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Credit Ratings and Stock Market Returns: Evidence from Germany

Analyzing the Influence of Credit Ratings on Stock Market Returns and the Credit Risk-Return Puzzle

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ABSTRACT

This thesis investigates the relationship between credit ratings and stock market returns in the German stock market. Using a sample of 106 companies from 2010 to 2023, this study examines how credit ratings affect monthly returns and whether companies with better credit ratings yield higher monthly returns. Analysis of rating-based portfolios that investigate firm characteristics and performance trends between the best-rated and worst-rated companies shows that indeed companies with better ratings yield higher monthly returns. This is primarily driven by the relatively poor performance of the worst-rated companies. However, the regression models show that this relationship is not as clear-cut, resulting in rather inconclusive results which can only indicate the trend of a negative relationship between rating downgrades and monthly returns. Thus, worse ratings generate lower returns. The effect of credit ratings varies significantly between investment grade and speculative grade rated companies, suggesting the presence of the distress effect and that high credit risk companies are more sensitive to rating changes. These findings show that credit ratings only play an important role in investor decision-making for companies with high credit risk and that other factors determine investment decisions in financially stable companies. This thesis contributes to the scarce literature on the German stock market, particularly on the credit risk-return puzzle, and offers insight into investor behaviour and price formation.

Keywords: Credit Ratings, Risk-Return Puzzle, Credit Risk, Portfolios

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CHAPTER 1 Introduction

The recent 2024 stock price explosion of NVIDIA Corp. and the resulting rapid increase in the company's valuation, with a price-to-earnings ratio of up to 90, has raised critical questions about the drivers of company valuation and the factors relevant to stock price formation. Professional investors utilize intense business analyses and sophisticated valuation techniques to derive an investment strategy. However, many investors lack the skills to perform this extensive analysis and often rely on different techniques and information to develop their investment strategies. Credit ratings, as third-party assessments of a company's creditworthiness, provide an intuitive tool to grasp a company's financial setup and the risks associated with an investment. Investigating the effect that credit ratings have on the stock market performance of companies can offer a better understanding of investor behaviour and price formation. The following study examines this relationship, particularly in the context of the German stock market, as academic research on this relationship is scarce.

One of the oldest, yet most influential academic papers in the finance literature is by Fama and MacBeth (1973). They empirically test the relationship between monthly stock market returns and risk factors. Their analysis finds that there is indeed a positive relationship between risk factors and stock returns. However, there likely is no other measure of risk, except for portfolio risk, that systematically affects returns. This paper inspired many academics to further investigate the risk-return relationship, focusing especially on the influence of idiosyncratic risk factors such as credit risk on stock returns. Griffin and Lemmon (2002) pick up on the analysis of idiosyncratic risk factors and investigate the relationship between the book-to-market ratio, distress risk and monthly stock returns. They find that companies with high distress risk yield higher returns when they have a high book-to-market ratio rather than a low one. The book-to-market premium cannot be explained through a risk-based explanation. Hence, they attribute it to the mispricing of companies with high distress risk and low analyst coverage. In a closer investigation of the credit risk effects on stock performance, Avramov et al. (2009) take on the credit risk-return puzzle in US companies. They find that better credit ratings correlate with higher returns, contradicting the belief that higher risk is rewarded with higher returns. This suggests that investors in high credit risk stocks pay a premium to take on risk. Moreover, they find that this premium is primarily explained by the relatively poor performance of the worst-rated companies, due to the “distress effect” and mispricing caused by retail investors.

While most of the literature on this topic focuses on the United States, there is only limited evidence on the relationship between credit ratings and returns in the German stock market. Kenjegaliev et al. (2016), for example, investigate the daily abnormal returns that are generated through rating upgrades and downgrades in the German market and find that most rating changes are anticipated and priced in. However, they do not give a holistic view of the general effect of credit ratings on stock market returns. This research aims to fill this gap by investigating the relationship and differences in stock returns and firm characteristics between the best-rated and worst-rated companies in the German stock market. Hence, the research question guiding my analysis is:

"How do credit ratings affect monthly stock market returns in Germany?"

To investigate this research question, the study uses all public companies that are headquartered in Germany from 2010 to 2023. Thus, the sample contains 106 companies over 168 months. The analysis of the relationship between credit ratings and monthly returns is split into two parts. The first part allocates the companies into five portfolios based on their credit ratings, comparing performance measures and firm characteristics of these portfolios to investigate trends and relationships. The second part of the analysis uses fixed-effects regression models to investigate the effect of credit rating on monthly returns. The results of the central regression model are further dissected by sub-group analysis to test the robustness of the results. On top of that, the credit rating variable is substituted by one-year default rates associated with each rating score. This research contributes insightful information on the credit risk-return puzzle and investor behaviour in the German stock market to the relatively scarce academic literature. Most research focuses on the event-driven returns around rating upgrades or downgrades, rather than seeing credit ratings as a measure of credit risk that can help explain stock market returns and investor behaviour. The findings offer insights into the distress effect and help explain return differences between the best-rated and worst-rated companies. Moreover, they can enhance our understanding of investor behaviour and price formation in the German stock market, providing a basis for further research. With this analysis, I expect to find that in the German market, companies with better credit ratings yield higher monthly returns and that this relationship is driven by the relatively poor performance of the worst-rated companies due to the distress effect. Furthermore, I expect that companies with better credit ratings yield lower book-to-market ratios. The expectations for the analysis are summarized in the following hypotheses:

H1: Companies with better credit ratings yield higher monthly returns.
H2: The worst-rated companies perform especially poorly in comparison.
H3: Companies with better credit ratings yield lower book-to-market values.

By addressing these hypotheses, the study aims to provide a comprehensive understanding of the relationship between credit ratings and stock market performance in Germany.

CHAPTER 2 Theoretical Framework

2.1 Literature Overview

The following chapter reviews the most relevant academic literature on credit ratings and their relationship with stock market returns. The literature review starts with background information on the topics and an explanation of credit ratings. The relevance and applications of these ratings are outlined and their use as a measure of credit risk is justified. Lastly, the literature on the relationship between stock returns and risk factors, especially credit risk is investigated.

2.1.1 Background Information

The origin of the credit rating industry lies at the beginning of the 20th century when John Moody sold his assessment of railroad bonds to interested investors. Other firms such as Standards Statistics Company and Fitch Publishing Company followed this business model, selling their opinion on corporate bonds to investors. These companies evolved to what we now know as Moody's, Standard & Poor's and Fitch Ratings. Initially, the investors paid to access the ratings, but in the 1970s this model changed to issuers paying the credit rating agencies for an opinion on their bonds (White, 2010). This shift caused a lot of criticism, especially during the Great Financial Crisis (GFC) when rating agencies overstated the creditworthiness of complicated financial instruments obligations to gain market share and increase their revenues (Mullard, 2012). The GFC ended up costing the U.S. government and therefore the U.S. taxpayer up to 14 trillion dollars (Atkinson, Luttrell, and Rosenblum, 2013). Due to their involvement in the GFC, regulators in the U.S. and the EU introduced stricter regulations to the until then mostly self-regulated industry (Utzig, 2010 and Securities and Exchange Commission, 2014). The European response was Regulation 2009/1060 - Credit rating agencies (EU Monitor, 2019) which requires credit rating agencies to register for operation in the EU, increases transparency and aims to ensure the quality of credit ratings.

2.2 Credit Ratings

With this necessary background information on the credit rating industry and its importance to the efficiency and stability of the global financial markets, the following sections outline the characteristics of the credit ratings used in this study.

2.2.1 Definition

Schröter (2013) describes two types of credit ratings, namely the issuer rating and the issue rating. Issuer credit ratings are the agency's professional and forward-looking opinion on an entity's ability and willingness to adequately serve its unsecured debt obligations in full and on time (Ashok, 2002) (S&P, n.d.). Issue credit ratings, however, focus on a specific financial debt obligation such as a bond and the issuers' ability to serve this debt obligation in full and on time (S&P, n.d.). This paper uses issuer credit ratings of corporate entities.

2.2.2 Issuer Credit Ratings

To receive an issuer credit rating or any credit rating, the entity typically requests the rating from the rating agency. After thorough due diligence, the credit ratings are given by a rating committee following a relative rating scale (Moody’s, 2010). For S&P and Fitch Ratings, the highest rated entities receive a “AAA”, incrementally decreasing to “D”. For Moody’s, the ratings range from “Aaa” to “D”. The credit rating scales and incremental steps between the highest and lowest ratings can be seen in Table 1. The additions “+” and “-“ for S&P and Fitch Ratings and the rating score additions 1, 2, 3 for Moody’s indicate the relative position of the entity in their rating score category. Thus, a company with an “AA+” rating is assessed to have a slightly better creditworthiness than an entity rated “AA”. In the rating process, the rated entities are compared and ranked globally, ensuring the consistency and comparability of credit ratings across geographical borders (Schröter, 2013, Chapter 35). Moreover, the rating scale is split into two categories, the investment grade ratings, which are ratings of “BBB-” and above and the speculative grade, which are ratings below “BBB-”. The difference between the categories is stark. While investment grade ratings indicate low default risk, speculative grade-rated assets are considered risky, and some financial institutions outright ban investments in these assets or require higher equity reserves to be held by investors (Parlour and Rajan, 2019). It is important to note, that rating scores do not adhere to specific default probabilities and should be understood as the relative creditworthiness of a company compared to other rated companies.

Table 1. Long-Term Issuer Credit Rating Scale

Interpretation	Fitch and S&P	Moody's	Numeric Score
	Investment Grade		
Highest quality	AAA	Aaa	1
High quality	AA+	Aa1	2
	AA	Aa2	3
	AA-	Aa3	4
Strong payment capacity	A+	A1	5
	A	A2	6
	A-	A3	7
Adequate payment capacity	BBB+	Baa1	8
	BBB	Baa2	9
	BBB-	Baa3	10
	Speculative Grade		
Likely to fulfill obligations, ongoing uncertainty	BB+	Ba1	11
	BB	Ba2	12
	BB-	Ba3	13
High-risk obligations	B+	B1	14
	B	B2	15

	B-	B3	16
Vulnerable to default	CCC+	Caa1	17
	CCC	Caa2	18
	CCC-	Caa3	19
Near or in bankruptcy or default	CC	Ca	20
	C	C	21
	D	D	22

Notes: Table 1 exhibits the credit rating scores by S&P, Fitch and Moody's as well as their interpretation and the numeric score that is used in this study to analyse the relationship between these credit rating scores and stock market returns. The information is retrieved from the IMF (2010).

2.2.3 Importance and Application of Credit Ratings

Corporations and governments use credit ratings to show their assessed creditworthiness to investors, banks, debtors, or any other interested entity. According to S&P (n.d.), ratings help corporations to access credit in new markets, they assist in estimating the cost of capital and serve as a declaration of creditworthiness to partners or banks that are not familiar with the firm's financial situation. Baghai et al (2014) outline three main contributions of credit ratings to the financial markets that academic literature has identified. Firstly, credit ratings have a market information function as credit rating agencies aggregate relevant public and non-public data and provide it to investors in the form of a standardized credit rating format. Secondly, credit ratings function as a certification that is used in the asset allocation and investment decision process of institutional investors and thus have a regulatory contribution to the financial markets. Thirdly, they assume a monitoring function as ratings are usually released with a credit outlook that is either "positive", "stable" or "negative", indicating where the company's rating is going. Ratings are adjusted, if deemed necessary, due to material changes in the creditworthiness. Additionally, credit ratings convey important private information that financial market participants cannot access (Langohr and Langohr, 2010). Parlour and Rajan (2020) and Piccolo and Shapiro (2022) claim that credit ratings can help to decrease information asymmetry in the financial markets, especially for less-informed investors.

2.2.4 Credit Ratings as a Measure of Credit Risk

Transferring this knowledge to the application of credit ratings in academia, the debate about the usefulness of credit ratings as a proxy for credit risk arises. The following section discusses credit risk and its connection to credit ratings.

To start off, one of the most influential academic papers in the field of corporate credit risk analysis is Edward Altman's 1968 paper on the predictive power of ratio analysis on corporate bankruptcy. The paper introduces Altman's Z-score which is still used in academia nowadays to predict bankruptcies and default probabilities. Many academics claim that credit ratings are much worse at anticipating bankruptcies. Galil (2003), for example, investigates the quality of corporate credit ratings with respect to default rate predictions by reviewing the Standard & Poor's rating process. He finds that credit ratings do not utilize all publicly available information to their full potential and that the rating categories are inefficient in differentiating credit risk between firms. This limits the accuracy of the ratings and the accurate assessment of default risks. He suggests that the actual default risk is higher than what is implied by a rating, but he acknowledges that it might be due to systematic changes and risks within certain industries. Hilscher and Wilson (2015) have similar findings to Galil (2003). They find that ratings tend to understate default probabilities, yet they take a more critical position on how well credit ratings reflect the actual credit risk of a company. They find that ratings are an imperfect measure of credit risk because they lag behind and are slow to adapt to new financial conditions, thus failing to accurately predict corporate defaults. Market-based measures such as Credit Default Swap (CDS) spreads give more timely and accurate information on default risk as they quickly adapt to market conditions and new information on the firm's creditworthiness. They suggest that CDS are better indicators for credit risk, specifically default risk, than credit ratings. However, Hilscher and Wilson state that ratings contain important information on systematic risk. Additionally, Hilscher and Wilson (2015) claim that credit risk is a multidimensional puzzle that cannot be described by only one variable.

The concept of comparing market-based measures of default risk can also be found in Löffler (2004). His paper assesses a market-based measure of credit risk, compares its accuracy in addressing default risks with credit ratings and investigates which instrument is better suitable to formulate investment governance rules. As the market-based measure, Löffler uses expected default frequency. Similar to Hilscher and Wilson (2015), he finds that the market-based measure adjusts timelier to changes in credit risk than ratings. However, he claims that ratings are more stable over time with a long-term view which makes them more suitable for long-term investment strategies and regulatory compliance. The paper suggests that credit ratings entail a trade-off between stability over time and short-term accuracy which is expressed as the timely adjustment to underlying credit risk changes. Nevertheless, Löffler proposes a complementary use of these two measures of credit risk to investors as this improves the overall understanding of a company's default risk.

Altman and Rijken (2006) pick up on the criticism that rating agencies are slow to adjust to changes in the creditworthiness of rated companies. They investigate credit rating's stability, timeliness and default prediction capacity and compare the through-the-cycle methodology of the rating agencies and the point-in-time perspective of bankers. Altman and Rijken conclude that the point-in-time method is timely and adjusts well to changes in a firm's creditworthiness whereas the through-the-time ratings are indeed not adjusting to slight changes in the financial conditions of a firm, but they provide a stable and long-term assessment of the firm's credit quality, ignoring fluctuations in the current financial environment. They also recommend a complementary use of both perspectives to enhance the assessment of creditworthiness and predict default rates more efficiently.

Concluding this section, the relationship between credit ratings and credit risk is a point of discussion in academia. However, established researchers suggest that there is not one measure of credit risk that is able to appropriately quantify the complexity of credit risk and default probabilities by itself and therefore suggest the use of multiple indicators. Nevertheless, credit ratings provide highly important information on a company's long-term creditworthiness and credit quality.

2.3 The Risk-Return Puzzle and Distress Risk

Building on the survey of the role of credit ratings as a measure of credit risk, this section focuses on the risk-return puzzle and the relationship between credit ratings and firm performance.

One of the oldest, yet most influential, academic papers in the financial economics literature is the 1973 paper by Fama and McBeth. Their goal was to test the Capital Asset Pricing Model (CAPM) and, thus the risk-return relationship. Fama and McBeth find a positive and linear relationship between the expected returns of a stock and its beta. Hence a stock with a higher beta, higher systematic risk, yields higher stock returns, supporting the CAPM assumption that higher risk exposure is rewarded with higher returns. However, Fama and McBeth acknowledge that other factors might influence stock returns, starting a new strand of academic papers that focus on the explanation of stock market returns through multifactor models. Fama and French (1992) explore possible factors that can be added to the CAPM to predict expected stock returns more accurately. They find a size effect that suggests smaller firms have higher average returns than larger firms and a value effect which suggests firms with higher book-to-market ratios have higher average returns than lower book-to-market firms. Furthermore, Fama and French state that the size and book-to-market effects capture the variation in average returns that are explained by size, earnings-to-price ratio, book-to-market ratio and leverage of a firm. Thus, size and book-to-market ratio are natural factor additions to the CAPM. Following this revelation by Fama and French, Dichev (2002) hypothesizes that the size effect and value effect are possibly explained by a distress risk factor. He uses bankruptcy risk as a proxy for distress risk and finds that the relation between distress risk and returns is unable to explain the size effect and value effect. He claims the size effect disappeared since 1980 and the relation between bankruptcy risk and book-to-market ratio is nonmonotonic. However, he finds that higher distress risk is not rewarded by higher returns. Thus, firms with higher distress risk earn lower average returns. In the same year, Griffin and Lemmon (2002) investigate a similar relationship, the relationship between book-to-market ratios and distress risk. Similar to Fama and French (1992), they find that high book-to-market firms yield higher average returns than lower book-to-market firms and that higher book-to-market values are related to higher distress risk. Additionally, like Dichev (2002) they find that controlling for distress risk does not cancel out the value effect, suggesting the value effect is driven by other factors. Furthermore, they find that higher distress risk does not yield higher returns, suggesting that distress risk is not systematically priced in by the markets. Avramov et al. (2009) use findings from Dichev and Griffin and Lemon, among others, to investigate the credit risk-return puzzle in the US. They use credit ratings as a measure of credit risk and create rating-based portfolios. They find that credit ratings have a significant role in predicting stock returns as they find that the best-rated portfolio yields higher returns than the worst-rated portfolio. Consequently, investors in high credit risk stocks pay a premium to take on risk. Moreover, they find that this premium is explained by the relatively bad performance of the worst-rated companies, due to the “distress effect” and mispricing caused by low liquidity, short selling constraints and uninformed retail investors. Daniel and Titman (2012) object to the idea that there are factor loadings that help explain excess returns in the stock market and reject Fama and French’s (1993) idea that a distress factor is responsible for the discount rate that small-size and high book-to-market value firms trade at. They claim that the size and value effect do not explain excess returns, but are mere proxies for firm characteristics, such as industry or regionality.

To conclude section 2.3, it becomes clear that factors beyond systematic risk influence stock market returns. The most known factors are described by Fama and French (1992). The subsequent research introduced in this section investigates the distress risk component in the risk-return relationship and factor models. While Dichev and Griffin and Lemon find that distressed companies yield lower returns, implying that the risk-return relationship does not hold for distressed companies, researchers such as Daniel and Titman refute the factor models’ efficiency in explaining expected returns and attribute the explanatory power to firm characteristics. Avramov et al. (2009) combine the findings on the distress effect with credit ratings as a measure of credit risk and find that credit ratings have predictive power over stock returns and that on average the best-rated companies outperform the worst-rated companies. These findings lay the foundation for this study.

CHAPTER 3 Data

3.1 Data Sample and Collection

This paper analyses the effect of corporate credit ratings on the stock market performance of public firms in Germany. The data sample that is used for this analysis, considers all publicly listed companies on German exchanges, with headquarters located in Germany for the sample period January 01, 2010 to December 31, 2023. Only focusing on companies that are listed and headquartered in Germany ensures that the companies in the sample are suitable for the research motivation. The financial data and credit ratings are collected monthly so that credit rating changes are captured timely. Furthermore, the sample period starts in 2010 because credit rating agencies are deemed to have played a significant part in the Great Financial Crisis in 2007/08' and subsequently came under closer investigation by regulators and tighter EU regulations in 2009 (EU Monitor, 2019). Thus, the sample period's start at the beginning of 2010 ensures consistency in the rating procedures and in the credit ratings throughout the time series. All data is retrieved from the LSEG database (LSEG, 2024).

3.2 Data Set

Out of more than 700 identified German companies, only 106 companies have available credit rating data. Credit ratings are not mandatory for German companies, so only some firms, especially large ones and those active internationally or in global debt markets, have issuer ratings. This means the dataset is likely biased towards larger established firms and financial institutions. Nevertheless, the data set consists of 106 companies over 168 months (14 years). Furthermore, it is important to mention that some companies went public after the sample period started in 2010 or were delisted before the sample period ended in 2023 and that rating coverage might not be available for the entire sample period. This means the data set does not have an equal number of observations for all companies. Therefore, this paper works with an unbalanced panel data set.

3.3 Variables

Section 3.3 explains the variables used in this study's analysis and descriptive statistics. It emphasizes the central variables for credit ratings and the performance metrics. The 1998 paper by Brennan et al. serves as the foundation for the variable selection and is also used by Avramov et al. (2009). Variables include the book-to-market ratio, market capitalization, momentum, trading volume, lagged returns, dividend yield, and price-to-earnings ratio, which have been identified to help explain variations in returns. Detailed calculations and measurements can be found in Appendix 3A.

3.3.1 Credit Rating Variable

The credit ratings that are used in this paper are long-term issuer credit ratings from S&P Global Ratings, Moody's or Fitch Ratings. The credit rating scores are converted to numerical values according to Table 1 in section 2.2.2. Throughout the time series, the number of credit rating observations increases incrementally, as shown in Appendix 1A. Furthermore, the distribution of credit rating scores as illustrated in Appendix 2A resembles a right-skewed normal distribution. There are significantly more observations of investment grade ratings, scores 1 to 10, than speculative grade ratings, scores 11 and higher. The best credit rating score in the data sample is a score of 3 or AA (Aa2) which multiple companies hold. On the tail end of the distribution, it is noticeable that there are very few observations for the worst ratings which suggests that very high distress risk is rare in the sample. This can possibly be explained by the fact that ratings are voluntary and firms that anticipate a low rating might shy away from getting a public credit rating. The average monthly rating score, referred to as *Credit Rating*, is calculated, giving equal weight to each available rating from either S&P, Fitch or Moody's. In the data set the retrieved credit ratings are carried forward from the rating date until they get changed or the rating coverage is discontinued.

3.3.2 Dependent Variable

To measure the stock market performance of the companies, monthly stock returns are used. Monthly returns are the dependent variable in the regression models and are calculated through the change in stock price at the end of each month.

3.3.3 Control Variables and Firm Characteristics

The following list shows the control variables and firm characteristics used in the regressions and portfolio analysis.

- *Market Value*: Logarithmically transformed to account for large size differences.
- *Turnover*: Logarithmically transformed to account for differences in traded share volume
- *Book-to-Market Ratio:* Logarithmically transformed to normalize distribution.
- *6 Month Cumulative Return:* Momentum variable derived from monthly returns.
- *Long-Term Debt to Equity (LTDE Ratio):* Measures leverage.
- *Dividend Yield:* Percentage of market capitalization returned to shareholders.
- *Return on Assets (ROA):* Measures profitability in percentage.
- *Price-to-Earnings ratio, Price-to-Sales Ratio, Price-to-Cashflow Ratio:* Used in descriptive statistics to compare firm characteristics and valuations.
- *Current Ratio:* Measures liquidity, excluded from regression due to missing observations.
- Other firm characteristics used: Number of employees, enterprise value, number of shares, and earnings per share (EPS).

3.4 Descriptive Statistics

The following section outlines the most important observations that can be made from the descriptive statistics table below, which contains all regression variables and firm characteristics used in this paper's analysis. Table 2 shows the mean, standard deviation, minimum, and maximum values and the number of observations for all variables.

Table 2: Descriptive Statistics

Variables	Mean	Standard Deviation	Min	Max	Observation
Regression Variables					
Credit Rating	8.848	2.868	3	22	12,202
Default probabilities (%)	0.657	3.830	0.02	100	12,002
Market Value (mln)	17,889.60	25,129.57	13.35	184,622.10	11,535
Monthly Returns (%)	0.517	0.0952	-79.099	143.87	11,461
6 Month Cum. Returns (%)	2.933	0.236	-90.089	205.705	11,087
Book-to-Market Ratio	0.847	0.711	-3.791	7.407	11,466
Return on Assets (%)	3.582	5.339	-21.69	53.58	12,006
LT Debt-to-Equity (%)	115.307	188.772	0	3,429.41	12,033
Dividend Yield (%)	2.708	2.575	0	55.07	11,535
Turnover	12,151.93	25,151.27	0	495,871.7	11,436
Firm Characteristics					
Price	66.699	120.286	0.391	1680	11,535
Enterprise Value (bln)	33.4	54.3	-176	429	11,637
Price-to-Earnings Ratio	24.848	74.790	0.4	1923.5	9,672
Price-to-Cashflow Ratio	0.398	204.935	-6,281.93	376.69	11,637
Price-to-Sales Ratio	1.589	2.268	0.01	18.53	11,637
Current Ratio	1.343	0.542	0.18	4.17	8,866
Number of Shares	542,615.5	1,052,024	2,884	9,738,721	11,535
Employees	70,091.16	111,889.9	37	684,025	11,788
EPS	4.282	7.234	0	98.31	11,440

Notes: Table 2 shows the descriptive statistics of the data set and variables used throughout the analysis in this study. The variables are described by their mean, standard deviation, minimum and maximum values as well as the number of observations they have. The data set has been cleaned of all the observations in periods where the companies do not have a credit rating. Be it due to them not being listed on a German stock exchange, the rating process not having started or discontinuation of the process. The values for Market Values are in millions and Enterprise Value are in billions of euros. The Default probabilities, Monthly and 6 Month Cumulative Returns, the LT Debt-to-Equity and Dividend Yield variables are in percent. The calculations used for the variables can be seen in Appendix 3A. The Data was retrieved from the LSEG in May 2024

The mean credit rating is 8.85 corresponding to a rating between BBB+ and BBB. Considering the range of values from a minimum of 3 to a maximum of 22, the standard deviation of 2.87 is relatively small, indicating that rating scores are not wildly dispersed. Interestingly, the mean default probabilities, which are calculated based on historical 1-year default rates, are 0.66 percent and have a standard deviation of 3.83 percent. This shows how low the default probability of most companies in Germany is. The mean market value is EUR 17.9 billion with a sizeable standard deviation of EUR 25.1 billion, that is explained by the large size difference ranging from 13.3 million to 184.6 billion, indicating a right-skewed distribution of the variable. The monthly returns have a mean value of 0.52 percent and a relatively small standard deviation of 0.09 percent. Consequently, the six-month cumulative returns have a mean of 2.93 percent and a standard deviation of 0.24 percent indicating a tight distribution with little dispersion for both return variables. The BM ratio has a mean of 0.85 with a high standard deviation of 0.71. The minimum value of -3.79 and negative values for the BM are rare occurrences and usually indicate financial distress. The return on assets has a mean of 3.58 percent and a much higher standard deviation of 5.34 percent which indicates a large dispersion of the values and looking at the min and max values of 21.69 and 53.58 percent respectively the high standard deviation is explained by large yet realistic outliers. The mean of LT Debt to Equity is 115.04 percent with a 188.77 percent standard deviation which indicates significant variation in the variable and large outliers, ranging from 0 to 3,429 percent. The mean of the dividend yield is 2.71 percent and the standard deviation is 2.58. Lastly, the turnover by volume has a mean of 12,151.9 and a standard deviation of 25,151.3.

CHAPTER 4 Method

The following section pertains to the statistical methodology employed to analyse the collected data set and investigate the relationship between corporate credit ratings and performance metrics of German companies. The central methods of this study are a descriptive portfolio table that investigates trends between the rated companies and a Fixed-Effects Regression model that can handle the unbalanced panel data set.

4.1 Rating-based Portfolio Tables

Following the methodology of Avramov et al. (2009), this paper begins the analysis with a comprehensive descriptive statistic that aims to investigate the raw differences between the best-rated and worst-rated firms. Each month the companies are allocated to five portfolios based on their credit ratings. The portfolio allocation in this study differs slightly from Avramov et al.'s approach as the companies are allocated based on their specific ratings. Table 3 shows which credit rating scores go into each portfolio and lists the observations and percentage split for each portfolio. For each month, the median values of firm characteristics within each portfolio are calculated. The descriptive statistics then summarize these monthly medians, providing an average mean value for each portfolio. The differences in firm characteristics between P1 and P5 are highlighted to investigate the differences between the best-rated and worst-rated companies and to identify trends.

Table 3: Rating Based Portfolio Characteristics

Portfolio	Ratings	Observations	Percent
P 1	AAA/AA	722	5.92
P 2	A	3,351	27.46
P 3	BBB	5,411	44.35
P 4	BB	1,736	14.23
P 5	B & below	982	8.05
Total		12,202	100

Notes: Table 3 shows the associated ratings, number of observations and percentage split for all five portfolios.

4.2 Central Statistical Analysis Methods

Diving into the methods to analyse the credit risk-return puzzle, this section lays out the regression models and diagnostic tests used to investigate the data.

4.2.1 Hausman Test

Starting off this analysis, a Hausman Test determines whether a fixed-effects or random-effects regression model is suited best for the unbalanced panel data. This test is crucial as it impacts the bias and consistency of the estimators used in the regression models. The null hypothesis of the Hausman Test claims that the individual company-specific effects (the random effects) are uncorrelated with the explanatory variables. The random-effects model assumes that the cross-sectional error term has zero mean and is independent of the individual observations error term. A rejection of the null hypothesis (p-value < 0.05) suggests that the random effects assumptions are violated, indicating that the fixed-effects model is preferable to produce consistent and unbiased results (Brooks, 2019, p.502).

4.2.2 Fixed-Effects Regression

Analyzing panel data poses the challenge of taking into account that variables may or may not vary over time and may or may not vary between entities. The fixed-effect regression model helps to address these issues by accounting for time-invariant firm characteristics. This model controls for unobserved heterogeneity, allowing for accurate estimation of the common effect across entities while controlling for the individual differences between entities (Stock and Watson 4th edition, 2020, p.367-368). The fixed-effect model used in this study is specified as follows:

$$Y_{it} = \alpha_i + \beta_1 * Average\ Credit\ Rating + \beta_2 * \textbf{Control Variables} + \boldsymbol{\upsilon_{it}}$$

where:

- α_i capture the entity-specific intercept, capturing all unobserved time-invariant characteristics
- Y_{it} denotes the monthly stock returns
- *Control Variables* – Control Variables described in Section 3.3.2
- υ_{it} denotes the error term that captures the unexplained variation in Y_{it}

4.2.3 Sensitivity Analysis

The fixed-effects regression model will be examined through several methods of sensitivity analysis in order to gain a better understanding of the independent variable's significance and explanatory power as well as the origins of uncertainty in the regression model. At first, the regression model suggested by Avramov et al. (2009) is investigated through a build-up of three models. Model 1 is without control variables, model 2 only contains the control variables and excludes the rating variable and lastly, model 3 combines all variables. The variables in these models are lagged by two periods. An alternative model specification helps to further enhance this model by expanding the set of control variables through proxies for leverage (LTDE), profitability (ROA) and dividend yield. On top of that, the lag of the variables is reduced to a one-period lag, from the two-period lag suggested by Avramov et al. (2009). As in the regression models before, the analysis is split into three models. Model 1 investigates the effect that the reduction of the lags has on the regression result and contains only the previous controls. The second model contains only credit ratings and the newly added control variables to gain insights into these variable's impact on the regression estimate. Lastly, model 3 combines all control variables and constitutes the central regression model of this paper.

Further dissection of these regression results is pursued through two sub-group regression models based on different time periods (2010-2016 and 2017-2023) and credit rating categories (investment grade vs. speculative grade). The first sub-group helps to identify potential differences in the regression estimates over the time series. The second sub-group further investigates the distress effect and the relationship between credit ratings and average returns. Lastly, the central credit rating scores used for the analysis converted to default rates as suggested by S&P Global (2023). The extended regression model is used to closer investigate the relationship between credit risk and average monthly returns. This is done because the credit rating score is an ordinal variable and the distance between rating scores corresponds to unequal changes in creditworthiness and credit risk. A downgrade from an A to an A- rating corresponds to a much lower change in credit risk than a downgrade from BBB- to BB+. S&P Global publishes annual reports on the historical default rates of their rating scores which this study uses to replace the rating scores. One-year default rates are used in the analysis. For the average credit ratings that are between integers, the implied difference between the corresponding default rates is taken. Appendix 4A shows the 1-year default rates and their corresponding credit ratings.

4.2.4 Robustness Checks

This section describes the diagnostic tests used to assess the efficiency and reliability of the fixed-effects regression model which are crucial for making accurate inferences from the results. To begin with, the data is checked for outliers and unrealistic or erroneous values. The normality of variables is inspected through simple visualization inspection and descriptive statistics. The robustness checks are employed for every regression model specification to ensure the quality of the regression estimates.

Heteroscedasticity of the error term poses an issue for any regression because regression models assume that the variance in the residuals is constant, i.e. homoscedastic. It is important to test this assumption, and if necessary, adjust the model with robust standard errors, else the standard errors could be biased which may lead to misleading or incorrect inferences from the results. A scatterplot of the residuals and fitted values of the regression model are used to check for heteroscedasticity. Thereafter, a Breusch-Pagan Test will be conducted to detect heteroscedasticity in the regression. This tests whether the residuals have constant variance (null hypothesis) or whether the residuals are heteroscedastic (alternative hypothesis). The null hypothesis is rejected if the p-value is below 0.05. To test for autocorrelation in the residuals (ϵ) of the fixed-effects regression the Woolridge Test is employed. The null hypothesis states that there is no evidence of first-order autocorrelation and is rejected if the p-value < 0.05. Continuing the robustness checks, multicollinearity in the unbalanced panel data set is investigated using a correlation matrix that contains all predictor variables. Finally, the normality of the error term is tested through visual inspection of a histogram plot and a Q-Q plot of the fixed-effects regression's residuals.

CHAPTER 5 Results & Discussion

Chapter 5 outlines and discusses the results of this paper and establishes the answers to the hypotheses of whether credit ratings have predictive and explanatory power over stock returns.

5.1 Descriptive Results

Financial markets are dynamic and constantly subject to changes. A model that tries to predict returns or relationships in the financial market needs to be equally as able to adapt to new conditions and behaviour in the markets. A fixed-effects model is not able to adapt as it assumes the relationship between the monthly returns (dependent variable) and credit ratings (independent variable) to be constant over time. Therefore, before the statistical analysis, the paper investigates portfolios that are dynamically sorted based on the credit rating scores of the companies.

Table 4: Rating Based Portfolios

Variables	P1	P2	P3	P4	P5	P1-P5
	AAA-AA	*A*	*BBB*	*BB*	*B & below*	
Average Rating Score	3.51	6.74	9	11.50	14.98	
Size Measures						
Market Value (mln)	25.65	22,65	6.71	3,66	0.98	24.67
Price	125.79	63.94	29.51	30,00	14.62	111.17
Enterprise Value (mln)	26.9	52.8	9.799	5.895	1.878	25.022
Employees	30,506	54,826	17,882	30,979	14,742	15,764
Performance Measures						
Monthly Return (%)	0.99	0.49	0.33	0.69	-0.07	1.06
6M cumulative Return (%)	3.52	3.23	1.78	3.79	-1.62	5.14
Dividend Yield (%)	4.27	2.56	2.54	1.39	0.00	4.27
EPS	9.83	3.76	1.85	1.70	0.15	9.68
Valuation Measures						
P/E Ratio	12.83	16.17	15.70	16.35	51.65	(38.82)
B/M Ratio	0.75	0.59	0.66	0.63	0.68	0.07
P/CF Ratio	5.64	8.35	7.10	7.02	4.51	1.13
P/S Ratio	0.79	0.89	0.82	0.65	0.46	0.33
Firm Characteristics						
Current Ratio	1.03	1.16	1.22	1.38	1.08	(0.05)
LT Debt to Equity	42,99	71,24	72.84	76.99	106.88	(63.89)
Number of Shares	179,236	427,389	184,704	114,173	154,391	24,845
Turnover	13,182	853	2,946	2,003	3,475	9,707
ROA (%)	1.28	3.84	3.98	4.14	0.49	0.79

Notes: Table 4 shows the descriptive statistics of the five rating-based portfolios; AAA-AA/A/BBB/BBB/B & below. The portfolios are sorted monthly. The median firm characteristics are calculated every month for each portfolio and the mean average characteristics over the 168 months from Jan. 2010 to Dec. 2023 are shown in the table.

A simple monthly allocation of the rated companies into five portfolios that go from best to worst rated allows for the comparison of firm characteristics and performance. Looking at Table 4, it is clear that there are size, stock performance and valuation differences between the best-rated companies in portfolio 1 and the worst-rated companies in portfolio 5. The table shows that companies with better ratings are bigger. They have a higher market capitalisation, enterprise value and number of employees. The market value difference between portfolios 1 and 5 is the most extreme as the average firm size goes from EUR 25.65 million in portfolio 1 to EUR 0.98 million in portfolio 5. Similar observations can be made when looking at the performance measures where the best-rated portfolio strongly outperforms the worst-rated portfolio. The difference between portfolios 1 and 5 in monthly returns is 1.06 percent and the six-month cumulative return difference is 5.14 percent. This large outperformance can be attributed to the relatively poor performance of the worst-rated firms as portfolio 5 is the only portfolio with negative returns in both measures. These findings already indicate that the hypotheses 1 and 2 hold. H1 states that companies with better ratings outperform those with worse ratings and H2 specifies this by suggesting that this outperformance is driven by the poor performance of the worst-rated companies because their financial distress is deterring investors.

However, looking at the valuation measures the picture is less clear. While the Price-to-Earnings ratios suggest a trend of higher valuations for worse-rated companies, other valuation ratios such as Price-to-Sales and Price-to-Cash flow indicate that companies with worse ratings yield lower valuations. Contrary to the academic literature that has identified higher book-to-market ratios for companies with better credit ratings (Avramov et al. 2009), the portfolios here do not show a clear trend in book-to-market ratio. The third hypothesis (*H3: Companies with better credit ratings yield lower book-to-market values.)* is partially rejected. Although portfolio 1 stands out with a slightly higher book-to-market ratio of 0.75, the other portfolios do not show a decreasing trend for the book-to-market ratio of worse-rated companies and seem to vary around a 0.65 book-to-market ratio. The firm characteristics show leverage, measured by Long-Term Debt-to-Equity, is higher for worse-rated companies. The large difference between portfolios 1 and 5, which is 63.89 percent, is again predominantly driven by portfolio 5 which has a relatively high leverage of 106.88 percent. Moreover, the liquidity measure, current ratio, remains relatively stable between portfolios 1 and 5 but has higher averages in the middle three portfolios. The same observations can be made for the profitability ratio Return on Assets which shows that the average profitability of portfolios 1 and 5 are much lower than the profitability of portfolios 2, 3 and 4, which are about four times as profitable. These characteristics do not allow for any conclusive analysis.

To conclude the learnings from this table, it is possible to see trends in the characteristics and performance of portfolios if they are created based on corporate credit rating scores. Trends in size, average returns, valuation and leverage support the research question that pertains to the relationship that credit ratings have with stock market returns and supports the relevance of the control variables that were chosen to be used in the analysis. However, the results of this table are likely skewed by the small sample size which might overemphasize the characteristics of some companies. This could be the reason why some characteristics fail to show trends with worsening credit ratings despite the findings of academic literature.

5.2 Preliminary Analysis

Before the regression analysis begins, the Hausman Test is employed for both regression specifications in Table 5 to determine whether a fixed-effects or random-effects model is more suitable for the analysis. The resulting p-values of 0.0000 and 0.0000 are smaller than 5 percent, thus the null hypothesis is rejected, which means the random-effects model's assumptions are violated and the fixed-effects regression model is used for the analysis (Appendix 1B). To ensure the robustness of the regression estimates, tests for autocorrelation and heteroscedasticity in the error terms are conducted for all regression models. On top of that, the normality of the error term is inspected as well as a check for multicollinearity. To detect heteroscedasticity, the Breusch-Pagan test is conducted and the Wooldridge test is employed to check for autocorrelation in the errors. These tests help mitigate the inefficiency and bias of the regression results allowing for better and more reliable interpretation of the regression results. The Breusch-Pagan test in Appendix 2B yields a p-value of below the five percent level for all regression models indicating heteroscedasticity in the data. For the extended regression model in Panel B of Table 5 the test statistic is 4251.61 with a p-value of 0.0000. Similarly, the Wooldridge test in Appendix 3B shows significant autocorrelation for all regression model specifications in the data. The test for the extended regression model shows a test statistic of 886.42 and a p-value of 0.0000. Hence, clustered standard errors at the firm level are employed to address the heteroscedasticity and autocorrelation in the error terms for all regression models. Clustering on firm level ensures that the robust standard errors account for within-firm correlation, enhancing the reliability of the regression estimates. Furthermore, the normality of the error terms is investigated through visualizations using a histogram and Q-Q plot. The error term is approximately normally distributed for all model specifications and the visualization of the error terms of the extended regression model can be seen in Appendix 4B. Lastly, Appendix 5B shows a correlation matrix containing all independent variables used in the regressions. It is not possible to identify any multicollinearity in the variables that would bias the estimates, thus the use of the variables is justified in this regard. The highest correlation is between the credit ratings and market value variables with a negative correlation of 46.6 percent showing that there is no multicollinearity in the predictors.

5.3 Statistical Results

The following section encompasses and describes the central findings on the effect of credit ratings on the average monthly stock market returns of German companies. The analysis begins with the regression models suggested by Avramov (2009). The model is then extended by three additional control variables that have been identified to help explain average returns and investor decision-making. The extended regression model is used as the central regression model and is further investigated through the use of sub-group division of the data by years and rating categories. Lastly, the non-monotonical credit rating variable is substituted by its historically derived one year default rate probabilities to accurately target the effects of underlying changes in creditworthiness.

Table 5: Central Regression Results

Panel A: Fixed-Effects Regression of Monthly Returns on Credit Ratings

Monthly Returns	(1)	(2)	(3)
Credit Ratings $_{t-1}$	0.0029		(0.0020)
Market Value $_{t-2}$ (log)		(0.0113)***	(0.0216)***
B/M Ratio $_{t-2}$ (log).		0.0189***	0.0189***
6 Month Cum. Returns $_{t-2}$		0.0120**	0.0081
Turnover $_{t-2}$ (log)		0.0016	0.0014
Constant	(0.0205)	0.1015***	0.2135
Number of observations	11,451	13,265	10,666
Overall R2	0.0001	0.0017	0.0009

Panel B: Fixed-Effects Regression of Monthly Returns on Credit Ratings

Monthly Returns	(4)	(5)	(6)
Credit Ratings $_{t-1}$	(0.0017)	0.0050***	(0.0031)*
Market Value $_{t-1}$ (log)	(0.0223)***		(0.0249)***
B/M Ratio $_{t-1}$ (log)	0.0189***		0.0220***
Turnover $_{t-1}$ (log)	0.0016*		0.0016*
6 Month Cum. Returns $_{t-1}$	(0.0000)		(0.0108)***
LT Debt to Equity $_{t-1}$ (log)		0.0006	0.0033*
Dividend Yield $_{t-1}$		(0.0008)	(0.0027)***
Return on Assets $_{t-1}$		0.0013***	0.0020***
Constant	0.2157***	(0.0403)***	0.2553***
Number of observations	10,727	11,258	10,691
Overall R2	0.0012	0.0008	0.0032

*Notes: Table 5 shows the relationship between credit ratings and monthly stock market returns using a fixed-effects regression model with at firm level clustered standard errors. Panel A builds up to the full model by using only credit ratings as the predictor in model (1), then only the control variables in model (2) and finally the full regression model in model (3). Similarly, Panel B describes the same relationship but uses more control variables and only one period lagged variables. Here, model (4) shows the previous model (3) from Panel A with the one-period lagged variables. Model (5) uses only the three new variables as controls for the regression and lastly model (6) shows the extended regression model which serves as the central regression in this study. Negative values are exhibited in parentheses. Significance levels are portrayed as: * p<0.1, **p<0.05, ***p<0.01.*

The central findings of this study are shown in Table 5. The model in Panel A is inspired by Avramov et al. (2009) approach to predicting stock market returns. The first regression excludes all control variables and yields a statistically insignificant coefficient of 0.0029 with almost no explanatory power. The results in model 2 show that the control variables yield statistical significance in explaining average monthly returns. The logarithmically transformed and two-period lagged market value has a negative effect on average monthly returns which indicates the size effect. The third model is complete and suggests that credit ratings have a statistically insignificant effect on monthly returns. A one notch worsening in the credit rating decreases the average monthly returns by 0.2 percent which implies that companies with worse ratings have lower stock market returns, but the credit rating variable is not robust to controlling for size, value, and past returns. Moreover, the model has low explanatory power (R-squared) and only explains 0.09 percent of the variation in monthly returns, while the second model that excludes the rating variable explains slightly more variation with an R-squared of 0.17 percent. These findings suggest that there is no significant relationship between a company's credit rating and its stock market performance.

That is why Panel B further investigates the relationship between credit ratings and monthly returns using more appropriate control variables and an extended regression model. Factors that the academic literature has identified to help explain stock market returns are added to the model. The measures of profitability, leverage and dividend yield are also commonly used by investors as part of their investment considerations. On top of that, the lag of variables is reduced to a one-month lag in contrast to the two-month lag used before. Looking at the complete model 6, these adjustments help to significantly improve the model's explanatory power by increasing the R-squared to 0.32 percent. An increase in the credit rating score by one decreases the average monthly returns by 0.31 percent, significant at a ten percent significance level. This suggests that companies with higher credit risk yield lower average stock market returns, going against the idea of the risk-return trade-off and supporting the first hypothesis of this paper. Model 4 shows the same control variables as the complete model in Panel A; however, the lags are reduced to one period. This adjustment slightly improves the R-squared to 0.12 percent but the effect of credit ratings on monthly returns remains insignificant. Model 5 uses only the newly added variables as controls. Credit ratings now have a positive and highly significant effect on monthly returns and it is clear to say that the addition of these variables has an impact on the model, however, the omittance of the other control variables such as market value and B/M ratio diminishes the suggestive power of model 5.

The results from the regression model in Panel A are inconclusive and yield little credible information on the effect of credit ratings on monthly stock returns. Moreover, results from Panel B are more credible and can explain more variation in the model but the variation in the predictor estimate between the model specifications is reason for concern as it suggests that the regression estimate is not robust and depends on the model specification. It is important to consider that the book-to-market ratio does not include intangible assets such as intellectual property or brand value of the firms. Firms with a high level of intangible assets might seem undervalued or less financially healthy than they are which can lead to misleading comparisons. This is especially problematic as intellectual property contributes to firms' competitive edge and thus their creditworthiness. Considering that they likely also influence stock performance this could introduce omitted variable problems into the model. Nevertheless, intellectual property is excluded from the regression because it is hard to consistently and reliably measure and compare intangible assets between firms. This would also introduce reliability problems to the model Moreover, the competitive edge that intellectual property describes, is partially reflected in other variables such as return on assets or the long term debt to equity. Thus, omitting proxies for intellectual property such as the number of patterns or brand value will likely not significantly bias the regression results. Still, it is interesting for future research to test the impact of intellectual property on the relationship studied in this paper. The missing reliability of the results prohibits causal inferences. That is why, the regression model in Panel B is investigated further by splitting it into two different sub-groups to test the robustness of the results.

Table 6: Sub-Group Fixed-Effects Regression of Monthly Returns on Credit Ratings

	Panel A		Panel B	
Monthly Returns	(1) *2010-2016*	(2) *2017-2023*	(3) *Investment Grade*	(4) *Speculative Grade*
Credit Ratings $_{t-1}$	(0.0052)**	(0.0044)	0.0006	(0.0155)***
Market Value $_{t-1}$ (log)	(0.0368)***	(0.0349)***	(0.0216)***	(0.0531)***
B/M Ratio $_{t-1}$ (log)	0.0209**	0.0281***	0.0284***	0.0122
Turnover $_{t-1}$ (log)	(0.0011)	0.0045***	0.0011	0.0040**
6 Month Cum. Returns $_{t-1}$	(0.0229)***	(0.0016)	(0.0136)***	(0.0016)
LT Debt to Equity $_{t-1}$ (log)	0.0021	0.0039	0.0027	0.0051
Dividend Yield $_{t-1}$	(0.0008)	(0.0027)***	(0.0034)***	(0.0013)
Return on Assets $_{t-1}$	0.0020***	0.0021***	0.0027***	0.0019***
Constant	0.3933***	0.3356***	0.2070***	0.5780***
Number of observations	4,197	6,494	8,428	2,092
Overall R2	0.0034	0.0021	0.0034	0.0013

*Notes: Table 6 shows the relationship between credit ratings and monthly stock market returns using the extended fixed-effects regression model with at firm level clustered standard errors from model (6) in Table 5 and sub-groups of the data. Panel A shows the split of the data set into two periods ranging from 2010-2016 in model (1) and from 2017-2023 in model (2). Panel B shows the split of the data set into investment grade rated companies, model (3) and speculative grade rated companies, model (4). Negative values are exhibited in parentheses. Significance levels are portrayed as: * p<0.1, **p<0.05, ***p<0.01.*

Table 6 shows these attempts to further dissect and investigate the model and the effect of credit rating on monthly returns. Panel A splits the model into equal seven-year periods to investigate the stability and consistency of the results over time. The two periods are from 2010 to 2016 and 2017 to 2023. Panel B looks individually at the investment grade and speculative grade ratings to gain closer insights into the distress effect and to show differences between those groups. In Panel A the first seven years have a higher R-squared of 0.34 percent compared to the 0.21 percent of model 2. Moreover, despite both credit rating variables having a negative effect on average monthly returns when increased by one, in model 1 this effect is statistically significant at a five percent level. From 2010 to 2016 an increase in credit rating score by one, decreases the monthly returns by 0.52 percent. This relationship cannot be statistically confirmed in the period between 2017 and 2023, although the suggested effect of a rating increase on average returns remains negative. The difference between the periods suggests structural changes during the time series possibly due to changes in market efficiency, behaviour or economic conditions.

Looking at the estimates in Table 6 and comparing them to Table 5, it is clear that the regression results are volatile and sensitive to changes in model specification and the split of the data sample. This shows that making causal inferences from the results is not possible and that the results are biased. However, the results of the regressions point predominantly to a negative relationship between worse ratings and market returns. In Panel B the difference between R-squares is higher than in Panel A, with model 3 having a value of 0.34 percent and model 4 with 0.13 percent explanatory power over the variation in the monthly stock market returns. Interestingly, although the regression specification of the investment grade rated companies has about four times the amount of observations, the coefficient of the credit rating variable is close to zero with a suggested positive, yet insignificant effect of 0.06 percent when the rating score increases by one.

On the other hand, the regression model using only speculative grade assets shows a highly significant negative effect of 1.55 percent average monthly returns for a one-score increase in credit rating. These findings are highly important as they confirm the assumption that the distress effect is responsible for the negative relationship between rating scores and average stock market returns. These regressions suggest that the credit rating for investment grade-rated companies does not determine or impact monthly returns. This is likely due to investors prioritising other factors such as size, profitability, value or the business model in their investment decisions when the company is financially stable. However, for companies with high credit risk, investors become much more careful, putting more emphasis on the credit ratings. Thus, stock returns are more sensitive to rating changes of poorly rated companies. This comparison perfectly illustrates the distress effect and investor behaviour towards high-risk assets. I expect that the distress effect and consideration of credit ratings in the investment decision process is especially strong in periods of high market uncertainty and volatility compared to calmer periods. This is because investors search for explanations and reassurance during volatile periods, especially when the market crashes and ratings could give an estimation on which assets are already connected to high levels of risk and thus deter investors from investing in poorly rated companies. However, this should be investigated further in subsequent studies.

Table 7: Fixed-Effects Regression of Monthly Returns on Default Probabilities

Monthly Returns	(1)
Default Probability $_{t-1}$	(0.0016)
Market Value $_{t-1}$ (log)	(0.0235)***
B/M Ratio $_{t-1}$ (log)	0.0222***
Turnover $_{t-1}$ (log)	0.0018**
6 Month Cum. Returns $_{t-1}$	(0.0109)***
LT Debt to Equity $_{t-1}$ (log)	0.0032*
Dividend Yield $_{t-1}$	(0.0025)***
Return on Assets $_{t-1}$	0.0021***
Constant	0.2157***
Number of observations	10,164
Overall R2	0.003

*Notes: Table 7 shows the relationship between one-year default probabilities and monthly stock market returns using the extended fixed-effects regression model with firm level clustered standard errors from model (6) in Table 5. This regression model substituted the previously used credit rating variable with one-year default probabilities as they are suggested by S&P (2023). Negative values are exhibited in parentheses. Significance levels are portrayed as: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.*

Converting the credit ratings into default rates to more accurately investigate the effect of credit risk on average monthly returns does not suggest a significantly different result from the prior findings. With a statistically insignificant regression coefficient of -0.16 percent and an R-squared of 0.3 percent, the regression suggests once again a negative relationship between credit risk and returns. A one percent increase in the default probability results on average in -0.16 percent lower monthly returns. Thus, even when the predictor variable represents the underlying default risk much better than the imperfect credit rating score that fails to capture the creditworthiness changes between different ratings, it does not significantly change the regression results.

CHAPTER 6 Conclusion

6.1 Summary of Research Findings

In this thesis, I have looked at the relationship between credit ratings and the stock market returns of German companies and investigated the credit risk-return puzzle. Previous research has shown that worse-rated companies yield lower returns and that this relationship is primarily driven by the worst-rated companies. It was also discovered that worse-rated companies tend to be smaller, have higher leverage and lower book-to-market ratios. In my analysis, I investigated all these factors. First, I used five rating-based portfolios that compare the average firm characteristics of their portfolio companies over the time series. The portfolio comparison finds that indeed the best-rated portfolio has 1.06 percent higher average monthly returns than the worst-rated portfolio and that this relationship is primarily driven by the relatively poor performance of the worst-rated portfolio. These findings can be attributed to the distress effect. However, there is no clear trend in the book-to-market ratio between the portfolios. It can only be concluded that the best-rated portfolio has the highest book-to-market ratio. Furthermore, I find that the worse-rated portfolios are smaller in size, have a higher leverage ratio and a much higher price-to-earnings valuation. The second part of the analysis uses several fixed-effects regression models to investigate the relationship between ratings and returns. The first regression model which is based on Avramov et al. (2009) finds that there is no significant relationship between credit ratings and average monthly returns and it yields almost no explanatory power over the variation in monthly returns. Thus, the model is adjusted by shortening the lag period of the controls from two to one period and by adding three proven controls. I find that the credit ratings have a significant negative coefficient of -0.0031, suggesting that a decrease in credit rating by 1 notch results on average in 0.31 percent lower monthly returns. These results must be taken with a grain of salt because the model cannot ensure unbiased and efficient estimates, although it addresses autocorrelation and heteroscedasticity through the use of clustered standard errors. Nevertheless, this extended model is investigated further in sub-groups of periods and rating categories. I find that the effect of credit ratings on average monthly returns is significantly stronger from 2010 to 2016 than from 2017 to 2023 as in the first seven years the estimate is significant, suggesting a one notch rating decrease lowers average monthly returns by 0.52 percent. However, more importantly, dividing the data sample into investment grade and speculative grade companies shows that investors seem to only care about credit ratings in their investment decisions when the companies have high credit risk. Hence, I find strongly significant results for the speculative grade companies, suggesting a one notch rating decrease lowers average monthly returns by 1.55 percent whereas the effect for the investment grade rated companies is insignificant and suggests 0.06 percent higher monthly returns. This is another indication of the distress effect as credit ratings have a much higher influence on the average monthly returns for high credit risk companies compared to low-risk companies. At last, the rating variable is substituted for one-year default probabilities that correspond to the rating scores. The resulting estimate of -0.0016 is insignificant and thus suggests that using a different measure of credit risk, which is able to more accurately reflect the changes in credit risk between the companies, does not improve the results.

6.2 Limitations

Despite the contributions to the literature that this paper offers, it comes with many limitations. The biggest limitation of this paper is the credit rating variable. It is sticky throughout the time series and offers little within firm variation as well as being categorical like, which makes statistical analysis and inferences tricky. It is hard to single out the effect of credit ratings on the stock market returns due to this stationarity. On top of that, the distribution of credit rating scores is influenced by the fact that having a rating is a voluntary decision by the company introduces systematic bias to the variable that might skew the results. A large panel data set with many rated companies over a long period would help mitigate the problems that come along with the imperfect ratings variable, however, the German stock market is relatively small and has very few rated companies. The small sample size of 106 companies does not help but worsens the problem of missing input data and variation in the data as the importance of each company is quite high for the data set. Especially, because a lot of companies in the sample do not have ratings for the entire sample period. The book-to-market ratio excludes intellectual property and intangible assets in its valuation and by that possibly understates the value of firms. The omittance of intellectual property as a control variable might introduce bias to the regression results but there is no consistent and reliable way to proxy these values and compare them between firms and industries without introducing other reliability concerns. Furthermore, there are always risks when data is taken from secondary sources like the database that is used for the financial data in this study. The databanks could report wrong values or have missing values for some variables due to unknown reasons.

6.3 Implications and Future Research

These findings suggest that credit ratings of German companies do not play an utterly decisive role in determining and predicting stock market returns and they do not seem to be a decisive factor in investors' decision-making due to the low explanatory power of the regressions and the issue with making causal inference as the estimates are likely biased and inefficient. However, this picture changes when looking at the difference between investment grade and speculative grade rated companies because they suggest that investors pay closer attention to the credit ratings when the companies are in financial distress compared to when they are financially stable and that investors are deterred by these poor credit ratings. This possibly yields relevant insights into investor behaviour towards high-risk assets and the distress effect of high credit risk companies. I acknowledge that this topic needs further investigation especially looking at periods of high market uncertainty compared to calm periods and with better and more data because statements based on the available data set are subject to bias. On top of the relevance to academia, investors should also be aware of this phenomenon even though it might seem like an obvious and logical occurrence it can benefit their investment decision-making and help them understand stock pricing and movements in the market. Furthermore, this paper understands itself as a stepping stone and part of the groundwork laid out for future research on the relationship between credit ratings and stock market returns. Although the findings are mostly inconclusive and biased it is worth mentioning that the paper suggests that there is a relationship between credit ratings and returns albeit a small and not that significant one. Besides, there likely is distress risk in the worst-rated companies in the German market. These topics should be studied further with a larger and more elaborate sample size over a longer time horizon. Moreover, the subject of the role that credit risk has in stock pricing can be extrapolated to Europe and other countries using for example decile rating-based portfolios.

REFERENCES

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2009). Credit ratings and the cross-section of Stock returns. *Journal of Financial Markets*, *12*(3), 469–499. https://doi.org/10.1016/j.finmar.2009.01.005

Baghai, R. P., Servaes, H., & Tamayo, A. (2014). Have rating agencies become more conservative? implications for capital structure and debt pricing. *The Journal of Finance*, *69*(5), 1961–2005. https://doi.org/10.1111/jofi.12153

Bhatia, A. V. (2002). Sovereign Credit Ratings Methodology: An evaluation. *IMF Working Papers*, *02*(170), 1. https://doi.org/10.5089/9781451858433.001

Brooks, C. (2019). *Introductory econometrics for finance* (4th ed.). Cambridge University Press.

European Commission. (2023, November 21). *Commission makes recommendations to EU countries and reviews 2024 draft budget plans*. https://commission.europa.eu/news/commission-makes-recommendations-eu-countries-and-reviews-2024-draft-budget-plans-2023-11-21_en

Securities and Exchange Commission. (2014, May 09). Dodd-Frank Act Rulemaking: Credit Rating Agencies. https://www.sec.gov/spotlight/dodd-frank/creditratingagencies.shtml

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance*, *52*(1), 1. https://doi.org/10.2307/2329554

Dichev, I. D. (1998). Is the risk of bankruptcy a systematic risk? *The Journal of Finance*, *53*(3), 1131–1147. https://doi.org/10.1111/0022-1082.00046

EU Monitor. (2019, April 09). *Regulation 2009/1060 - Credit rating agencies*. https://www.eumonitor.eu/9353000/1/j4nvk6yhcbpeywk_j9vvik7m1c3gyxp/vitgbgiu7nzb#:~:text=It%20seeks%20to%20regulate%20the,quality%20of%20the%20ratings%20issued.&text=better%20consumer%20and%20investor%20protection.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427. https://doi.org/10.2307/2329112

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and Bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405x(93)90023-5

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Federal Reserve Bank of Dallas. (2013). Assessing the Costs and Consequences of the 2007-09 Financial Crisis and Its Aftermath, Volume 8, Number 7. *Economic Letter: Insights from the Federal Reserve Bank of Dallas*. https://fraser.stlouisfed.org/title/6362/item/607683, accessed on July 14, 2024.

Galil, K. (2003). The quality of corporate credit rating: An empirical investigation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.406681

Griffin, J. M., & Lemmon, M. L. (2002). Book-to-Market equity, distress risk, and stock returns. *The Journal of Finance*, *57*(5), 2317–2336. https://doi.org/10.1111/1540-6261.00497

Hilscher, J., & Wilson, M. (2015). Credit ratings and credit risk: Is one measure enough? *Management Science*, *63*(10), 3414–3437. https://doi.org/10.1287/mnsc.2016.2514

Kenjegaliev, A., Duygun, M., & Mamedshakhova, D. (2016). Do rating grades convey important information: German evidence? *Economic Modelling*, *53*, 334–344. https://doi.org/10.1016/j.econmod.2015.11.021

Langohr, H., & Langohr, P. (2010). *The rating agencies and their credit ratings what they are, how they work, and why they are relevant Herwig Langohr ; Patricia Langohr*. John Wiley & Sons.

Löffler, G. (2004). Ratings versus market-based measures of default risk in portfolio governance. *Journal of Banking & Finance*, *28*(11), 2715–2746. https://doi.org/10.1016/j.jbankfin.2004.06.007

Moody's. (2010). Best practices guidance for the credit rating process. ... https://www.moodys.com/sites/products/ProductAttachments/Compliance/Exhibit 3/Best Practices Guidance for the Credit Rating Process.pdf

Mullard, M. (2012). The credit rating agencies and their contribution to the financial crisis. *The Political Quarterly*, *83*(1), 77–95. https://doi.org/10.1111/j.1467-923x.2012.02268.x

Parlour, C. A., & Rajan, U. (2019). Contracting on credit ratings: Adding value to public information. *The Review of Financial Studies*, *33*(4), 1412–1444. https://doi.org/10.1093/rfs/hhz083

Piccolo, A., & Shapiro, J. (2022). Credit ratings and market information. *The Review of Financial Studies*, *35*(10), 4425–4473. https://doi.org/10.1093/rfs/hhac005

S&P Global Ratings. (n.d.). *Issuer credit ratings.* https://www.spglobal.com/ratings/en/products-benefits/products/issuer-credit-ratings

S&P Global. (2023, May 01). *General Criteria: Principles Of Credit Ratings.* https://disclosure.spglobal.com/ratings/en/regulatory/article/-/view/type/HTML/id/2980589

Stock, J. H., & Watson, M. W. (2020). *Introduction to econometrics*. Pearson.

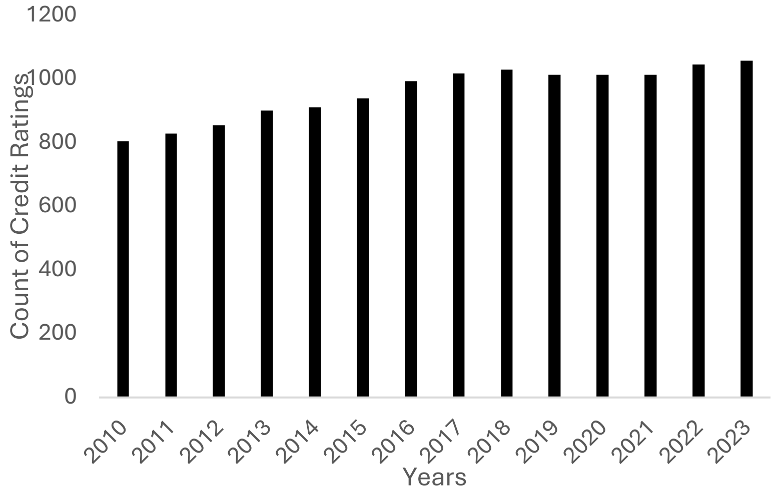
LSEG (2024). *Company Data. https://www.lseg.com/en/data-analytics*

Utzig, S. (2010). The financial crisis and the regulation of Credit Rating Agencies: A european banking perspective. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1592834

White, L. J. (2010). Markets: The credit rating agencies. *Journal of Economic Perspectives*, *24*(2), 211–226. https://doi.org/10.1257/jep.24.2.211

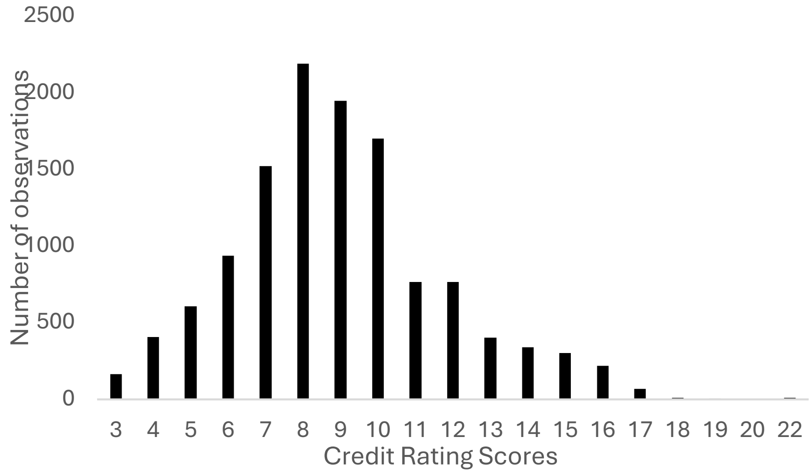
APPENDIX A Variables & Descriptive Statistics

Figure 1A: Annual Credit Rating Observations



Notes: Figure 1A shows the annual number of credit rating observations from 2010 to 2023 in a bar graph with the years on the horizontal axis and the number of credit ratings on the vertical axis.

Figure 2A: Number of Observations per Credit Rating Score



Notes: Figure 2A shows a histogram with the number of observations for each credit rating score. The Average Credit Rating scores are rounded to the integer and range from 3 which constitutes an AA rating to 22 which constitutes a D.

Table 3A: Variable Description

Variable Name	Formula	Number of Measurements
Credit Ratings	NA	12,202
Monthly Returns	$\frac{Price\ at\ the\ end\ of\ the\ month}{Price\ at\ the\ end\ of\ the\ previous\ month} - 1$	11,461
Market Value	$Share\ Price \times Number\ of\ Shares\ Outstanding$	11,535
Turnover	NA	11,436
Book-to-Market Ratio	$\frac{Book\ Value\ per\ Share}{Share\ Price}$	11,466

6M Cumulative Returns	$(\sum_{i=1}^{6}(1+R_{t-i}))-1$	11,087
LT Debt to Equity	$\frac{Long\ Term\ Debt}{Common\ Equity}$	12,033
Dividend Yield	$\frac{Most\ recent\ Dividends}{Current\ Market\ Value} * 100$	11,535
Return on Assets	$\frac{Net\ Income}{Total\ Assets}$	12,006
Price to Earnings	$\frac{Share\ price}{Earnings\ per\ Share}$	9,672
Price to Sales	$\frac{Share\ Price}{Sales\ per\ Share}$	11,637
Price to Cashflow	$\frac{Share\ Price}{Operating\ Cashflow\ per\ Share}$	11,637
Current Ratio	$\frac{Current\ Assets}{Current\ Liabilities}$	8,866
Enterprise Value	$Market\ Value\ of\ Equity + Total\ Debt - Cash\ \&\ Cash\ Equivalents$	11,637
EPS	$\frac{Net\ Income - Preferred\ Dividends}{\text{Weighted Average Number of Common Shares Outstanding}}$	11,440

Notes: Table 3A exhibits the formulas used to calculate the variables as well as the number of observations for each variable used in this study.

Table 4A: Conversion of Credit Ratings to 1-Year Default Probabilities

Fitch and S&P	Moody's	Numeric Score	Default Probability (%)
AAA	Aaa	1	0.00
AA+	Aa1	2	0.00
AA	Aa2	3	0.02
AA-	Aa3	4	0.02
A+	A1	5	0.04
A	A2	6	0.05
A-	A3	7	0.05
BBB+	Baa1	8	0.09
BBB	Baa2	9	0.14
BBB-	Baa3	10	0.21
BB+	Ba1	11	0.28
BB	Ba2	12	0.45
BB-	Ba3	13	0.88
B+	B1	14	1.86
B	B2	15	2.73
B-	B3	16	5.33
CCC/C	Caa/C	17/21	25.98
D	D	22	100

Notes: Table 4A shows the conversion from credit rating scores to 1-year default probabilities based on historical data provided by S&P (2023). The table assumes that the ratings by Fitch and Moody's that have the same level as the S&P rating, also have the same implied default probability. The default probabilities for ratings from CCC to C are clustered into one category. Source S&P (2023)

APPENDIX B Robustness Checks

Table 1B: Hausman Test

Panel A Regression

$\chi^2 = 133.35$	Degrees of freedom 5	p-value = 0.0000

Panel B Extended Regression

$\chi^2 = 225.51$	Degrees of freedom 8	p-value = 0.0000

Notes: Table 1B shows the Hausman test that compares the estimates of the fixed effect and random effect models of the panel data regression model in Table 5 of this study. The Panel A Regression refers to the regression model in Panel A of Table 5 and Panel B Extended Regression refers to the regression model in Panel B of Table 5. Table 1A shows the test statistic, degrees of freedom and p-value of the Hausman Test for both regression models.

Table 2B: Breusch-Pagan Test

	Test results
Chi2 (1)	4251.62
P-value	0.0000

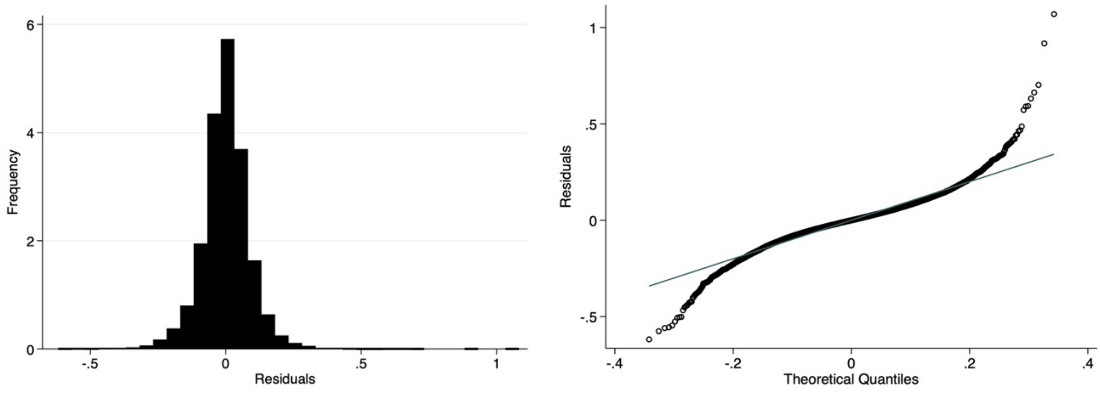
Notes: Table 2B shows the Breusch-Pagan Test for groupwise heteroscedasticity in fixed effect models for the extended regression model in Panel B of Table 5 that servesw as the central regression model of this study.. The test determines whether the error term varies across firms (years); H0: σ(i)2= σ2. Under H0, there is no effect i.e. homoscedasticity whereas Ha suggests that there is heteroscedasticity in the regression.

Table 3B: Woolridge Test

	Test results
F-test (1, 102)	886.420
P-value	0.0000

Notes: Table 3B shows the Woolridge-Dukker test for first-order autocorrelation in panel data for the extended regression model in Panel B of Table 5. This test for serial correlation investigates the presence of autocorrelation in the error term of the regression. Under H0, the error term is uncorrelated over time, i.e. there is no first-order autocorrelation whereas Ha suggests the error term is first-order correlated.

Figure 4B: Normality of the Error Term



Notes: Figure 4B shows the visualisation of the normality of the error term of the extended regression model in Panel B of Table 5. The figure on the left shows the distribution of the regression's error term in a histogram and the figure on the right shows a Q-Q plot of the error term.

Table 5B: Correlation Matrix of the Predictor Variables

	Credit Ratings	Market Value	6 Month Cumulative Returns	Book to Market Ratio	Turnover	LT Debt to Equity	Dividend Yield	Return on Assets
Credit Ratings	1.000	(0.4658)	(0.0203)	0.0228	(0.0219)	0.0749	(0.2982)	(0.0746)
Market Value		1.0000	0.0832	(0.1936)	0.1574	(0.1020)	0.0890	0.0729
6 Month Cumulative Returns			1.0000	(0.1932)	(0.0648)	(0.0524)	(0.1926)	0.2216
Book to Market Ratio				1.0000	0.0139	0.1820	0.0996	(0.1800)
Turnover					1.0000	(0.0378)	0.0642	(0.0176)
LT Debt to Equity						1.0000	(0.0109)	(0.2303)
Dividend Yield							1.0000	0.0141
Return on Assets								1.0000

Notes: Table 5B shows the correlations between all predictor variables used in this study in a matrix. This correlation matrix is used to investigate multicollinearity in the control variables used in the analysis.