Does the Merton model apply to the specific circumstances of emerging markets?

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Abstract

Title	Does the Merton model apply to the specific circumstances of emerging markets?
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Authors	David Buschermöhle and Tobias Cromme
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Five key words	The Merton model, emerging markets, ratings, emerging markets rating, market efficiency
Purpose	The purpose was to investigate whether the Merton Model works in emerging markets and if it does how efficient it works there compared to in mature markets.
Methodology	The calculated default probability of the Merton model and the ratings were run in a regression.
Theoretical perspective	The Merton Model by Robert C. Merton (1974) which is based upon work by Black and Scholes (1973)
Empirical foundation	Data of 100 non-financial firms was collected, 50 companies of mature countries and 50 of emerging countries.
Conclusion	Findings show that the Merton model works in emerging markets and considers country specific information, yet only through stock prices and volatility. However, the model does not account for quality and availability of information in these countries which in turn have a negative impact on market efficiency.

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1 Introduction

This Chapter will introduce the reader to the topic of the thesis; it will provide an understanding of the ideas and intention behind the project. Therefore, the previous research in the area of this topic will be discussed; furthermore, the research objective, the problem statement and the limitations to this study will be presented.

1.1 Background to the study

"*There are two superpowers in the world today in my opinion. There's the United States and there's Moody's Bond Rating Service. The United States can destroy you by dropping bombs, and Moody's can destroy you by downgrading your bonds. And believe me, it's not clear sometimes who's more powerful*"

Thomas Friedman (Langohr & Langohr, 2010)

Credit ratings first were applied to securities markets in the U.S. dating back to the 19th century as a consequence of an increasing distance between debtors and creditors but were later expanded to Europe and also included corporations. The need for further transparency, as well as new laws and regulations led to a wider incorporation of credit ratings in the financial markets resulting in recognition of rating agencies as Nationally Recognized Statistical Rating Organization (NRSROs) by the U.S. Congress in 2006 ((SEC), 2014).

Nowadays, credit ratings and agencies have a substantial importance for the economy as they provide important insights into the creditworthiness of countries and corporations for investors and creditors. The expertise of rating agencies is needed as participants in the market often lack skill and time to perform a fundamental credit analysis. Additionally, credit ratings are an integral part of financial transactions and structuring as well as for capital requirements of corporations through warranting the creditworthiness of securities, corporations, and countries.

Therefore, companies like Moody’s and S&P also have a duty to society, since misevaluated companies can cause corporate scandals such as Ahold in Europe and Enron in the US, which had a significant impact on the economy as a whole. Because of these recent examples of corporate scandals and the impact of credit ratings provided by rating agencies the role of respective agencies in issuing ratings to corporations has been criticized.

In light of the subprime mortgage crisis doubts about the integrity of the “big three” (Standard & Poor’s, Moody’s, and Fitch) and the ratings they provide have risen as they cannot be held accountable for the accuracy of their assessment of creditworthiness. When attempting to remove this insulation of liability rating agencies refused to accept and argued with the principle of freedom of speech and claimed that they would merely express an opinion very much like in an editorial review. This is seen as controversial as many institutions like banks or pension funds are bound by law to invest in “investment grade” securities (Cane, Shamir, & Jodar, 2011). Furthermore, the argument of researchers that credit ratings will have an even more substantial impact on capital markets with regard to Basel II and Basel III should be considered carefully (Hwang, Chung, Siao, & Lin, 2012).

As credit ratings gain further importance in mature markets after the adoption of Basel II and III it is reasonable to assume that this importance also extends to emerging market countries because of their rapid development to assimilate with mature markets. Especially, since emerging markets impose an additional uncertainty for foreign investors. Moreover, mature markets are mostly saturated nowadays in terms of investment opportunities leading to an amplified capital attraction by emerging markets.

Presuming that mature markets are more efficient than emerging markets it is interesting to establish a link between the accuracy of the assigned credit ratings relative to the Merton model and country specific risk factors for emerging market countries such as governance and corruption indices. The accuracy of the Merton model relates to the completeness of market information as it uses public information comprised by stock and balance sheet data. Findings of the Merton model being accurate would therefore suggest that the same information used to determining a credit rating is also publicly available in market data. Empirical evidence suggests that the Merton model is more accurate in developed economies as their stock markets process information more efficient. Morck, Yeung, and Yu (2000) find that countries with deficits in investors’ property protection have increased synchronous stock price movements driven by a big general impact of politically shifts and trading noise. Therefore these stock markets are less efficient in processing information. On the contrary, developed economies’ stock markets with high standards for property rights for example, exhibit more firm specific fluctuations in stock returns.

1.2 Previous research

Previous research on the Merton model and other structural models arrived at different conclusions about the adequacy of the Merton model for determining default. Stein (2002) concludes that the model can easily be improved whereas Bohn, Arora, & Korablev (2005) conclude that the Merton model is adequate in capturing all information relevant for traditional credit ratings. Other studies focus on the functioning of the model in specific circumstances like in India or conclude that the Merton mode is not significant as a statistic for default in general (S. Bharath & Shumway, 2004).

Furthermore, research has been done on the efficiency of stock markets in emerging and developed countries as well as for information asymmetry between market data and credit ratings. Findings show that publicly available market data can be used to predict credit events between 90 to 60 days prior to a credit event (Norden & Weber, 2004). In terms of comparing emerging with mature markets Griffin, Kelly, and Nardari (2010) show that a potential information bias exists, since an analysis of stock market efficiency through trading strategies does not account for different frequencies of publishing information as well as the general availability of information.

1.3 Problem statement

Previous research applies the Merton model in emerging markets but they rarely compare it to ratings derived from rating agencies. Another limitation of further studies is that they apply the model in most of the cases in only one market, which could also explain the different results of the various studies. Therefore this study will fill this gap and give valuable results about the impact of the Merton Model on company credit ratings in emerging and developed countries. Due to the nature of the model, which relies on market data it will also shed light on the completeness of information in emerging and mature markets' stock markets. For the purpose of this research it is assumed that both emerging and mature countries have efficient markets based on the definition given later in chapter 2.2.

H1: Distance to default has a significant influence on credit ratings in emerging markets.

This research revolves around the two central questions of whether country specific credit risks are already included in market information and therefore also in the distance to default derived from the Merton model, in comparison to credit ratings.

The ratings provided by agencies are based, among other criteria, on distance-to-default derived from the Merton model or models that are based on that approach. The other foundation of the rating is based on a qualitative analysis. This research aims to determining the relation between a credit rating and the distance to default computed in the Merton model. Because of the mentioned characteristics of mature markets, the relationship between credit rating and the Merton model might be stronger in mature markets compared to emerging markets. Consequently, the relationship between regulatory quality and corporate ratings should be stronger in emerging markets as it becomes of greater importance here. Therefore, regulatory quality and control of corruption, taken from the Worldwide Governance Indicators of the World Bank Group D. K. Kaufmann, Aart; Mastruzzi, Massimo (2013), will be examined in terms of their relevance for credit ratings in developed and emerging countries.

H2: Regulatory quality and control of corruption have a significant influence on credit ratings in emerging markets.

H3: Regulatory quality and control of corruption have a greater impact on credit ratings in emerging markets.

The established differences between emerging markets and mature markets, as well as credit rating and Merton distance to default, explain the qualitative adjustments made in credit rating methodologies to account for country and industry specific risks. Based on the literature review the fundamental assumption is that mature stock markets are more effective in processing market information whereas emerging markets are less effective in doing so.

H4: Distance to default has a greater impact on credit ratings in mature than in emerging markets.

1.4 Research objective

For the purpose of comparing the two types of markets with each other the ratings and default probabilities of five mature markets will be matched against each other in comparison to ratings and default probabilities in five emerging markets. The Merton model incorporates only market and company data, which is provided by the stock markets and S&P CapitalIQ. This means that capital markets will be indirectly tested how well they account for the country specific risks of the environment they are operating in.

Because of information asymmetry and other efficiency issues the Merton model should work more accurately in mature than in emerging markets, by applying the model in these two different markets and further analysing in total 10 different countries with 10 different companies each, it is intended to mitigate any country specific biases as much as possible.

This study contributes to previous research through setting distance to default into context with credit ratings with regard to information included into publicly available market data. To a big extend this was previously done in the context of trading strategies and stock returns whereas the relationship between the Merton model using public company data and company credit ratings will be analysed in this paper.

1.5 Limitations to the study

This subchapter presents the limitations of this thesis, which can be grouped according to limitations in the data sample and limitations in the methodology.

A geographical limitation can be seen in the sample data since mature countries are entirely represented by European countries. Still, the United Kingdom is represented and therefore the Anglo-Saxon region finds consideration although there are no U.S. companies included. Furthermore, only five emerging and five mature countries are represented in the sample. Besides the geographical limitations, the chosen period of six years (2007-2012) can contain inherent biases considering the financial crisis from 2007 to 2008. However, there is no empirical evidence that rating agencies behaved differently during the crisis.

Limitations in the methodology are the usage of only two governance indicators of which one was dropped because of high correlation is a major limitation. Using a wider selection of governance indicators could lead to a higher explanatory power of the regression. A major limitation regarding the Merton model is the use of a standard normal distribution, while the model applied by Moody’s (Moody’s KMV) uses a proprietary database of real-world distribution, mitigating the fat-tail problem (This will be further discussed in Chapter 2). Another limitation of the Merton model is that it does not capture risks of companies that carry sizeable off-balance sheet exposures; nonetheless these exposures are indirectly represented in the stock market data. Besides that, the simplifications applied for the Merton model comprise some limitations (Chapter 3.3.5). In order to compare the ratings of S&P’s and Moody’s with the distance to default derived from the Merton model, a numerical table has been assigned to the alphabetic ratings. It assumes a linear relationship between distance to default and the ratings, which is not the case in reality. The impact of this is discussed in chapters 3.4 and 3.8.3.

Another source of error can be seen in the way the Merton model and the rating agencies handle changes of environment concerning the rated company. Whereas the Merton model directly reflects this in a changed distance to default, the rating agencies rather put the relevant company “on watch” and change the rating when the new conditions seem to be stable.

Finally, for the purpose of this research it has to be assumed that credit ratings are correct and timely adequate in capturing a firm’s creditworthiness which is a further limitation of this study. It can be possible that the distance to default derived from the Merton model is closest to reality whereas agencies failed to do so or did not in an appropriate timely fashion. Past scandals like Enron are proof for this possibility.

2 Theory

This chapter covers the fundamental knowledge necessary to enable the reader in understanding the relevant theories applied in this paper. In order to ensure that the reader can follow the argumentation, all the relevant literature considered will be discussed. At the end of the chapter, the research hypothesises will be presented.

2.1 Emerging markets

Emerging markets are generally associated with rapid growth and industrialization, the emerging markets applied in this paper are based on the classification of the IMF. The IMF classifies 150 countries as emerging markets based on several selection criteria as for instance composition of countries, export earnings and other income from abroad.

Although emerging markets capture interesting investment opportunities, they also inherent various risks associated with the investments. In effect investors have less information available in these markets, moreover are they characterized by less presence of intermediaries as for instance financial analysts (Khanna, Palepu, & Sinha, 2005). Therefore, credit ratings might play an important role in these markets since they extend the information in these markets. On the other hand also rating agencies are facing the problem of information availability. Bekaert and Harvey (1997) identify credit ratings besides other criteria as a major barrier to invest in emerging markets.

An empirical study by Kamin and Von Kleist (1999) observed that besides national factors creditworthiness of emerging markets is also influenced by some internationals determinants as for instance: Interest rates, S&P 500 returns and oil prices. An increase in the mentioned factors would lead to a decrease of creditworthiness in emerging markets and therefore also the rating.

During former times credit ratings agencies had a policy of not rating companies above the sovereign rating, the so called “sovereign ceiling”. Nowadays CRA’s claim that they have moved away from this policy, still it seems like they still apply this policy to some extent. Especially looking at the big emerging market firms that generate their cash flow to a large extent from global operations, it does not seems appropriate to downgrade them based on a lower sovereign rating. On the other hand, the sovereign rating can be seen as a key factor since a country in default can push its corporate sector down. Borensztein, Valenzuela, and

Cowan (2007) call this phenomenon “sovereign ceiling lite”, since the sovereign rating is not an absolute constraint but can push the rating down.

An empirical study performed by (Kräussl, 2005) found out that CRA’s have a huge influence on size and volatility of emerging capital markets, which highlights their critical role in these markets. Especially because of the aforementioned limitations of information, rating changes can be a sign for new information available.

Bruce et al. (2005) summarise in their study the challenges of emerging markets, the challenges that apply especially for CRA are: Inadequate market data, not transparent regulation, government support and the lack of reliable market research firms.

2.2 Market efficiency

There are different ways to define the efficient functioning of a market and the efficient market hypothesis is probably the most prominent among them Fama (1991) which states that stock prices fully contain all information that is available. A weaker yet more adequate version of this hypothesis is that information is reflected until the benefits of acting on information do not exceed the costs stipulated by Jensen (1978). Fama (1991) furthermore arrives at the conclusion that the reaction speed of stock prices to changes in information is vital for efficient markets. The basis of the efficient market definition here is also based on a comparison between normal and abnormal stock returns.

A similar setting was used by Jegadeesh and Titman (1993) who tried to assess stock market efficiency through the trading strategy buying last week’s winners and selling its losers. This is the opposite approach to the contrarian strategy (short-term reversal) analysed by (Griffin et al., 2010). The efficiency here is defined as an investor’s inability to achieve abnormal returns or profits through arbitrage. Because markets are efficient it is not possible to achieve profits on information since it would be available to every participant in the market.

However, Griffin et al. (2010) also talk about potential biases with regard to information. This indicates an ongoing discussion with regard to emerging market efficiency and a general convention is hard to determine which creates a good opportunity for a comparison between credit risk derived from pure market data and credit ratings subject to a comprehensive fundamental analysis conducted by a specialized organization. Furthermore, the definition of market efficiency is an important factor as it could be measured by information incorporation speed or for example analyst coverage and availability of information which would yield different results.

For the purpose of this research an efficient market is defined through a significant match between the independent variables (distance to default & regulatory quality) and the dependent variable (credit rating). The credit rating is thereby used as the benchmark of all available information in the market that is compared against DD and regulatory quality in the given country for a company.

2.3 Credit risk

In the following, credit risk will be defined based on a top-down approach proposed by S&P. This process clearly exhibits all relevant components of credit risk and gives a clear understanding of how credit risk is examined and determined.

Ganguin and Bilardello (2005) define credit risk as a firm’s ability to meet its financial obligations in adequate timely fashion. This ability varies among companies, industries, and countries. Because of increasing volatility in debt markets and default levels, new procedures emerged to cope with these developments, like new statistical models and credit default swaps which complement the fundamental analysis of corporate credit risk. Edward Z. Emmer noted that this analysis is more of an art than a science as there is no generalizable recipe that applies to corporations (Ganguin & Bilardello, 2005).

Credit rating agencies like Standard & Poor’s apply a scoring system to rank a company’s risk of default on their obligations specified in their contracts. In this system grades are assigned which vary from an imminent non-payment to virtually risk-free lending. Furthermore, Ganguin and Bilardello (2005) note that two types of credit risk exist, the default risk itself and the risk of recovering a lenders prospects which is described as default risk in terms of the capacity and willingness to service debt in an adequate manner and recovery prospects as an evaluation of loss and recovery of the investment of a lender in the event of default.

The credit risk for businesses is defined by six elements or levels that exert influence over a company’s credit risk in different ways, Ganguin and Bilardello (2005) proposed the following top-down approach for assessment. Country and sovereign government risk influences credit risk in terms of established laws within a country, its physical and social component, financial markets, and macroeconomic factors as well as exchange rate risks. The physical component in this case refers to e.g. infrastructure of a country , whereas the social component describes the cultural background as credit policies have evolved in different ways over the past centuries in different cultures.

The industry a corporation is operating in, is another important factor to consider when analysing credit risk as industry patterns, cyclicality, entry barriers, and the sales and revenue potential differ among industries, directly affecting a firm's ability to service its debt obligations. Mature industries will for example exhibit less potential for growths than newly emerging industries based on e-commerce.

In terms of company specific business risk, direct competitors, a firm's market position and their strategy play an important role. This basically captures how a company utilizes its assets to generate value in order to service their debt obligations. The stability of this value creation process in form of revenue stream and cash generation capability is an important factor. Basically, this component of credit risk can be linked to Porter's Five Forces to analyse a company's competitive position within its industry and among its peers. Other contributing factors are product and sales diversity to withstand shocks and add stability, the market share works as a co-insurance factor through the seize of a company, and asset tractability enabling firms to liquidate non-core assets.

The management factor in terms of corporate credit risk plays an important role in relation to the governance of a company and their willingness to meet contractual debt obligations. An evaluation of corporate governance informs about the uprightness management, which is an important point to consider for lenders. A clean and transparent historical track record of management decisions is of course more favourable than a management team that has for example exhibited dishonest behavioural patterns. Furthermore, strategic and financial policies establish a firm's risk profile which is a key factor for the assessment of creditworthiness. A company's management team determines the usage of its assets in order to achieve targeted performance levels. Their success and failure in doing so sheds light on the quality of an organization's management and therefore ultimately on its future performance as the company's management lastly determines the success no matter how favourable the market's position or assets, which come in form of, for example, intellectual property or organizational structure. This assessment has to be conducted over time and not for single occurrences to determine consistency. But one cannot forget that management usually is driven by shareholder expectations who have different goals and expectations towards a company's performance which could make an assessment of management subjective from a creditor's point of view.

The financial risk profile of a company lastly is directly linked to profitability, cash generation and the liquidity of an organization and also informs on future cash flow projections affecting the capability of servicing contractual debt obligations.

2.4 Importance of credit risks for companies and countries

For corporations and investors, credit ratings traditionally have been a tool to reduce investment risks, to determine the spread of debt instruments and to assess bankruptcy risks. In the article “Present and Future Position of Credit Rating” Dziawgo (2012) argues that with regard to the financial crisis of 2007 credit ratings and the respective risks were of greater consequence for ABS (asset-backed securitization) than for bonds. This is due to the fact that agencies mispriced the securities which nonetheless had the same rating letters. The underlying problem in this case was that investors had no alternatives when obtaining information about creditworthiness, whereas more objective information was available for bonds (Dziawgo, 2012). Furthermore, it is arguable that governments relying less and less on conventional credit ratings could be a warning signal for investors and organizations not to rely too much on the assessment of rating agencies. The article “Do Credit Ratings Matter?” by Ronald L. Delegge (2011) states that the SEC (Securities and Exchange Commission) is increasingly abandoning the dependence on credit ratings for eligibility requirements as a consequence of the crisis. For instance, the SEC is planning to regulate credit ratings tied to investment regulation through an “Office of Credit Ratings” in the USA as many regulations relied on ratings provided by private organizations. In addition, the author argues that although agencies employ a sovereign rating ceiling, which states that corporations cannot obtain funds at better conditions that their host country, companies like Exxon Mobil and Microsoft for example maintain a better rating than the US (DELEGGE, 2011). However, if employed correctly the sovereign ceiling actually has a negative effect on a firm’s ability to obtain funds.

With regard to countries credit risk in the form of ratings, as already mentioned, is part of many investment regulations to date. Dziawgo (2012) states in his article that downgrading on a large scale like during the 2007 crisis can even worsen the crisis through loss of trust as it is common for rating agencies to be rather reluctant to frequently change credit ratings in order to display stability. Furthermore, Delegge (2011) argues in his article that rating agencies are hardly accurate and adequate in their predictions of sovereign default, since Russia and Argentina both held investment grade ratings before defaulting in 1998 and 2001 respectively. This shift in the landscape of today’s credit ratings leads to questioning the relevance of traditional credit risk assessment. However, the information of creditworthiness has become increasingly more important. (Dziawgo, 2012).

2.5 Moody's & S&P's credit rating methodology

Rating agencies are private, profit oriented institutions that determine the credit risk for companies of all sectors as well as that of governments. The results of their investigation are presented in credit ratings and a credit rating scale usually goes from AAA (best) to D (default).

The recent financial crisis has not only increased the knowledge on rating agencies, it has also shown their critical role in investment decisions. Although credit rating agencies are subject of governmental supervision, the regulatory use of credit ratings has given (quasi) – regulatory authority to credit rating agencies. National regulatory authorities have made use of rating agencies in order to increase the risk sensitivity of investment restrictions. This trend is however reverting as regulatory authorities began to strive for a reduction of the dependency on credit rating agencies after the crisis of 2007 (Delegge, 2011). On an international level, the Basel II act provided for the use of credit ratings from approved rating agencies. This has increased their role in the financial system. Through so-called "sovereign ratings" credit rating agencies might even be in a position to influence economic and financial policies of states (Scott, 2002).

Rating agencies also often employ a sovereign rating ceiling to corporate ratings. This means that companies residing in a country cannot get a higher rating than its host country, as a firm is not able to borrow at better conditions than the government in theory. Borensztein et al. (2007) however find that, although agencies tend to move away from this rule, sovereign ratings still have an important role in corporate credit ratings. This may have an impact on the findings of this study as findings could be distorted through the application of this rule, which has an increased importance for corporate ratings in emerging markets (Borensztein et al., 2007). Additionally, the authors propose a reconsideration of this rule as sovereign defaults not always affect private defaults and if so there is not necessarily a causal connection between the two events. The argument is that this rule imposes a possibly extensive, unnecessary penalty on the private sector.

Moody's states that ratings involve many unique factors with regard to country, industry, and company. Therefore, a generalized approach would not capture a company's credit risk factors in an adequate manner. In order to address this problems Moody's for example utilizes a multidisciplinary approach to risk analysis (Moody's, 2014). Based on the relevant industry key factors are chosen for the methodology which also consist of sub factors. At the example of the methodology for the oil and gas industry, Moody’s includes sub factors for average daily production, proved reserves, and total crude distillation capacity for the main factor scale. A similar approach is applied by Standard & Poor’s (S&P, 2014).

There are different types of ratings that can be distinguished, most important are:

Table 1. Different ratings of Moody's

Type of rating	Description
Issuer rating	Creditworthiness of public & private borrowers
Issue rating	Rating of specific financial products, bonds, loans & CDO’s
Long-term rating	Rating for a time horizon greater than one year
Short-term rating	Rating for a time horizon smaller than one year
Confidential rating	Most of the ratings are published and freely available
Published rating	
Solicited ratings	Requested by and prepared in consultation with the issuer of the rated financial product
Unsolicited ratings	Less common case, a rating agency produces a rating on its own (unpaid) unsolicited ratings tend to be lower since they are solely based on publicly available information

There are a lot of theories that focus on potential biases in the relationship between credit agencies and their clients in solicited ratings (Covitz & Harrison, 2003). However due to the limited time available for this paper, this will not be discussed further. In general, credit rating agencies base their analysis of corporate credit risk on a company’s financial statement, franchise value, management quality and competitive position in the industry. The basic function of credit rating agencies in financial markets is, to lower transaction costs and to reduce information asymmetries between borrowers and lenders in financial markets (Overbeek, Van Apeldoorn, & Nölke, 2007). Credit rating agencies act as intermediaries between capital supply and demand. Their ratings as discussed above are broadly categorized as either investment grade or speculative grade ratings. These ratings enable potential investors to compare different issuers and financial products. Bad ratings lead to steeply increasing interest rates and may even prevent actors from getting access to private capital (Scott, 2002).

The number of actors within the credit rating industry has increased since the 1990's but Moody's and Standard & Poors tend to dominate the market, since they produce 80% of ratings issued worldwide (Scott, 2002). Therefore this study will only use data provided by these two rating agencies.

2.5.1 Moody's

Moody's was founded in 1909 and has it's headquarters in New York City. The company has a very interesting acquisition history for the purpose of this study. In 2002 Moody's acquired KMV, the leader in quantitative credit risk management tools. KMV applies the framework of Merton (1974) (S. T. Bharath & Shumway, 2008). It is therefore possible that this investigation yields similar results as Moody's does, however Moody's does not publish to what extent they apply the Merton model; therefore it is only possible to speculate about its influence on the final rating.

However, there are significant differences between the KMV-Merton and the Merton model. The KMW model is a generalization of the Merton model that allows for various classes and maturities of debt. Moreover Moody's is using its large historical database to estimate the empirical distribution of changes in distances to default. The KMV model may also make proprietary adjustments to the accounting information that is used to calculate the face value of debt.

2.5.2 Standard and Poor's

S&P was founded in 1941 and its headquarters also located in New York City. Besides its rating activities, S&P also creates stock indices for instance the well-known S&P 500. There is no evidence which quantitative model S&P uses and to what extent they apply it. Since most of Moody's and S&P's ratings are very close to each other, it is very likely that S&P

applies a similar model as Moody's, however the two might differ for instance in the ratios they apply to different variables (Moon & Stotsky, 1993).

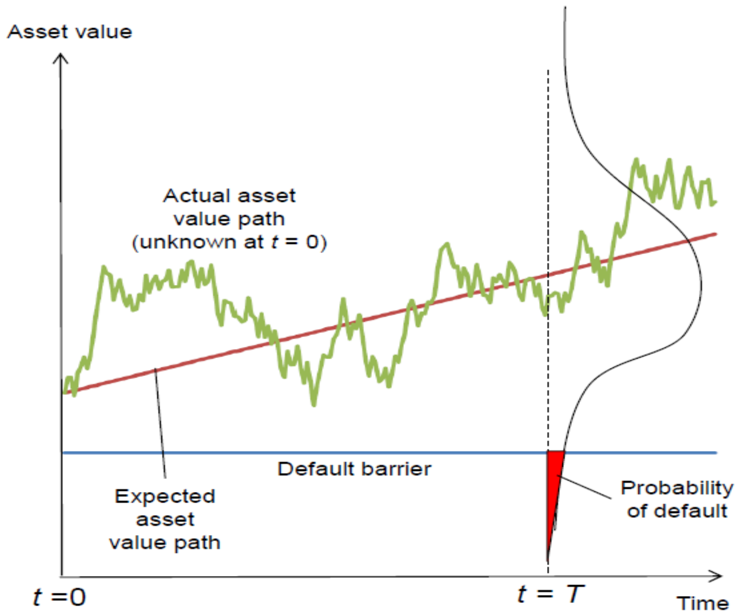
2.6 Merton model

The Merton model is based on the Black and Scholes option pricing model and was developed by Robert C. Merton in 1971. The model is used to evaluate the credit risk of a company's debt. Different brokerage firms, analysts and some investors employ the model in order to determine a company's ability to service its debt. Moreover, the model is the fundamental base of well-known credit rating agencies as for instance Moody's.

The Merton Model's origin as an option pricing model can be seen in the way the model determines its variables. The value of equity is regarded as a call option on the assets of a firm, whereas the value of debt is also dependent on the value of firm's assets. Liabilities and equity of a firm are seen as a contingent claim. Since the value of debt is a fixed claim, its market value can never be greater than its face value.

There is always a certain risk that the asset value falls below the face value of debt which reduces the market value of debt. The probability that this case occurs and the company defaults is called the credit risk.

Figure 1. Visualisation of the Merton model



The y-axis measures the asset value, whereas the x-axis measures time. The blue line represents the default barrier and is driven by principle and interests due within the time T. The asset value itself is represented in the red line and consists of the market value of equity, debt and its expected growth. The assets grow by asset return and since the asset value represents the total company value, the Merton Model assumes a company to grow by its asset returns. The asset path, which is shown in green, is unknown at time T. Assuming a log normal distribution of the asset value, the probability of default at time T can be predicted by calculating the number of standard deviations between the expected asset value and default barrier at time T. The red area below the default barrier is the probability of default. When the distance between the asset value and the default barrier decreases, asset growth decreases or asset volatility increases, the probability of default increases. According to Gropp et al (2006). and as mentioned above, the distance to default (DD) is measured in terms of the standard deviations between the current asset value and liabilities where the event of default is marked by the asset value equalling the liabilities. Models using this type of approach are referred to as structural models as they analyse the structural relationships between asset value, debt, and equity value. The formula for calculating the distance to default is

$$d_2 = \frac{\ln\left(\frac{A_0}{B}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{1}$$

- The value of the firm now - A_0
- The risk-free rate – r
- The volatility of asset value – σ
- The default barrier (debt) – B
- The time horizon - T

2.6.1 Non-structural models

Other models using a non-structural approach like the Altman Z-score also have been developed in the past. Z-scores are calculated using a multivariate discriminate analysis for which Altman considered 22 financial inputs of which five accounting ratios were proven to be adequate for bankruptcy risk assessment. The formula used for calculating the Z-score for manufacturing firms is displayed below as an example:

$$Z = 1.20\,\frac{WC}{V} + 1.40\frac{RE}{V} + 3.30\frac{EBIT}{V} + 0.60\frac{ME}{BL} + 1.00\frac{S}{V} \tag{2}$$

- The working capital - WC
- The function of liquidity measure WC/V
- The market value of the firm - V
- The retained earnings - RE
- The cumulative profitability, leverage, and age indicator – RE/V
- The earnings power indicator – EBIT/V
- The market value of equity - ME
- The book value of liability - BL
- The distress barrier indicator – ME/BL
- Sales - S
- The asset turnover ratio – S/V

This was later revised and complemented by several other researchers like Shumway or Hillegeist and applied to different situations like private companies, non-manufacturing companies, or emerging markets. The interpretation of the Z-score is slightly different than the default probabilities derived from the Merton model as the Z-score is not a default probability but an indicator for a company’s default in the next year. The scores for the manufacturing model are:

- $Z \leq 1.80 \; = high\ probability\ of\ default$
- $1.80 \; < Z \; \leq 2.99 = zone\ of\ ignorance$
- $Z \; > 2.99 = safe\ zone$

Ohlsons O-score was another statistical model that was developed in 1980 and employs a conditional logistic model in order to predict financial distress for companies. Whereas statistical models are based on large samples and examine relationships between the introduced relevant variables, structural models examine structural relationships on the balance sheets of corporations. Therefore, statistical models like the Altman Z-score are inadequate for this study as they are not based on present market data but large historical databases. Consequently they are unable account for market specific circumstances in terms of assessing a company’s creditworthiness.

2.7 Literature review

Investigating the previous research, there are two important fields of research to study, first studies that apply the Merton Model or similar models in emerging markets and secondly studies that analyse the specific circumstances of emerging markets and their influences on the national stock market. First, general literature on the Merton model that is relevant to this paper will be presented. Then, the model will be set into context with market efficiency and finally implications of previous research on sovereign ratings for this study will be shown.

There have been several studies about the contribution of the Merton model, not all of them arriving at the same conclusion. The first ones that analysed the model were experts employed by KMV or Merton. Whereas Stein (2002) came to the conclusion that the Merton model can be easily improved, Bohn, Arora, and Korablev (2005) believe that the model captures all information in traditional agency ratings. For both perspectives reasonable arguments can be found.

Kulkarni, Mishra, and Thakker (2005) compared the distance to defaults derived from Robert C. Merton's model to credit ratings in India and came to the conclusion that the model is able to differentiate top-rated firms from those in default. Another valuable finding is that the model depends significantly on equity volatility. On the other hand S. Bharath and Shumway (2004) find that the model is not a significant statistic for default. It is however difficult to compare the results of these two studies, since the first only differentiates between top ratings and default and the second analyses its ability to forecast default in general.

In their study Duyvesteyn and Martens (2012) apply the Merton Model in thirteen emerging countries, four of the five countries used in this study are represented also in theirs. They intend to forecast sovereign default risk with the Merton Model, therefore they use the approach by Gray, Merton, and Bodie (2007), which adapts the Merton Model in order to work with sovereign balance sheets. The model outcomes (distance to default, default probability and spreads) are strongly correlated with the market CDS spreads. They further discover that the exchange rate volatility has a huge impact, which is equivalent to the equity volatility in the corporate version of the Merton model. Therefore, it supports the previously mentioned findings (Kulkarni, Mishra, & Thakker, 2005).

Chen, Chou, Wang, and Zaabar (2011) apply the Merton Model in comparison to Duan (2000) transformed-data maximum likelihood estimation. Duan's model estimates the unobservable parameters necessary to apply the Merton Model, for instance it claims that default barrier is 30% of the firm’s assets. They base their research on a study of Tudela and Young (2003) that states that companies can default before the maturity of debt, therefore they release the default point setting. Further Crosbie and Bohn (2003) argue that some companies are still in business even though asset values are below debt values, these companies were first regarded as default when assets were far below value of debt. Hence each company has a unique default barrier. For the purpose of their research Chen, Chou, Wang, & Zaabar (2011) collected data of 1406 firms in Taiwan for the period of 2002-2006. When comparing the Barrier Option Model to the Merton model, they obtained empirical evidence that both models have better predictive power on the Taiwan stock exchange than for Taiwan’s over-the-counter market. This observation is explained by there being less information available in the over-the-counter market.

So far, the literature implies that there is no clear consensus yet with regard to the Merton model’s ability to forecast default. The different results can essentially be explained by the different research settings and comparisons that were applied.

Griffin et al. examine the correctness of market efficiency measures in a comparison between developed and emerging market countries. They find that trading strategies like the “short-term reversal strategy” show similar returns in emerging and developed markets before transaction costs. However, emerging markets exhibit much higher transaction costs which diminish the returns of a trading strategy. They argue that efficiency in these terms is derived from transaction costs and information production and find that emerging markets are less efficient in this regard. But the incorporation of information also causes biases as firms with less published news appear to be more efficient in incorporating information than those, for example, that publish information daily. For emerging markets it has been found that there is a general lower analyst coverage and less available public information on corporations which can make emerging market firms appear more efficient (Griffin et al., 2010).

When comparing market efficiency to the efficiency or completeness of credit ratings with regard to information, Norden and Weber (2004) find that both CDS and stock markets react between 90 and 60 days prior to a downgrade. This leads to the conclusion that markets and rating agencies have access to equal information. The sample of this study consists of companies listed on major stock indices as for instance the S&P 500 across emerging and developed countries. These findings are prerequisite for this study as they suggest that the information necessary for predict credit events by S&P and Moody’s are already included in publicly available market data. A failure of the Merton model to capture credit relevant information would therefore be related to deficiencies of the model itself and not the publicly available information in the market.

Henisz and Zelner (2010) discuss country risks in emerging markets from a foreign investor's perspective. They claim that the risks in emerging markets have changed where governments in former times took a rather direct and drastic approach to gain value from foreign investors, they now take a rather sustainable and indirect one. The former approach of downsizing a firm's assets has nearly disappeared, whereas nowadays emerging countries have learned that they can gain much more money through regulatory contracts. A study done by PricewaterhouseCoopers finds, that an opaque policy-making environment is equivalent to at least 33% in taxation. Furthermore the paper questions the efficiency of ratings, since they claim them to be only backwards looking but they state that an analyst needs to be looking backwards and forwards. Moreover they say that ratings fail to acknowledge that levels of risk policies vary among investors in a country.

Concluding the research with regard to market efficiency, it suggests that the Merton model works better in efficient markets. However, Griffin et al. (2010) show that biases with respect to efficiency exist and also the efficiency of credit ratings is questioned. The impact of market efficiency on the Merton model implies that a comparison of the Merton model and credit ratings can shed light on the information content of the analyzed markets, as the model will be more accurate in determining credit ratings in efficient markets.

An important aspect of a rating is the corporate governance system, since it deals with the level of investor's protection. Borensztein et al. (2007) analysed in their paper 321 firms in 25 emerging countries, only two of these 321 firms have an above average rating, 319 were below average.

However, an investigation by in which he analysed the efficiency of corporate governance systems in emerging markets based on CEO turnover, exemplified, that poorly performing CEO's are more likely to lose their jobs. This can be seen as one indicator for corporate governance systems being efficient. Nevertheless, CEO's of firms with large domestic shareholders are not more likely to lose their jobs when performing badly, which can be seen as an indication for low minority shareholders protection.

In most of the cases, the rating of the country the company is operating in has another significant impact on a company's rating. R. Brooks, Faff, Hillier, and Hillier (2004) discussed in their paper the impact of sovereign rating changes on the stock market. They found evidence that downgrades have an impact on the markets returns in two different ways.

First of all the domestic stock market is affected; secondly the dollar value of the country's currency depreciates. An interesting outcome was that of the four rating agencies examined only S&P and Fitch rating downgrades resulted in significant market falls.

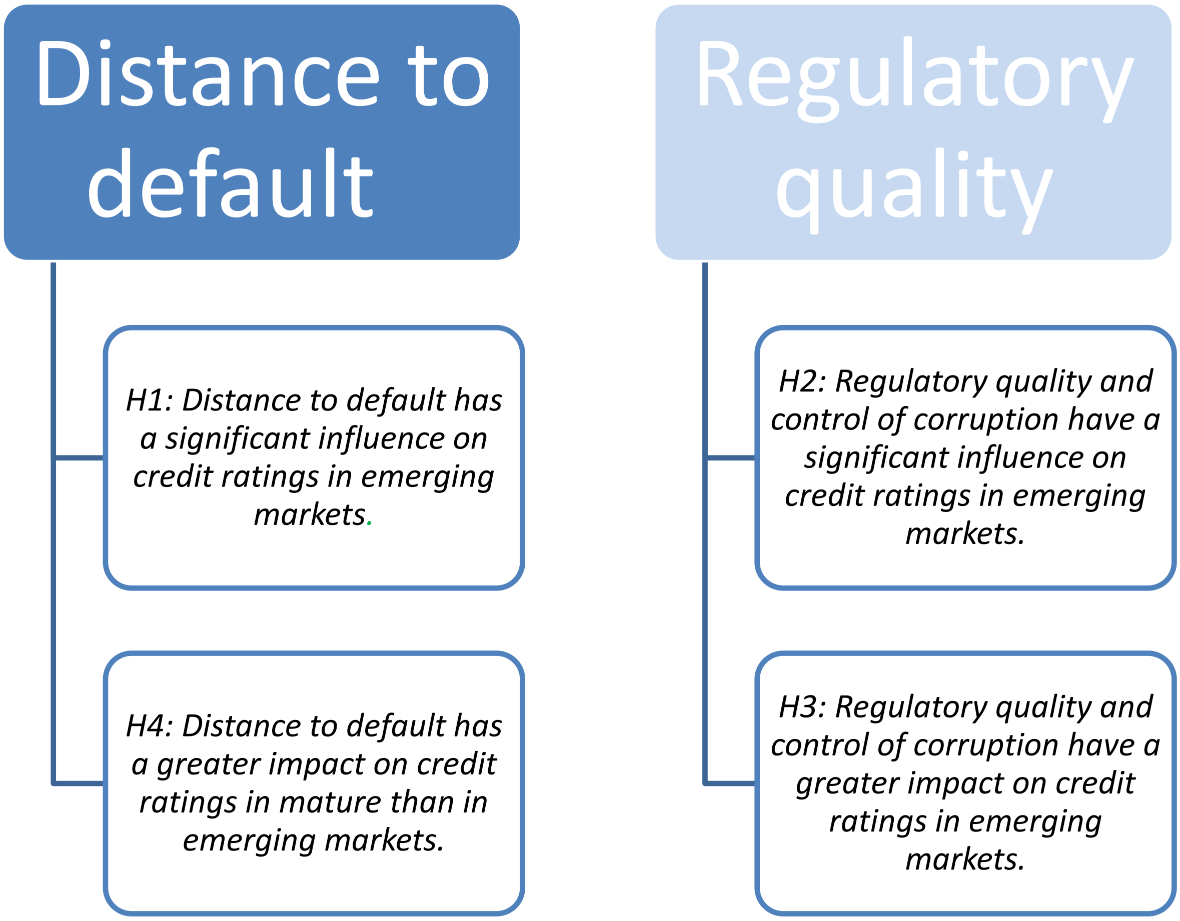
Since the sovereign credit ratings are assumed to have a huge impact on the corporate ratings, it is very surprising to see that there are various differences between the sovereign ratings of the different rating agencies.Alsakka and ap Gwilym (2010) analyze the causes and extent of split sovereign ratings. They did this over a period of nine years, from 2000-2008, by using a 20-point numerical scale in order to compare the ratings of the different agencies. Surprisingly, they found a high frequency of disagreement across agencies on emerging sovereign ratings. Whereas S&P and Fitch have the lowest frequency of disagreement, Moodys & S&P have the highest frequency with 59,4%. However most of the rating differences are small only a few are big. The differences can be explained by the consideration of different macroeconomic factors of each of the rating agencies and the use of different weights for the factors. The study further proved the bias home hypothesis, which claims that national agencies tend to come up with different ratings than foreign agencies.

It might seem as if studies around corporate governance are not directly associated with this topic in the first place - however all of these studies deal with the impact of the emerging markets environment on ratings or with a specific variable as for instance sovereign ratings. Especially the paper of Alsakka and and Gwilym provided valuable input, since it validates the choice of a foreign rating agency in order to avoid bias home hypothesis. Moreover, the articles above help to provide a general understanding of the specific frauds in an emerging market.

2.8 Research hypotheses

Figure 2 summarises the research hypotheses outlined in chapter 1.3.

Figure 2. Graphic visualization of the research hypotheses



3 Methodology

Within this chapter, the methodology applied is presented. The given information should enable the reader to follow and replicate our method. In the beginning of the chapter, the sample of companies studied will be discussed, afterwards, the different Merton model variables will be shown, followed by the regression analysis. At the end a graphical summary of the methodology is presented.

3.1 Sample

The set of emerging market countries is chosen according to a list published by the International Monetary Fund (IMF) at the end of 2012 (IMF, 2012). As the timeframe of the research is 2007 to 2012 the economy should at least be declared as emerging or developing until the end of that year. Argentina, Brazil, India, Indonesia and Mexico were chosen due to their growing economies and sufficient number of public companies. Other than that there were no particular selection criteria in place for emerging market countries. The developed nations were chosen with the same criterion of relatively big economies. For the sample only European firms were chosen in order to maintain consistency within the sample, as there are some substantial differences between the European and the U.S. economy.

For each country a stock index is chosen in order to select the companies: France CAC 40, Germany DAX, Netherlands AEX, Sweden OMXS 30, United Kingdom FTSE 100, Argentina MERVAL, Brazil Bovespa, India BSE Sensex, Indonesia IDX Composite, and Mexico IPC. All companies were first taken into an alphabetic order and afterwards selected randomly from the relevant stock index. Only non-financial firms are taken into considerations, since financial organizations differ in the structure of their balance sheet and hence the way they are rated. A complete list of the companies can be found in the appendix. The data is collected with S&P's software Capital IQ within the period of 2007-2012. Additional data needed such as stock prices are taken from Yahoo finance Yahoo! (2014), the ratings are taken from the websites of Moody's and S&P's.

The selection criteria for firms were first of all the availability of the data itself. For the period of 2007 until 2012 the chosen organization were required to have available daily stock data, annual balance sheet publications, and credit ratings. Industries or company size in terms of market capitalization is not specified in order to generate more generalizable results. In addition, the companies will not be compared against each other but only internally through different distances to default derived from the Merton model and credit ratings. Therefore the particular size or industry does not have an impact on the accuracy of Merton distance to default relative to credit ratings.

In total a random sample of 100 firms, 50 from mature and 50 from emerging countries was collected. In order to avoid country specific biases and with respect to the limited time available for the project, the research is limited to the aforementioned five emerging and five mature countries. However, for some years the ratings were withdrawn, therefore these years are dropped from the sample which is more frequently the case for emerging than mature companies. In order to balance dropped ratings, 20% more companies (two companies) for each country are collected. In some cases this buffer was however not sufficient, therefore countries with both more and less than 10 companies and with less than ten companies are represented in the sample.

Table 2. Number of companies in each county, in emerging and mature countries

Mature countries	Num. of company's	Emerging countries	Num. of company's
France	10	Argentina	7
Germany	12	Brazil	10
Netherlands	12	India	10
Sweden	11	Indonesia	5
United Kingdom	10	Mexico	7

The collected data is separated between mature and emerging markets and divided among 10 different industries, as presented in Graph 3.1 and 3.2. This helps to get a further understanding of the data and hence locate potential sources of biases. Comparing both graphs, a rather strong focus on oil & gas and energy companies in emerging markets in contrast to mature markets can be detected, whereas mature market companies are rather strong in industrial goods. It seems natural to assume that gas & oil companies have higher ratings as a result of their stable income and high profits. Since larger or smaller gaps between distance to default and the ratings among different industries are not expected, this should not have any negative influence on the results.

Figure 3. Distribution of mature market companies among 10 industries

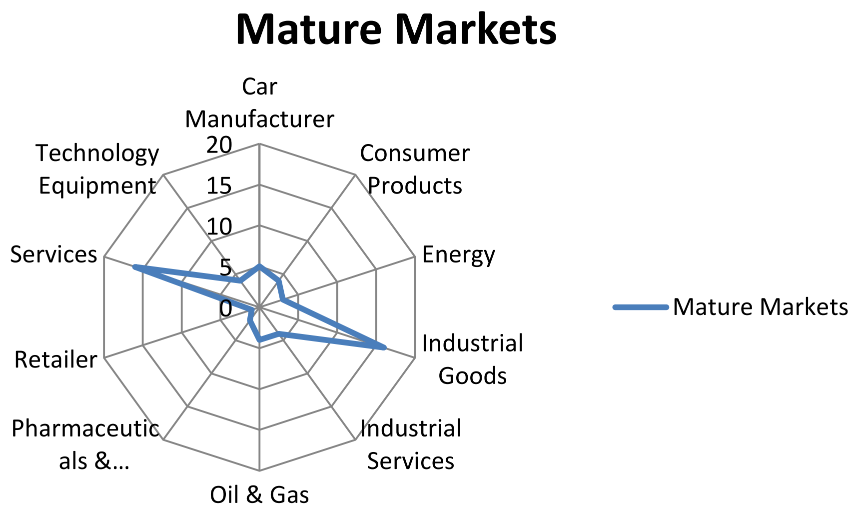
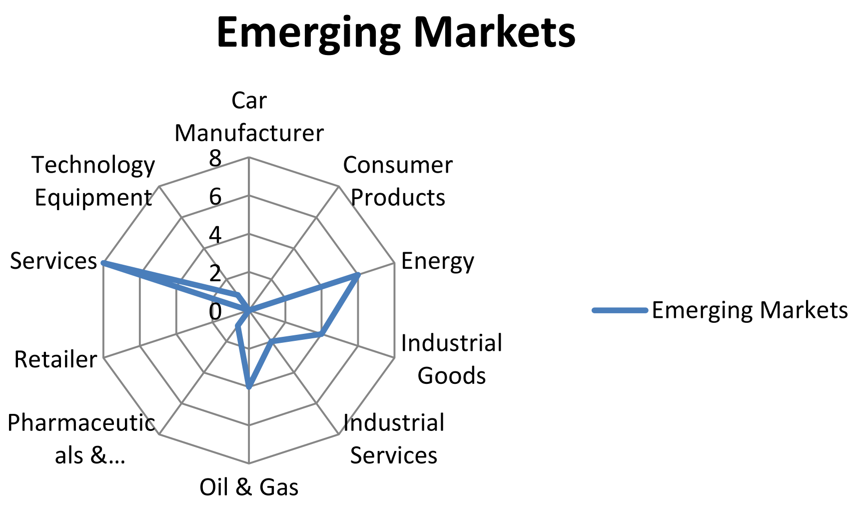


Figure 4. Distribution of emerging market companies among 10 industries



Although the sample is randomized, in each market a tendency towards certain industry attributes can be seen. Whereas mature markets have a strong focus on industrial goods and services, emerging markets exhibit an equal focus on services, energy and oil & gas. One explanation for this can be, that oil & gas , industrial goods, and energy companies highly benefit from scaled operations. Therefore they are naturally larger and more frequently represented in stock market indices with an increased chance of having rated debt. Consequently they meet the data requirements more easily and appear more often in the sample data.

3.2 Moody’s and S&P’s ratings

Moody’s and S&P’s ratings are only used for comparisons. Past studies found that local rating agencies tend to get different results from foreign rating agencies, therefore only foreign rating agencies were chosen in order to mitigate potential biases (Ferri, Lacitignola, & Lee, 2013).

3.3 Merton model variables

3.3.1 Distress barrier

The distress barrier is calculated as the sum of short-term debt, current portion of long-term debt and half the amount of long-term debt on a company’s balance sheet. By incorporating the current portion of long-term debt and half the amount of long-term debt into the distress barrier, it is intended to account for the principle and interest payments (P&I) due within the fiscal year.

Later versions of the Merton Model can already incorporate interest rates in various ways, however this is a very complex and time-consuming process. Due to the limited time available and for reasons of simplification, the above mentioned assumption is made, which is also suggested by Gray & Malone (2008).

Calculating the distress barrier in the way discussed above overestimates the principle and interest payments, nevertheless it brings the model and hence the calculated result closer to reality. It is further an advanced approach compared to the original version of the Merton model which implies only short-term debt. Moreover, empirical data from KMV did find that firms usually had gone into default between long & short-term debt (Crouhy, Galai, & Mark, 2000). Not including long-term debt would therefore underestimate the default-barrier.

All required data is collected with S&P’s Capital IQ, since yearly balance sheets are used the debt is assumed to be stable during the year.

3.3.2 Market value of assets

Since the Merton model is a contingent claims model it only requires collecting data for the market value of equity, which is fairly easy observable for listed companies. The market value of a company’s assets is assumed to be equal to the market value of equity plus the face value of total debt. The required market value of equity is equal to market capitalization, which is calculated as shares outstanding multiplied by the share price.

First of all, the daily stock prices are collected for each company from Yahoo! finance; then a yearly average stock price is calculated and multiplied by the average shares outstanding during the fiscal year in order to determine the market capitalization. The time horizon for the study is 2007-2012.

3.3.3 Predicted asset growth

According to Gray & Malone (2008) there are two probabilities of default, the “actual” probability with expected asset return(μ) and the “risk-adjusted” or “risk-neutral” probability calculated with the risk-free rate as expected asset return. They differ in terms of the distribution of assets in relation to the default barrier being greater than assets growing at the risk-free rate since market prices for risk in reality are greater than zero. For the scope of this paper and because the Merton model is built under the assumption of a risk-free environment, the risk-free rate is used as proxy for predicted asset growth derived from one year government bonds as it is not the purpose of this investigation to find more practical alternatives for asset growth.

3.3.4 Volatility of asset growth

As the volatility of asset growth is an unobservable variable, it is derived from the formula:

$$\frac{E}{A} x\sigma_E = \sigma_A \tag{3}$$

To solve this equation for the volatility of asset growth, it is necessary to calculate market value of assets and equity, as well as equity volatility. For the market value of assets the simplification of adding the default barrier (B) is applied, computed as discussed below, to equity market capitalization (E). The market value of equity is derived from an annual average stock price and the total shares outstanding on the balance sheet date. Annual stock price is computed from the mean of daily observations in the given year. Empirical evidence for the application of this simplification can be found in various study’s (Afik, Arad, & Galil, 2012; S. T. Bharath & Shumway, 2008; Hull, Nelken, & White, 2004) The volatility in equity is derived from the standard deviation between the percentage changes in daily closing prices for a year multiplied by the radical of trading days. To maintain consistency the assumption of 260 trading days across the entire sample is used.

3.3.5 Simplifications

There is no market data available for the variables *asset value* and *asset volatility* and therefore they need to be estimated through the face value of debt, market capitalization, and equity volatility. The relations in the equation system of the Merton model can be solved through a generalized reduced gradient method in order to get an estimate for asset value and asset volatility. Special software tools like Excel Solver are necessary in order to solve these equations for the two unknown. Considering the fairly large data set, this is a very time consuming process. Therefore the following simplifications are introduced: (1) asset value equals market capitalisations plus face value of debt and (2) asset volatility equals market capitalisation divided by asset value multiplied by equity volatility. Equity volatility is computed as the standard deviation of daily stock prices, multiplied by the square root of trading days. The understatement problem of the probability of default through the usage of the face value of debt was already discussed but will not affect the probabilities in the sample due to their small size (Du & Suo, 2007).

The table below shows a comparison of the calculations of distance to default (DD) and probability of default (PD) with the simplifications assumed above and through an iterative process with Excel Solver. As can be seen, the differences are insignificantly small and the assumed simplifications therefore do not affect the outcome of our research. For the first iteration asset value and volatility are used, obtained through the simplifications as a first estimate. The equation system of the four Black & Scholes formulas for d1, d2, equity volatility, and equity value is then solved with the objective to minimize data deviations:

$$\frac{VEformula}{VEestimate - 1}^{2} + \frac{\sigma E\ formula}{\sigma E\ estimate - 1}^{2} \qquad (4)$$

The variables here represent the actual formulas set in Excel to calculate equity value and volatility whereas the estimate values are just the hardcoded simplifications. With the four formulas and initial estimates Excel can solve for the two unknown variables asset value and volatility for the above stated relationship (Löeffler & Posch, 2011).

Table 3. Excel solver method vs. applied simplification

Country	Company	Method	Year	Distance to default	Default probability
UK	SSE*	Solver	2007	33.6990	2.9845E-249
UK	SSE	Simplification	2007	33.7012	2.7728E-249
UK	SSE	Solver	2008	15.0860	1.00039E-51
UK	SSE	Simplification	2008	15.0877	9.75449E-52
UK	SSE	Solver	2009	22.5931	2.5315E-113
UK	SSE	Simplification	2009	22.5937	2.5012E-113
UK	SSE	Solver	2010	31.3110	1.6538E-215
UK	SSE	Simplification	2010	31.3117	1.6149E-215
UK	SSE	Solver	2011	30.3153	3.6048E-202
UK	SSE	Simplification	2011	30.3157	3.5571E-202

*SSE = Scottish and Southern Energy plc

Due to the fact that short-term bond yields were not available for Argentina for the chosen timeframe an annualised lending rate from the World Bank database is used as a substitute for the risk free rate (World Bank Group, 2014). In addition, short-term bond yield for the Netherlands and Sweden were only available for bonds with a two-year maturity. Due to the financial stability of these economies the differences between one and two year bond yields in these countries will not affect our results severely as interest rates within the EU are converging towards zero after the financial crisis of 2007.

3.4 Transformation of Moody's and S&P's ratings

In order to run a regression and compare the distance to default with Moody's and S&P's ratings, it is required to assign numbers to the ratings, since letter ratings cannot be easily analysed. Starting off with the first rating Aaa (Moody's) or AAA (S&P), to which the number 20 is assigned, towards the lowest rating C (Moody's) or D (S&P) corresponding to the value zero. Hence, the better the rating and the higher the credit quality the higher the number we assigned to the rating. Nevertheless the numerical scale is imperfect since rating levels do not necessarily progress linearly. However, Afonso, Furceri, and Gomes (2012) suggest that logistic or exponential rating transformations only provide little advantages over the linear approach. Therefore, the linear approach will be applied which then is accounted for through the introduction of a quadratic term in the regression analysis.

Table 4. Numerical ranks assigned to Moody's and S&P's rating scale

Investment Grad		
Moody's	**S&P**	**Rank**
Aaa	AAA	20
Aa1	AA+	19
Aa2	AA	18
Aa3	AA-	17
A1	A+	16
A2	A	15
A3	A-	14
Baa1	BBB+	13
Baa2	BBB	12
Baa3	BBB-	11

Non-investment Grade		
Moody's	**S&P**	**Rank**
Ba1	BB+	10
Ba2	BB	9
Ba3	BB-	8
B1	B+	7
B2	B	6
B3	B-	5
Caa1	CCC+	4
Caa2	CCC	3
Caa3	CCC-	2
Ca	CC	1
	C	1
C	D	0

3.5 Institutional variables

Two institutional variables from the Worldwide Governance Indicators for regulatory quality and control of corruption are introduced into the regression to test their significance with regard to corporate credit ratings (D. K. Kaufmann, Aart; Mastruzzi, Massimo, 2013). These indicators consist of the six dimensions voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. Due to the overlap between these dimensions two exemplary dimensions are chosen and control of corruption is later dropped because of high correlation. The indicators are based on an aggregate of 31 data sources comprised of survey responses and expert assessments. For each year and country where data is available the index gives an estimate of governance, standard error, number of sources, the percentage rank among all countries, lower, and upper bounds. The estimate ranges from -2,5 weak performance to 2,5 strong performance whereas lower and upper bound are the 90% confidence levels for the percentage rank (D. Kaufmann, Kraay, & Mastruzzi, 2011). The percentile rank is chosen as input for the regression in order to establish a context for a country's scoring.

3.6 Regression analysis

In order to analyse the regression between the outcomes of the Merton model (distance to default) and the ratings derived from Moody's and S&P a panel data set is created. A panel data set is a combination of cross-section and time-series data sets. Whereas time-series data is limited to one observation per time period, cross-section data is composed of one observation per cross-section which can be things and people for example. A panel data set combines the two data sets into one regression. The general formula for such a regression is:

$$y_{it} = \propto \ + \beta X_{it} + u_{it} \quad (5)$$

The investigation should provide statistical evidence of the Merton model's DD predicting ability in both markets, due to the time series analysed and the nature of the investigation; it is a past-looking regression. A linear interaction model regression is chosen, it has been well established that the intuition behind the conditional hypothesis is captured quite well by multiplicative interaction models (Aiken & West, 1991; Friedrich, 1982; Wright Jr, 1976). This means that a conditional hypothesis is an increase in X associated with an increase in Y when condition Z is met. In the given case this means that the emerging markets are the interaction term, therefore if the given country is an emerging country, condition Z is met.

3.7 Dummy variable

Dummy variables can be introduced into the regression in order to account for qualitative measures the regression would not be able to capture otherwise. They usually are assigned the values zero and one, as in this case, and they can be used for cross-sectional and time-series regression. For the panel data regression on credit ratings and distance to default the variable stated below is introduced in order to account for the country specific attributes emerging (0) and developed (1) country(C. Brooks, 2008).

Table 5. Dummy variables applied in the regression

Dummy variable	Explanation
dv_emerging_country	0 = emerging country 1 = developed country

3.8 Regression

The statistical analysis of the data is done through a cross-sectional regression with the software tool EViews 8. The data is therefore summarised in one Excel sheet containing information about the country, years, company, DD, governance indicators, the credit rating and its translation into numeric values. In order to include company information a company identifier variable is introduced, which assigns each company its own number. The mentioned dummy variable *dv_emerging_country* distinguishes the different countries between developed and emerging country whereas the governance indices “control of corruption” and “regulatory quality” include country specific information. As aforementioned, the governance indicator chosen is the annual percentage ranking based on an estimate, the standard error, and number of data sources. Countries are ranked through an annual percentage ranking, 100 is the best achievable ranking, whereas zero is the worst. The index used is “The Worldwide Governance Indicators 2013”, based on an aggregate of governance indicators between 1996 and 2012 (D. K. Kaufmann, Aart; Mastruzzi, Massimo, 2013).

The credit ratings per year are translated in accordance with the table discussed earlier in the methodology. The data then is imported into EViews as dated panel data. In order to examine the relation between credit rating as the independent variable and the dependent variables DD, control of corruption, regulatory quality, and country classification the following simplified equation is used for the analysis

$$Rating_{it} = \alpha + \beta_1 Merton\,DD_{it} + \beta_2 Regulatory\,quality_{it} + \beta_3 Control\ of\ Corruption_{it} \qquad (6)$$

The dependent variable and the rating assigned by Moody’s and S&P’s is assumed to be influenced by the distance to default that is derived from the Merton model and the regulatory quality of that country in the specific year.

This regression would however not account for the fact that a linear numerical scale is assigned to Moody’s and S&P’s ratings, whereas their ratings are clearly not following linearity. The problem incurred can be solved by introducing a quadratic term which is discussed later in chapter 3.8.3. The second problem is that it would require running two separate regressions in order to get results for both, emerging and mature markets. Therefore an interaction term is being used, by utilising the above discussed dummy variable. This leads us to the following formula:

$$\begin{aligned} Rating_{it} = \ & \alpha + \beta_1 Merton\ DD_{it} + \beta_2 Regulatory\ quality_{it} \\ & + \beta_3 Control\ of\ corruption_{it} + \beta_4 Merton\ DD_{it}\ x\ DV \\ & + \beta_5 Regulatory\ quality_{it}\ x\ DV \\ & + \beta_6 Control\ of\ corruption_{it} x\ DV \end{aligned} \quad (7)$$

Interaction terms have, due to their, only an observable influence on the regression when a certain condition is fulfilled. In practice this looks like:

H1: An increase in X is associated with an increase in Y when condition Z is met.

For this specific case it means, that an increase of distance to default / regulatory quality / control of corruption in mature markets is associated with an increase in the rating, if the value of the dummy variable is 1 (Brambor, Clark, & Golder, 2006).

They further allow for running both markets in one regression and thus simplify interpretation of the results. The interpretation of the results will however be slightly different than in a "normal" regression. The interaction terms are:

$$\beta_4 Merton\ DD_{it}\ x\ DV\ \&\ \beta_5 Regulatory\ quality_{it}\ x\ DV \quad (8)$$

This gives the opportunity to make a differentiated interpretation of the influences of the Merton model DD and the regulatory quality in emerging and mature markets. Since the dummy variable is 0 for emerging and 1 for mature markets, the interaction terms measure the influences on mature markets. In the output of the regression, the results for emerging markets can be simply found under Merton DD and regulatory quality. The results for mature markets are the accumulation of the independent variable and the interaction term of that variable, e.g. Merton DD and Merton DD x DV.

EViews "Estimate equation – tool" is used in order to run the regression. Since the given data set is a panel data set, adjustments had to be made. Further tests of the independent variables also resulted in adjustments to the equation. All adjustments included, three different regressions are run. The first includes mature and emerging markets by including the above discussed interaction term. The two last regressions only include one of the analysed markets. This results in different outcomes, one from both for emerging and mature markets, one from emerging markets and one from mature markets.

3.8.1 Adjustments to the regression analysis

Due to the nature of panel data adjustments are necessary. First of all, it has to be tested whether fixed effects in the cross section and in the period can be applied. By applying fixed effects, dummy variables are added to each variable in the regression. This enables the model to filter e.g. time specific variations in the data. A significance test of the dummy variables gives insights into whether fixed effects can be applied or not. The results of the tests can be seen in Table 6.

Table 6. Results for significance test applied for fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	88.2968	(79.321)	0,0000
Cross-section Chi-square	1283.8415	79	0,0000
Period F	10.3071	(5.321)	0,0000
Period Chi-square	61.1943	5	0,0000
Cross-Section/Period F	85.4235	(84.321)	0,0000
Cross-Section/Period Chi-square			

Cross-sectional fixed effects and period fixed-effects show both highly significant results and can therefore be applied. Another adjustment that has to be made due to panel data is the covariance method which is changed from ordinary to white (diagonal). Also for this a verification test has to be made. For the applied standard diagnostic test, the used software EViews does not contain any standardised function; therefore it has to be made manually. The results can be seen in Table 7.

Table 7. Results of standard diagnostic test

Cross-section-fixed (dummy variables) Period-fixed (dummy variables			
R-squared	0.4089	Mean dependent variable	0.2391
Adjusted R-squared	0.2450	S.D. dependent variable	0.5713
S.E. of regression	0.4964	Akalke info criterion	1.6279
Sum squared resid	79.0962	Schwarz criterion	2.5079
Log likelihood	-244.5345	Hannan-Quinn criter.	1.9760
F-statistic	2.4951	Durbin-Watson stat	2.2302
Prob(F-statistic)	0.0000		

Since the relevant value of the F-statistic is ~2,5, the test is significant, which signals that this research setting can be applied.

3.8.2 Adjustments to the equation

Before the regression can be interpreted, tests have to be run that prove its significance. Consequently a correlation test between the independent variables was done which results in a high correlation between control of corruption and regulatory quality, as presented in Table 8.

Table 8. Correlation analysis of independent variables

	DISTANCE_TO_DEFAULT	REGULATORY_QUALITY	CONTROL_OF_CORRUPTION
DISTANCE_TO_DEFAULT	1	0.1815	0.0994
REGULATORY_QUALITY	0.1815	1	0.9597
CONTROL_OF_CORRUPTION	0.0994	0.9598	1

Due to the high correlation between control of corruption and regulatory quality, one of the two independent variables needs to be excluded from the regression. Running the correlation test for the regression, the results show a higher significance for regulatory quality. Therefore, control of corruption will be excluded from the equation leading to the final equation:

$$\begin{aligned} Rating_{it} = {} & \alpha + \beta_1 Merton\ DD_{it} + \beta_2 Regulatory\ quality_{it} \\ & + \beta_3 Merton\ DD_{it}\ x\ DV + \beta_4 Regulatory\ quality_{it}\ x\ DV \end{aligned} \qquad (9)$$

3.8.3 Quadratic term

The linear translation of the alphabetic rating bears problems that have to be accounted for in the regression. A graphical explanation can be seen in Figure 4 and 5. Whereas the distance to default is distributed in a non-linear way the numerical transformation of the ratings is done linearly. This problem can be solved through the introduction of a quadratic term which is the DD squared, hence quadratic term. The quadratic term basically helps to create the exponential slope seen in Figure 5 for the regression instead of the linear transformation exhibited in Figure 6.

$$\begin{aligned} Rating_{it} = {} & \alpha + \beta_1 Merton\ DD_{it} + \beta_2 Merton\ DD_{it}{}^2 \\ & + \beta_2 Regulatory\ quality_{it} + \beta_3 Merton\ DD_{it}\ x\ DV \\ & + \beta_4 Regulatory\ quality_{it}\ x\ DV \end{aligned} \qquad (10)$$

Figure 5. Graphical visulisation of the distance to default based on the data from the sample collected within this study

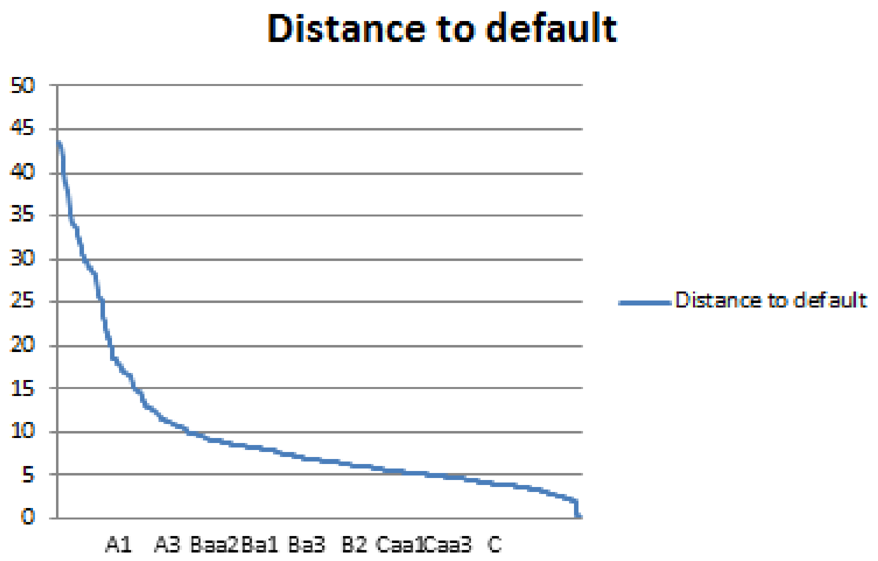
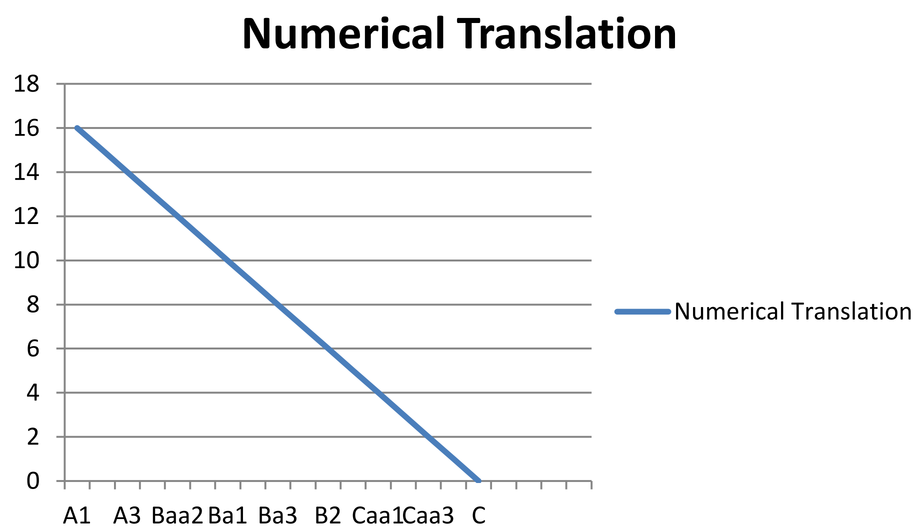


Figure 6. Visualisation of the numerical translation discussed in chapter 3.4



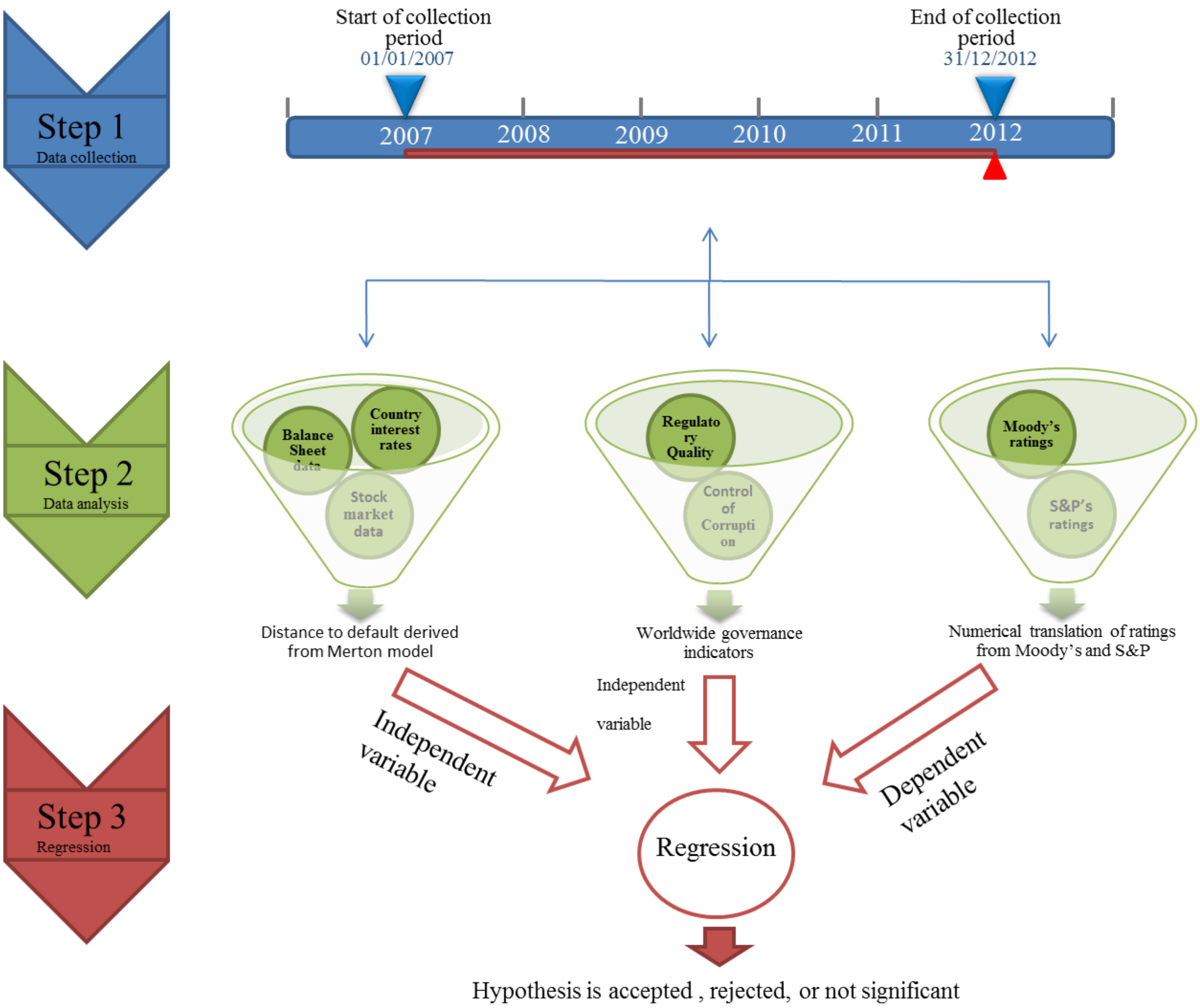
3.8.4 Robustness of the regression

In order to ensure robustness of the regression two sub-regressions are run. The sub-regression only contain one of the markets (emerging or mature), meaning that two regressions are required to being run in order to capture both markets. The results should be similar to the ones deriving from the interaction-term regression that runs the data from both markets at once. The sample is the same as for the interaction-term regression, hence both sub-samples should together contain an equal number of observations as the interaction-term regression does.

3.9 Visualisation of methodology

Figure 7 is a three-step visualisation of the applied methodology, in the first step, the data is collected for the period of 2007-2012, the second step shows the data analysis and the different types of data used. In step three, the data analysed previously is run in a regression, the result of the regression indicates whether it is significant or not and whether the sample data supports or rejects the hypotheses.

Figure 7. Visualisation of methodology



4 Data Analysis

The following chapter contains the panel data analysis of the sample starting with descriptive statistics, explaining the sample characteristics and the actual analysis. This is followed by the analysis of the fixed effects regression model. Furthermore, a robustness test will be provided.

4.1 Descriptive statistics

The analysed, unbalanced panel data sample consists of 411 observations in total, including six periods and 80 cross sections. The original planned number of observation was 500, with company data of 100 firms being analysed over a six year time horizon, but several years for which no credit rating was available were dropped.

The Durbin-Watson statistic for the regression analysis, which tests for auto correlation of the residual series, is 1,259464. In this case this would mean that the residuals are positively auto correlated since the value would be below the critical value threshold d_L of 1,42 (C. Brooks, 2008). This is however disregarded as the Durbin-Watson statistic for panelled data with fixed effects, for cross sections and periods, is rather inconclusive and very difficult to interpret. Similar circumstances apply to R-squared and the adjusted R-squared through the fixed effects assigning dummy variables to every variable in the regression, leading to very high R-squared values.

Table 9 shows an analysis of the data collected for the purpose of this thesis; it breaks down the base sample into a set of sub samples according to: type of country, type of rating, average country/company rating and industry diversification. By doing so, it provides the reader with a deeper understanding of the data and its structure for the regression analysis, which will be discussed later in this chapter.

Table 9. Descriptive statistics

Type of country	No. of observations	Avg agency rating	Avg distance to default	Avg regulatory quality
Emerging	125	10.34	7.59	43.44
Mature	286	13.27	10.26	93.38
Type of rating				
Investment-grade in emerging markets	54	12.85	9.18	49.48
Non-investment-grade in emerging markets	71	8.42	6.38	38.85
Investment-grade in mature markets	242	14.00	10.59	93.29
Non-investment-grade in mature markets	44	9.30	8.44	93.89
Average Country / Company ratings				
France, average country rating: 19,83*	70	13.53	6.67	85.53
Germany, average country rating: 20	56	13.36	6.24	93.34
Netherlands, average country rating: 20	54	13.44	7.98	97.33
Sweden, average country rating: 20	53	12.51	8.22	96.87
United Kingdom, average country rating: 20	53	13.43	23.62	96.28
Argentina, average country rating: 5	27	7.41	5.76	23.04
Brazil, average country rating: 11	33	10.18	5.59	54.94
India, average country rating: 9,83	31	11.26	8.49	39.97
Indonesia, average country rating: 9,17	16	10.00	12.53	41.13
Mexico, average country rating: 13	18	13.72	8.05	61.00
Industry diversification				
Car manufacturer	34	11.82	4.48	82.21
Consumer products	12	15.00	13.64	91.50
Energy	43	11.88	8.90	64.58
Industrial goods	92	12.30	7.31	86.82
Industrial services	22	12.00	10.56	76.68
Oil & gas	45	12.87	11.42	54.49
Pharmaceuticals & Medical research	20	13.45	14.70	88.15
Retailer	6	14.00	5.84	85.67
Services	30	11.97	6.92	94.93

Starting with the first row, type of county, the fact that the amount of observations in mature markets is significantly higher than in emerging markets stands out. As already mentioned before, initially the same amount of data was collected for both markets. However, a significant amount of ratings in emerging markets was withdrawn and could therefore not be included in the sample. Looking at the average ratings, they are 10 in emerging markets (Ba1 Moody's, BB+ S&P) and reflect a non-investment grade rating, whereas the average rating in mature countries is 13 (Baa1 Moody's, BBB+ S&P) and reflect an investment-grade rating. The Merton model seems in general to support the rating agencies, since the distance to default in emerging countries is lower than in mature countries. A significant gap between emerging and mature markets can be seen in the average regulatory quality, which is twice as high for mature markets.

The next row, type of rating, provides insights into the distribution of investment-grade and non-investment grade ratings among emerging and mature countries. Although the results from row one could lead to the conclusion that mature markets could contain a higher amount of investment grade rated companies, it is still surprising that in emerging markets only 40% of the companies are rated investment grade, whereas 85% of the companies are rated investment grade in mature markets. This can be traced back to the fact that rating agencies still employ the rule of a sovereign rating ceiling in many cases. The assigned ratings by the agencies are also on average higher in emerging than in mature countries, both in investment-grade and in non-investment grade. Again, from looking at the raw numbers, it seems that the Merton model supports the ratings of the rating agencies, since it arrives on average at a higher distance to default for mature market firms than for emerging market firms.

Row three provides an overview over the distribution of the observations among the countries, the average ratings of these countries, the average ratings assigned to the companies by Moody's and S&P and the average results derived from the Merton model. Congruent with the results from row one, row three also shows a higher amount of observations from mature than from emerging markets. Excluding Mexico, emerging market countries companies have in general a lower rating than mature country companies. A relationship between high ratings and high distance to default can be observed, however it does not seem to be as strong as in the previous examples. It is difficult to say whether lower country ratings also lead to lower company ratings, since the origin of these ratings cannot be concluded from the given data. Still, most of the company ratings are not higher than the ratings of their "home country". However, what can be concluded is that all five mature countries have very high values for regulatory quality, in contrast to the emerging countries. Argentina has the lowest regulatory quality and yields also the lowest average ratings, while Mexico has the highest regulatory quality and accordingly yielded the highest average ratings.

Row four shows the distribution of the companies among nine different industries, the randomly selected companies show a good distribution. Concerning the assigned ratings and the distance-to-default, it seems rather difficult to draw any scientific conclusion.

The mean of the numerically translated credit ratings is 12,38 with a standard deviation of 2,85. This corresponds to a rating of approximately Baa2 with a range from A2 to Ba1/Ba2 and the minimum and maximum values were five and 19 with B3 and Aa1 ratings respectively. The median of credit ratings corresponds to a Baa1 rating.

For distance to default the median for the sample was 6,67 with a mean value of 9,45. The standard deviation for this value is fairly high with 8,30, giving a range of 17,75 to 1,15. Furthermore, it is peculiar that the minimum value for distance to default is negative with -0,04. This can be explained by findings of Crosbie & Bohn (2003) who find that companies can still be in business even though asset values have fallen below debt values. Hence, these companies are only regarded to being in default when asset values are far below the debt values.

The sample mean for regulatory quality is fairly high as well with 78,19 due to the concentration of high scorings in mature countries and Brazil for example. Similar is observed for the median and the standard deviation although the minimum value of the sample is 19. This further points at a concentration of country scorings around the mean value.

Table 10. Descriptive statistics of variables

	Mean	Median	Standard deviation	Minimum	Maximum
Rating	12.38	13	2.85	5	19
DD	9.45	6.67	8.3	-0.04	43.39
Regulatory Quality	78.19	92	24.51	19	100

4.2 Regression analysis

Table 11. EViews 8 output of regression analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.8919	1.5277	5.8205	0.0000
DISTANCE_TO_DEFAULT	0.0999	0.0267	3.7390	0.0002
SQUR	-0.0013	0.0004	-3.1817	0.0016
DV*DISTANCE_TO_DEFAULT	-0.0199	0.0179	-1.1148	0.2658
REGULATORY_QUALITY	0.0669	0.0266	2.5149	0.0124
DV*REGULATORY_QUALITY	-0.0362	0.0349	-1.0349	0.3015
R-squared	0.9711	Mean dependent variable		12.380
Adjusted R-squared	0.9631	S.D. dependent variable		2.8451
S.E. of regression	0.5468	Akalke info criterion		1.8214
Sum squared resid	95.9824	Schwarz criterion		2.7014
Log likelihood	-284.2987	Hannan-Quinn criter.		2.1695
F-statistic	121.1038	Durbin-Watson stat		1.2595

When interpreting the above results of the regression, the first coefficient of 0,099872 for DD in emerging markets means that if DD increases by one standard deviation the credit rating increases by 0,099872 notches. The fact that the coefficient has a positive value is logical since a greater distance to default leads to a better credit rating where an AAA rating has the highest possible value of 20.

SQUR, as already discussed, was introduced into the regression in order to account for non-linearity of credit ratings. The problem at hand can be observed with Figure 5 and 6 of the previous section. Therefore, the quadratic term was introduced to achieve the non-linear slope of Figure 5 for DD. The coefficient is negative in this case which is a logical consequence since the slope for DD is decreasing due to the fact that there is a rating ceiling of AAA or 20 in numerical values and the reduced impact of DD on the rating.

The coefficient for regulatory quality in emerging markets is interpreted that a one unit increase in regulatory quality leads to an increase of about 0,067 notches in the credit rating.

The dummy variable DV multiplied by DD gives the magnitude of the impact of DD for credit ratings in mature countries. Because of the negative value of the coefficient it has to be deducted from the original coefficient of DD in order to arrive at the DD coefficient for developed countries. The value of the coefficient being negative also means in this case that DD has a reduced impact on credit ratings in mature markets compared to emerging market countries. However, the probability of this variable is insignificant meaning that DD there is no significant difference between the effects of DD in developed and emerging countries.

Essentially, the same can be observed for regulatory quality in developed countries. The value for regulatory quality in developed countries needs to be deducted from the coefficient of regulatory quality in emerging markets, as regulatory quality has a reduced impact on developed markets. But the probability is insignificant as well which is interpreted as regulatory quality having no significantly different effects on credit ratings in developed countries compared to emerging markets.

4.2.1 Impact of distance-to-default

The variable DISTANCE_TO_DEFAULT has a positive coefficient and is statistically significant. The regression supports the hypothesis that stock markets of emerging countries are efficient and DD therefore have a high explanatory power, at a 99% confidence level, representing the variable with the highest statistical significance. The results indicate that an increase of the DD derived from the Merton model will lead to an increase of the rating assigned to the company. The descriptive analysis strengthens the result, since it shows a well-distributed sample among the emerging countries analysed. The sample data analysis in chapter 3.1 further shows a good average distribution of the emerging country companies among the industries. However, it shows a certain concentration for energy and oil & gas companies which is not surprising for emerging market countries. As far as it is possible to draw a conclusion based on the descriptive analysis, it does not seem that there are industry specific biases for energy and oil & gas companies in the ratings they got assigned and the distance-to-default derived from the Merton model.

Hypothesis 1: Distance to default has a significant influence on credit ratings in emerging markets.

Result: Hypothesis is supported by the sample at a 99% confidence level.

For the variable DV*DISTANCE_TO_DEFAULT the regression yields a negative coefficient. Since it is an interaction term, it has to be interpreted as the sum of the variable DISTANCE_TO_DEFAULT, which in turn results in a positive accumulated coefficient. Nevertheless the coefficient DV*DISTANCE_TO_DEFAULT is not significant. This indicates that DD has the same effect on ratings in mature and emerging markets. Therefore, emerging and mature markets exhibit similar information content in stock market data measured through experiencing the same impact of DD. Although the descriptive analysis indicates a good distribution of the companies among mature markets and also among the industries, a potential bias could still be that only European companies are included within the study. For the reason of their differences in investor protection and corporate governance systems, compared to central European countries it would be interesting to run the regression on a sample of US companies. Still, as shown in the descriptive analysis around 19% of the mature market companies are from the UK, since the UK as part of the Anglo-Saxon region has a similar financial market framework to the US it is questionable, if including US companies would have led to another result.

Hypothesis 4: Distance to default has a greater impact on credit ratings in mature than in emerging markets.

Result: Not significant

4.2.2 Influence of regulatory quality and control of corruption

The positive coefficient REGULATORY_QUALITY confirms our expectation that the ratings are influenced by certain risk measuring indices. Being significant at a 99% level the sample supports the hypothesis, that regulatory quality has a significant influence on credit ratings in emerging markets. According to the regression an increase in regulatory quality would result in an increase of the rating, which seems fairly reasonable. The descriptive statistics further supports this since it reports on average values twice as high for regulatory quality in mature compared to emerging countries which is in line with the lower ratings assigned to companies from emerging country.

Hypothesis 2: Regulatory quality and control of corruption have a significant influence on credit ratings in emerging markets

Result: Hypothesis is supported by the sample at a 99% confidence level.

Contrary to the expectations regulatory quality does not have a greater impact on ratings for mature market companies. It only has a small impact as it can be seen in the sum of the variables REGULATORY QUALITY and DV*REGULATORY QUALITY; however, this is not significant. Therefore, the coefficient for mature markets can be disregarded as there is no significant difference between the impact if regulatory quality in emerging and developed countries. The descriptive statistics does not support the result of the regression, since it shows very high regulatory quality in all mature countries and fairly low in all emerging. It would therefore be reasonable to assume that the lower regulatory quality has a greater impact whereas the high regulatory quality is seen as a standard in mature markets. However, based on the given regression and sample data, regulatory quality is considered equally important by rating agencies in both markets.

Hypothesis 3: Regulatory quality and control of corruption have a greater impact on credit ratings in emerging markets.

Result: Not significant

The essence of these findings is that regulatory quality and DD have a significant impact on credit ratings for emerging market firms whereas they do not differ significantly for developed countries, which is controversial to what was initially assumed. Hence, the sample data could not give any evidence that the Merton model has a greater impact on ratings in mature compared to emerging markets. Because of the insignificance of the findings for DD and regulatory quality the coefficients can be disregarded. Therefore, the DD derived from the Merton model has the same implication for the efficiency of developed and emerging markets. One explanation for that can be that emerging markets only seem more efficient than mature markets since there is less information available in these markets; hence they seem to be better at incorporating information although they are not.

4.3 Robustness of the regression

In order to test for robustness of the regression and verify the above stated results, the same regression is being run on sub samples (emerging and mature markets) the regression is assumed to be robust when the results of the sub samples in general support the interaction-model regression that works with both markets at once. The results of the sub-regressions can be seen in tables 12 and 13. It will be further examined if the high r-square is a consequence of the applied fixed-effects. Moreover tests will be run in order examine if the data shows evidence of non-normality and heteroskedasticity.

Table 12. Regression output of emerging market data sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.7533	1.5031	4500840	0.0000
DISTANCE_TO_DEFAULT	0.1601	0.0629	2.5439	0.0127
PDSQ	-0.0027	0.0014	-1.9846	0.0503
CONTROL_OF_CORRUPPTION	0.0108	0.0250	0.4336	0.6656
REGULATORY_QUALITY	0.0493	0.0289	1.7042	0.0919
R-squared	0.9580	Mean dependent variable		10.336
Adjusted R-squared	0.9402	S.D. dependent variable		2.7237
S.E. of regression	0.6667	Akalke info criterion		2.2710
Sum squared resid	38.608	Schwarz criterion		3.1308
Log likelihood	-103.94	Hannan-Quinn criter.		2.6203
F-statistic	53.672	Durbin-Watson stat		1.3598
Prob(F-statistic)	0.0000			

Table 13. Regression output of mature market data sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.2996	4.6794	1.3462	0.1796
DISTANCE_TO_DEFAULT	0.0577	0.0256	2.2513	0.0253
PDSQ	-0.0009	0.0005	-1.8829	0.0610
CONTROL_OF_CORRUPPTION	0.0370	0.0494	0.7486	0.4549
REGULATORY_QUALITY	0.0329	0.0220	1.4965	0.1359
R-squared	0.9660	Mean dependent variable		13.273
Adjusted R-squared	0.9571	S.D. dependent variable		2.4052
S.E. of regression	0.4984	Akalke info criterion		1.6292
Sum squared resid	56.1363	Schwarz criterion		2.3962
Log likelihood	-172.9825	Hannan-Quinn criter.		1.9367
F-statistic	108.6718	Durbin-Watson stat		1.2391
Prob(F-statistic)	0.0000			

Both sub-regressions support the interaction-term regression. Whereas in mature markets DISTANCE_TO_DEFAULT and REGULATORY_QUALITY are positive and significant, both variables yield insignificant results for mature markets, which is in line with the results of the interaction-term regression.

Sub-samples and interaction-term regression report very high results for R-squared. Since the applied fixed effects add dummy variables, they could be the potential source of explanation. This is especially the case when the ratings stay constant over time and do not change. In the given scenario the dummy variable would adjust to upcoming differences between distance-t-to default, regulatory quality and the rating and hence increase the R-squared. In order to address this potential source of bias, the rating changes over the studied period are analysed. Therefore an average rating of the numerical translated company rating is calculated for each company and year. Afterwards, the average rating is retransformed into a rating according to Moody’s rating scale, which is presented in chapter 3.4. The results are presented in table 14.

Table 14. Average company rating per country and year

	2007	2008	2009	2010	2011	2012
Argentina	Ba2	Ba3	B1	B1	B1	B2
Brazil	Ba1	Ba1	Ba1	Ba1	Ba1	Ba1
Mexico	A3	A3	Baa1	A3	A3	A3
India	Baa2	Baa2	Baa3	Baa3	Baa3	Baa3
Indonesia	Ba1	Ba1	Ba2	Ba1	Ba1	Ba1
France	A2	A3	A3	Baa1	Baa1	Baa1
Germany	A3	Baa1	Baa1	Baa1	Baa1	Baa1
UK	A3	Baa1	Baa1	Baa1	Baa1	Baa1
Netherlands	A3	A3	Baa1	Baa1	Baa1	Baa1
Sweden	Baa1	Baa1	Baa1	Baa2	Baa2	Baa2

The original calculated average numerical ratings can be found in appendix 7.1. Concluding the results of the table, the company ratings stay on average fairly constant, this is more often the case in mature than emerging countries. Therefore the high r-squared is a result of the applied fixed effects. A test run of a regression without fixed effects resulted in a r-square of 0,37, which seems more realistic then the given result.

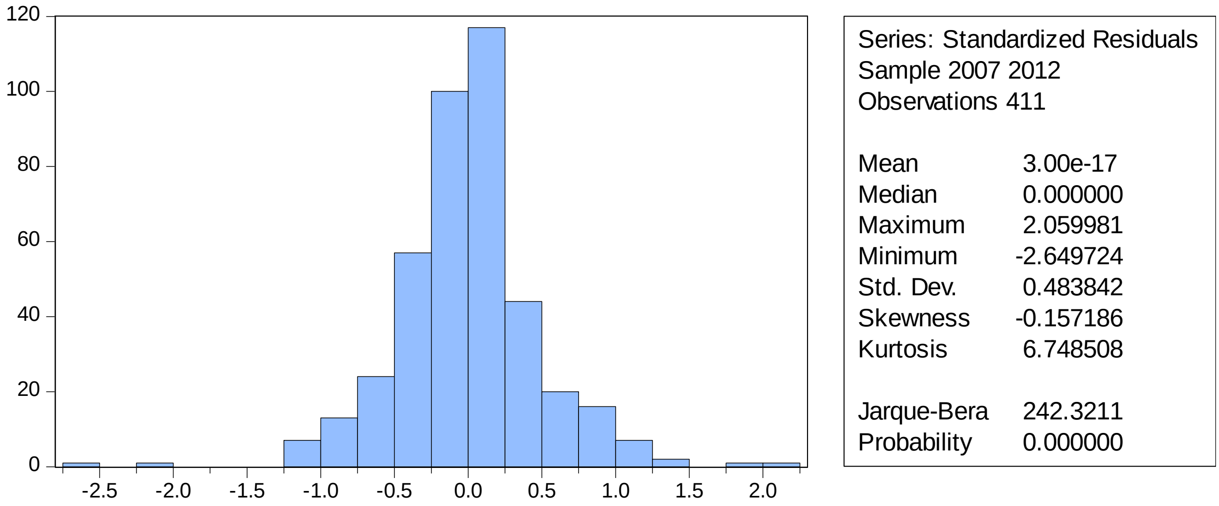
To ensure that the regression accounts for heteroskedasticity, the regression model white-diagonal-sections was run. The results of the corresponding white test for heteroskedasticity can be taken from table 15. The dependent variable has been changed to RESIDSQ. The resulting F-statistic of ~2,5 signals that the regression passed the test.

Table 15. Heteroskedasticity test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.2996	4.6794	1.3462	0.1796
DISTANCE_TO_DEFAULT	0.0577	0.0256	2.2513	0.0253
PDSQ	-0.0009	0.0005	-1.8829	0.0610
CONTROL_OF_CORRUPPTION	0.0370	0.0494	0.7486	0.4549
REGULATORY_QUALITY	0.0329	0.0220	1.4965	0.1359
R-squared	0.9660	Mean dependent variable		13.273
Adjusted R-squared	0.9571	S.D. dependent variable		2.4052
S.E. of regression	0.4984	Akalke info criterion		1.6292
Sum squared resid	56.136	Schwarz criterion		2.3962
Log likelihood	-172.98	Hannan-Quinn criter.		1.9367
F-statistic	108.67	Durbin-Watson stat		1.2391
Prob(F-statistic)	0.0000			

Table 16 below shows, non-normality is not an issue in our regression - the sample data is well-distributed. Moreover, the Jarqua-Beta and the corresponding probability suggest a very high significance.

Table 16. Non-normality test



5 Conclusion and discussion

This chapter will conclude the main findings of our study. Furthermore, an outlook for future research will be proposed that could provide a deeper understanding of the findings.

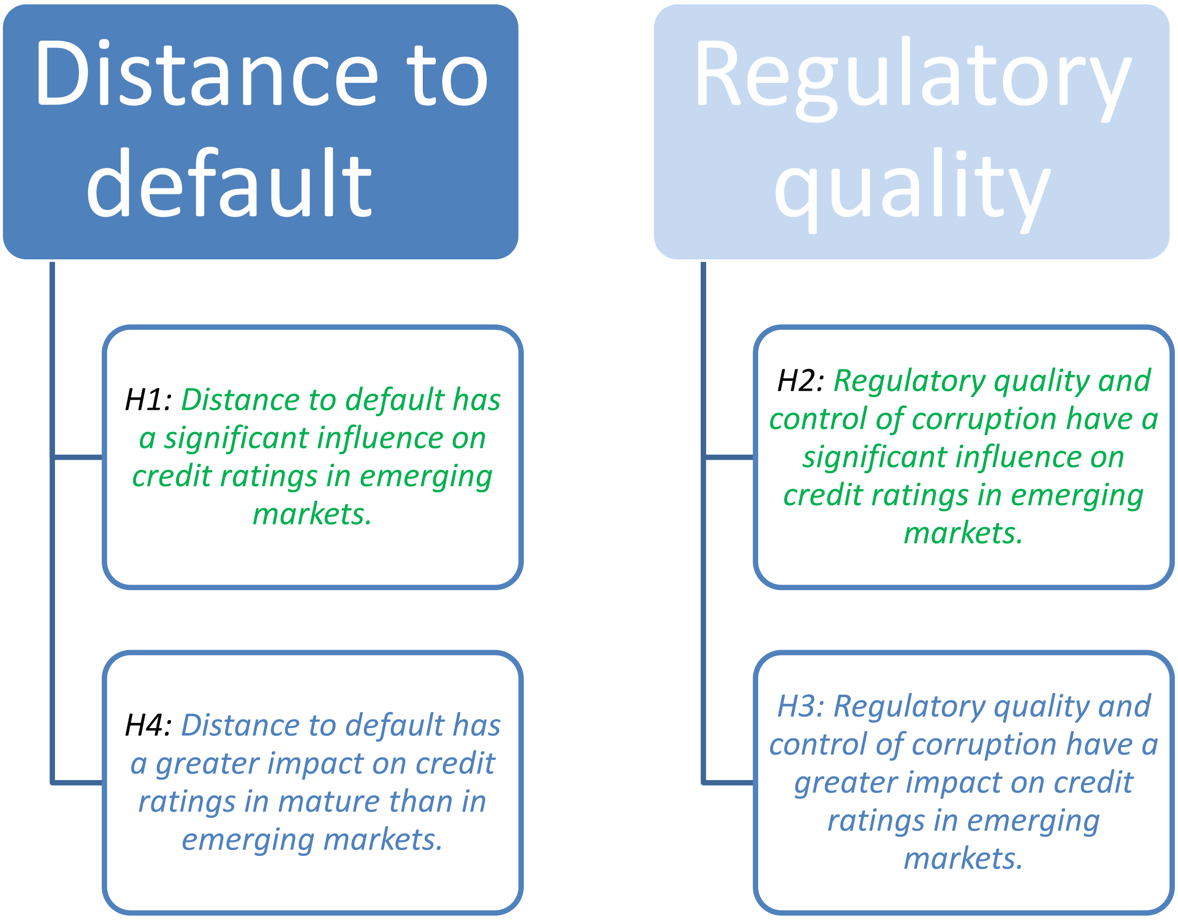
5.1 Conclusion

The hypotheses that were established for the emerging markets are supported by the sample data, whereas the results for the hypotheses related to mature markets were insignificant. This leads to the conclusion that the DD from the Merton model works equally accurate with market data from emerging markets and developed markets. A possible explanation could be that the DD is equally considered by rating agencies when determining corporate credit ratings.

The overall goal was to determine whether the Merton model has a greater impact on ratings in developed markets than in emerging markets, which was not supported by the sample data due to an insignificant difference between credit ratings and DD derived from the Merton model. Findings show that the Merton model yields significant results in emerging markets and considers country specific information, yet only through stock prices and volatility. Concluding this means that country specific circumstances of emerging markets are included in Market data, hence the Merton model accounts for the specific circumstances to emerging markets. The results show that DD and the institutional factor regulatory quality have a similar impact on ratings in both markets. However, the model does not account for quality and availability of information in these countries, which in turn have a negative impact on market efficiency. But no examination was made with regard to the quality of information or publishing frequency. As Griffin et al. (2010) pointed out emerging markets can appear to be equally or even more efficient because mature markets have more information available which is released more frequently in comparison to emerging markets. This biases findings towards determining similar efficiencies in emerging and mature markets. Therefore, it is increasingly difficult for the market to react in time and factor new information into stock prices for example. This is in line with (Du & Suo 2007) who find that "…credit quality information contained in the equity value of a firm is not fully utilized by structural credit risk models". The distance to default does not capture qualitative circumstances with regard to information like publishing frequency relative to incorporation speed. This could explain why emerging markets in this study appear to be equally effective in incorporating market information into equity data because of the mentioned differences in frequency. The Merton model captures market information in emerging markets to determine a firm's creditworthiness but cannot account for qualitative factors of information. The Merton model yields equally results in emerging and mature markets,

Because of correlation issues between the independent variables CONTROL_OF_CORRUPTION and REGULATORY_QUALITY the variable for corruption is dropped as regulatory quality yields more significant results for the regression. The impact of the regulatory quality on credit ratings in emerging markets is similar to the distance to default whereas the results are not significant for the coefficient of mature countries. Therefore regulatory quality has the same impact in both markets. For future research it would therefore be interesting to examine if governance indicators or other influencing factors for credit ratings actually behave similarly to the distance to default in emerging markets and mature markets.

Figure 8. Summarised hypothesises



Accepted

Not significant

Rejected

5.2 Future research

Most of the present literature today focuses on the adequacy of the Merton model to forecast default, changes in a company’s credit rating, or ways to improve it either as it is discussed in the literature review. For example, Bohn et al. (2005) and Stein (2002) differ in their opinions about the adequacy of the inputs of the Merton model. Others arrived at different conclusions about the impact of the model with regard to its statistical significance for default. Little attention is actually paid to the quality and availability of information within the analysed countries, used to calculate the outputs of the model. It would therefore be interesting to examine the impact of different qualities of information on the outcome of the Merton model for very similar firms. In this regard, market efficiency in the present literature is mostly examined through effectiveness of different trading strategies and for example based on returns and transaction costs. As the results of this study show similar results for emerging and developed countries, future researchers could try and determine an adequate qualitative statistic for information publishing frequency and incorporation speed of companies that is tested for significance in this setting.

Due to the fact that there exist many other credit risk models like the KMV model, or models using actuarial approaches like Credit Metrics by JP Morgan or CreditRisk+ by Credit Suisse, it would be interesting to match the results of this paper against those retrieved from a study using one of these models in a similar setting.

Furthermore, due to the limitation of this study, different country specific variables like REGULATORY_QUALITY could be added to the regression model in order to determine more relevant explanatory variables for credit ratings. This would especially be interesting for developed markets as findings showed no significant differences for this variable in the two markets when explaining credit ratings by S&P and Moody’s. It is also suspected that these country specific variables behave similarly to the distance to default shown in Figure 5. Examining the validity of this assumption for regulatory quality as well as other possibly newly introduced variables would be an interesting start for future research in this regard.

Moreover, the duration of the analysed period could be increased to circumvent the bias of the financial crisis of 2007, which is present in all the gathered data. An increase would then also include more past crises, their prelude, peak, aftermath, and normalization periods. As for the period of 2007 until 2012, there was no or little data available as we are just now navigating towards the aftermath and normalization period of the 2007 crisis.

6 References

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7 Appendices

7.1 Numerical translation of average company ratings per year

	2007	2008	2009	2010	2011	2012
Argentinia	9	8	7	7	7	6
Brazil	10	10	10	10	10	10
Mexico	14	14	13	14	14	14
India	12	12	11	11	11	11
Indonesia	10	10	9	10	10	10
France	15	14	14	13	13	13
Germany	14	13	13	13	13	13
UK	14	13	13	13	13	13
Netherlands	14	14	13	13	13	13
Sweden	13	13	13	12	12	12

7.2 Emerging markets

Emerging Countries		
Country	Company	Industry
Argentina	Aluar	Industrial Goods
Argentina	Celulosa	Industrial Goods
Argentina	Pampa Energia	Energy
Argentina	Petrobras	Oil & Gas
Argentina	Telecom Argentinia	Software & IT Services
Argentina	Transportadora de Gas del Sur	Oil & Gas
Argentina	YPF	Oil & Gas
Brazil	Brasksem	Industrial Goods
Brazil	BRF	Consumer Goods
Brazil	CCR	Industrial Services
Brazil	CESP	Energy
Brazil	Companhia Energetica de Minas	Energy
Brazil	CPFL Energia	Energy
Brazil	Diagnosticos da America	Pharmaceuticals & Medical Research
Brazil	Eletropaulo	Energy
Brazil	Light SA	Technology Equipment
Brazil	Vale	Mineral Resources
India		
Indonesia	Astra International	Industrial Conglomerate
Indonesia	BT Bumi	Energy
Indonesia	Indosat	Software & IT Services
Indonesia	Perusahaan Gas	Oil & Gas
Indonesia	Telekomunikasi	Software & IT Services

Mexico	Alfa	Industrial Conglomerate
Mexico	America Movil	Software & IT Services
Mexico	Cemex	Industrial Goods
Mexico	Grupo Aeroportario del Pacifico	Industrial Services
Mexico	Grupo Bimbo	Consumer Goods
Mexico	TV Azteca	Software & IT Services
Mexico	Telefonos de Mexico	Software & IT Services

7.3 Mature markets

Mature Countries		
Country	Company	Industry
France	Bouygues	Industrial Services
France	Carrefour	Retailer
France	Saint-Gobain	Industrial Goods
France	Electricite de France	Energy
France	L'Oreal	Consumer Products
France	Peugeot	Car Manufacturer
France	Renault	Car Manufacturer
France	Sanofi	Pharmaceuticals & Medical Research
France	Schneider Electric	Technology Equipment
France	Suez	Industrial Goods
France	Total	Oil & Gas
France	Vivendi	Consumer Services
France	Accor	Consumer Services
France	Cap Gemini	Software & IT Services
Germany	Adidas	Consumer Products
Germany	BASF	Industrial Goods
Germany	Bayer	Industrial Goods
Germany	BMW	Car Manufacturer
Germany	Beiersdorf	Consumer Goods
Germany	Continental	Industrial Goods
Germany	Daimler	Car Manufacturer
Germany	EON	Energy
Germany	Lufthansa	Services
Germany	Deutsche Post	Services
Germany	Deutsche Telekom	Services
Germany	Allianz	Services
Netherlands	Fugro	Industrial Services
Netherlands	Heineken	Consumer Products
Netherlands	Koninklijke DSM	Industrial Goods
Netherlands	KPN	Services
Netherlands	Philips	Technology Equipment
Netherlands	Post NL	Services
Netherlands	Reed Elsevier	Software & IT Services

Netherlands	Unilever	Consumer Products
Netherlands	AkzoNobel	Industrial Goods
Netherlands	ASM International	Industrial Services
Netherlands	Royal Dutch Shell	Oil & Gas
Netherlands	Wolters Kluwer	Industrial Services
Sweden	Volvo	Car Manufacturer
Sweden	Atalas Copco	Industrial Goods
Sweden	Electrolux	Technology Equipment
Sweden	Ericsson	Technology Equipment
Sweden	SKF	Industrial Goods
Sweden	Assa Abloy	Industrial Goods
Sweden	Holmen	Industrial Goods
Sweden	Sandvik	Industrial Goods
Sweden	SSAB	Industrial Goods
Sweden	Swedish Match	Consumer Goods
Sweden	Telia Sonera	Software & IT Services
United Kingdom	BAE Systems	Industrial Goods
United Kingdom	BAT	Consumer Goods
United Kingdom	Centrica	Oil & Gas
United Kingdom	Diageo	Consumer Goods
United Kingdom	GKN	Industrial Goods
United Kingdom	GlaxoSmithKline	Pharmaceuticals & Medical Research
United Kingdom	Pearson	Consumer Services
United Kingdom	Rolls Royce	Industrial Goods
United Kingdom	SSE	Energy
United Kingdom	Tullow Oil	Oil & Gas