we can estimate if there are significant differences in the median level of debt capacity between diversified and single-industry firms.

Lastly, we will be using Spearman's rank correlation coefficient. We test the statistical dependence between debt capacity and diversification. The coefficient explains how well the relationship between the variables can be described as a monotonic function. Using this test we can asses the correlation between both variables, without the need to assume a particular function.

Figure 2: Sample Distribution of Debt Capacity estimates



5 Results

5.1 Credit Score Regression

Table 21 shows the results of the credit score regression using both market and book debt ratios. Both regressions indicate that debt ratio, firm size, profitability, liquidity and tangibility have an significant impact on a firms credit rating. Moreover, the majority of year dummies is significant, showing a impact of time on credit rating.

Additionally, we observe several significant industry dummies, differing in size. This confirms our predictions that certain industries have specific characteristics that affect the credit rating. Firms that operate in the Agricultural and Retail industries have lower credit ratings, while those firms that operate in the Soft Drinks and Publishing industries have higher credit ratings.

In order to assess the predictive power of our debt capacity model, we compare the credit ratings predicted by the credit score regression found in table (NR) to the actual credit ratings assigned by Standard&Poor's. Table 25 shows the accuracy of the credit ratings predicted by the credit score. Using market debt ratio, our credit score regression assigns a rating identical to Standard&Poor's rating in 52.75% of the firm-year observations. Moreover, for 94.61% of the observations, the predicted credit rating deviates less than 1 category from the actual credit rating.

Table 5: Accuracy of Credit Rating Predictions

Delta Credit Rank	**Market Value**		**Book Value**	
	N	Perc.	N	Perc
-7	1	0.00	0	0.00
-6	0	0.00	7	0.03
-5	29	0.13	36	0.15
-4	141	0.62	139	0.57
-3	51	0.23	78	0.32
-2	497	2.20	687	2.80
-1	4,447	19.67	4,945	20.16
0	12,114	53.59	12,066	49.19
1	4,867	21.53	5,635	22.97
2	390	1.73	764	3.11
3	34	0.15	107	0.44
4	34	0.15	63	0.26
5	1	0.00	3	0.01
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	1	0.00	0	0.00
Total	22,607	100.00	24,530	100.00

Source: COMPUSTAT Database

5.2 Parametric Tests

5.2.1 Market Value Based Estimations

In order to estimate the correlation between diversification and debt capacity we run both univariate and multivariate regression analysis using the Berry-Herfindahl Index and the number of 2-digit SIC segments as explanatory variables. Table 6 shows the results of these regression using the market value based estimations of debt capacity. We find significant and positive coefficient for all variables in both the multivariate and univariate regressions. These results indicate a positive correlation between diversification and debt capacity. The univariate regression indicates a positive correlation between debt capacity and the BHI as well as between debt capacity and the number of segments. Moreover, the multivariate regression indicates that the Berry-Herfindahl index has additional power over the broad measure of diversification[5] as we find a significant coefficient for both factors and an increased R^2.

Table 6: Univariate and Multivariate Regression Analysis using Market Values

Variable		**Coefficient** (Robust Std. Err.)	
Berry_HHI	0.3816^{**}		0.0758^{**}
	(0.0074)		(0.0146)
Nsegments		0.0951^{**}	0.0807^{**}
		(0.0017)	(0.0033)
Intercept	0.3949^{**}	0.2955^{**}	0.3080^{**}
	(0.0021)	(0.0033)	(0.0041)
		Summary Statistics	
N	22607	22607	22607
R^2	0.0939	0.1161	0.1171
$F_{(2,22604)}$	2672.4	3094.7	1635.0

Significance levels : † : 10% $*$: 5% $**$: 1%

In order to further check for correlation between debt capacity and diversification we estimate Pearson's correlation coefficient. We find significant and positive correlations between both diversification measures and debt capacity. This confirms the results from the regressions referred to before. Furthermore, we find the expected positive correlation between both diversification measures. The correlation variables are strongly, but not perfectly, correlated. This further confirms that the Berry-Herfindahl adds to the broad measure of diversification, as it captures additional firm characteristics.

[5] Number of segments

Table 7: Correlation Analysis using Market Value Based Estimates

Summary Statistics				
	Mean	Std. Dev	Min	Max
Debt Capacity	0.4509	0.4509	-1.2858	1.3211
NSegments	1.6339	0.9654	1	10
Berry_HHI	0.1469	0.2165	0	0.8578

Correlation Matrix			
	Debt Capacity	NSegments	BerryHHI
Debt Capacity	1.0000		
NSegments	0.3407	1.000	
BerryHHI	0.3065	0.8502	1.000

5.2.2 Book Value Based Estimations

Using the book value based estimates of debt capacity we apply the same parametric tests as used for the market value based estimates. Table 8 shows the results of the univariate and multivariate regression analysis. The results using book values are in line with those using market value based estimates. We find a positive and significant results for both univariate regressions, indicating a positive relation between diversification and debt capacity. Furthermore, we find a positive and significant coefficient for both the BHI and the number of segments in the multivariate regression. This does not only indicate a positive relationship, but also confirms the added value of the Berry-Herfindahl index. It should however be noted that the additional addition of the BHI does only marginally increase the R^2.

The absolute values of the coefficients for book value estimates cannot be compared to those for the market values, as the average book debt capacity is higher than the average market debt capacity. We however observe that the R^2 for market values is higher than the R^2 for book values (11.7% vs 6.6% for the multivariate regression). It therefore appears that diversification is more strongly related to market debt capacity than book capacity. This is in line with previous research indicating a relation between diversification and market capitalization. Market capitalization is used in the computation of market value based estimates of debt capacity, however it is not included in the book value based estimates.

Table 8: Univariate and Multivariate Regression Analysis using Market Values

Variable	Coefficient		
	(Robust Std. Err.)		
Berry_HHI	0.5187**		0.0796**
	(0.0133)		(0.0257)
Nsegments		0.1301**	0.11497**
		(0.0029)	(0.0057)
Intercept	0.4585**	0.3221**	0.3354**
	(0.0036)	(0.0056)	(0.0070)
Summary Statistics			
N	24530	24530	24530
R^2	0.0523	0.0660	0.0663
$F_{(1,24528)}$	1525.4	1954.9	996.1

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

The positive coefficients found using the regression analysis are further supported by Table 9. We find positive correlations between both the broad spectrum of debt capacity and the BHI. These correlations are slightly lower than the correlations found for market value based estimates, in line with the R^2 found using the univariate and multivariate regression. This further supports the stronger relation between diversification and market based estimates.

5.3 Non-Parametric Tests

In order to further test the relation between debt capacity and diversification we use various non-parametric tests, as defined in the methodology. Non-parametric tests in general rely on fewer assumptions than parametric tests and can therefore provide additional insights in the relationship between our variables of interest. Moreover, several non-parametric tests examine for specific relations or differences between samples. The more narrow nature of these tests allows for more specific results.

Similarly to the procedure used for parametric tests, we differentiate between market value based estimations and book value based estimations

Table 9: Correlation Analysis using Book Value Based Estimates

Summary Statistics				
	Mean	Std. Dev	Min	Max
Debt Capacity	0.5290	0.4795	-2.4174	1.9902
NSegments	1.5900	0.9465	1	10
Berry_HHI	0.1359	0.2114	0	0.8578

Correlation Matrix			
	Debt Capacity	NSegments	BerryHHI
Debt Capacity	1.0000		
NSegments	0.2569	1.000	
BerryHHI	0.2287	0.8532	1.000

when using non-parametric tests.

5.3.1 Market Value Based Estimations

Using market value based estimates, we use Kendall's tau rank correlation coefficient to measure the association between debt capacity and diversification. The τ-test is a measure of rank correlation, meaning it shows the similarity of the ordinal ranking of data when observations are ranked separately based on both values of interest.

Table 10 shows the results of the Kendall's τ-test. We find positive values for Kendall's τ-a and τ-b. The latter value is corrected for ties.[6] Considering that multiple ties occur in our dataset, tau-b is the preferred measure. Tau-b indicates positive rank association between the variables of interest.

These finding are in line with the results of the parametric tests. As the Kendall's τ-test does not assume any distribution for either of the variables, this further confirms the correlation found using the parametric tests.

In addition to the Kendall's τ-test we also test the relation using the

[6] The Kendall's tau test uses a sum of all ranks as part of the computation. When ties occur, two or more observation get assigned the same rank. Since all tied observations get assigned the lower rank (i.e. a tie between the first 2 places results in both observations receiving rank 1. The sum of these two ranks equals 2, while without ties this would have been 1 + 2 = 3.). The τ-b measure corrects for these ties.

Table 10: Kendall's Tau using Market Value Based Estimates

Number of obs	22607	
Kendall's tau-a	0.1940	
Kendall's tau-b	0.2429	
Kendall's score	49580777	
SE of Kendall's score	1002192	(corrected for ties)
Test of Ho: Debt Capacity and Berry-Herfindahl are independent		
Prob > $\lvert z \rvert$	0.0000	(continuity corrected)

two-sample ranksum Mann-Whitney U test. The Mann-Whitney U test shows if the probability that an observation from one population exceeds an observation from the other population is different from 0.5. If both samples are drawn from populations with the same distribution, we would not be able to predict which of two randomly selected observations is higher. The probability would be exactly 0.5. Since the Mann-Whitney U test looks at the probability of one observation exceeding the other, it is not only able to detect differences in mean or median but also differences in distribution (e.g. skewness and kurtosis).

In order to run this and other non-parametric tests, our dataset is divided into two sub-samples. Those firm-year observations with a BHI higher than 0.25 are considered to be diversified, while those with lower values are defined as non-diversified.

Table 11 shows the results of the Mann-Whitney U Test. We find that the H_0 can be rejected at all commonly used significance levels. This implies that the distribution of debt capacity of diversified firms is not equal to the distribution of non-diversified firms.

In order to specifically test for differences in median, we apply Mood's median test. The median test, unlike the Mann-Whitney U test ignores potential differences in distribution.Mood's median test calculates the median of the total dataset and divides the subsamples into a group below and above the median. If both subsamples have a similar median, we expect that for each subsample roughly 50% of the observations falls on either side of the median. Table 12 shows the results of the Median test using market value

Table 11: Two-Sample Ranksum Mann-Whitney U Test using Market Value Based Estimates

	Obs.	Rank Sum	Expected
Non-Diversified	16233	1.653e+08	1.835e+08
Diversified	6374	90291227	72051696
Combined	22607	2.555e+08	2.555e+08

Unadjusted Variance	1.949e+11
Adjustment for Ties	-2.0246277

Adjusted Variance	1.949e+11

Ho: Debt $\text{Capacity}_{\text{Diversified}}$ = Debt $\text{Capacity}_{\text{Non-Diversified}}$

Z	-41.311
$Prob > \|Z\|$	0.0000

based estimates.

It can be observed that the majority of non-diversified firms has a debt capacity below the median, while the majority of diversified firms has a debt capacity above the median. This indicates that both subsamples do not represent populations with equal medians. Using the Pearson Chi^2 we find that the medians of both populations differ at all conventional significance levels.

To test for differences in cumulative frequency distributions, we use a Two-sample Kolmogorov-Smirnov test. Table 13 shows the results of the Kolmogorov-Smirnov test using estimates based on market values. From the results as presented, we can conclude that the frequency distributions of both subsamples differ substantially at all significance levels. We furthermore find support for the hypothesis that the debt capacity of diversified firms is higher.

5.3.2 Book Value Based Estimations

Table 15 shows the results of the Kendall's τ-test using book value based estimations of debt capacity. Using the tau-b score we find a significant

Table 12: Median Test using Market Value Based Estimates

Greater than Median	Non-Diversified	Diversified	Total
No	9,323	1,981	11,304
Yes	6,910	4,393	11,303
Total	16,233	6,374	22,607

Pearson chi2(1)	1.3e+03	Pr =	0.000
Continuity corrected:			
Pearson chi2(1)	1.3e+03	Pr =	0.000

Table 13: Two-sample Kolmogorov-Smirnov test using Market Value Based Estimates

Smaller Group	**D**	**P-Value**	**Corrected**
Non-Diversified	0.2700	0.000	
Diversified	-0.0006	0.997	
Combined K-S	0.2700	0.000	0.000

Note:	Ties exist in the combined dataset;
	There are 22587 unique values out of 22607 observations

Table 14: Spearman Rank Correlation using Market Value Based Estimates

Debt Capacity and Berry-Herfindahl Index			
Number of Obs	22607	Spearman's Rho	0.3292
Test of H_0	Test of Ho: DebtCapacity and Berry-HI are independent		
Prob > $\|t\|$	0.00		

Debt Capacity and Nr. of Segments			
Number of Obs	22607	Spearman's Rho	0.3437
Test of H_0	Test of Ho: DebtCapacity and Berry-HI are independent		
Prob > $\|t\|$	0.00		

positive rank correlation. The rank coefficient is lower than the coefficient found using market value based estimations. In line with parametric tests this indicates a stronger relation between debt capacity and diversification if market value is used to compute leverage.

These findings are further supporting the theory that a part of the relation between market value based estimates of debt capacity is driven by market capitalization. Research has shown that the market capitalization of diversified firms is lower. This diversification discount can be expected to be present in the market debt ratio used in the credit score regression and hence influence our analysis. The significant results using book value, which is unaffected by the diversification discount, indicate that the diversification discount is not the sole driver of observed relation.

Table 15: Kendall's Tau using Book Value Based Estimates

Number of obs	24530	
Kendall's tau-a	0.1429	
Kendall's tau-b	0.1839	
Kendall's score	43002838	
SE of Kendall's score	1109553	(corrected for ties)
Test of Ho: Debt Capacity and Berry-Herfindahl are independent		
Prob $> \|z\|$	0.0000	(continuity corrected)

In order to further test for differences in distribution, we use the Mann-Whitney U test. Table 16 summarizes results. We once again split the dataset into two subsamples. We find, for all commonly used levels of significance, a difference in distribution between the diversified and non-diversified subsample. Unfortunately, due to the difference in sample size and extreme values for all measures, results cannot be compared to the Mann-Whitney U test using the market value based estimates. These results however do further confirm that the results found using market value based estimates are not solely driven by the diversification discount present in the market values.

To test if the difference in frequency distributions found with the market based Kolmogorov-Smirnov test holds in absence of the diversification

Table 16: Two-Sample Ranksum Mann-Whitney U Test using Book Value Based Estimates

	Obs.	Rank Sum	Expected
Non-Diversified	18118	2.066e+08	2.222e+08
Diversified	6412	94303906	78646386
Combined	24530	3.009e+08	3.009e+08

Unadjusted Variance	2.375e+11
Adjustment for Ties	-2.800

Adjusted Variance	2.375e+11

Ho: Debt $\text{Capacity}_{\text{Diversified}}$ = Debt $\text{Capacity}_{\text{Non-Diversified}}$

Z	-32.130
$Prob > \lvert Z \rvert$	0.0000

discount, we apply the Kolmogorov-Smirnov test to the book value based estimates. Table 18 shows the results.

We find a significant inequality of distribution functions for all significance levels. Comparing the results to the test using market values, we find a lower value for D. From the results displayed we can conclude that the diversification discount is not the sole factor driving the difference in frequency distributions.

Table 17: Two-sample Kolmogorov-Smirnov test using Book Value Based Estimates

Smaller Group	**D**	**P-Value**	**Corrected**
Non-Diversified	0.2043	0.000	
Diversified	-0.0002	1.000	
Combined K-S	0.2043	0.000	0.000

Note: Ties exist in the combined dataset;
There are 24501 unique values out of 24530 observations

Table 18: Spearman Rank Correlation using Book Value Based Estimates

Debt Capacity and Berry-Herfindahl Index			
Number of Obs	24530	Spearman's Rho	0.2478
Test of H_0	Test of Ho: DebtCapacity and Berry-HI are independent		
Prob > $\|t\|$	0.00		

Debt Capacity and Nr. of Segments			
Number of Obs	24530	Spearman's Rho	0.2594
Test of H_0	Test of Ho: DebtCapacity and Berry-HI are independent		
Prob > $\|t\|$	0.00		

5.4 Amended Credit Score Regression

Lastly, we test whether or not the accuracy of the debt capacity model increases if diversification measures are included. Debt capacity is estimated using a order logit regression, which includes size, profitability, liquidity, tangibility, industry, year and age for each of the firm-year observations. To test if diversification measures increase the accuracy of this model, we amend the model to include both the Berry-Herfindahl index and the broad spectrum diversification measure. The ordered logit regression found can be used to estimate the critical debt capacity at which a firm has a chance p to get downgraded below a credit rating j.

Table 19 shows the result of the ordered logit regression. We find that the amended model has a significant coefficient for the Berry-Herfindahl index. The coefficient for the broad spectrum definition of diversification (nr. of segments) is significant at the 10% level for market value based estimates, but insignificant for book value based estimations. This may indicate that the BHI is more accurate proxy for firm diversification and riskiness. These finding further indicate that there is a positive relationship between diversification and credit rating i.e. firm with a higher level of diversification tend to have superior credit rating. This implies that, all others constant, firms with a higher level of diversification are expected to have a higher debt capacity. These findings are in line with the results from the parametric and non-parametric tests using the original regression.

Table 19: Amended Model: Credit Score Regression

Variable	**Coefficient** (Std. Err.)	
	Market Value	Book Value
DebtRatio	-8.396**	-4.429**
	(0.088)	(0.056)
Berry-HI	0.428**	0.488**
	(0.115)	(0.112)
Nr. of Segments	0.046†	-0.025
	(0.026)	(0.025)
FirmSize	1.995**	1.757**
	(0.021)	(0.019)
Profitability	0.012	0.475**
	(0.016)	(0.016)
Liquidity1	0.016	-0.010
	(0.017)	(0.018)
Liquidity2	0.115**	0.181**
	(0.019)	(0.018)
Tangibility	0.259**	0.434**
	(0.020)	(0.019)
Year Dummies	33/33 significant	24/33 significant
Industry Dummies	26/43 significant	32/43 significant
Age Dummies	0/10 significant	2/10 significant
Summary Statistics		
N	22607	24530
Log-likelihood	-24936.32	-29509.82
$\chi^2_{(82)}$	25861.96	24338.33
Pseudo-R^2	0.3415	0.2920

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

To benchmark the power of this method, we compare the credit ratings generated by the ordered logit regression to the actual credit ratings assigned by Standard & Poor's. We compare the distribution of the delta in credit rating (i.e. how many full rating steps do the actual and predicted rating differ) to the distribution of the delta using the original model as used previously.

Table 22 shows a comparison of the distributions for the original and amended model using market value based estimates of the debt ratio. Although we find some increased accuracy (53.73% versus 53.59%) when considering fully accurate estimations, these changes are minor and mostly offset (94.86% versus 94.79%) if we consider the -1 to +1 range of delta's. This implies that the majority of the effects of diversification is already captured by the variables used in the original regression.

Table 23 shows distribution of delta for the estimates using book values. We find a small increase in the number of fully accurate estimations, but a small decrease in the number of estimations with a delta of 1 or -1. This is in line with the findings using market value based estimates.

6 Further robustness tests

In order to further test the robustness of our results, we will be looking at several subsamples of our dataset. Through the use of subsamples, will empirically test whether this relationship holds for various specific types of firms and time periods. We strive to control for firm success, non-organic growth and time-specific effects.

6.1 Non-Organic Growth

Over time, firms might go through significant changes in strategic direction which sometimes results in large fluctuations in the capital structure. Moreover, changes that affect capital structure can also have an indirect effect on business continuation. Mergers and acquisitions are examples of events when firms are experiencing drastic change in terms of size of assets, profitability, financial policy, credit ratings or other factors. Epstein (2004) has shown that the process of integrating two firms, post-merger integration, takes a lot of time and efforts and affects the firm in several ways. It has also been argued that firms that engage in mergers see large impacts on profitability and market share which can affect industry structure and aggregate concentration levels. Mergers are often driven by the potential of realizing synergies. Research show that synergies are often overestimated, whereas indirect costs of implementation are often underestimated which results in either negative synergies, or longer lead times for actual synergies to materialize. Therefore, although mergers are expected to have a positive effect on diversification, the added value can be lagged in time.Moreover, mergers make firms end up in different size categories and might therefore result in inconsistencies for results.

Ravenscraft and Scherer (1987) regressed profits on individual lines of business between 1975-77 on industry dummies and a variable that measured the fraction of the line of business that later had been acquired since 1950. While controlling for the fact if the merger was hostile or not, market share and some accounting issues they found that the profit rates of the acquired lines of business were 2.82% below those of non-acquired units. These negative effects can in some cases affect the firm for a couple of consecutive years going forward. Therefore, when a firm is identified as jumping, it will be identified as jumping for all future years.

In order to eliminate the effect of mergers and acquisitions, we will look at a sub-sample of non-jumping firms. I.e. firms with changes in total assets not exceeding 50% a year for any of the previous years in the dataset. The binary variable used to define a firm as "jumping" is "sticky". If a firm experiences more than 50% growth for any of the time periods in the sample, it will be classified as jumping going forward.

6.1.1 Results

Using both subsamples, we estimate the debt capacity for each firm-year observation. Tables 24 and 27 show the result for the ordered logit regression using market and book debt ratios for both sub-samples.

It can be observed that the "jumping" firms' credit score regressions for book and market values have fewer significant industry observations. This may indicate that the current industries are less important for firms whom engage in non-organic growth. These results could be explained given that for firms that grow organically, current industries more correlated with future industries and therefore more important.

Using the results from the credit score regression, we estimate debt capacity. We use the estimates to run several univariate and multivariate regressions. Tables 26 and 29 show the results of these regressions. We find that the Berry-Herfindahl index is more significant and adds more power (R^2) to the regression for firms that grow non-organically. This indicates that relative size of segments is more important for firms that engage in mergers and acquisitions. If we assume that the Berry-Herfindahl is not only a proxy for the diversification of cash flows, but also indicates the relative size of recent acquisitions, we could explain this difference. The relative size of an acquisition impacts a firm through several mechanisms and can be expected to be correlated with debt capacity (e.g. through profitability and liquidity).

6.2 Firm success

Firstly, we create a sub-sample of surviving firms (i.e. firms still active according to the Compustat database). There may be a relationship between firm survival and the impact of diversification on debt capacity. Hypothetically, firms that survive are more likely to have built up a track record in the bond market. For these firms, the benefits of diversification may differ from the benefit of those firms that do not have a strong reputation in the markets. We therefore analyze active and inactive firms separately, to test whether or not our results are robust for firm success.

6.2.1 Results

Using sub-samples of active and inactive firms, we use the credit score regression to estimate debt capacity. We use univariate and multivariate regression analyse the relation between debt capacity and diversification.

Tables 30 till 35 show the result using survival based sub-samples. These results found are in line with the general results. We find that the accuracy of the credit score regression is higher for inactive firms. It should however be noted that there are no significant differences between inactive and active firms, indicating that the relationship between debt capacity and diversification holds for both "succesful" and "unsuccessful" firms. Findings are consistent using both book value and market value based estimates of debt capacity.

6.3 Economic Cycle

Extreme changes in the market leads academics and practitioners to question widely believed theories about corporate diversification. The generally negative view that emerged in the 80s made many conglomerates disappear and during 2000s the debate of diversification discount or the lack of it was kicking off. The global financial crisis revived the views about the added value of corporate diversification and that the conglomerates were ready for a comeback. The broader question is to understand if diversification and its underlying drivers matters more during recessions or extreme market conditions or if changes are driven by investor sentiments or perceptions.

The idea behind diversification being more valuable when a crisis hits, is that banks and bondholders may prefer to lend their scarce funds to safer conglomerates rather than to riskier stand-alone businesses. Therefore, stand-alone firms will find it harder to engage in investment activities and become disadvantaged and lose competitiveness.

In order to estimate the impact of diversification and explore capital structure dynamics when markets are extreme and external financing is constrained, we create a subsample including specific time-periods in between 1981-2013. Following the discussion of **?** et al we study the impact of diversification within business cycles and in particular, the effects of diversification in times of recession. As we only look at US data, we study four recessions, as defined by ECRI (Economic Cycle Research Institute). Each of the firm-year observations will be assigned to a subsample. Halling et al find strong evidence for active capital structure management and that leverage is related to firm characteristics and business cycles. Following these findings, it is therefore meaningful to study if diversification matters more in recessions. Based on economic theory and research by **?** and Kuppuswamy and Villalonga (2010) we expect to find tendencies of procyclical dynamics and an overall larger impact of diversification in these time periods.

6.3.1 Results

Using sub-samples of firm-year observations during recessions and observations during "normal" time periods we control for the impact of the economic cycle on the impact of diversification. We apply the credit score regression to estimate debt capacity and use univariate and multivariate regression analysis to estimate the relation between diversification and maximum leverage.

Results are summarized in Tables 36 until 41. The results are in line with the general findings. We find no significant deviations from the results of the overall analysis, indicating our results are robust across the economic cycle.

6.4 Geographic Diversification

During the last decades, many firms have used international expansion as a growth strategy. Given the rapid increase in firms expanding globally, we extend our analysis by including geographical segment data. In the Compustat database, there is no standard for reporting geographical segments. The quality of the data is to a certain extent less accurate as firms themselves report the geographical segments and therefore create noise. For instance, certain firms might classify their global operations as domestic and non-domestic whereas other firms might report each specific country separately.

6.4.1 Results

Tables 42, 43 and 44 show the results based on geographical diversification measures. The results found are in line with our findings using industry diversifications.

In contrast to the findings using industry diversification, we find a negative coefficient for the number of segments, indicating that a presence in a large number of geographical regions may not be beneficial to debt capacity.

7 Conclusions

In this paper we use a commonly used, well documented method to estimate firm debt capacity. Using these estimates we shed a light on the relation between debt capacity and diversification. Firstly, we find evidence for a positive relation between debt capacity and diversification using both parametric and non-parametric tests. These findings support Lewellen's co-insurance theorem and are further backed up by various sub-samples. Secondly, we find a stronger relation using market value based estimates than using book value based estimates, indicating that the "diversification discount" found in equity markets influences our results. We control for this using book values and find a significant relations, confirming market value based findings.

Using an amended model for the estimation of debt capacity, we find that there is a significant and positive relation between diversification measured by the Berry-Herfindahl index and credit ratings. This implies that those firms which are diversified are expected to have higher credit ratings. All other constant, this indicates that firms operating in multiple segments have a higher debt carrying capacity. We however find little improvement in the accuracy of the credit rating estimations found using the credit score regression.

Prior to our analysis, we formulated two hypotheses:

1. Diversification is positively associated with debt capacity
2. The inclusion of diversification when estimating debt capacity improves model accuracy.

In this paper, we find evidence supporting hypothesis 1. A clear relation between diversification and maximum leverage can be observed using both parametric and non-parametric tests. This relation is further confirmed by a significant coefficient for the BHI in the amended credit score regression.

It is to be expected, that if hypothesis 1 holds, hypothesis 2 follows. If there is a strong relation between diversification and debt capacity, we would expect diversification to increase the accuracy of the estimation model. Through our analysis we, however, find limited support for hypothesis 2. Although the coefficient for the BHI is significant is both the credit score regression for book values, we find little or no improvement in the accuracy of credit rating estimates. This may indicate that most of the effects of diversification are already captured by other variables, such as firm size, profitability, tangibility and liquidity.

Moreover, using sub-samples of "jumping" and "non-jumping" firms to control for the impact of non-organic growth, we find that the additional power of the Berry-Herfindahl index of diversification over the number of industries is low for firms that rely on organic growth. These firms also show a larger impact of industry on overall debt capacity. This implies that for those firm that grow organically, the number of segments has more explanatory power than the relative size of segments. For firms that grow exponentially, relative size matters. A potential explanation is that for firms that grow through acquisitions, relative size of segments is a proxy for the size of the acquisitions. Therefore, the BHI captures acquisition behavior rather than absolute diversification of cash flows.

8 Implications and Suggestions for further research

The findings and conclusions presented in this paper have several implications for future research. Furthermore, based on our findings, several additional questions worth researching arise. Lastly, we recognize several areas of potential refinement in the methodology used in this paper. By implementing these suggestions, several of the limitations of the method applied in this thesis may be circumvented.

8.1 Potential topics for further research

Our findings in this paper indicate that there is a strong relation between the degree of diversification and the maximum leverage a firm can sustain. Economic theory, such as the co-insurance theory, indicate that the decreased volatility of cash flows is a key driver of such a relation. Our finding based on the amended credit score regression model however indicate that the inclusion of diversification measures, albeit significant, adds little accuracy to the original model. This indicates that most of the relation between diversification and debt capacity is explained by variables in the original model.

The original model includes firm size, profitability, liquidity and tangibility. Volatility is not a component of the original model, but is expected to be related to diversification. A possible area for further research would be the relation between volatility, diversification and the variables in the original. Our research indicates that the variables in the original model may serve as a proxy for diversification and volatility, eliminating the need to include these variables. Further research into this relationship could further explain our findings.

8.2 Potential refinements in methodology

8.2.1 Measure of diversification

Due to the nature of this paper, which aims to investigate the potential relationship between debt capacity and diversification and the implications for debt capacity estimation, rather than look into the details and exact drivers of this relationship, we rely on well-documented measures of diversification. As mentioned in the data section, we observe that the Berry-Herfindahl index has several shortcomings in measuring. Firstly, it does not include any measure of correlation between industries. This could potentially be corrected by developing a more complex measure of diversification that includes the correlations between industries. A potential approach would be to divide segments according to the Fama-French industries and use the correlations between the annual stock returns as a proxy for the correlations between underlying cash-flows. Further research into the accuracy of diversification measures is required.

8.2.2 Data selection

The analysis in this paper is limited to firms which are listed and issuing bonds in either Canada or the United States. It is too be expected that the findings in this paper do also hold for those firms listed outside the North American market. It should however be noted that most non-western financial markets are less developed than the North American markets. Therefore firms may be constrained in their access to capital, which may impact the relations as found in this paper.

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A Appendix

A.1 Appendix: Data Description

Table 20: Distribution of Sample Industries

Fama-French industry code	**Freq.**	**Percent**
Agriculture	106	0.33
Food Products	735	2.26
Candy & Soda	203	0.62
Beer & Liquor	120	0.37
Tobacco Products	131	0.40
Recreation	200	0.62
Entertainment	753	2.32
Printing and Publishing	398	1.23
Consumer Goods	570	1.75
Apparel	364	1.12
Healthcare	571	1.76
Medical Equipment	298	0.92
Pharmaceutical Products	758	2.33
Chemicals	1,232	3.79
Rubber and Plastic Products	317	0.98
Textiles	253	0.78
Construction Materials	765	2.35
Construction	527	1.62
Steel Works Etc	738	2.27
Fabricated Products	79	0.24
Machinery	1,107	3.41
Electrical Equipment	400	1.23
Automobiles and Trucks	676	2.08
Aircraft	308	0.95
Shipbuilding, Railroad Equipment	121	0.37
Defense	85	0.26
Precious Metals	92	0.28
Non-Metallic and Industrial Metal Minin	223	0.69
Coal	59	0.18
Petroleum and Natural Gas	2,186	6.73
Utilities	4,564	14.05
Communication	2,837	8.73
Personal Services	306	0.94
Business Services	1,111	3.42
Computer Hardware	460	1.42
Computer Software	695	2.14
Electronic Equipment	1,081	3.33
Measuring and Control Equipment	284	0.87
Business Supplies	845	2.60
Shipping Containers	253	0.78
Transportation	1,626	5.00
Wholesale	884	6.63
Restaraunts, Hotels, Motels	542	1.67
Almost Nothing	471	1.45
Total	32,488	100.00

Source: COMPUSTAT Database

A.2 Appendix: Original Credit Score Regression

Table 21: Original Credit Score Regression

Variable	**Coefficient** (Std. Err.)	
	Market Value	Book Value
DebtRatio	-8.387**	-4.427**
	(0.088)	(0.056)
FirmSize	2.030**	1.774**
	(0.021)	(0.019)
Profitability	0.002	0.471**
	(0.016)	(0.016)
Liquidity1	0.012	-0.013
	(0.017)	(0.018)
Liquidity2	0.107**	0.178**
	(0.019)	(0.018)
Tangibility	0.231**	0.414**
	(0.020)	(0.019)
Year Dummies	32/33 significant	24/33 significant
Industry Dummies	27/43 significant	36/43 significant
Age Dummies	2/10 significant	2/10 significant
Summary Statistics		
N	22607	24530
Log-likelihood	-24978.30	-29530.11
$\chi^2_{(82)}$	25778.00	24297.75
Pseudo-R^2	0.3404	0.2915

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

A.3 Appendix: Amended Model

Table 22: Amended Model: Accuracy of the Credit Rating Predictions using Market Values

Delta Credit Rank	**Original**		**Amended**	
	N	Perc.	N	Perc
-7	1	0.00	1	0.00
-6	0	0.00	0	0.00
-5	29	0.13	26	0.12
-4	141	0.62	143	0.63
-3	51	0.23	50	0.22
-2	497	2.20	479	2.12
-1	4,447	19.67	4,437	19.63
0	12,114	53.59	12,147	53.73
1	4,867	21.53	4,860	21.50
2	390	1.73	394	1.74
3	34	0.15	34	0.15
4	34	0.15	34	0.15
5	1	0.00	1	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	1	0.00	1	0.00
Total	22,607	100.00	22,607	100.00

Source: COMPUSTAT Database

Table 23: Amended Model: : Accuracy of the Credit Rating Predictions using Book Values

Delta Credit Rank	**Original**		**Amended**	
	N	Perc.	N	Perc
-6	7	0.03	6	0.02
-5	36	0.15	36	0.15
-4	139	0.57	140	0.57
-3	78	0.32	79	0.32
-2	687	2.80	678	2.76
-1	4,945	20.16	4,921	20.06
0	12,066	49.19	12,101	49.33
1	5,635	22.97	5,642	23.00
2	764	3.11	750	3.06
3	107	0.44	109	0.44
4	63	0.26	65	0.25
5	3	0.01	3	0.01
Total	24,530	100.00	24,530	100.00

Source: COMPUSTAT Database

A.4 Appendix: Sub-samples for Non-Organic Growth

A.4.1 Appendix: Sub-sample for Non-Organic Growth: Market Values

Table 24: Non-Organic Growth Sub-sample: Credit Score Regression using Market Values

Variable	**Coefficient** (Std. Err.)	
	Non-Jumping	Jumping
DebtRatio	-8.064**	-9.918**
	(0.096)	(0.228)
FirmSize	2.081**	2.060**
	(0.023)	(0.051)
Profitability	-0.003	-0.022
	(0.018)	(0.039)
Liquidity1	0.029	-0.045
	(0.020)	(0.039)
Liquidity2	0.107**	0.137**
	(0.021)	(0.050)
Tangibility	0.247**	0.200**
	(0.022)	(0.048)
Year Dummies	30/30 significant	31/32 significant
Industry Dummies	28/43 significant	18/42 significant
Age Dummies	0/10 significant	0/10 significant
Summary Statistics		
N	18081	4526
Log-likelihood	-20142.46	-4622.96
$\chi^2_{(82)}$	20130.48	5569.41
Pseudo-R^2	0.3332	0.3759

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 25: Non-Organic Growth Sub-sample: Accuracy of Credit Rating Predictions using Market Values

Delta Credit Rank	**Non-Jumping**		**Jumping**	
	N	Perc.	N	Perc
-7	1	0.01	0	0.00
-6	0	0.00	0	0.00
-5	26	0.14	2	0.04
-4	127	0.70	14	0.31
-3	46	0.24	5	0.11
-2	397	2.20	91	2.01
-1	3,540	19.58	831	18.36
0	9,623	53.22	2,614	57.76
1	3,942	21.80	892	19.71
2	331	1.83	62	1.37
3	25	0.14	8	0.18
4	24	0.13	7	0.15
5	1	0.01	0	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	1	0.01	0	0.00
Total	18,081	100.00	4,526	100.00

Source: COMPUSTAT Database

Table 26: Non-Organic Growth Sub-sample: Univariate and Multivariate Regressions using Market Values

Variable	(Coefficient)					
	(Robust Std. Err.)					
	Non-Jumping			Jumping		
Berry_HHI	0.4100**		0.0656**	0.2623**		0.1006**
	(0.0088)		(0.0170)	(0.0136)		(0.0295)
Nsegments		0.1016**	0.0894**		0.0664**	0.0252**
		0.0020	(0.0038)		(0.0034)	(0.0007)
Intercept	0.3684**	0.2623**	0.2727**	0.4933**	0.4242**	0.4434**
	(0.0024)	0.0038	(0.0047)	(0.0045)	(0.0071)	(0.0089)
	Summary Statistics					
N	18081	18081	18081	4526	4526	4526
R^2	0.0980	0.1249	01256	0.0637	0.0691	0.0714

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

A.4.2 Appendix: Sub-sample for Non-Organic Growth: Book Values

Table 27: Non-Organic Growth Sub-sample: Credit Score Regression using Book Values

Variable	**Coefficient** (Std. Err.)	
	Inactive	Active
DebtRatio	-3.911**	-5.000**
	(0.058)	(0.158)
FirmSize	1.721**	1.861**
	(0.020)	(0.050)
Profitability	0.468**	0.603**
	(0.018)	(0.041)
Liquidity1	0.017	-0.135**
	(0.021)	(0.043)
Liquidity2	0.164**	0.258**
	(0.019)	(0.049)
Tangibility	0.266**	0.061
	(0.021)	(0.048)
Year Dummies	25/31 significant	21/32 significant
Industry Dummies	33/43 significant	16/42 significant
Age Dummies	2/10 significant	0/10 significant
Summary Statistics		
N	20203	4378
Log-likelihood	-24583.76	-4926.03
$\chi^2_{(82)}$	19476.42	4658.41
Pseudo-R^2	0.2837	0.3210

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 28: Non-Organic Growth Sub-sample: Accuracy of Credit Rating Predictions using Book Values

Delta Credit Rank	**Inactive**		**Active**	
	N	Perc.	N	Perc
-7	0	0.00	0	0.00
-6	7	0.03	0	0.00
-5	30	0.15	3	0.07
-4	127	0.63	17	0.39
-3	75	0.37	4	0.09
-2	578	2.86	108	2.47
-1	4,024	19.92	851	19.44
0	9,882	48.91	2,349	53.65
1	4,646	23.00	936	21.38
2	688	3.41	86	1.96
3	91	0.45	24	0.55
4	51	0.25	0	0.00
5	4	0.02	0	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	0	0.01	0	0.00
Total	20,203	100.00	4,526	100.00

Source: COMPUSTAT Database

Table 29: Non-Organic Growth Sub-sample: Univariate and Multivariate Regressions using Book Values

Variable			**(Coefficient)**			
			(Robust Std. Err.)			
		Inactive			**Active**	
Berry_HHI	0.5739**		0.0377	0.4155**		0.1796**
	(0.0169)		(0.0318)	(0.0276)		(0.0572)
Nsegments		0.1456**	0.1386**		0.1025**	0.0647**
		0.0036	(0.0069)		(0.0068)	(0.0138)
Intercept	0.4015**	0.2477**	0.2538**	0.1589**	0.0539**	0.0880**
	(0.0043)	0.0068	(0.0085)	(0.0089)	(0.0141)	(0.0174)
	Summary Statistics					
N	20203	20203	20203	4378	4378	4378
R^2	0.0492	0.0660	0.660	0.0424	0.0448	0.0446

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

A.5 Appendix: Sub-samples for Survival

A.5.1 Appendix: Sub-sample for Survival Book Values

Table 30: Survival Sub-sample: Credit Score Regression using Book Values

Variable	**Coefficient** (Std. Err.)	
	Inactive	Active
DebtRatio	-3.740**	-4.763**
	(0.0748)	(0.086)
FirmSize	1.479**	1.790**
	(0.0276)	(0.025)
Profitability	0.483**	0.471**
	(0.0256)	(0.022)
Liquidity1	0.146**	-0.163
	(0.0269)	(0.024)
Liquidity2	0.198**	0.175**
	(0.0276)	(0.024)
Tangibility	0.621**	0.206**
	(0.0289)	(0.026)
Year Dummies	24/30 significant	22/33 significant
Industry Dummies	31/43 significant	31/43 significant
Age Dummies	0/10 significant	1/10 significant
Summary Statistics		
N	10531	13999
Log-likelihood	-12654.17	-16166.30
$\chi^2_{(82)}$	9789.02	14895.77
Pseudo-R^2	0.2789	0.3154

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 31: Survival Sub-sample: Accuracy of Credit Rating Predictions using Book Values

Delta Credit Rank	**Inactive**		**Active**	
	N	Perc.	N	Perc
-7	0	0.00	0	0.00
-6	4	0.04	1	0.01
-5	19	0.18	16	0.11
-4	86	0.82	40	0.29
-3	50	0.47	34	0.24
-2	295	2.80	369	2.64
-1	1,967	18.68	2,880	20.57
0	5,304	50.37	7,046	50.33
1	2,354	22.35	3,261	23.29
2	367	3.48	287	2.05
3	55	0.52	37	0.26
4	27	0.26	27	0.19
5	3	0.03	1	0.01
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	0	0.00	0	0.00
Total	10,531	100.00	13,999	100.00

Source: COMPUSTAT Database

Table 32: Survival Sub-sample: Univariate and Multivariate Regressions using Book Values

Variable			**(Coefficient)**			
			(Robust Std. Err.)			
		Inactive			**Active**	
Berry_HHI	0.5356^{**}		0.0303	0.5208^{**}		0.0981^{**}
	(0.0242)		(0.0493)	(0.0174)		(0.0323)
Nsegments		0.1412^{**}	0.1351^{**}		0.1277^{**}	0.1095^{**}
		0.0057	(0.0117)		(0.0037)	(0.0068)
Intercept	0.3085^{**}	0.1605^{**}	0.1669^{**}	0.5455^{**}	0.4111^{**}	0.4266^{**}
	(0.0060)	0.0101	(0.0136)	(0.0049)	(0.0075)	(0.0088)
	Summary Statistics					
N	10531	10531	10531	13999	13999	13999
R^2	0.0395	0.0513	0.0513	0.0542	0.0680	0.0685

Significance levels : † : 10% $*$: 5% $**$: 1%

A.5.2 Appendix: Sub-sample for Survival: Market Values

Table 33: Survival Sub-sample: Credit Score Regression using Market Values

Variable	**Coefficient** (Std. Err.)	
	Inactive	Active
DebtRatio	-7.206**	-8.264**
	(0.130)	(0.118)
FirmSize	1.752**	1.969**
	(0.032)	(0.027)
Profitability	0.044	-0.022
	(0.026)	(0.021)
Liquidity1	0.180**	-0.153**
	(0.030)	(0.024)
Liquidity2	0.091**	0.160**
	(0.030)	(0.025)
Tangibility	0.357**	0.139**
	(0.032)	(0.027)
Year Dummies	22/29 significant	33/33 significant
Industry Dummies	34/43 significant	23/43 significant
Age Dummies	0/10 significant	2/10 significant
	Summary Statistics	
N	8989	13618
Log-likelihood	-10019.26	-14484.43
$\chi^2_{(82)}$	9245.68	16310.72
Pseudo-R^2	0.3157	0.3602

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 34: Survival Sub-sample: Accuracy of Credit Rating Predictions using Book Values

Delta Credit Rank	**Inactive**		**Active**	
	N	Perc.	N	Perc
-7	1	0.01	0	0.00
-6	0	0.00	0	0.00
-5	14	0.16	14	0.10
-4	91	1.01	40	0.29
-3	35	0.39	28	0.21
-2	185	2.06	293	2.15
-1	1,713	19.06	2,655	19.50
0	4,805	53.45	7,520	55.22
1	1,918	21.34	2,848	20.91
2	178	1.98	197	1.45
3	30	0.33	8	0.06
4	17	0.19	15	0.11
5	1	0.01	0	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	1	0.01	0	0.00
Total	8,989	100.00	4,526	100.00

Source: COMPUSTAT Database

Table 35: Survival Sub-sample: Univariate and Multivariate Regressions using Market Values

Variable			**(Coefficient)**			
			(Robust Std. Err.)			
		Inactive			**Active**	
Berry_HHI	0.4536**		0.1329**	0.3885**		0.0669**
	(0.0132)		(0.0278)	(0.0102)		(0.0195)
Nsegments		0.1156**	0.0883**		0.0954**	0.0831**
		0.0033	(0.0068)		(0.0023)	(0.0043)
Intercept 0	0.3136**	0.1952**	0.2198**	0.4352**	0.3344**	0.3447**
	(0.0034)	0.0059	(0.0080)	(0.0030)	(0.0046)	(0.0054)
	Summary Statistics					
N	8989	8989	8989	13618	13618	13618
R^2	0.1046	0.1200	0.1223	0.0855	0.1086	0.1094

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

A.6 Appendix: Sub-sample for Recessions

A.6.1 Appendix: Sub-Sample for Recessions: Book Values

Table 36: Recession Sub-sample: Credit Score Regression using Book Values

Variable	**Coefficient** (Std. Err.)	
	No Recession	Recession
DebtRatio	-4.420**	-4.595**
	(0.059)	(0.184)
FirmSize	1.773**	1.780**
	(0.020)	(0.059)
Profitability	0.470**	0.450**
	(0.017)	(0.051)
Liquidity1	-0.023	0.105
	(0.019)	(0.057)
Liquidity2	0.184**	0.133**
	(0.019)	(0.057)
Tangibility	0.419**	0.379**
	(0.020)	(0.060)
Year Dummies	24/30 significant	3/6 significant
Industry Dummies	33/43 significant	14/43 significant
Age Dummies	3/10 significant	1/10 significant
Summary Statistics		
N	22090	2440
Log-likelihood	-26598.38	-2861.66
$\chi^2_{(82)}$	21984.41	2435.32
Pseudo-R^2	0.2924	0.2985

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 37: Recession Sub-sample: Accuracy of Credit Rating Predictions Market

Delta Credit Rank	**No Recession**		**Recession**	
	N	Perc.	N	Perc
-7	0	0.00	0	0.00
-6	7	0.03	0	0.00
-5	33	0.15	4	0.16
-4	130	0.59	7	0.29
-3	68	0.31	9	0.37
-2	616	2.79	69	2.83
-1	4,450	20.14	488	20.00
0	10,887	49.28	1,235	50.61
1	5,039	22.81	555	22.75
2	700	3.17	59	2.42
3	97	0.44	10	0.41
4	59	0.27	4	0.16
5	4	0.02	0	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	0	0.00	0	0.00
Total	22,090	100.00	4,526	100.00

Source: COMPUSTAT Database

Table 38: Recession Sub-sample: Univariate and Multivariate Regressions using Book Values

Variable			**(Coefficient)**			
			(Robust Std. Err.)			
		No Recession			**Recession**	
Berry_HHI	0.5206**		0.0800**	0.5263**		0.0703
	(0.0140)		(0.0274)	(0.0427)		(0.0772)
Nsegments		0.1307**	0.1154**		0.1315**	0.1183**
		0.0031	(0.0061)		(0.0090)	(0.0163)
Intercept	0.4607**	0.3238**	0.3372**	0.4335**	0.2940**	0.3056**
	(0.0038)	0.0060	(0.0075)	(0.0106)	(0.0168)	(0.0202)
	Summary Statistics					
N	22090	22090	22090	2440	2440	2440
R^2	0.0521	0.0656	0.0659	0.0563	0.0725	0.0728

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

A.6.2 Appendix: Sub-sample for Recessions: Market Values

Table 39: Recession Sub-sample: Credit Score Regression using Market

Variable	**Coefficient** (Std. Err.)	
	No Recession	Recession
DebtRatio	-8.461**	-8.733**
	(0.093)	(0.286)
FirmSize	2.034**	1.983**
	(0.022)	(0.066)
Profitability	-0.007	0.054
	(0.017)	(0.051)
Liquidity1	0.005	0.099
	(0.018)	(0.054)
Liquidity2	0.112**	0.074
	(0.020)	(0.062)
Tangibility	0.238**	0.182**
	(0.021)	(0.065)
Year Dummies	30/30 significant	4/6 significant
Industry Dummies	27/43 significant	9/43 significant
Age Dummies	1/10 significant	1/10 significant
Summary Statistics		
N	20376	2231
Log-likelihood	-22512.09	-2394.50
$\chi^2_{(82)}$	23288.75	2619.81
Pseudo-R^2	0.3409	0.3546

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 40: Recession Sub-sample: Accuracy of Credit Rating Predictions using Market Values

Delta Credit Rank	**No Recession**		**Recession**	
	N	Perc.	N	Perc
-7	1	0.00	0	0.00
-6	0	0.00	0	0.00
-5	27	0.13	2	0.09
-4	131	0.64	9	0.40
-3	46	0.23	5	0.22
-2	441	2.16	49	2.20
-1	3,989	19.58	444	19.90
0	10,940	53.69	1,201	53.83
1	4,379	21.49	484	21.69
2	356	1.75	35	1.57
3	31	0.15	1	0.04
4	33	0.16	1	0.04
5	1	0.00	0	0.00
6	0	0.00	0	0.00
7	0	0.00	0	0.00
8	1	0.00	0	0.00
Total	20,376	100.00	2,231	100.00

Source: COMPUSTAT Database

Table 41: Recession Sub-sample: Univariate and Multivariate Regressions using Market Values

Variable			**(Coefficient)**			
			(Robust Std. Err.)			
		No Recession			**Recession**	
Berry_HHI	0.3799^{**}		0.0803^{**}	0.3799^{**}		0.0338
	(0.0077)		(0.0154)	(0.0244)		(0.0449)
Nsegments		0.0944^{**}	0.0791^{**}		0.0973^{**}	0.0910^{**}
		0.0018	(0.0035)		(0.0051)	(0.0095)
Intercept	0.3926^{**}	0.2943^{**}	0.3075^{**}	0.4183^{**}	0.3138^{**}	0.3192^{**}
	(0.0022)	0.0035	(0.0043)	(0.0063)	(0.0098)	(0.0118)
	Summary Statistics					
N	20376	20376	20376	2231	2231	2231
R^2	0.0943	0.1155	0.1167	0.0932	0.1249	0.1251

Significance levels : † : 10% $*$: 5% $**$: 1%

A.7 Appendix: Analysis on Geographic Data

Table 42: Geographic Diversification : Credit Score Regression

Variable	**Coefficient** (Std. Err.)	
	Market Values	Book Values
DebtRatio	-8.138**	-4.399**
	(0.083)	(0.055)
FirmSize	2.107**	1.867**
	(0.020)	(0.019)
Profitability	-0.041**	0.482**
	(0.015)	(0.016)
Liquidity1	-0.008	-0.018
	(0.016)	(0.017)
Liquidity2	0.145**	0.213**
	(0.021)	(0.023)
Tangibility	0.238**	0.367**
	(0.019)	(0.019)
Year Dummies	31/33 significant	24/33 significant
Industry Dummies	34/47 significant	33/47 significant
Age Dummies	2/10 significant	2/10 significant
Summary Statistics		
N	25466	26721
Log-likelihood	-27901.43	-32064.83
$\chi^2_{(82)}$	29506.44	26683.24
Pseudo-R^2	0.3459	0.2938

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 43: Geographic Diversifaction: Accuracy of Credit Rating Predictions

Delta Credit Rank	**Market Values**		**Book Values**	
	N	Perc.	N	Perc
-7	1	0.00	0	0.00
-6	0	0.00	7	0.03
-5	25	0.10	32	0.15
-4	133	0.52	125	0.47
-3	47	0.18	80	0.30
-2	538	2.11	764	2.86
-1	5,052	19.84	5,504	20.60
0	13,742	53.96	13,149	49.21
1	5,423	21.30	6,085	22.77
2	415	1.63	784	2.93
3	38	0.15	120	0.45
4	27	0.11	67	0.25
5	24	0.09	4	0.01
6	1	0.00	0	0.00
7	0	0.00	0	0.00
8	0	0.00	0	0.00
Total	26,721	100.00	25,466	100.00

Source: COMPUSTAT Database

Table 44: Geographic Diversification: Univariate and Multivariate regression analysis

Variable	(Coefficient)					
	(Robust Std. Err.)					
	Market Values			**Book Values**		
Berry_HHI	0.2308**		0.2315	0.3933**		0.3955**
	(0.0062)		(0.0059)	(0.0108)		(0.0104)
Nsegments		-1.74E-6**	-1.74E-6**		-2.71E-6**	-2.71E-6**
		3.85e-8	(3.50e-8)		(5.84e-8)	(5.61e-8)
Intercept	0.7070**	0.8327**	0.7652**	0.4619**	0.6692**	0.5626**
	(0.0025)	0.0020	(0.0026)	(0.0041)	(0.0036)	(0.0045)
	Summary Statistics					
N	25,466	25,466	25,466	26721	26721	26721
R^2	0.0516	0.0984	0.1503	0.482	0.0866	0.1354

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%