НАЦИОНАЛЬНЫЙ ИССЛЕДОВАТЕЛЬСКИЙ УНИВЕРСИТЕТ

ВЫСШАЯ ШКОЛА ЭКОНОМИКИ

Международный Институт Экономики и Финансов

МАГИСТЕРСКАЯ ДИССЕРТАЦИЯ

по образовательной программе высшего профессионального образования, направление 080100.68 Экономика

на тему:

The quality of bond credit ratings

Студент второго курса магистратуры

Карягин Николай Анатольевич

Научный руководитель

Шпренгер Карстен

PhD Economics, доцент

МОСКВА, 2013 год

Аннотация

Магистерская диссертация на тему «Оценка качества кредитных рейтингов облигаций» посвящена исследованию вопроса насколько верно и адекватно кредитные рейтинги, присвоенные ведущими рейтинговыми агентствами облигациям, отражают кредитные риски инструментов. Также автор был заинтересован провести анализ информации, содержащейся в рейтингах, об основных индикаторах которые рейтинговые агентства включают в свои отчеты о точности произведенных оценок, таких как вероятность дефолта инструмента и процент возврата при дефолте (или, что эквивалентно, потерь в случае дефолта) и возможности использования альтернативных индикаторов качества. Рейтинги в мировой экономике являются важными индикаторами как для регуляторов, так и для индивидуальных инвесторов. Несмотря на более чем 100 летнюю историю с момента присвоения первого рейтинга и постоянное развитие методологий вопрос об адекватности оценки инструментов со стороны рейтинговых агентств остается актуальным в свете мирового финансового кризиса 2008 года, в ходе которого многие инструменты с высоким рейтингом испытывали трудности, что является результатом неточности оценки.

В магистерской диссертации были исследованы и получены ответы на следующие вопросы:

1. Какую информацию несут в себе рейтинги облигаций и насколько надежна данная информация для участников финансовых рынков?
2. Обладают ли рейтинги информацией о показателях, отличных от рассмотренных в первом вопросе и возможно ли ее использовать инвесторам для более детального анализа при принятии инвестиционных решений? Возможно ли использовать эту информацию чтобы идентифицировать облигации, рейтинг которых завышен или занижен?
3. Какие характеристики облигаций оказывают существенное влияние на потери при дефолте, вероятность присвоения неправильного рейтинга и каков характер этой взаимосвязи?

Для ответа на эти вопросы была использована коммерческая база данных рейтингового агентства Moody's, содержащая детальную информацию обо всех инструментах, которым агентство присваивало рейтинги, а также о дефолтах и эмитентах. Методика исследований вопросов 1 и 2 предполагала построение кривых Лоренца независимо для облигаций эмитентов финансового и нефинансового секторов экономики и расчет коэффициентов Джини для определения степени информации, содержащейся в рейтингах для каждого конкретного случая. В результате автор получил следующие выводы:

- Рейтинги корректно отражают информацию о вероятности дефолта для обоих рассматриваемых секторов экономики. Тем не менее, объяснительная сила рейтингов для вероятности дефолта у финансовых облигаций существенно меньше, чем у нефинансовых, и одинакова для всех рассмотренных временных интервалов. Что касается нефинансовых облигаций, то рейтинги существенно лучше отражают вероятность дефолта на временном промежутке до 1 года. Автор полагает, что для корректной оценки вероятности дефолта финансовых организаций требуется использовать дополнительные к рейтингам источники информации.
- Рейтинги слабо коррелированы с потерями в случае дефолта. Они практически не объясняют вариацию для облигаций финансового сектора и слабо объясняют для нефинансового. Тем не менее, для облигаций нефинансового сектора наблюдается резкое увеличение корреляции рейтингов и потерь в случае дефолта на временном промежутке меньше 1 года. Это дает основание считать, что в данном случае рейтинги можно использовать как одну из переменных для объяснения потерь на малых временных интервалах.
- Автор протестировал альтернативную меру качества кредитных рейтингов – «реализованный убыток». Данная мера в силу определения учитывает как вероятность дефолта, так и потери в случае дефолта и определена для всех облигаций, а не только тех, по которым произошел дефолт (в отличие от потерь в случае дефолта). Оказалось, что рейтинги содержат информацию о «реализованном убытке». Более того, данная мера превосходит вышеприведенные два индикатора, и так как Moody’s упоминает в методологии, что при присвоении рейтингов учитываются оба индикатора, это приводит к выводу, что новая мера является более подходящей оценкой качества рейтингов. Кроме этого, автор показал возможность использования данной меры для выявления облигаций с завышенным и заниженным рейтингами, что делает ее применимой для использования инвесторами.

Ответ на третий поставленный вопрос показал, что между характеристиками облигаций и потерями при дефолте, а также вероятностью присвоения неправильного рейтинга существует взаимосвязь. Значительные эффекты наблюдаются для следующих величин:

- время до погашения, коэффициент положителен, что свидетельство того, что для облигаций с большим временем до погашения характерны большие потери и им чаще присваиваются неверные рейтинги
- наличие обеспечения уменьшает потери, а также такие облигации реже имеют неверные рейтинги
- принадлежность к определенной индустрии среди облигаций нефинансового сектора оказывает значительный эффект на рассматриваемую взаимосвязь. Облигации индустрий, продукты которых пользуются спросом даже в рецессиях имеют меньшие потери, что объясняется способностью восстановить деятельность в условиях непрекращающегося спроса
- остальные характеристики не продемонстрировали значительных эффектов, что может быть вызвано малым количеством облигаций с такими характеристиками в выборке

Вопросы и направления для дальнейших исследований:

1. Как могут рейтинговые агентства скорректировать свою методологию для учета показателя «реализованных убытков» и будет ли более подходящим публиковать в отчетах данный показатель вместо текущих двух?
2. Такие характеристики как тип облигации, приоритетность долга и валюта выпуска показали значимые эффекты в некоторых случаях, но как было объяснено, это ложная взаимосвязь в виду малого количества облигаций с такими характеристиками в выборке. Исследование на большей выборке представляет дальнейший интерес.
3. Значение R^2 у регрессий довольно низкое, тем не менее, они значимы в силу высокого значения F-статистики. Это может быть следствием того, что оставшаяся вариация в зависимой переменной объясняется внешними данными, такими как показатели финансовой отчетности эмитента и макроэкономическими переменными. Данная гипотеза представляет интерес для дальнейших исследований.

Table of Contents

Introduction

Influence of credit ratings on the world economy became extremely significant in the last 30 years. The contemporary credit rating market started forming in 1970s when the US Security and Exchange Commission accepted a number of resolutions for brokers, issuers, banks and number of other financial market participants.

Nowadays ratings are very important economic and political factor because they essentially determine the cost of funding for issuing companies. Before the financial crisis 2008 ratings were unquestionable indicators of issuer creditworthiness. Nevertheless, after significant defaults number of highly rated companies it became clear that at least in the past rating methodology had not taken into account all possible risks properly.

There is always asymmetry in information which makes exceptionally difficult for investor to estimate all possible risks inherent in particular instrument. This happens because rating process takes into account many factors and requires strong expertise for it. Thus, quality assessment procedure of the issue becomes almost unrealistic to be conducted by individual investor without external assistance. Exactly for that purpose auditors, rating agencies and number of other companies are operating. Their work is dedicated to decrease asymmetry in information and help to reduce costs that individual investor would bear if conducted this original research.

In light of discussed above it is quite hard to imagine the present-day world without credit rating, which underlines extremely importance for them to be properly assigned. In this paper author's intention was to investigate the last problem and to find answers on the following questions:

1. What kind of information is present in assigned ratings and how reliable is this information for the participant of financial market?
2. Do ratings contain any additional information that can be used by investors for more detailed analysis of their financial decisions? Is it possible to use this information to find inconsistently rated bonds?
3. Which of the bond specific variables are responsible for inconsistent ratings and in which direction do they affect the bond losses?

In order to answer these questions author studied existing scientific literature and publicly available rating agencies methodologies. Sample used in this research was constructed using Moody's Default Risk Service proprietary database which contains detailed information about each debt's characteristics rated by Moody's as well as brief summary for the default event and issuer details. For answer on the first question author studied the presence of information about default frequency and loss given default in assigned ratings because Moody's methodology explicitly states that ratings reflect these both indicators. Approach used to answer this question involved Lorenz curves and calculation of accuracy coefficients as rating agencies often do. Based on the obtained results author claims that ratings do reflect correctly probability of default. Nevertheless, they are poor predictors of loss given default and may be used for the last purpose only in the 1 year period after rating assignment as additional source of information for prediction.

For the second question author tested newly introduced measure called realized lifetime loss on the described above dataset. The idea for this indicator was mentioned in working paper by Hainsworth (2012) but was not assessed by the author on the real data. Methodology was essentially the same as for the first question and resulted in conclusion that information about realized lifetime loss is contained in ratings and moreover, ratings reflect it better that default probability. Because this measure implicitly accounts for both default frequency and loss given default by construction it can be used as alternative indicator by rating agencies for accuracy of their predictions.

Finally, using this new measure author counted inconsistently rated issues and used indicator of misclassification in regression analysis to determine which variables are responsible for inconsistent rating. It turned out that there are few bond specific variables that are significant and can explain such ratings. Results obtained are significant but do not explain all variation in realized losses. Although author's goal was not to build the model which explains total variation observed it would be interesting in further studies to utilize firm-specific variables and additional set of macroeconomic indicators which may account for the unexplained variation in losses.

The rest part of the master thesis is constructed as follows:

- Chapter 1 discusses the existing topic-related literature
- Chapter 2 is dedicated to study the relationship between rating classes, probability of default and loss given default
- Chapter 3 introduces realized lifetime loss and investigates its relationship with rating classes. These results are used to count inconsistently rated bonds and to find out which bond specific variables explain this phenomenon using regression models.
- Master thesis is completed with conclusion and tables in Appendix 1-4 which give more insights about sample used and other data.

Chapter 1. Literature review

1. Studies investigating presence of information about default frequency and loss given default in assigned ratings

There are number of studies on credit ratings quality and the relationship between default frequencies (which is good proxy for default probability) as well as recovery rates in case of default but they do not constitute a substantial amount in scientific literature. One possible explanation is that rating agencies are publishing their own very detailed papers and special comments and are able to do this on broad data sample. It is quite reasonable to think that properly assigned ratings should reflect information about both probability of default and loss given default. The purpose of this chapter is to investigate empirical results that were obtained in the literature and highlight the most important points about rating agencies methodology.

1.1. Examination of information about default frequency contained in assigned ratings

One of the earliest found papers is Altman (1989). This study gives an idea that for bondholders important information would be not only default probability but also volume lost in case of default. Here it should be noted that it is basically the idea for loss given default (or equally the recovery rate; this concept was actually introduced by three major rating agencies after recent financial crisis). Altman introduced the concept named mortality rate and defined it for each rating class for a given year as

$$MMR_{rating\ class}(t) = \frac{Total\ value\ of\ defaulting\ debt\ in\ the\ year\ (t)}{Total\ value\ of\ the\ population\ of\ bonds\ at\ the\ start\ of\ the\ year\ (t)}$$

The result is that author found significant correlation between rating classes and this indicator of defaults, specifically as it was expected the lowest mortality rates were obtained for the highest rated (“AAA”) bonds which are increasing dramatically when moving into non-investment grade issue classes.

Although at the time this article was published rating agencies have not used the notion of recovery rates, Altman did the research on relationship between the percentage of par that investor could get by selling defaulted bond and rating classes. He found that actually there is no correlation between first assigned rating and recovery in case of default. Moreover, there is no relationship for investment-grade and junk bond as well as time to default also has no impact on recovery.

In Godlewski (2007) paper author assessed quality of ratings assigned to banks from emerging economies. Sample consisted of 483 banks from developing markets in Europe, Asia and South America. On this data author run a logistic model for defaults prediction. Then according to these probabilities empirical distribution was reconstructed and used to predict ratings. Finally, these ratings were used as inputs for scoring model as well as Moody's ratings to find appropriate scale for replicated possibilities. As the result, for the given model author Godlewski came to the conclusion that Moody's ratings are on average in line with default frequencies presented in the data.

Another important question that was raised in Bruche and Gonzalez-Aguado (2010) is about relationship between default probabilities and state of economy. In addition to that question authors also studied the correlation between recoveries and credit cycle as well as default frequency. Bruche and Gonzalez-Aguado claimed that in recessions default frequencies should grow significantly and have to be followed by substantial drop in realized recoveries. In the sample of about 2000 US issues experienced default event in period 1974 – 2005 they found that stated above hypothesis is correct. In order to model state of economy they introduced a two-parameter Markov chain. Main feature of the model is that it is completely defined by two probabilities that are connected with credit cycle: one for downturn state (which is actually the probability of switching into normal state) and the other for probability of going into recession, i.e. alteration from the normal state. This new additional variable indicating the state of economy was also compared to the set of macroeconomic variables. The results show that correlation between recoveries and probability of default is much higher that correlation between each of this two variables and macroeconomics indicators. This is explicit evidence shows that for explanation of recovery it is more reasonable to use default frequency as the basic explanatory variable (and vice versa) and macroeconomic ones should be used to account for the rest of unexplained variation in recovery rates.

The working paper by Hilscher and Wilson (2013) is the most recent one. The main message of the paper is that for risk-averse bondholder credit ratings given that they are proper measure of issuer quality should contain both information about probability of default and market risk. The first question was assessed by modeling defaults with logistic regression using as explanatory variables available bookkeeping data and market-based information. Model output was compared with actual default frequency. Prediction horizon was selected to be in the range from one month to five years. For the shortest time period authors found that ratings do not contain significant amount of supplementary information compared to the used model. As time horizon expands it is reasonable to think that prediction power of the model will decline due to uncertainty. This is what actually was found in the paper. For all other time periods ratings turned out to be inferior to the used model except the longest one, but ratings performance over model in this case is negligibly higher. As for the second question, namely whether ratings incorporate information for market risk authors constructed specific measure called failure beta. They obtained that there is strong correlation between this measure and rating classes. More specifically, failure beta grows as rating class quality declines (from the highest to the lowest). This fact proves that ratings are good indicators of market risk. To conclude, authors state that rating agencies do not incorporate all relevant information about default probability into ratings but they turned out to be good predictors of market risk.

In Figlewski et al (2012) authors consider how various macroeconomic variables together with firm-linked ones effect on default probability among rating classes. The main instrument for this purpose was Cox hazard model in reduced form. It should be noted that sample of debts utilized in the paper was extracted from Moody's Default Risk Service database which is similar to those used in the master thesis. As the result author stated that rating classes incorporate probability of default properly for each rating category and predictive power of the model increases with utilization of macroeconomic variables. This fact is in line with previous studies. In addition the higher the initial rating results in the lower probability for such bond to experience a default event as well as to be downgraded. Another important conclusion is about effects connected with time to maturity – default intensity depends on this bond specific characteristic, namely the longer the time horizon the higher the probability of default, which seems to be quite reasonable.

The last paper in this subsection mostly refers not to the default frequency and rating classes but actually to inconsistently rated issues. This study is important since in the master thesis author also calculated inconsistently rated issues and paper may provide with some insights. Perraudin and Taylor (2004) considered sample of 1430 straight US dollar denominated bonds that satisfied to some particular requirements. For these issues Nelson – Siegel algorithm was implemented to extract term structures for yields of different rating classes on everyday basis. In addition yield curves for different maturities were also constructed. Using term structure of interest rates fitted bond prices were calculated and based on them misclassified issues were defined. Finally, authors found that about 25% "AA" bonds have misclassified rating. Authors claimed that such substantial amount of misclassified issues may be due to significant effect of unaccounted risk premiums or taxes which have effectively make impact on discount rates. After accounting for these factors authors decreased number of inconsistently rated bonds considerably but it still remains significant.

1.2. Examination of information about loss given default contained in assigned ratings

There are a few major papers that author found which investigate the empirical relationship between loss given default (and equivalently recovery rate) and rating classes. Explanation of this phenomenon is that rating agencies introduced this measure only after numerous default numbers during past financial crisis. Before that is was broadly common to assume that probability of default and recovery are not correlated. The recent crisis showed that it is quite strong and unreasonable assumption. Moreover, estimated recoveries are published by agencies only for small amount of issues that are rated and author was unable to find out why rating agencies do not publish estimated recoveries for the rest debts.

As in above review for default probability results from the articles are not in line with each other. The first paper was already discussed; it is Altman (1989) where author specified that there is no dependence between first assigned rating and realized recovery after default. Also it was stated that if one considers subsamples of non-investment and investment grade bonds separately the result remains unchanged indicating that there is no relationship irrespectively for these subclasses.

In paper by Carey (1998) author investigates main features of bond portfolios – distribution of losses given specific issue risk. Sample consists of debts covering period 1986 – 1992. This issue specific risk is estimated via supervisory ratings. As the result Carey states that distribution of losses has poor correlation with debt classes which supports Alman's conclusion.

The next paper is of the recent ones. In Bade et al (2011) it is stated that there should be strong correlation between rating classes and recoveries. In this article Heckman-type regression model was introduced for simultaneous estimation of default probability and recovery rate. Set of explanatory variables consisted of ratings itself and broad set of macroeconomic indicators. The choice for the model was made for Heckman regression because on the used sample (obtained from Moody's database for US issues) authors found significant correlation between recoveries at default and probabilities of such events, thus they were intended to estimate both parameters simultaneously. In paper mentioned one possible explanation of phenomenon that in previous studies no correlation for recoveries and rating classes was found – recovery rate is observable only for defaulted issues and is not defined for non-defaulted ones. Therefore, it may be the case that previous papers suffered from biased data. Estimating the introduced model authors claimed that they considered this problem carefully when studied the empirical relationship. In addition, four different subtypes of model were estimated and some of them turned out to have high explanatory power. In these models parameter lambda was significant and it is explicit proof that results of the model correctly accounts for correlation between recoveries and probability of default.

Varma et al (2003) presented a special comment from Moody's research division which also gives the evidence that recovery rates are correlated with rating classes – there is positive relationship indicating that recoveries decline for lower quality rating classes, the highest ones are for AAA issues and monotonously go down for non-investment grade bonds. The sample used consisted of corporate debts only covering defaults happened in period from 2000 to 2003. All computational process was conducted for equally weighted and value weighted portfolios. The last one was implemented to check whether ratings perform better for issues with higher outstanding amount and it was found that defaults on higher volume issues are followed by lower recoveries. This is reasonable to study these two cases separately and in this master thesis author implemented both approaches. The sample used was again Moody's DRS database and consisted of both bonds and preferred stocks, although number of stocks is quite small (111 compared to 2500 for bonds). In spite of found positive relation it is mentioned that results are not extremely robust.

Altman and Kishore (1996) present a comprehensive research on recovery rates. There are many variables that potentially may influence the recovery, the most important ones are:

- Debt seniority – as it was pointed out, on average in the sample recoveries decline with decrease in seniority. This is quite reasonable to assume, since in case of default bondholders with the highest priority claims (senior secured) will receive more because they are paid first
- Debt industry also should affect the recovery. The highest recovery rates are observed for utilities, chemicals, petroleum and food industries. This seems reasonable since even in case of default products of companies from these industries will be in demand thus would give the ability for business to recover more value.

Tests for statistical significance conducted in the article proved that debt seniority and belonging to particular industry describes diverse recovery rates. Nevertheless, authors note that rating class has no impact on recovery taking explicitly under consideration debt seniority (considering separately investment and non-investment grade categories).

In Altman et al (2005) authors analyzed the relation between default probabilities and loss given default using on corporate bonds sample. As it was mentioned earlier, before the crisis 2008 the vast majority of empirical studies as well as practical models treated default frequency and recovery rates as uncorrelated variables. Functional dependence of recoveries was based only on previously observed recoveries, sometimes collateral and bond seniority were also taken into account. Nevertheless, authors in 2005 on used data managed to obtain the results that such approach has to be changed due to presence of correlation between these variables. Statistical models used were able to describe the most part of variation in recovery rates using default frequencies, debt classes and backing indicators as explanatory variables. This leads to very important conclusion for risk-managers and credit analysts.

2. Methodologies of rating agencies for default probability and loss given default estimation

2.1. Moody's methodology

Moody's methodology is described in more details than Standard & Poor's and Fitch ones for two reasons: first is because author used sample extracted from Moody's database and second because the rest two agency's methodologies have more in common that each of them with Moody's.

As it is stated in Moody's corporate brochure: "credit ratings are opinions of the credit quality of individual obligations or of an issuer's general creditworthiness" (Moody's Ratings Symbols and Definitions, 2009, p.1). Thus, agency assigns ratings analyzing total creditworthiness of the issuer, its ability to repay the debt on its own, possibility to obtain support from the parent structure (if it is applied), accounting data, open information sources and information that the issuer provides on the meetings. Some of these factors have higher weight but these weights are not determined beforehand. As Moody's says each issuer is analyzed separately and methodology has only general scheme.

For default probability and loss given default estimation Moody's uses original approaches:

- For default probability is utilized Moody's KMV RiskCalc v.3.1 model. This model uses accounting information for particular company, namely ratios for profitability, leverage, debt coverage, liquidity etc. as inputs for KMV model (which is practical implementation of Merton's model 1974). Through KMV structural model these indicators are transformed into distance to default which is then mapped with expected default probability using own proprietary default database. This model is purely econometric.
- For loss given default – Moody's LossCalc V2 model. This model is also purely econometric and as inputs it requires data on debt backing as well as possible support from the parent structure, class of the debt, firm- and industry-specific variables and finally macro indicators. For the last one are used dummies for states and the same distance to default as in previous model. Model also uses proprietary database for realized recoveries for bonds, loans and preferred stocks. The aim is to estimate the market price of debt in 30 days after default event.

There is discrete time period scale for which estimates are produced: Moody's assesses recovery as if default would have happened at the very moment and after 1 year from the moment.

As it was mentioned above approach for estimation is based on statistical information. Crucial point here is that in spite of highlighted correlation between probability of default and recovery rate as articles state (which is simply one less loss given default) Moody's is estimating these two variables separately.

Moody's defines recovery rate as percentage of par value which constitutes market price of defaulted issue 30 days after default event. As for default the definition is the following:
"a missed or deferred payment of interest and/or principal, <…> bankruptcy, administration, legal receivership, or other legal blocks, a distressed exchange occurs where the issuer offers a new security or package of securities of lower amount <…> or the exchange had the apparent purpose of helping the borrower avoid default" ("Frequently Asked Questions", Moody's Corporate Default Risk Service, p.1)

Having estimated rating for the particular issue Moody's uses the following procedure to determine the rating for a bond: agency adjusts issuer's rating in upward or downward direction based on difference between estimated LGD and LGD for set of issuers from the same industry. Moody's claims that only relative values of LGD are vital for rating assignment. LGD ranking as well as rating scheme are the following

Table 1
Moody's ratings and loss given default scales

Assessments	Loss range
LGD1	≥0% and <10%
LGD2	≥10% and <30%
LGD3	≥30% and <50%
LGD4	≥50% and <70%
LGD5	≥70% and <90%
LGD6	≥90% and ≤100%

Investment grade ratings	Aaa, Aa, A, Baa
Non – investment grade ratings	Ba, B, Caa, Ca, C

The source: Moody's Ratings Symbols and Definitions. Moody's Investor Service, 2009. pp. 12,19

Thus, Moody's ratings implicitly account for recovery rates through loss given default as indicated above. Using this result it makes reasonable to compare information contained in ratings about probability of default and recoveries with realized lifetime loss measure that will be introduced in Chapter 2. This measure as it will be shown includes these both parameters by construction.

2.2. Standard & Poor’s and Fitch methodology

Both rating agencies again claim that assigned ratings reflect opinions of their analysts about credit risk. “Standard & Poor’s ratings express the agency’s opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time” (“Guide to Credit Rating Essentials”, Standard & Poor’s, p.5). Indicators which are used by these agencies for credit rating estimation are very similar to those which Moody’s uses.

Standard & Poor’s and Fitch as well as Moody’s may use technical analysis in order to determine ratings but only as a component for the process, “Ratings Not Determined by Models.<…> The importance of a model in generating rating opinions ranges from substantial to minor” (“Managing and Developing Criteria and Models” Fitch Ratings, 2011, p.1). S&P and Fitch also have separate approaches for default probability and recovery rates estimation but on contrary to Moody’s their approaches are based on fundamentals and not on statistics (like modeling changes in future cash flows, possible path for company’s asset values etc.). Nevertheless, agencies admit that they may use the same subset of indicators for both probability of default and loss given default. These approaches have implied limitations – they have extreme dependence on analyst’s assumptions. Also, S&P and Fitch are estimating the value of the issue at the end of bankruptcy period while Moody’s estimates market price 30 days after default event.

Rating process again incudes issue analysis with preliminary rating assignment and afterwards take place process called “notching”. It is very similar to adjustment technique that uses Moody’s, although matching scales are different: S&P has seven instead of six levels of recoveries. Also, S&P and Fitch adjust ratings using estimated recoveries while Moody’s uses loss given default. Nevertheless, due to unambiguous relationship between those two indicators such difference seems to be not very important. Notching standards for S&P and Fitch respectively are listed below

Table 2

Standard & Poor’s and Fitch recovery rate scales

Standard & Poor’s			**Fitch**		
Recovery level	**Recovery range**	**Notches from issuer rating**	**Recovery level**	**Recovery range**	**Notches from issuer rating**
1+	100%	+3	RR1	≥91% and ≤100%	+3
1	≥90% and <100%	+2	RR2	≥71% and ≤90%	+2

2	≥70% and <90%	+1	RR3	≥51% and ≤70%	+1
3	≥50% and <70%	0	RR4	≥31% and ≤50%	0
4	≥30% and <50%	0	RR5	≥11% and ≤30%	-1
5	≥10% and <30%	-1	RR6	≥0% and ≤10%	from -2 to -3
6	≥0% and <10%	-2			

The source: A Guide To The Loan Market. Standard & Poor's, 2011, p. 34

Ratings and Notching Criteria for Non-Financial Corporate Issuers. Fitch Ratings, 2012. p. 1

3. Conclusions for Chapter 1

1. Existing literature presents very controversial conclusions on relationship between default probability and rating classes as well as recovery rates and debt ratings.
2. Nevertheless, the trend in presented articles is the following:
    - from the beginning of studies on default probability to nowadays number of articles in which argued strong correlation between default frequency and rating classes increased
    - almost all papers present statement that ratings are good indicators for default probability, although in some of them authors argue that ratings all alone do not explain defaults and suggest to use additional explanatory variables
3. All three rating agencies have their own approach for default probability and recovery (loss given default for Moody's). Approaches have similar trait – first step is preliminary rating assignment, second is to make an adjustment for that rating using estimated loss given default or recovery rates. The most crucial difference among agencies is how they estimate recovery rates:
    - Moody's uses purely statistical approach based on KMV model for loss given default assessment
    - Standard & Poor's as well as Fitch conduct quantitative estimation process based on various expectations about future outcomes for balance sheet items and other indicators

Chapter 2. Empirical research on credit ratings classes and information contained in ratings

Credit ratings emerged more than century ago as an assessment of risk associated with particular debtor. They present an opinion of credit rating agency about the credit quality of the debt issuer which reflects ability to meet the obligations. The measure of risk incorporated in obligation is closely associated with likelihood that the issuer will default. Therefore, having historical data on the pool of securities one should find the correlation between assigned ratings and default frequencies in the sample. In their methodologies, credit rating agencies typically plot such graphs indicating that the most part of happened defaults are concentrated amongst low rated issues. If this is the case then it may be interpreted as the evidence that agencies do make accurate forecasts on default probabilities.

The empirical question that arises is what would be the appropriate way to estimate the quality of ratings? Is it enough just simply to count defaults as credit rating agencies frequently report. Or maybe the quality of ratings is better reflected by realized recovery or alternatively loss given default? Perhaps it is the case empirically that default frequency in a given rating class and loss given default in the same rating class are highly correlated. In that case, the default experience alone would be a sufficient statistic on the goodness of a rating. But if the correlation is low, both statistics could give different answers about the goodness of the ratings of a rating agency.

In the real world investors vary with their risk appetite. Such investors may be interested not only in likelihood that particular issuer would go into default but also when default will occur and what the recovery rate would be. In this paper author proposes alternative measure for quality of credit ratings called realized lifetime loss. This measure as its name indicates compares actually made payments during the lifetime of the bond with "promised" payments. The idea for this measure was introduced by Richard Hainsworth in the unpublished paper "The meaning of ratings". The goal of this paper was to test this new measure on the real data to find how well does it perform.

According to the realized lifetime loss promised payments are simply ones scheduled in final terms of the issue. It could be calculated as "one" minus the ratio of the present value of realized cash flows and the present value of promised cash flows. In this case, it would show the percentage of promised payment that was actually lost by the bondholder. Another way is to use difference between promised and realized payments which will be the loss indicator of lost amount of money. This measure has several preferences over simple method of default counting like: can be calculated for all bonds (not only for defaulted as recovery rate) thus it avoids selection bias and may be used in regression analysis for the whole sample, has direct relationship with lifetime of the issue, i.e. time to maturity for non-defaulted and time to default for the rest etc.

1. Descriptive statistics of the sample used

The main source of the data was Moody's Default Risk Service (DRS) proprietary database created on November 11th, 2010. This database is Microsoft Access format and is the same source of data that is used by Moody's analysts for rating assignment research. It contains 16 distinct tables describing all Moody's rated debts, corresponding issuers, defaults history, watch lists etc. More comprehensive description could be found in DRS Technical Specifications.

Initially DRS database contained of 442818 debts from 34340 distinct issuers. The data spans from 1970 to the date of database creation. Numbers of constraints were imposed on the initial sample to make it satisfying for the requirements of this research. They are the following:

1. Leave only bonds since the paper is dedicated to bond analysis
2. Exclude all debts without record of coupon rate (needed for realized lifetime loss)
3. Moody's reported that since 1982 methodology changed significantly, restrict sale date to be later than 1982. Also drop all bonds without record for maturity date (needed for realized lifetime loss)
4. For calculation purposes needed data on issuers domicile
5. For regression analysis needed information about industry
6. First assigned rating is in 1982 (for realized lifetime loss and Lorenz curves since methodology changed in 1982)
7. Author was interested in examining rating quality of long term ratings, thus all short term and provisional ratings were excluded (the last ones excluded due to fact that they constituted a very small amount in the sample and only part of them was later assigned a "regular" rating)
8. For realized lifetime loss one needs proper discount rates. Author calculated this measure only for U.S. debts for two reasons: U.S. bonds constitute the vast majority of sample and discount rates for such issues can be easily obtained for broad list of maturities.

   Also to analyze value weighted portfolio needed the record on bond's face value.

   All debts with variable and unknown frequencies were excluded for computational purposes.

Also technical defaults were excluded. Default types are shown in Appendix 2. Default was considered to be technical for the following combinations of *default type – resolution types – bankruptcy types*:

Grace period default – * – * (* stands for any value of the item)

Missed interest payment – Made Interest Payment/Creditors paid in full/Made principal payment – *

Missed principal and interest payments – Null/Creditors paid in full/Made principal payment/Made interest payment – *

9. Subsample of defaulted bonds consists of the following frequencies: monthly, quarterly, semiannual, annual and accrued. As for bonds from non-defaulted subsample, their frequencies take the same values plus additional ones: biweekly, bimonthly, and biannual (for instance, biannual bond pays coupon every two years). Author counted number of such bonds and come up with the following numbers: 1 for biweekly, 1 for bimonthly and 39 for biannual. These 1 + 1 + 39 = 41 bonds represent a negligible amount in non-defaulted subsample, so author decided to exclude them to make frequency types among two subsamples identical.
10. Due to significant discrepancies in methodologies only corporate bonds were left

Finally sample consisted of 47398 debts (19055 from financial and 28343 from non-financial sectors), 1664 defaulted debts (436 and 1228 defaults in financial and non-financial subsamples respectively) and 5854 issuers.

Sample selection summary is listed in the table

Table 3

Sample selection process

Step	Number of issues in the sample	Number of issuers in the sample
1	379330	15385
2	256316	13292
3	244710	11825
4	244705	11822
5	241684	11123
6	237399	11123
7	231439	10653
8	121777	5893
9	121736	5893
10	47398	5854

The source: author's calculations based on Moody's DRS database

Summary for the initial Moody's DRS database is listed in Appendix 1.

Characteristics of the final sample are the following:

- Number of debts is 47398, number of issuers is 5854
- Number of defaulted issues is 1664, number of non-defaulted issues is 45734
- Number of bond types is 5: regular bond/debenture, convertible/exchange bond/debenture, first mortgage bond, revenue bond and secured lease obligation bond
- Number of seniority types is 7: junior subordinated, subordinated, senior unsecured, senior subordinated, senior secured, multiple seniority and revenue bonds
- All bonds sold in period 1982-2010
- Number of coupon frequency types is 5: monthly, quarterly, semiannual, annual and accrued
- Technical defaults were excluded: carefully analyzing sample, author came to the conclusion that all other cases, except three ones listed in subentry 8 above, resulted in default on bond (to avoid here misunderstanding, in each scenario bankruptcy type was such that is was non-technical default)
- Number of debts with collateral is 9846, number of debts without collateral is 37552
- Number of industries is 35 and distributions of debts and issuers across industries are presented in Appendix 2
- Rating distribution is listed in Appendix 2

2. The methodology and obtained results

2.1. Investigation of relationship between rating classes and default frequency

The first question that arises is whether quality of assigned ratings can be assessed by simply counting number of defaulted debts as rating agencies often report. For this purpose author plotted graphs that show the relationship between cumulative share of different rating classes in total defaults number and cumulative share of different rating classes in total debts number for two cases: equally weighted portfolio and value weighted portfolio. For the first case author simply calculated share of bonds in each rating class treating them as having the same face values, and in the second case author utilized issue's recorded face value as a measure for assigning weight. To clarify the last point, used face value is the total issue value that is recorded in Moody's Default Risk Service database, for instance, if bond's face value is 100 and issue size was 5000 then used face value is equal to 500000.

For equally weighted portfolio all auxiliary steps can be summarized as follows:

- Take the subsample of defaulted bonds, calculate shares of each rating class (C, Ca, Caa, B, Ba, Baa, A, Aa, Aaa) in this subsample simply dividing number of issues from a particular class by total number of issues in subsample
- Calculate cumulative shares of this rating classes in subsample of defaulted bonds, i.e. cumulative share for C class is simply its share in subsample of defaulted issues, cumulative share of Ca class is cumulative share of C class plus share of Ca issues in defaulted subsample, etc.
- Do the same steps but use the whole sample instead of only sample with defaulted issues
- Plot cumulative shares calculated for defaulted subsample against cumulative shares of the same classes calculated for the whole sample

For value weighted portfolio the algorithm is essentially the same with one minor exception: for this case author calculated shares of ratings classes by summing up face values of issues in particular rating class and then dividing by the total face value of issues in the whole sample (for share in the whole sample) or by the face value of issues in defaulted subsample (for share in the defaulted subsample). Then author calculated cumulative shares as described in case of equally weighted portfolio.

Such plot is called a cumulative accuracy plot also known as Lorenz curve. If assigned ratings contain no relevant data about likelihood of default, the curve on average would be diagonal. On contrary, if ratings possess a perfect information about default, only issues with the lowest ratings would default (i.e. they accumulate all defaults happened in the sample).

For the purpose of accuracy estimation author used broadly utilized definition of accuracy ratio (Gini coefficient) defined as ratio of the area between the empirical curve and the straight diagonal line (random model) over the area between ideal case and random model.

Also, considering this case author's intention was to investigate whether the rating agencies better assess quality of issues over the shorter horizon than in the long run. This was done by plotting the same graphs described above (equally and value weighted portfolios) for cases when bonds gone into default in period less than 1 year after initial rating assignment and for the case when default happened after 1 year.

Sample used is the same as described in this chapter. This sample consists of corporate debts only. Nevertheless, these bonds are from both financial (commercial and investment banks, brokerages etc.) and non-financial industries. Rating methodologies have some differences for these industries, namely accounting standards and disclosure requirements are different for banks and non-banks. That is why when rating agencies perform their credit analysis they operate with different indicators and in different ways for these two industries.

Results for relationship between default frequency and first assigned rating for the subsample of debts from financial industry is shown in diagrams 1 and 2. Here and thereafter marks "Ca" – "Aaa" on diagrams denote the right end of the interval, for instance, "Baa" denotes the cumulative share of all Baa rated issues. That is it is the share of Ca, Caa, B, Ba, Baa bonds in total amount.

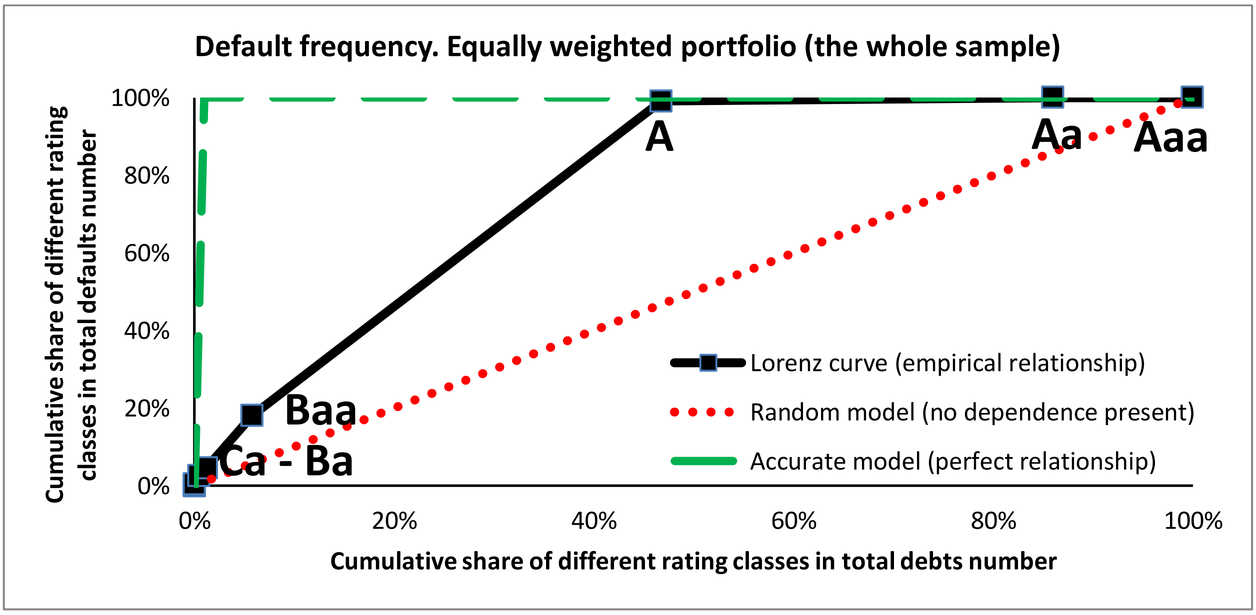

Diagram 1

The source: author's calculations based on Moody's DRS database

Diagrams that relate default frequency and rating classes for defaults happened in period less than 1 year and after 1 year from first rating assignment are not presented here for debts from financial industry because they show almost no difference to the diagram for the whole financial industry subsample.

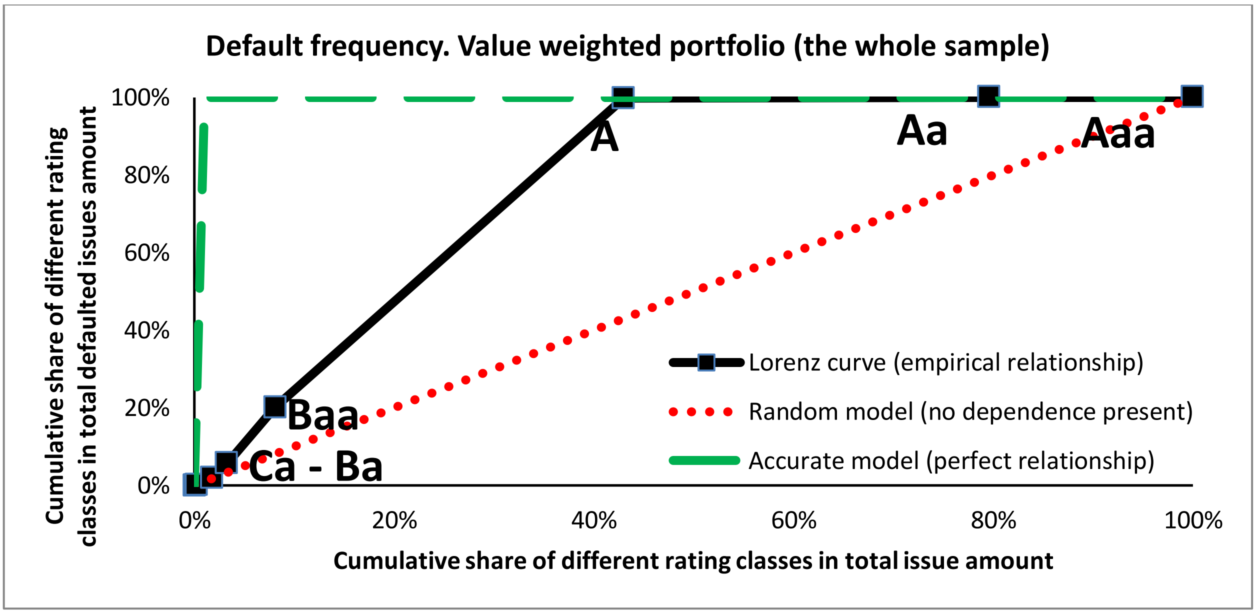

Diagram 2

The source: author's calculations based on Moody's DRS database

As for equally weighted portfolio, diagrams for the horizon less than 1 year and after 1 year from initial rating assignment are skipped again for the same reason.

The same approach was applied for the subsample of debts from non-financial industry. Results for relationship under investigation for this subsample are shown below in diagram 3 to diagram 6

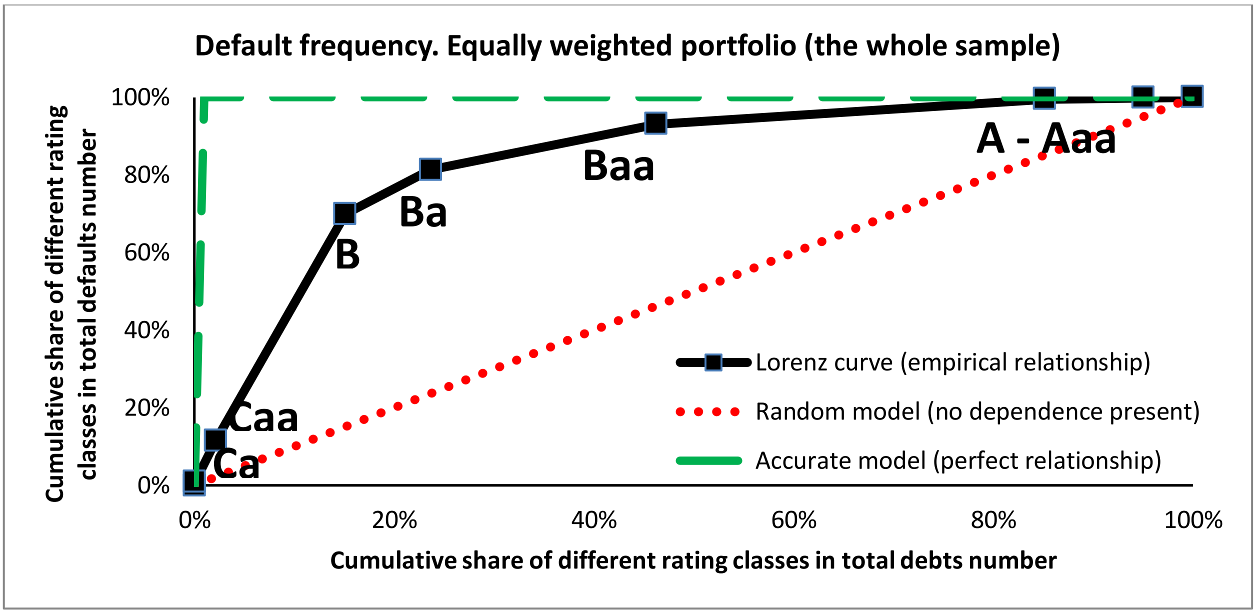

Diagram 3

The source: author's calculations based on Moody's DRS database

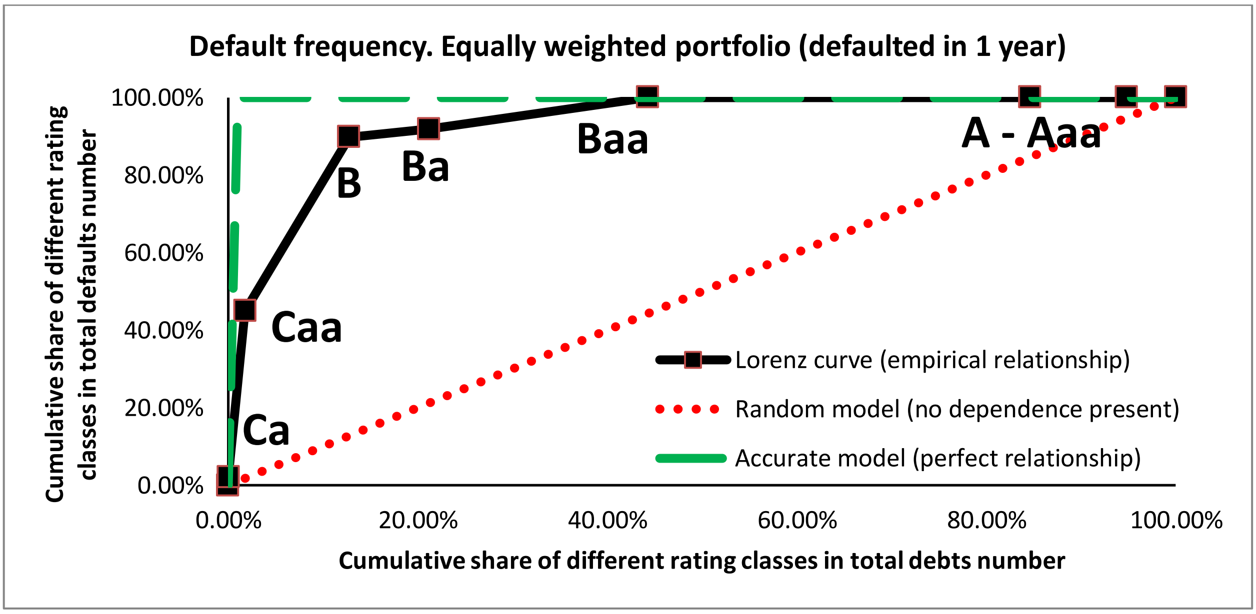

Diagram 4

The source: author's calculations based on Moody's DRS database

Diagram for defaults happened in period after 1 year from first rating assignment is missed because it is essentially the same as for the whole sample.

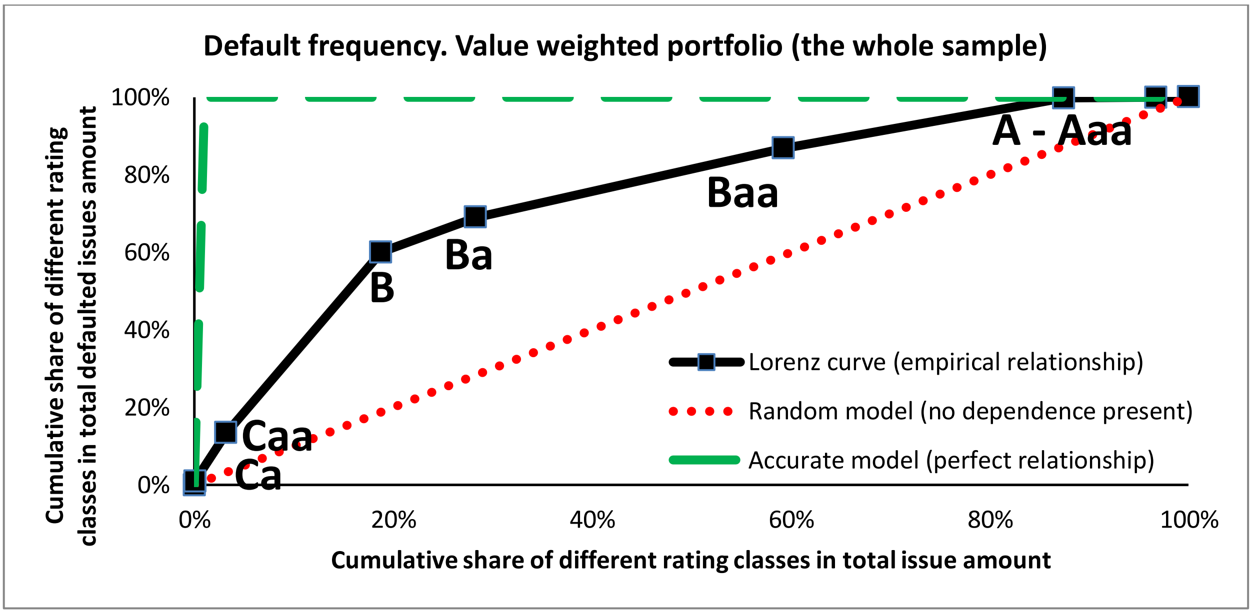

Diagram 5

The source: author's calculations based on Moody's DRS database

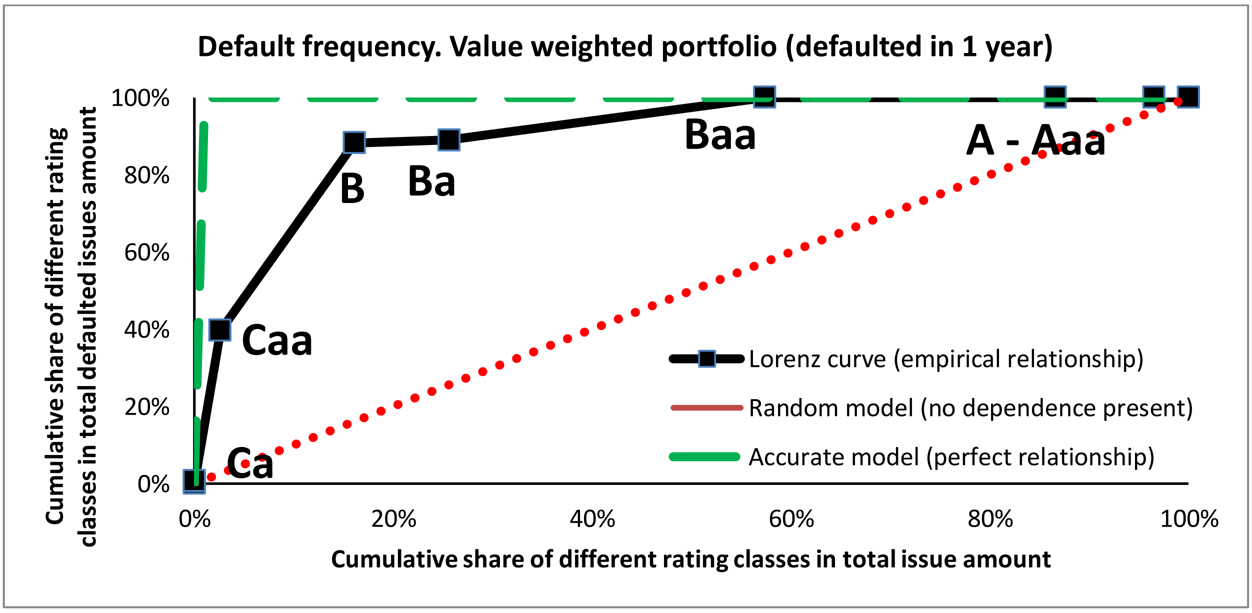

Diagram 6

The source: author's calculations based on Moody's DRS database

As for equally weighted portfolio, diagram that relates default frequency and rating classes for defaults happened in period after 1 year from first rating assignment is skipped again for the same reason.

As measure of accuracy author has used Gini coefficients. They are listed for both financial and non-financial subsamples below as well as for all time periods described in the beginning of this section

Table 4

Gini coefficients for default frequency and assigned ratings

Gini coefficient		All sample debts	Default occurred in period less than 1 year from first rating assignment	Default occurred in period after 1 year from first rating assignment
Financial debts subsample	**Equally weighted portfolio**	0.552	0.540	0.554
	Value weighted portfolio	0.572	0.588	0.574
Non-financial debts subsample	**Equally weighted portfolio**	0.676	0.867	0.671
	Value weighted portfolio	0.501	0.804	0.486

The source: author's calculations based on Moody's DRS database

It can be seen from the diagrams for sample that includes only debts from financial industry assigned ratings on average contain information for default probability but ratings should be used together with some other explanatory variables:

- Gini coefficients take moderate values (around 0.55 for all cases under consideration)
- due to high regulation and government support financial subsample consisted mostly of the highest rated debts (roughly less than 90% of total issues are "A"-"Aaa" rated, the rest are Ba-Baa). The highest defaults number is in "A" category (81%) which is due to the fact that sample horizon includes 2008 crisis when a lot of high rated banks defaulted
- this may be the evidence that rating agencies do not properly take into account all risks of the financial industry and methodology should be adjusted
- ratings better reflect default probability for value weighted portfolio as measured by Gini coefficients although there is no big difference. It means that rating agencies assess slightly better higher volume issues. This relationship becomes even stronger for the short run in this case but it is not observed for equally weighted portfolio

Results for non-financial subsample differ dramatically:

- we see that equally weighted portfolio performs much better in this case than for financial subsample. It is the evidence that in spite of past crisis ratings methodology properly accounts for possible risks in non-financial industry
- ratings predictive power (accuracy coefficients) for default probability dramatically rises on the 1 year horizon for both equally and value weighted portfolios. It means that ratings itself are sufficient predictors in the short run

- value weighted portfolio demonstrates poorer performance for non-financial industry compared to equally weighted one, which indicates that lower size issues are rated better

The results for both subsamples are in line with Altman (1989) in sense that there exists strong evidence that ratings possess information of default probability, for financial subsample are partially consistent with Godlewski (2007). The most probable explanation for the last is that in Godlewski sample's time period had not overlapped with crisis 2008 (on contrary with sample used in master thesis) as well as his model did not took into account economy cycles. The results are also in good match with Brude and Gonzales-Aguado (2010) which explains significant defaults number in financial debts subsample. Also better performance of ratings on 1 year horizon is line with Hilscher and Wilson (2013) and Figlewski et al (2012)

2.2. Investigation of relationship between rating classes and loss given default

The second question that arises is whether credit ratings reflect any additional information namely if they can be used for prediction of recovery rate at default or loss given default, since these two measures are connected via relationship LGD = 1 – RR. For this purpose author plotted graphs that show the relationship between cumulative share of different rating classes in total loss given default and cumulative share of different rating classes in total defaulted debts number. The crucial point here which makes the main difference with previous part that author had to work only with defaulted subsample, since LGD is observable only for defaulted issues. Again, two cases were considered separately: equally weighted portfolio and value weighted portfolio. Issue's recorded face value was utilized as a measure for assigning weight.

Calculation steps for equally weighted portfolio:

- Consider only subsample of defaulted bonds
- Calculate shares of each rating class (C, Ca, Caa, B, Ba, Baa, A, Aa, Aaa) in total loss given default of the subsample, assuming all face values equal (for instance, equal to 1)
- Calculate cumulative shares of this rating classes in total loss given default, i.e. cumulative share for C class is simply its share in total loss given default of the subsample, cumulative share of Ca class is cumulative share of C class plus share of Ca issues in total loss given default of the subsample, etc.
- Calculate shares of each rating class (C, Ca, Caa, B, Ba, Baa, A, Aa, Aaa) in this subsample simply dividing number of issues from a particular class by total number of issues in subsample
- Calculate cumulative shares of this rating classes in subsample as was described above

For value weighted portfolio the algorithm is almost identical with the difference that in this scenario author used “true” face values recorded in the database (these are issue face values not bond ones). The reason to apply both methods is to investigate the sensitivity with respect to size of the issue. This is reasonable since treatment of all bonds as having the same face value is quite a strong assumption as well as using indicator for issue size helps to find out whether rating quality differs for issues amongst the size.

Accuracy was again assessed with Gini coefficients, as well as approach of considering defaults happened in period less than 1 year after rating assignment and after 1 year.

Results for relationship between loss given default and first assigned rating for sample consisting of financial industry debts is shown in diagram 7 to diagram 8

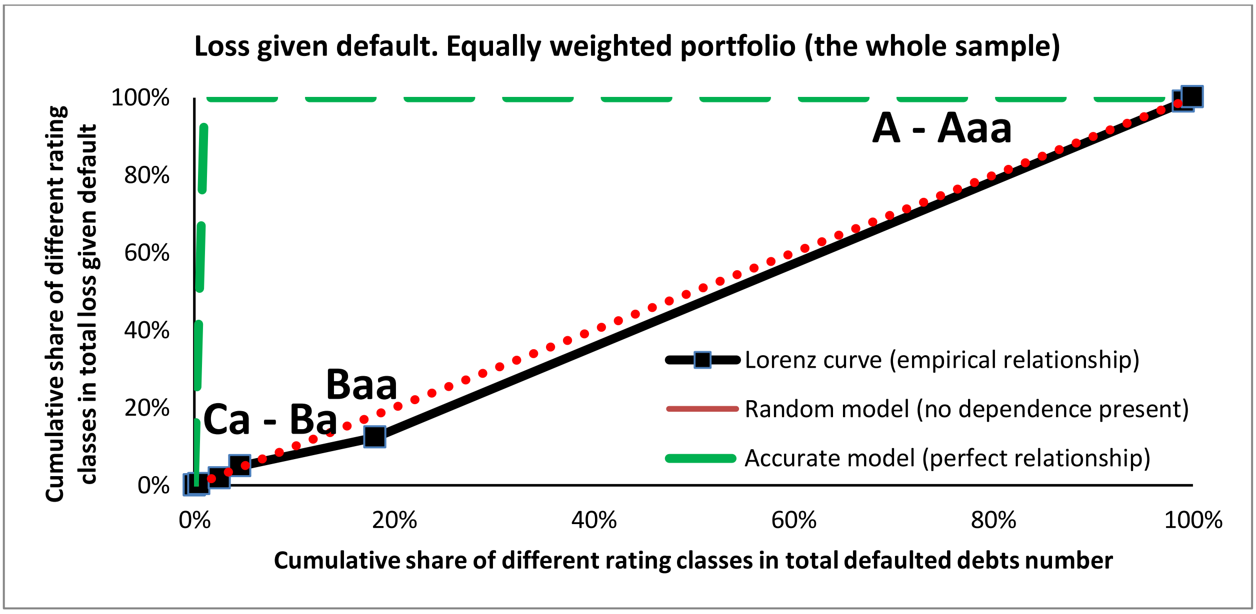

Diagram 7

The source: author’s calculations based on Moody’s DRS database

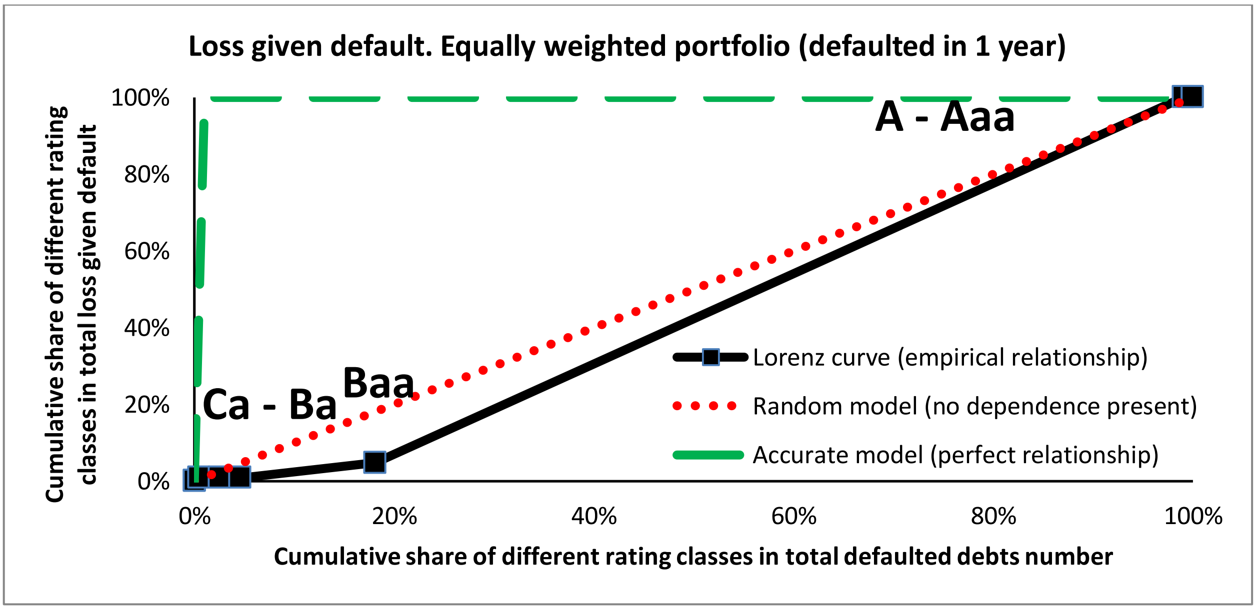

Diagram 8

The source: author's calculations based on Moody's DRS database

Diagram for defaults happened in period after 1 year from first rating assignment is not presented here because it makes no difference compared to diagram for the whole sample.

Author also performed the same analysis for value weighted portfolio. The diagrams for this case are not shown here because their shapes repeat the respective diagrams for equally weighted portfolio. The reader can get acquainted with accuracy coefficients for both cases from the table which will be listed below in the text.

The results for non-financial subsample are a bit different (diagrams 9 and 10) from the financial debts and need a brief discussion:

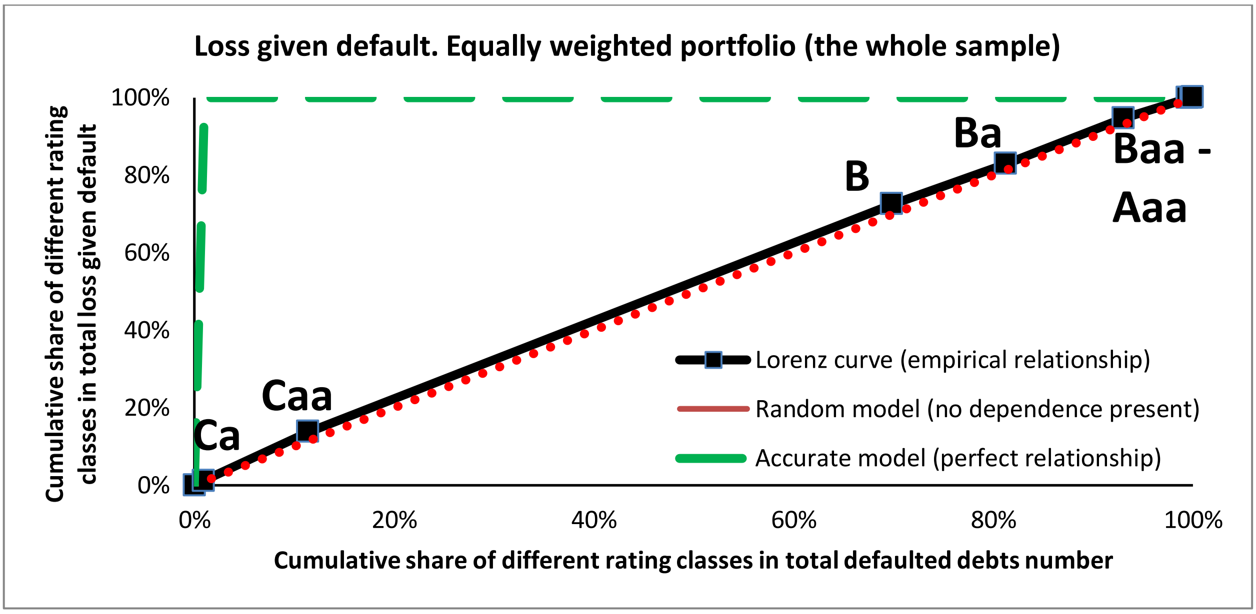

Diagram 9

The source: author's calculations based on Moody's DRS database

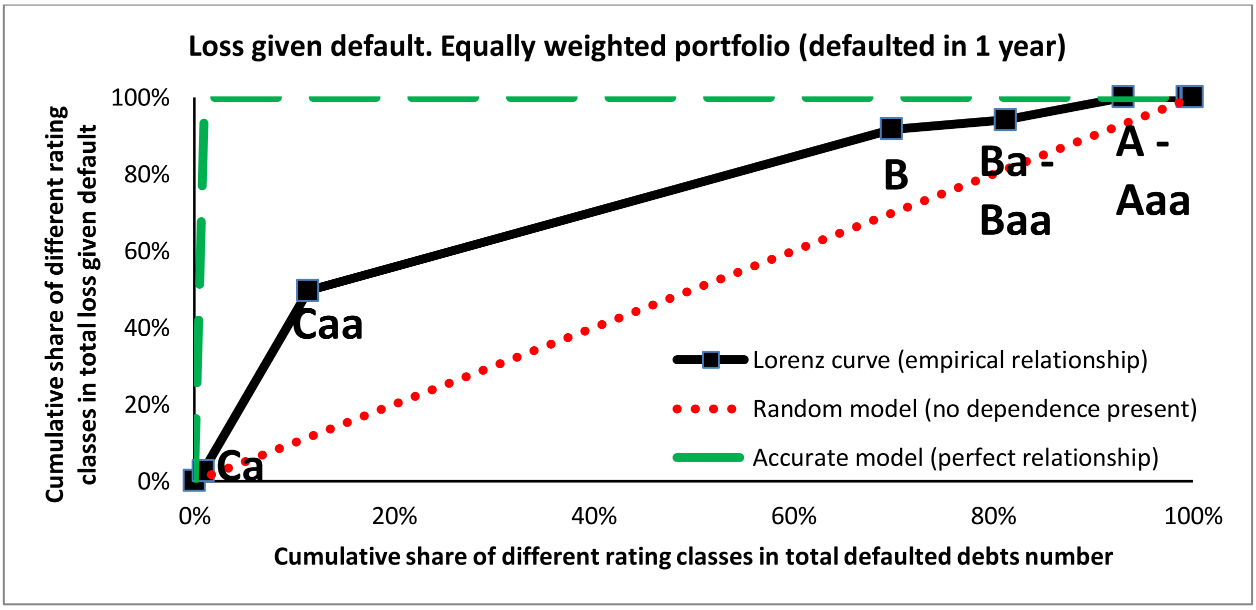

Diagram 10

The source: author's calculations based on Moody's DRS database

Diagrams for the defaults occurred in period after 1 year since first rating assignment are not shown again for the same reason. It is interesting whether ratings reflect better loss given default for issues with higher weight. For such purpose author also performed analysis for value weighted portfolio. Very similar results were obtained, so they are not given here.

Table 5

Gini coefficients for loss given default and assigned ratings

Gini coefficient		All sample debts	Default occurred in period less than 1 year from first rating assignment	Default occurred in period after 1 year from first rating assignment
Financial debts subsample	Equally weighted portfolio	-0.056	-0.125	-0.049
	Value weighted portfolio	-0.016	-0.053	-0.009
Non-financial debts subsample	Equally weighted portfolio	0.041	0.461	0.021
	Value weighted portfolio	-0.078	0.344	-0.109

The source: author's calculations based on Moody's DRS database

Red dotted line on all diagrams presents the case when on average there is no relationship between accumulated loss given default and rating classes. It can be obtained by sufficiently large number of simulations of random relationship between LGD and ratings and then averaging over all of them. That is why negative Gini coefficients mean that on average relationship in data is inferior to one explained by random model. The results can be summarized as follows:

- subsample of financial industry debts shows no relationship between LGD and rating classes. This conclusion is true for all time horizons and both equally and value weighted portfolios. Diagrams illustrate that for LGD prediction one has to employ additional explanatory variables
- subsample of non-financial industry debts indicates that there is the relationship between assigned ratings and time horizon. Gini coefficients significantly exceed 0 for defaults happened in 1 year period but still take moderate values. This result states that for the short run ratings contain some information about LGD but one still needs to use additional information LGD estimation for that period. There is almost no difference between equally and value weighed portfolios which means that issue size has no

substantial impact on realized LGD. Nevertheless, in the long run as diagrams indicate ratings are not reliable indicators of LGD

Demonstrated results are in perfect match with Altman (1989), Carey (1998) for financial subsample for all time horizons and in long run for non-financial one. The outcome on average contradicts to Bade et al (2011) but is partially consistent with article in sense that demonstrates relationship for non-financial subsample in the short run. Explanation is that in the article authors made correction for bias in data caused by property or recoveries – they are observed only for defaulted debts and approach used in this work does not take it into account. Another reason that obtained results are for initially assigned ratings and in article authors also used altered ratings during the lifetime of debt. Also, results for non-financial subsample for value weighted portfolio are in line with Varma et al (2003) – value weighted portfolio performs worse thus indicating lower recoveries for higher weighted issues.

3. Conclusions for Chapter 2

1. Author came to the conclusion that ratings indeed can be used as indicators for default frequency, this fact is in line with number of studies.
    - Nevertheless, for financial debts subsample
        a) Lorenz curves and Gini coefficients imply that some other explanatory variables should be used for default probability prediction
        b) this subsample consists mostly of “A”-“Aaa” rated issues and the most part of which suffered default events
        c) it is consequence of risks underestimation revealed by financial crisis 2008
    - For non-financial industry issues there is evidence that rating methodology correctly takes into account risks inherent in bonds and ratings itself can be used as a single predictor for default probability. This result becomes even stronger in the short run.
2. There is a completely different situation with information contained in ratings for loss given default
    - diagrams indicate that on average ratings are inadequate source of information for that purpose and predictive power in the long horizon is negligible for both financial and non-financial industries
    - it was shown that ratings can be used at least as one of the explanatory factors for LGD prediction in the short run for non-financial debts
    - this is the case since they still contain some piece of information as Lorenz curves and Gini coefficients imply.

Chapter 3. Empirical research on presence of additional information in credit ratings

Realized lifetime loss measure is used in this paper as an alternative to probability of default. Employment of this measure can be justified for the next two reasons:

- Due to Moody's definition of default, debt restructuring situation with the following significant loss of value, for instance 70% and case when company defaults but then afterwards manages to repay the most part of the debt, i.e. case when present value of payments suffers not too much are treated equally as default. For legal purposes these two events may be named as default but for ordinary investor such cases are indeed not the same. Thus, if ratings reflect only probability of default such information would not be enough for investor who is interested also in type of default
- This measure takes into account what fraction the investment could be repaid i.e. recovery in case of default as well as it implicitly depends on time when default occurred

Therefore, evaluation of ratings quality based only on historical default frequency may not be the optimal way nowadays. As it was pointed out in previous sections information about default probability is contained in ratings and is reliable but ratings poorly predict possible loss given default. Investor probably would like to know both estimates for the bond but the problem is how to choose the issue for example out of two with very close ratings and estimated losses (if it was possible) if they still different. For instance, if according to Standard & Poor's scale one issue is AA rated and has level 3 of estimated recovery and the other is AA- rated and has estimate of level 2 for recovery rate, recovery rates are scaled in such way that the higher the number the better is the recovery. Having these two pieces of information it is not quite clear in which bond it would be more appropriate to invest. The realized lifetime loss implicitly accounts for default event and explicitly for recovery and thus this combine measure may be helpful for such situation.

1. Investigation of relationship between rating classes and realized lifetime loss

It was already mentioned realized lifetime loss is based on present value of promised and realized cash flows. In order to calculate it one needs to obtain set of appropriate discount rates. Author made an assumption about the investor type. In this paper realized lifetime loss was calculated from the viewpoint of an investor with a perfect foresight. Such investor has perfect knowledge about stream of cash flow which bond will provide him, that is he knows exactly amount and schedule of coupons and face value paid in case of no default and in case when default happens he knows time when he will get the recovery value and preceding coupons.

Using this assumption all payments were discounted with US government bond yields[1] which are reliable proxies for risk free rates. They are listed in Appendix 3.

For non-defaulted issues realized lifetime loss was set 0 by definition. For issues experienced a default event two closely connected definitions of realized lifetime loss were used in this paper. The first one is

$$L = \sum_{t}^{t \le T} \frac{C_t}{(1+r_t)^t} + \frac{FV}{(1+r_f)^f} - \sum_{t}^{t \le Tdef} \frac{C_t}{(1+r_t)^t} + \frac{FV \times recovery\ rate}{(1+r_d)^d}$$

which is actually equal to present value lost due to default event.

t – time interval between date when bond was sold and every coupon payment (expressed in years), t increases for each summand by 365/(coupon frequency indicator), where coupon frequency indicator equals 12, 4, 2 and 1 for monthly, quarterly, semiannually and annually paid coupons respectively. For accrued frequency the coupon and face value were paid at maturity simultaneously and discounted with rate for maturity

C_t – coupon payment at this moment equal (coupon rate/coupon frequency indicator)*face value for monthly, quarterly, semiannually and annually paid coupons and coupon rate*face value for accrued frequency (such bond simply pays face value plus coupon simultaneously at maturity)

T – time interval between date when bond was sold and maturity date (expressed in years)

T_{def} – time interval between date when bond was sold and date of default plus 30 days, since market value was estimated 30 days after default (expressed in years)

f – time interval between date when bond was sold and date when face value was paid (expressed in years)

d – time interval between date when bond was sold and date when recovery value was paid (expressed in years)

r_t – discount rate for moment of time from sale date to coupon payment date (annualized)

r_f – discount rate for moment of time from sale date to face value payment date (annualized)

r_d – discount rate for moment of time from sale date to recovery value payment date (annualized)

As it can be seen from Appendix 3 risk free rates are listed for each year from 1982 to 2012 (which covers all bond's sale dates) for periods of 3 months, 6 months, 1 year, 2 years, 3 years, 5 years, 7 years, 10 years, 20 years and 30 years. There was some discontinuity in interest rates due to fact that for some years these rates were not present. Author calculated these rates in such way that they do not disturb pattern for all periods and across each year. Interest rates from this table do not cover all necessary data points for payments. In order to obtain appropriate rates

[1] http://www.federalreserve.gov/releases/h15/data.htm

for maturities that are between dates in the table author used linear interpolation which does not influence result too much for two reasons: such approximation is in line with yields term structure and rates for closest maturities do not differ too much. This interpolation was the following and is presented in annualized rates for the calculated time period, since rates used are annualized:

- for periods less than 3 months was used rate $r_{3m} \times$ (time period)/91
- for periods more than 3 months but less than 6 months was used rate $r_{3m} + (r_{6m} - r_{3m}) \times$ (time period - 91) / (182 - 91)
- for periods more than 6 months but less than 1 year was used rate $r_{6m} + (r_{1y} - r_{6m}) \times$ (time period - 182) / (365 - 182)
- for periods more than 1 year but less than 2 years was used rate $r_{1y} + (r_{2y} - r_{1y}) \times$ (time period - 365) / (730 - 365)
- for periods more than 2 years but less than 3 years was used rate $r_{2y} + (r_{3y} - r_{2y}) \times$ (time period - 730) / (1095 - 730)
- for periods more than 3 years but less than 5 years was used rate $r_{3y} + (r_{5y} - r_{3y}) \times$ (time period - 1095) / (1825 - 1095)
- for periods more than 5 years but less than 7 years was used rate $r_{5y} + (r_{7y} - r_{5y}) \times$ (time period - 1825) / (2555 - 1825)
- for periods more than 7 years but less than 10 years was used rate $r_{7y} + (r_{10y} - r_{7y}) \times$ (time period - 2555) / (3650 - 2555)
- for periods more than 10 years but less than 20 years was used rate $r_{10y} + (r_{20y} - r_{10y}) \times$ (time period - 3650) / (7300 - 3650)
- for periods more than 20 years but less than 30 years was used rate $r_{20y} + (r_{30y} - r_{20y}) \times$ (time period - 7300) / (10950 - 7300)

where *time period* is measured in days.

The above definition was used to make conclusion about how introduced measure is reflected in assigned ratings. In previous sections author utilized equally weighted and value weighted portfolios and plotted Lorenz curves as well as provided Gini coefficients for them. This way of accuracy assessment also was utilized for this definition. For equally weighted portfolio realized lifetime loss for each issue was calculated with this formula taking face value the same for all bonds (namely equal to 1). For value weighted portfolio face value was used from the record for each bond. Realized lifetime loss for portfolio of bonds was calculated as sum of realized lifetime losses for each entity in the portfolio.

The second definition of realized lifetime loss is

$$L = 1 - \frac{\sum_{t}^{t \le Tdef} \frac{C_t}{(1+r_t)^t} + \frac{FV \times recovery\ rate}{(1+r_d)^d}}{\sum_{t}^{t \le T} \frac{C_t}{(1+r_t)^t} + \frac{FV}{(1+r_f)^f}}$$

which is relative realized lifetime loss taking values from 0 to 100% by the construction; numerator is present value of cash flows that investor actually received, denominator is what was promised by bond's term sheet. This definition was used further in this research to estimate the number of "misclassified" or inconsistently rated issues.

As it was mentioned above two subsamples were studied: financial and non-financial industry's debts. In this section author again considered the same bonds to make comparison of realized lifetime loss with previous results.

Using introduced above definitions author calculated realized lifetime losses for each issue in the sample using macro code written on MS Excel VBA. Summary for the financial debts is presented in the single diagram below

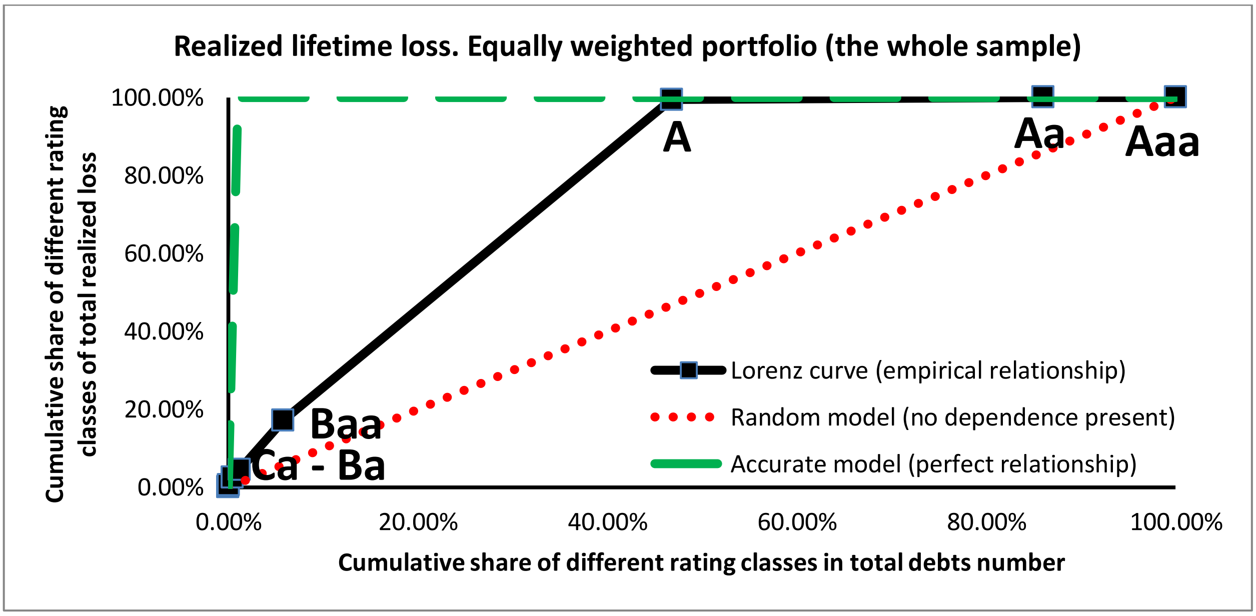

Diagram 11

The source: author's calculations based on Moody's DRS database

The shape repeats the diagram for the relationship between rating classes and default frequency. The explanation is essentially the same as it was given for that case. Diagrams for defaults happened in 1 year and after 1 year since first rating assignment are not illustrated here as well as all diagrams for value weighted portfolio since they do not possess any remarkable difference compared to Diagram 11. Accuracy statistic for them will be reported in Table 6.

As for subsample of non-financial industry debts it contains much more information and will be presented more detailed in the following diagrams:

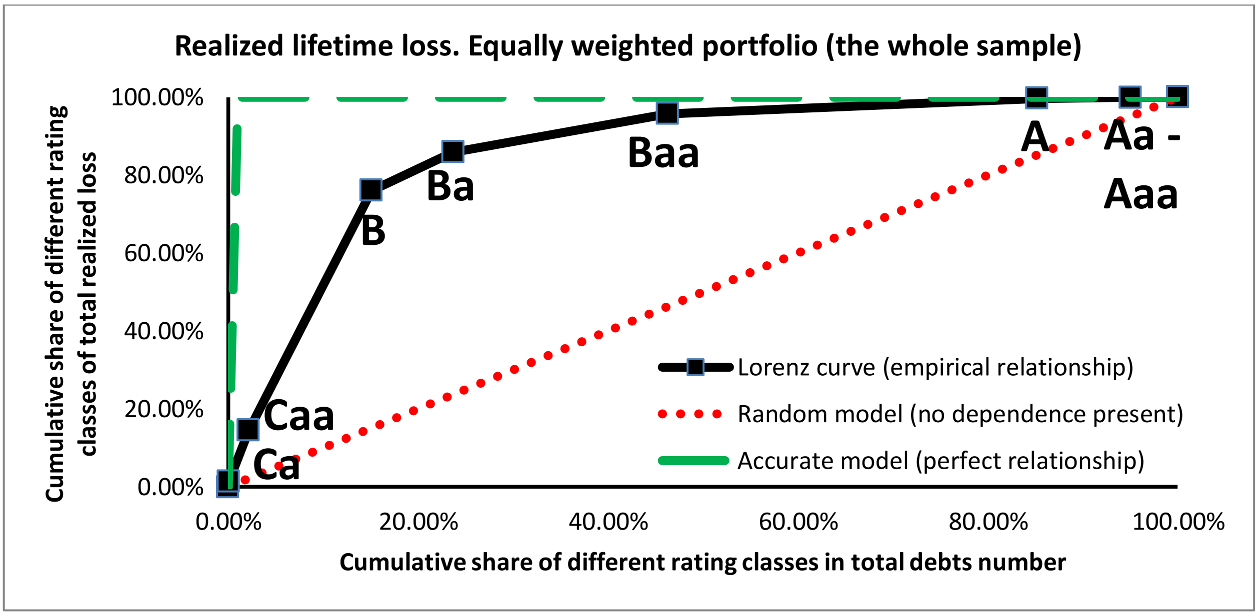

Diagram 12

The source: author's calculations based on Moody's DRS database

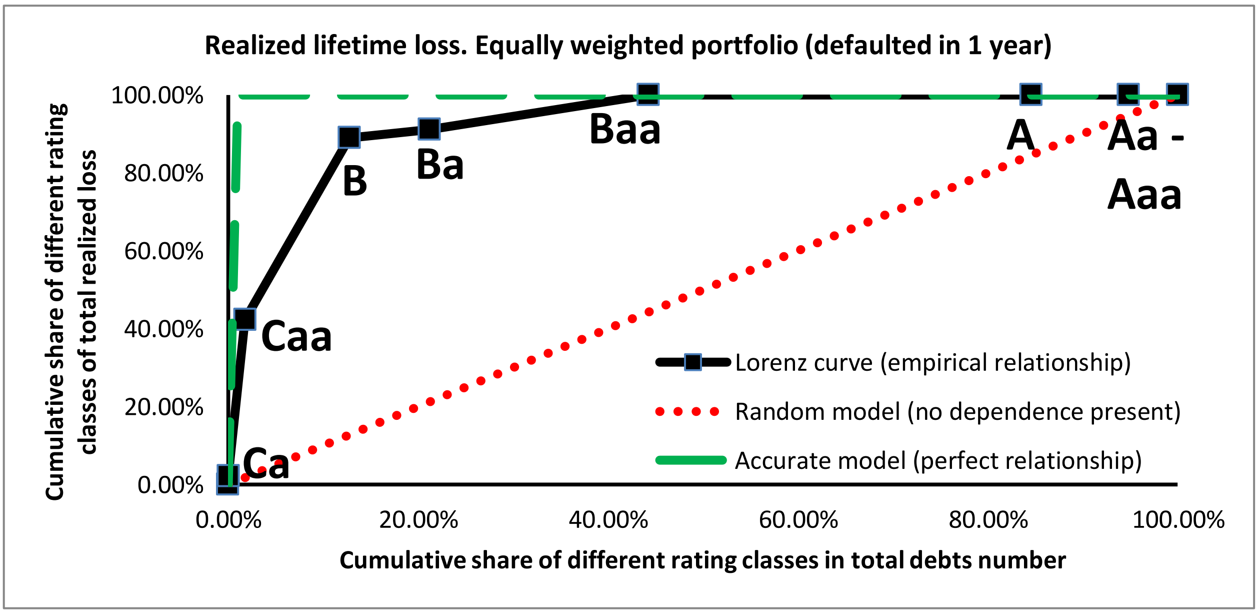

Diagram 13

The source: author's calculations based on Moody's DRS database

Diagram for realized lifetime loss for defaults happened in period after 1 year from first rating assignment is missed for the similar reason as before.

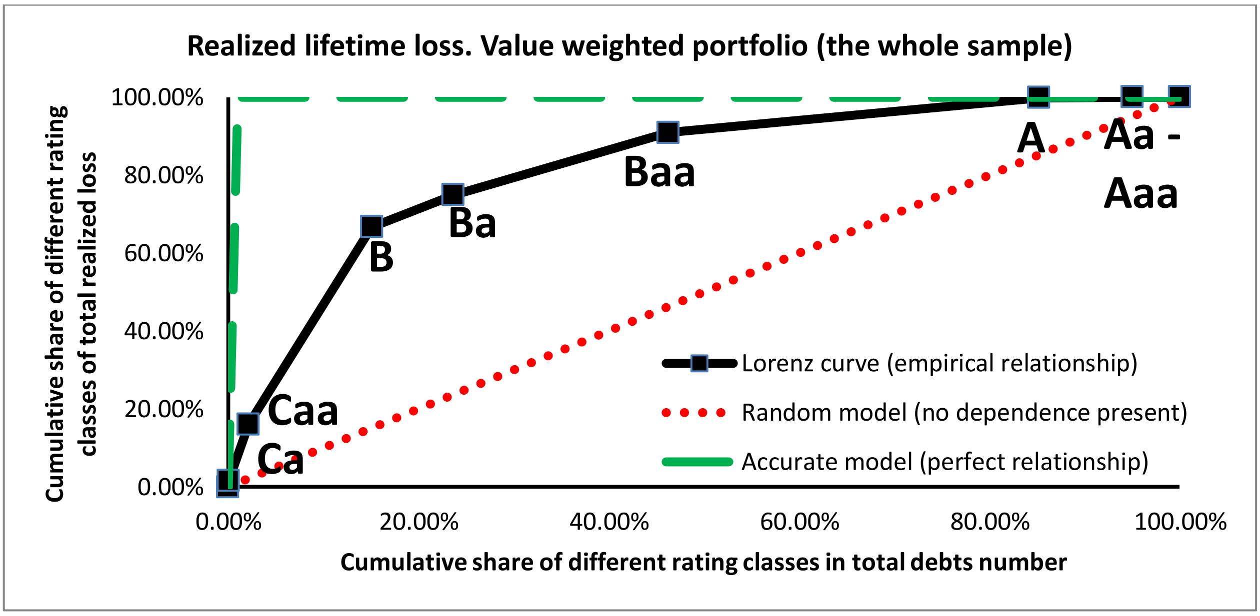

Diagram 14

The source: author's calculations based on Moody's DRS database

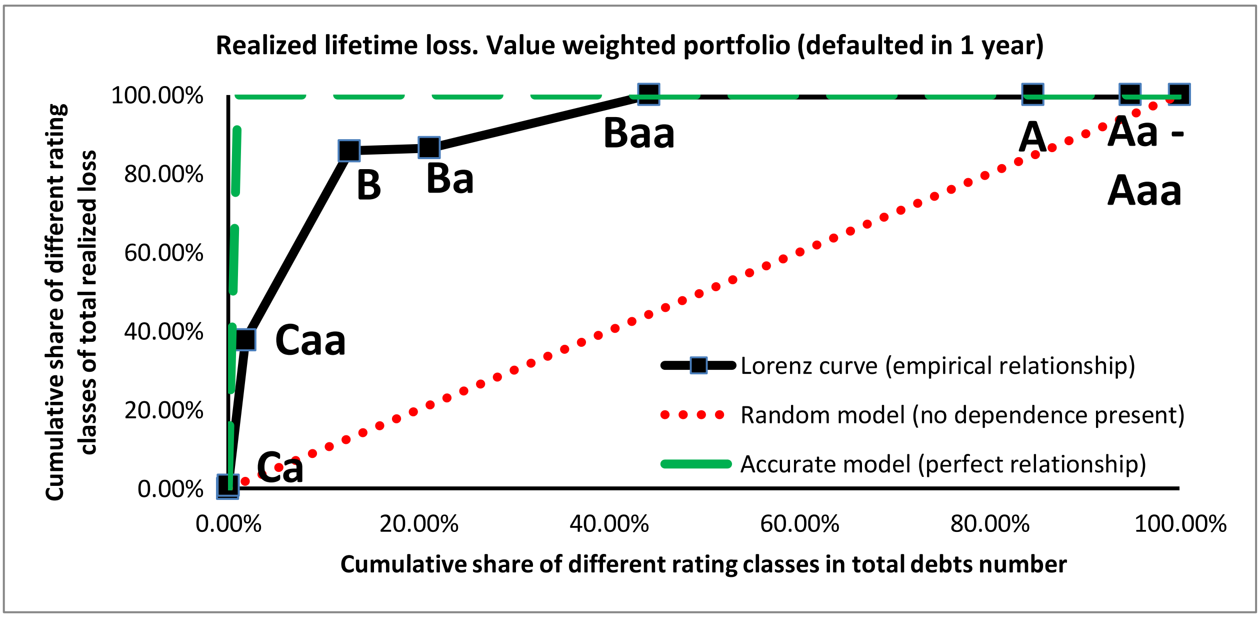

Diagram 15

The source: author's calculations based on Moody's DRS database

Table 6

Gini coefficients for realized lifetime loss and assigned ratings

Gini coefficient		All sample debts	Default occurred in period less than 1 year from first rating assignment	Default occurred in period after 1 year from first rating assignment
Financial debts subsample	**Equally weighted portfolio**	0.550	0.543	0.553
	Value weighted portfolio	0.573	0.589	0.573
Non-financial debts subsample	**Equally weighted portfolio**	0.727	0.859	0.722
	Value weighted portfolio	0.645	0.832	0.631

The source: author's calculations based on Moody's DRS database

The results obtained are very similar to ones for relationship between default frequency and rating classes in terms of Gini coefficients dynamics (one can compare with Table 4). Diagrams for both considered subsamples indicate that information about newly introduced measure is contained in ratings, especially in case of non-financial subsample:

- realized lifetime loss for financial industry is reflected essentially the same as default frequency in the sample
- accuracy of the new measure for non-financial issues is much better than for default frequency for both equally and value weighted portfolios and all time horizons. Equally weighted portfolio performs also better than value weighted as measured by Gini coefficients for all periods (less than 1 year and more than 1 year). This may be again the case that rating agencies assign ratings better for lower sized issues
- in the short run ratings in non-financial industry do perform better compared to the whole lifetime for value weighted portfolio and similarly for equally weighted. This means that ratings have higher predictive power for losses in the short run as measured by Gini coefficients.

To conclude this section, ratings turned out to be much better predictors of realized lifetime loss that of default probability. As it was stated in Chapter 1 Moody's ratings reflect both probability of default and recovery rate. Results above show that ratings contain more information about realized lifetime loss thus this concept would be more appropriate measure of ratings quality than usual default probability and loss given default.

2. Additional way for rating quality assessment using realized lifetime loss

Conclusions of the previous subsection show that once one accounts for debt industry namely, considers financial and non-financial subsamples separately it produces results that are in line with each other. In the meantime, when industry is taken into account the information value about realized lifetime loss stored in ratings increases as measured by accuracy coefficients when switching to non-financial issues. There is no doubt that newly introduced measure is indeed reflected in assigned ratings and is superior to simple approach of counting defaults and loss given default as measured by Gini coefficients. Accuracy coefficients for realized lifetime loss exceed those for default frequency ones in all cases for non-financial industry. The next empirical question that arises is how to use realized lifetime loss measure to assess quality of credit ratings. Using the second introduced definition namely relative realized lifetime loss author analyzed the sample on the presence of incorrectly rated bonds. As “misclassified” rating author defined issues that were either underrated or overrated. In order to do this using relative realized lifetime loss the next definition was utilized:

- The bond was considered to be underrated if its relative lifetime loss rate is lower than the average loss rate of the next superior rating category
- The bond was considered to be overrated if its relative lifetime loss rate is higher than the average loss rate of the next inferior rating category
- All other bonds were considered to be are consistently rated

For example, assume that loss rate Ba bond is known and equal to 3%. Using the sample the average unconditional loss rates for B and Ba issues were calculated and equal to 5.6% for B rated bonds and 3.1% for Baa bonds. In this example according to the definition specified above the Ba rated bond would be treated as underrated since its loss rate is lower than the average loss rate of the next superior rating category, namely Baa.

Utilizing this definition author counted inconsistently rated bonds by calculating relative loss rates for each bond in the sample using VBA macro for MS Excel, then calculated average loss rates for each rating class and compared these values. Results are the following, for the financial subsample

Table 7

Inconsistently rated issues in financial subsample

	Ca	Caa	B	Ba	Baa	A	Aa	Aaa	Total
Underrated	0	2	9	5	4	48	0	0	68
Overrated	0	0	0	4	16	272	2	0	294
Correctly rated	0	7	71	135	853	7492	7475	2660	18693
Inconsistent ratings, %	0.00%	22.22%	11.25%	6.25%	2.29%	4.10%	0.03%	0.00%	1.90%

The source: author's calculations based on Moody's DRS database

The same approach for non-financial industry yields

Table 8

Inconsistently rated issues in non-financial subsample

	Ca	Caa	B	Ba	Baa	A	Aa	Aaa	Total
Underrated	5	36	420	102	89	25	0	0	677
Overrated	6	40	207	38	42	27	3	0	363
Correctly rated	3	515	3050	2289	6274	10982	2784	1406	27303
Inconsistent ratings, %	78.57%	12.86%	17.05%	5.76%	2.05%	0.47%	0.11%	0.00%	3.67%

The source: author's calculations based on Moody's DRS database

These tables indicate the following:

- Number of "misclassified" bonds according to the stated definition is very low: 1.90% and 3.67% of total subsample's amount. This indicates that on average ratings correctly account for possible losses. However, almost monotonous increase in percentage of incorrectly rated issues is observed from the table: it is equal 0% for the highest rated bonds and 22.22% (78.57%) for the lowest non-investment category. It is possible that such situation may take place due to incorrect market estimation of the low graded issue's value 30 days after default which makes calculated realized lifetime loss inaccurate. This result can be also explained by arguments listed in Perraudin and Taylor (2004), namely that number of inconsistently rated issues may be lower if account explicitly for risk premium. Nevertheless, author argues that obtained results are reliable within the framework of the model.
- For financial subsample, incorrect ratings are mostly assigned for "A" rated issues which are overrated. This supports previous explanation that such issues were rated without taking into account all possible risks. As it is known this led to significant default numbers in the industry during crisis 2008
- For non-financial subsample another trend is seen, if rating agency assigns incorrect rating it rates bond lower than should according to the above definition. Possible

explanation may be that in case of uncertainty about the debt agency chooses prudent policy and prefers to rate below than above the actual rating. This is supported by Lorenz curves and accuracy coefficients, indicating that such debts were rated properly since the most part of defaults is accumulated by non-investment grade issues.

3. Relationship between ratings quality and characteristics of the bond

3.1. Regression model description and variables used

Author's intention was to investigate whether quality of assigned ratings depends on certain characteristics of a bond. Moody's DRS database contains all relevant information on each issue, namely debt class, debt seniority, collateral etc. It is interesting empirically whether these characteristics have an impact on ratings quality. In order to do this, author run several types of regressions on all relevant independent variables presented in the Moody's database. As for dependent variable two types of regressions were estimated. These two types of regressions use dependent variable which indicates ratings misclassification. The first one is ordinary least squares regression with dependent variable equal to calculated realized lifetime loss for the issue less average loss for this bond's rating category (called "lmal"). The second regression is logistic model and uses dependent variable "misclass" which takes value of 1 if bond is rated inconsistently and 0 otherwise. Acronym for the first variable stands for **l**oss **m**inus **a**verage **l**oss, for the second **misclass**ified. All regressions were performed in statistical analysis software Stata 12.

As in the previous chapter, analysis would be conducted for financial and non-financial subsamples separately to make results comparable with ones obtained before. Considering the whole information available in the database author decided to use the following independent variables that may have explanatory power. They are listed below as well as the hypothesis for these variables that were tested in the first type regression. Explanation for these variables for the second type regression would be given simultaneously with its results.

- **debt class:** all bonds in the sample belong to one of the five following debt classes
    a) "REG" - Regular Bond/Debenture. These bonds are the classical debt instruments. Bondholders get paid only after secured creditors are paid, although they will usually be paid before common stockholders. They are issued by companies to raise money.
    b) "CON" - Convertible/Exchange Bond/Debenture. These bonds can be transformed into a stated quantity of shares of common stock or, thus are the

hybrid type securities. They are most often issued by companies with a low credit rating.

c) "FMB" - First Mortgage Bonds. These bonds are usually secured by mortgage on real estate/property (although this is not the case in the used sample). If issuer defaults bondholders have a claim on the underlying which has a priority over all other claims on this property.

d) "IRB" - Revenue Bonds. These bonds are usually secured by a particular venture. They are municipal bonds used to fund revenue-generating projects and backed such projects.

e) "SLB" - Secured Lease Obligation Bond. These bonds are backed by lease payments on a particular asset which issuing company owns and receives rent payments on it.

According to the description listed above author was interested in whether it can be found empirically that some of debt classes can explain inconsistent ratings. In order to study this question 4 dummy variables named "debt_con", "debt_fmb", "debt_irb", "debt_slb" equal 1 if bond belongs to a particular class and 0 otherwise were introduced. Regular bond was chosen as base category due to the highest frequency in the sample.

Author's intention was to test how these classes affect the dependent variable. Here and after if it is not stated explicitly hypotheses are formulated for "lmal" dependent variable. Author expected to get positive coefficient for convertible bonds ("debt_con") since they usually are issued by low rated companies so on average they should have higher losses than regular bonds. Also he expected to obtain negative coefficients for first mortgage bonds, revenue bonds and secured lease obligation bonds because they are often backed (as it is stated in description above)

- **time to maturity.** This variable was simply created using information about sale date and maturity date, named "time_to_mtr" and expressed in years. Obviously it is more difficult to predict default over a longer horizon, so hypothesis to test is that coefficient for "time_to_mtr" is positive and significant.

- **debt seniority:** this indicator should affect rating quality since priority of claims in case of bankruptcy do has influence on assigned rating. As a matter of fact senior debt would be ranked higher than junior, all other factors being equal. To investigate this five broadly presented debt seniority classes were considered: senior secured, senior unsecured, senior subordinated, subordinated and junior subordinated ranked from the highest to the lowest priority. Consequently, four dummies named “seniority_su”, “seniority_sr”, “seniority_sb” and “seniority_js” for senior unsecured, senior subordinated, subordinated and junior subordinated respectively were introduced. Senior secured class was chosen as base category.

For these variables hypothesis to test was that coefficients are positive since the base category bondholders are paid first in case of default. Thus, it seems reasonable that all other categories compared to senior secured should have higher losses (which is the case if coefficients are positive)

- **debt currency**: in spite of the fact that sample consists only of US issued bonds and most part is denominated in US dollars author decided to investigate the relationship between ratings and issue currency. For that purpose currency dummy named “curr” was introduced, it takes value of 1 if bond’s currency is different from US dollar and 0 otherwise.

  Hypothesis for this coefficient is that it should be positive. The idea behind it is that all bonds considered are issued in the United States and those that are denominated in different currency have higher risks due to exchange rate exposure and consequently have higher losses.

- **payment schedule** namely coupon frequency. Sample consists of 5 different coupon frequencies, thus as a rule 4 dummies were introduced: “coup_freq_mon”, “coup_freq_qtr”, “coup_freq_ann” and “coup_freq_acr” standing for monthly, quarterly, annual and accrued frequencies respectively. To clarify the last one it should be noted, that Moody’s assigns accrued frequency for issues which are paying coupons and face value simultaneously at maturity. Dummies were chosen to be equal 1 if bond has coupon schedule as named dummy and 0 otherwise; semiannual coupon frequency was chosen as base category.

  The hypothesis to test is that for issues with coupons paid more frequently than for those of base category, namely for quarterly and monthly coefficient would be negative showing that such issues on average have relatively smaller losses because investor receives payments more frequently (kind of risk reduction). On contrary, author expects to get positive coefficients for annual and accrued frequencies, especially for the last one. The intuition is that companies that are unable to make scheduled coupon payments are more risky that is why they choosing policy to pay out coupon and face value simultaneously.

- **collateral**: this dummy uses information from column in the database which contains binary information about security's backing (has backing/does not have backing). Variable "collateral" is equal 1 bond has a collateral and 0 otherwise. The hypothesis to test is that coefficient for this variable is negative and significant which will indicate that collateral reduces losses.

- **industry dummies**. They were introduced to find out whether rating quality is different among industries. Because author again considered two subsamples separately, these dummies will be different for subsamples. The following approach was applied:
  a) For financial debts subsample the singe dummy was introduced – "banks". It is equal 1 if bond from this subsample was issued by bank and 0 otherwise.
     The idea was to check how losses differ for banks and non-banks keeping all other variables being equal.
  b) For non-financial debts six dummies were introduced – "utilities", "energy", "services", "media", "consumer_goods" and "transportation" for industries which names coincide with dummy's names. As base category real sector was chosen. They are listed in Appendix 4.
     Again, introducing these dummies author wanted to find out how losses differ for bonds from these industries compared to real sector bonds, all other variables being equal.

3.2. Regression results and discussion

The first step is again to study the financial debts subsample. For this purpose ordinary least squares regression with **lmal** dependent variable was estimated. It should be noted that financial subsample contains only convertible, revenue and regular bonds. That is why for this data dummies "debt_fmb" and "debt_slb" take zero values across all observations and should be omitted in estimation.

Table 9

Ordinary least squares regression for financial subsample

Source	SS	df	MS
Model	259572.755	14	18540.911
Residual	100410825	19040	5273.67779
Total	100670398	19054	5283.42594

Number of obs =	19055
F(14, 19040) =	3.52
Prob > F =	0.0000
R-squared =	0.0026
Adj R-squared =	0.0018
Root MSE =	72.62

lmal	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
debt_con	-1.480844	3.21117	-0.46	0.645	-7.775022	4.813334
debt_irb	.2470916	19.47586	0.01	0.990	-37.92733	38.42151
time_to_mtr	.211379	.089308	2.37	0.018	.0363274	.3864306
seniority_su	14.73279	10.10055	1.46	0.145	-5.06518	34.53075
seniority_sr	11.28164	11.12426	1.01	0.311	-10.5229	33.08618
seniority_sb	16.87558	10.31965	1.64	0.102	-3.35185	37.10301
seniority_js	-3.625789	12.21847	-0.30	0.767	-27.57506	20.32349
curr	-.0757347	2.049811	-0.04	0.971	-4.093546	3.942077
coup_freq_mon	-6.700684	1.637102	-4.09	0.000	-9.909548	-3.491819
coup_freq_qtr	-2.464994	1.867908	-1.32	0.187	-6.126259	1.19627
coup_freq_ann	1.825007	2.353849	0.78	0.438	-2.788745	6.438759
coup_freq_acr	-2.405498	1.749484	-1.37	0.169	-5.834641	1.023645
collateral	-5.236044	1.584863	-3.30	0.001	-8.342515	-2.129572
banks	2.081092	1.308814	1.59	0.112	-.4842991	4.646482
_cons	-15.14987	10.10518	-1.50	0.134	-34.95692	4.657169

The source: author's model estimation in Stata 12

First that catches sight is that regression demonstrates extremely low R-squared = 0.0018 which indicates that used explanatory variables explain even less than 0.2% of total variation in dependent variable. Nevertheless, regression as whole is significant which is indicated by F-test.

- Signs for debt class coefficients contradict with author's expectation but they are insignificant at any reasonable level and thus show that debt class has no impact on dependent variable.
- Coefficient for "time_to_mtr" is significant at 5% level and positive which is in line with hypothesis, value of 0.211 indicates that each additional year increases difference between realized loss of the bond and average loss in given category for 0.211 million.
- Signs for seniority classes coincide with expectation except for junior subordinated bonds for which it is insignificant at any reasonable level. The rest coefficients are also insignificant at 5% level and show that in the sample debt classes inferior to senior secured have no effect on realized losses.
- Sign for the "curr" is negative which contradicts the hypothesis but is insignificant at any reasonable level. Thus one can conclude that in the sample currency has no impact on realized lifetime losses
- Signs for payment schedule are in line with expectations except accrued frequency. In the meantime, coefficient is significant only for monthly paid coupons. It states that bonds with monthly coupon frequency have 6.7 million smaller losses than for semiannually ones all other variables being equal.

- Coefficient for collateral is negative and significant which coincides with expectation (bonds secured by collateral have 5.23 million smaller losses ceteris paribus)
- Coefficient for "banks" is positive but insignificant in the sample. Thus no conclusion could be made about difference in losses for banks and non-banks.

One possible explanation of low R-squared is that financial subsample consists mostly of non-defaulted issues (there are only 436 default events out of 19055 observations). Realized lifetime loss for non-defaulted debts is 0 which constitute the most part of the sample. It would be interesting to perform similar analysis for sample which contains higher number of defaulted debts.

The same right hand side variables as above were used in ordered logistics regression model.

```
note: debt_irb != 0 predicts failure perfectly
      debt_irb dropped and 14 obs not used
note: seniority_js != 0 predicts failure perfectly
      seniority_js dropped and 125 obs not used
Iteration 0:   log likelihood =  -1790.629
Iteration 1:   log likelihood = -1703.4551
Iteration 2:   log likelihood = -1557.5671
Iteration 3:   log likelihood = -1549.6832
Iteration 4:   log likelihood = -1548.8995
Iteration 5:   log likelihood = -1548.8692
Iteration 6:   log likelihood = -1548.8669
Iteration 7:   log likelihood = -1548.8667
Iteration 8:   log likelihood = -1548.8667
Iteration 9:   log likelihood = -1548.8667
```

Table 10

Logistic regression for financial subsample

```
Logistic regression                               Number of obs   =      18916
                                                  LR chi2(12)     =     483.52
                                                  Prob > chi2     =     0.0000
Log likelihood = -1548.8667                       Pseudo R2       =     0.1350
```

misclass	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
debt_con	.0544196	.5186064	0.10	0.916	-.9620303	1.07087
debt_irb	0	(omitted)				
time_to_mtr	.070704	.006254	11.31	0.000	.0584464	.0829617
seniority_su	13.63399	883.6163	0.02	0.988	-1718.222	1745.49
seniority_sr	13.41552	883.6164	0.02	0.988	-1718.441	1745.272
seniority_sb	13.41517	883.6163	0.02	0.988	-1718.441	1745.271
seniority_js	0	(omitted)				
curr	-1.349547	.4534471	-2.98	0.003	-2.238287	-.4608074
coup_freq_mon	-.1220031	.1312415	-0.93	0.353	-.3792318	.1352256
coup_freq_qtr	-1.554161	.3425186	-4.54	0.000	-2.225485	-.8828367
coup_freq_ann	-1.017915	.4515117	-2.25	0.024	-1.902862	-.1329685
coup_freq_acr	-3.339188	1.00621	-3.32	0.001	-5.311323	-1.367052
collateral	-.6878333	.2575314	-2.67	0.008	-1.192586	-.183081
banks	-1.62495	.2267194	-7.17	0.000	-2.069311	-1.180588
_cons	-17.42262	883.6163	-0.02	0.984	-1749.279	1714.433

The source: author's model estimation in Stata 12

Stata dropped out two variables since they both predicted perfectly bonds rated correctly (program treats failure as 0 outcome and dependent variable is equal to zero means that bond is rated consistently). Table above shows that coefficients for time to maturity, currency, quarterly, annual and accrued coupon frequency, collateral and banks are all significant at 5% level.

- For time to maturity a one year increase one should expect 0.07 increment in the log odds of going "misclass" in 1 that is of bond rated inconsistently, ceteris paribus. This can be explained by fact that it is more difficult to rate bonds with longer time to maturity.
- Negative coupon frequency coefficients show that compared to semiannual frequency bonds with such frequencies have lower probabilities to be rated inconsistently. This result is contradictory on the first sight with OLS regression results and hypotheses for annual and accrued frequencies. It can be explained in the following way – most bonds in the sample with annual and accrued frequencies are rated consistently. Among inconsistently rated issues these bonds constitute 11 and 2 respectively. Therefore, such signs are determined by consistently rated issues and relationship is spurious.
- Currency coefficient indicates that for non-dollar denominated debts the log odds of bond to be rated inconsistently decline by 1.35 all other variables being equal. This is quite contradictory result since such issues considered to be more risky than those issues in US dollar, but is again explained by low number of non-dollar denominated bonds among defaulted issues (only 12).
- Negative collateral coefficient illustrates the statement that backed bonds have lower probability to be rated inconsistently. This is in line with OLS regression results

Table 11

Ordinary least squares regression for non-financial subsample

Source	SS	df	MS
Model	6389931.8	21	304282.467
Residual	423698152	28321	14960.5647
Total	430088084	28342	15174.9377

Number of obs	=	28343
F(21, 28321)	=	20.34
Prob > F	=	0.0000
R-squared	=	0.0149
Adj R-squared	=	0.0141
Root MSE	=	122.31

lmal	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
debt_con	.5190131	5.029992	0.10	0.918	-9.340011	10.37804
debt_fmb	3.026139	4.216692	0.72	0.473	-5.23878	11.29106
debt_irb	-14.48421	8.015517	-1.81	0.071	-30.19501	1.226585
debt_slb	-2.319661	20.86905	-0.11	0.911	-43.22399	38.58467
time_to_mtr	.2756277	.0800782	3.44	0.001	.1186706	.4325848
seniority_su	.9157437	2.852394	0.32	0.748	-4.675085	6.506573
seniority_sr	-27.56322	4.11971	-6.69	0.000	-35.63805	-19.4884
seniority_sb	-29.34113	6.076449	-4.83	0.000	-41.25126	-17.431
seniority_js	-17.09853	9.414129	-1.82	0.069	-35.55067	1.353611
curr	-14.9687	5.973569	-2.51	0.012	-26.67718	-3.26022
coup_freq_mon	-2.082316	2.949806	-0.71	0.480	-7.864077	3.699446
coup_freq_qtr	.5229906	4.085869	0.13	0.898	-7.485508	8.531489
coup_freq_ann	13.2452	5.525241	2.40	0.017	2.415464	24.07494
coup_freq_acr	94.14105	6.696056	14.06	0.000	81.01646	107.2656
collateral	-1.682053	1.839303	-0.91	0.360	-5.287175	1.923068
utilities	-10.04042	2.466803	-4.07	0.000	-14.87547	-5.205367
energy	-2.627419	2.412615	-1.09	0.276	-7.356261	2.101422
services	-5.965288	2.382075	-2.50	0.012	-10.63427	-1.296307
media	23.65924	3.858957	6.13	0.000	16.0955	31.22298
consumer_goods	-5.559108	4.777886	-1.16	0.245	-14.92399	3.805777
transportation	10.81191	2.905925	3.72	0.000	5.116161	16.50766
_cons	-.498391	3.132728	-0.16	0.874	-6.638688	5.641906

The source: author's model estimation in Stata 12

Regression as for financial debts demonstrates low R-squared = 0.0149. Nevertheless, as whole it is significant which is indicated by F-test.

- All debt class coefficients are insignificant at 5% level and thus show that debt class has no impact on dependent variable.
- Coefficient for "time_to_mtr" description is essentially the same as for financial debts.
- Signs for seniority classes for significant variables differ from expected. On contrary to financial sample, number of bonds belonging to these debt classes is significant among defaulted (291 and 122 respectively) and non-defaulted (1648 and 872). One possible explanation is that on this dataset such bonds experienced lower losses than senior secured due to external factors that are not included in the model.
- Sign for the "curr" is negative which contradicts the hypothesis and is significant at 5% level. In the meantime, defaulted issues contain only 6 out of 1228 debts denominated in currency different from US dollar. Thus, this effect is purely explained by non-defaulted issues and is spurious.

- Signs for payment schedule are in line with expectations except quarterly frequency. In the meantime, coefficient is significant only for annual and accrued coupons. Result is in line with expectation.
- Coefficient for collateral is negative which coincides with expectation. Although it is insignificant thus one can conclude that collateral has no impact on losses in this sample.
- As for industry dummies they show that bonds from utilities and services have lower losses compared to real sector and debts from media and transportation have higher losses respectively. The first part of the statement can be explained as following – products from such industries are in high demand even in recessions and even if default event takes place companies manage to recover without substantial losses. For the second part the explanation is the opposite –demand in downturns on their products declines significantly and companies experience big losses (use Appendix 4 for more insight about companies from these sectors).

The same right hand side variables were used in ordered logistic regression for the whole subsample and only defaulted issues.

```
note: debt_irb != 0 predicts failure perfectly
      debt_irb dropped and 319 obs not used
note: debt_slb != 0 predicts failure perfectly
      debt_slb dropped and 35 obs not used
Iteration 0:   log likelihood = -4444.7288
Iteration 1:   log likelihood = -4025.0925
Iteration 2:   log likelihood = -3881.8011
Iteration 3:   log likelihood = -3870.9028
Iteration 4:   log likelihood = -3869.6106
Iteration 5:   log likelihood =  -3869.532
Iteration 6:   log likelihood = -3869.5319
```

Table 12

Logistic regression for non-financial subsample

Logistic regression		Number of obs	=	27989
		LR chi2(19)	=	1150.39
		Prob > chi2	=	0.0000
Log likelihood = -3869.5319		Pseudo R2	=	0.1294

misclass	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
debt_con	-.7832556	.1726774	-4.54	0.000	-1.121697	-.4448141
debt_fmb	.1328881	.3099044	0.43	0.668	-.4745134	.7402896
debt_irb	0	(omitted)				
debt_slb	0	(omitted)				
time_to_mtr	.0032908	.0036535	0.90	0.368	-.0038698	.0104515
seniority_su	-.5266136	.1424284	-3.70	0.000	-.8057681	-.2474591
seniority_sr	.9349088	.1538263	6.08	0.000	.6334148	1.236403
seniority_sb	1.251942	.2019224	6.20	0.000	.8561811	1.647703
seniority_js	.6292444	.4573605	1.38	0.169	-.2671658	1.525654
curr	-1.17309	.4489438	-2.61	0.009	-2.053004	-.2931764
coup_freq_mon	-3.683706	1.001895	-3.68	0.000	-5.647384	-1.720028
coup_freq_qtr	-.6806919	.2421976	-2.81	0.005	-1.155391	-.2059932
coup_freq_ann	-.8942437	.3895053	-2.30	0.022	-1.65766	-.1308273
coup_freq_acr	1.091177	.1870854	5.83	0.000	.724496	1.457857
collateral	-.3452059	.0872902	-3.95	0.000	-.5162916	-.1741203
utilities	-2.596143	.2770613	-9.37	0.000	-3.139173	-2.053113
energy	-.2462923	.104232	-2.36	0.018	-.4505833	-.0420013
services	-1.534426	.1823506	-8.41	0.000	-1.891827	-1.177026
media	.6079565	.113238	5.37	0.000	.3860141	.8298988
consumer_goods	.5179184	.1453497	3.56	0.000	.2330382	.8027985
transportation	.6371106	.1024138	6.22	0.000	.4363833	.8378379
_cons	-2.702643	.1477433	-18.29	0.000	-2.992215	-2.413071

The source: author's model estimation in Stata 12

As in financial subsample regression Stata dropped out two variables since they both predicted perfectly correctly rated bonds.

- Coefficient for convertible bond is negative and significant indicating that log odds for bonds of this debt class to be rated inconsistently decreases by 0.783 compared to regular bond. It was stated that convertible bonds are issued mostly by low rated companies. Therefore, such result is questionable. There are only 90 convertible bonds out of 1228 defaulted and this inference may be spurious due to small amount of debts.
- Time to maturity remains positive but becomes insignificant.
- All debt seniorities are significant and positive (except senior unsecured) showing strong relationship between misclassified issues and bond seniorities
- Currency coefficient explanation is the same as before (it is mostly determined by correctly rated issues thus is spurious)
- Coupon frequencies coefficients are also all significant demonstrating impact on misclassification
- Negative collateral coefficient illustrates the statement that backed bonds have lower probability to be rated inconsistently. This is in line with OLS regression results

- Utilities, energy, services, media, consumer goods and transportation industries also reflect the dependence with inconsistent ratings.

4. Conclusions for Chapter 3

1. Lorenz curves for realized lifetime loss and default frequency are very similar in their shape. Therefore it can be concluded that ratings implicitly contain information on possible losses and may be used by investors for such purpose.
2. Realized lifetime loss compared to simple default counting method by accuracy coefficients turned to outperform default frequency in all cases for non-financial issues and shows that can be used for proper calculation of inconsistently rated issues from financial industry
3. Thus, bond quality assessment using this new measure seems sensible and moreover, this measure implicitly takes into account default and loss given default and may be used for purposes when these two indicators would need to be incorporated into single factor. Also, as Moody's stated their rating reflect both indicators, it seems that for bond ratings quality estimation realized loss is more appropriate measure due to higher accuracy than default frequency
4. Regression analysis showed low value of R-squared. Nevertheless author claims that it is not a matter of concern because results present significant effects (and as whole all regressions are significant by F-test value). Author's purpose was not to create the model which explains all variation in realized losses but to find out which of the bond specific variables are responsible for inconsistent ratings and determine the signs of their effects. Author achieved this goal and found that
   - time to maturity coefficient is positive in all cases and almost always significant, which is in line with Hilscher and Wilson (2013) and Figlewski et al (2012) meaning that default is more probable for issues with longer time to maturity and such issues experience higher losses and are rated inconsistently more often.
   - collateral coefficient is always negative, thus showing that for backed bonds probability to get inconsistent rating is lower as well as realized losses
   - industries among non-financial debts have significant impacts on realized losses. This can be explained that essential goods are in demand even in economy's downturns thus companies from these industries in case of default are able to recover.
   - payment schedule barely explains misclassified bonds as well as realized losses

- all other variables, namely debt class, seniority and currency showed significant effects in some cases but as it was explained these effects are spurious.

5. Finally, these variables explain only a small portion of the variation in the dependent variable. Author conjectures that R-squared may be sufficiently increased by introduction external variables, like firm-specific and macroeconomic: profitability, balance sheet ratios, GDP growth, unemployment rate etc. It would be interesting to conduct similar exercise on this sample or on sample that will be presented with higher amount of defaults as it was stated earlier in the text.

Conclusion

Author dedicated this master thesis to answer on the three questions that were already stated in the Introduction. The summary of the obtained results is the following:

1. Ratings do contain relevant information for the individual investor. In particularly, they can be used for default frequency estimation and this result is in accordance with number of papers. Two types of debts were considered in this work:

- Financial debts subsample showed that ratings moderately explain defaults and this is possibly due to overlap of the sample period with financial crisis 2008. This subsample consists mostly of “A”-“Aaa” rated issues and the most part of which suffered default events. This is in line with some papers which state that number of defaults increases dramatically in the recessions. Thus, financial crisis of 2008 revealed that rating agencies underestimate risks inherent by financial debts. Author suggests to use some other explanatory variables to account correctly for default probability
- Non-financial industry issues ratings seem to take correctly all risks and ratings itself can be used as the only explanatory variable, especially in the 1 year period from rating assignment.

2. Loss given default turned out to be poorly reflected in ratings. Only in 1 year period for non-financial debts ratings can be used for loss given default prediction but still require additional source of information due to moderate Gini coefficients.
3. Newly introduced measure, namely realized lifetime loss was proved to be superior to simple default counting method. It outperformed default frequency in all cases for non-financial issues and showed the same accuracy for financial debts. Therefore, due to implicit account for default probability and loss given default it seems to be more appropriate measure for bond quality estimation. Moreover, this measure also can be used to count inconsistently rated bonds.
4. Author achieved his goal and found some significant effects in regression analysis:

- **time to maturity** coefficient is positive in all cases and almost always significant proving the hypothesis that issues with long time to maturity are more probable to go into default and experience higher losses. Also they are more often to be rated inconsistently.
- **collateral** coefficient is always negative, thus showing that for backed bonds probability to get inconsistent rating is lower as well as realized losses
- **industries** among non-financial debts have significant impacts on realized losses.

To conclude, author had found answers on all stated questions. Open questions for further research are:

4. How can rating agencies adjust their methodology to reflect better loss given default in their ratings and would it be more appropriate to publish realized lifetime loss in the reports instead of other two indicators?
5. Other variables from regression analysis, namely debt class, seniority and currency showed significant effects in some cases but as it was explained these effects are spurious. This happened due to low amount of bonds with these characteristics among defaulted issues. It would be interesting to check these hypotheses on more broad sample
6. Author’s purpose was to find which of the bond specific variables are responsible for inconsistent ratings and determine the signs of their effects. Listed above variables do have impact on the dependent variable but do not explain all variation. Introduction of firm-specific and macroeconomic variables can resolve this problem and it would be interesting to do this exercise in further studies.

References

Journal articles:

1. *Altman Edward I*. Measuring Corporate Bond Mortality and Performance. Finanzmarkt and Portfolio Management – 4. Jahrgang, 1990. Nr.1
2. *Altman Edward I., Kishore Vellore M.*. Almost everything you wanted to know about recoveries on defaulted bonds. Financial Analysts Journal, Nov/Dec 1996. 52, 6
3. *Altman Edward I., Brady Brooks, Resti Andrea, Sironi Andrea*. The Link between Default and Recovery Rates: Theory, Empirical Evidence and Implications. Journal of Business, 2005. Vol. 78, no. 6
4. *Bade Benjamin, Rosch Daniel and Scheule Harald*. Default and Recovery Risk Dependencies in a Simple Credit Risk Model. European Financial Management, 2011. Vol. 17, No. 1, 120–144
5. *Bruche Max and Gonzalez-Aguado Carlos*. Recovery rates, default probabilities, and the credit cycle. Journal of Banking & Finance, 2010. 34 713–723
6. *Carey Mark*. Credit Risk In Private Debt Portfolios. The Journal Of Finance, 1998. Vol. Liii, No. 4
7. *Dwyer Douglas W., Kocagil Ahmet E., Stein Roger M.* Moody's KMV RiskCalc v.3.1 model. Moody's KMV, Next-Generation Technology for Predicting Private Firm Credit Risk, 2004
8. *Figlewski, Frydman and Liang*. Modeling the effect of macroeconomic factors on corporate default and credit rating transitions. International Review of Economics and Finance, 2012. 21 57-105
9. *Godlewski Christophe J.* Are Ratings Consistent with Default Probabilities. Emerging Markets Finance and Trade, 2007. Vol.43, no.4
10. *Gupton Greg M., Stein Roger M*. LossCalc V2: Dynamic Prediction of LGD. Moody's KMV, Modelling methodology, 2005
11. *Merton Robert C.* On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance, 1974. p. 449-478
12. *Perraudin William and Taylor Alex P.* On the consistency of ratings and bond market yields. Journal of Banking & Finance, 2004. 28 2769–2788
13. *Varma Praveen, Cantor Richard, Hamilton David*. Recovery Rates on Defaulted Corporate Bonds and Preferred Stocks, 1982–2003. Moody's Investors Service, Global Credit Research, 2003

Books:

14. *Walkenbach John*. Excel 2010 Power Programming with VBA. Wiley Publishing, Inc., 2010

Working papers:

15. *Hainsworth Richard*. Meaning of Credit Rating, 2012
16. *Hilscher Jens and Wilson Mungo*. Credit ratings and credit risk: Is one measure enough? March 2013

Rating agencies methodologies:

17. A Guide To The Loan Market. Standard & Poor's
18. Corporate Default and Recovery Rates, 1920-2008. Special Comment, Moody's Global Credit Policy, 2009
19. DRS Technical Specifications. Moody's Corporate Default Risk Service
20. Frequently Asked Questions. Moody's Corporate Default Risk Service
21. Guide to Credit Rating Essentials. Standard & Poor's
22. Managing and Developing Criteria and Models. Fitch Ratings, 2011
23. Moody's Ratings Symbols and Definitions. Moody's Investor Service, 2009
24. Ratings and Notching Criteria for Non-Financial Corporate Issuers. Fitch Ratings Recovery, 2012

Internet resources:

25. Board of Governors of the Federal Reserve System, historical interest rates for US market http://www.federalreserve.gov/releases/h15/data.htm

Appendix 1

Country	Number of debts	Country	Number of debts	Country	Number of debts
Albania	6	France	13768	New Zealand	604
Alderney	2	Georgia	9	Nicaragua	14
Andorra	6	Germany	27661	Norway	3371
Angola	3	Ghana	2	Oman	34
Argentina	779	Gibraltar	2	Pakistan	107
Armenia	15	Greece	493	Panama	196
Aruba	49	Guatemala	16	Panama (off shore)	2
Australia	10182	Guernsey	2030	Papua New Guinea	3
Austria	4607	Honduras	27	Paraguay	4
Azerbaijan	24	Hong Kong	869	Peru	77
Bahamas	622	Hungary	229	Philippines	467
Bahamas (off shore)	4	Iceland	700	Poland	183
Bahrain	25	India	381	Portugal	659
Bahrain (off shore)	22	Indonesia	223	Puerto Rico	74
Bangladesh	3	Iran	4	Qatar	43
Barbados	16	Ireland	3537	Romania	49
Belarus	17	Isle of Man	15	Russia	762
Belgium	879	Israel	595	Saint Lucia	2
Belize	8	Italy	4446	San Marino	2
Bermuda	457	Jamaica	60	Sark	2
Bolivia	88	Japan	12358	Saudi Arabia	82
Bosnia and Herzegovina	5	Jersey	1959	Serbia	3
Botswana	8	Jordan	15	Singapore	485
Brazil	985	Kazakhstan	141	Slovak Republic	79
British Virgin Islands	69	Korea	1713	Slovenia	64
Bulgaria	73	Kuwait	40	South Africa	283
Cambodia	9	Kyrgyzstan	2	Spain	2266
Canada	10654	Latvia	40	Sri Lanka	5
Cayman Islands	2515	Lebanon	79	St. Vincent and The Grenadines	4
Cayman Islands (off shore)	74	Liberia	4	Supranational	9087
Channel Islands	708	Liechtenstein	10	Suriname	3
Chile	178	Lithuania	60	Sweden	4352
China	352	Luxembourg	8366	Switzerland	1181
Colombia	131	Macau	18	Taiwan	349
Costa Rica	17	Macedonia	2	Thailand	323
Croatia	50	Malaysia	307	Trinidad & Tobago	28
Cuba	3	Malta	44	Tunisia	43

Cyprus	97	Marshall Islands	9	Turkey	282
Czech Republic	110	Mauritius	48	Turkmenistan	3
Denmark	2324	Mexico	1295	Turks and Caicos Islands	7
Dominican Republic	23	Micronesia	2	Ukraine	188
Dublin	19	Moldova	11	United Arab Emirates	221
Ecuador	18	Monaco	2	United Kingdom	25319
Egypt	34	Mongolia	14	United States	255455
El Salvador	17	Montenegro	6	Uruguay	131
Estonia	38	Morocco	34	Uzbekistan	17
Faroe Islands	5	Multinational - Asia	1	Venezuela	226
Fiji	106	Netherlands	12651	Vietnam	51
Finland	1467	Netherlands Antilles	3403	Unnamed	22

Country	**Number of debts**	**Country**	**Number of debts**
United States	255455	Norway	3371
Germany	27661	Cayman Islands	2515
United Kingdom	25319	Denmark	2324
France	13768	Spain	2266
Netherlands	12651	Guernsey	2030
Japan	12358	Jersey	1959
Canada	10654	Korea	1713
Australia	10182	Finland	1467
Supranational	9087	Mexico	1295
Luxembourg	8366	Switzerland	1181
Austria	4607	Brazil	985
Italy	4446	Belgium	879
Sweden	4352	Hong Kong	869
Ireland	3537	Argentina	779
Netherlands Antilles	3403	Russia	762

Country	**Number of issuers**	**Country**	**Number of issuers**	**Country**	**Number of issuers**
Albania	3	France	443	Nicaragua	2
Alderney	1	Georgia	4	Norway	65
Algeria	1	Germany	409	Oman	13
Andorra	4	Ghana	2	Pakistan	9
Angola	2	Gibraltar	2	Panama	21
Argentina	191	Greece	32	Panama (off shore)	1
Armenia	8	Guatemala	6	Papua New Guinea	2
Aruba	3	Guernsey	44	Paraguay	2
Australia	508	Honduras	3	Peru	10

Austria	63	Hong Kong	200	Philippines	37
Azerbaijan	12	Hungary	24	Poland	39
Bahamas	29	Iceland	13	Portugal	57
Bahamas (off shore)	2	India	39	Puerto Rico	20
Bahrain	8	Indonesia	112	Qatar	15
Bahrain (off shore)	7	Iran	2	Romania	17
Bangladesh	2	Ireland	345	Russia	247
Barbados	7	Isle of Man	9	Saint Lucia	1
Belarus	8	Israel	19	San Marino	1
Belgium	119	Italy	239	Sark	1
Belize	2	Jamaica	7	Saudi Arabia	27
Bermuda	230	Japan	599	Serbia	3
Bolivia	47	Jersey	91	Singapore	108
Bosnia and Herzegovina	2	Jordan	6	Slovak Republic	21
Botswana	2	Kazakhstan	53	Slovenia	9
Brazil	289	Korea	115	South Africa	48
British Virgin Islands	41	Kuwait	14	Spain	193
Bulgaria	20	Kyrgyzstan	1	Sri Lanka	1
Cambodia	4	Latvia	14	St. Vincent and the Grenadines	2
Canada	785	Lebanon	7	Supranational	27
Cayman Islands	417	Liberia	6	Suriname	2
Cayman Islands (off shore)	8	Liechtenstei n	2	Sweden	110
Channel Islands	19	Lithuania	6	Switzerland	187
Chile	57	Luxembourg	433	Taiwan	49
China	60	Macau	7	Thailand	45
Colombia	24	Macedonia	2	Trinidad & Tobago	6
Costa Rica	3	Malaysia	49	Tunisia	11
Croatia	9	Malta	8	Turkey	45
Cuba	2	Marshall Islands	3	Turkmenistan	2
Cyprus	20	Mauritius	13	Turks and Caicos Islands	4
Czech Republic	28	Mexico	457	Ukraine	52
Denmark	77	Micronesia	1	United Arab Emirates	44
Dominican Republic	7	Moldova	2	United Kingdom	1452
Dublin	21	Monaco	1	United States	19073
Ecuador	5	Mongolia	4	Unknown	18
Egypt	12	Montenegro	3	Uruguay	20
El Salvador	7	Morocco	6	Uzbekistan	9
Estonia	9	Multinationa	1	Venezuela	31

		l - Asia			
Faroe Islands	2	Netherlands	583	Vietnam	9
Fiji	2	Netherlands Antilles	66	Unnamed	4349
Finland	46	New Zealand	81		

Country	Number of issuers	Country	Number of issuers
United States	19073	Italy	239
United Kingdom	1452	Bermuda	230
Canada	785	Hong Kong	200
Japan	599	Spain	193
Netherlands	583	Argentina	191
Australia	508	Switzerland	187
Mexico	457	Belgium	119
France	443	Korea	115
Luxembourg	433	Indonesia	112
Cayman Islands	417	Sweden	110
Germany	409	Singapore	108
Ireland	345	Jersey	91
Brazil	289	New Zealand	81
Russia	247	Denmark	77

Industry	Number of debts	Industry	Number of debts
Aerospace & Defense	1949	Hotel, Gaming, & Leisure	3542
Automotive	6465	Media: Advertising, Printing & Publishing	1899
Banking	159762	Media: Broadcasting & Subscription	3219
Beverage, Food, & Tobacco	4884	Media: Diversified & Production	1080
Capital Equipment	6829	Metals & Mining	2762
Chemicals, Plastics, & Rubber	3933	Retail	4842
Construction & Building	3193	Services: Business	2227
Consumer goods: Durable	934	Services: Consumer	905
Consumer goods: Non-durable	2344	Sovereign & Public Finance	140910
Containers, Packaging, & Glass	1510	Telecommunications	7107
Energy: Electricity	3327	Transportation: Cargo	4775
Energy: Oil & Gas	7773	Transportation: Consumer	3138
Environmental Industries	666	Unassigned	9524
FIRE: Finance	31553	Unassigned	1277
FIRE: Insurance	11599	Utilities: Electric	17062
FIRE: Real Estate	4697	Utilities: Oil & Gas	3156

Forest Products & Paper	1506	Utilities: Water	491
Healthcare & Pharmaceuticals	3958	Wholesale	968
High Tech Industries	4813		

Industry	Number of issuers	Industry	Number of issuers
Aerospace & Defense	226	High Tech Industries	638
Automotive	492	Hotel, Gaming, & Leisure	572
Banking	4880	Media: Advertising, Printing & Publishing	276
Beverage, Food, & Tobacco	675	Media: Broadcasting & Subscription	454
Capital Equipment	684	Media: Diversified & Production	128
Chemicals, Plastics, & Rubber	487	Metals & Mining	527
Construction & Building	559	Retail	580
Consumer goods: Durable	134	Services: Business	357
Consumer goods: Non-durable	404	Services: Consumer	117
Containers, Packaging, & Glass	215	Sovereign & Public Finance	1100
Empty	8412	Telecommunications	903
Energy: Electricity	364	Transportation: Cargo	460
Energy: Oil & Gas	1144	Transportation: Consumer	200
Environmental Industries	74	Unassigned	484
FIRE: Finance	2270	Utilities: Electric	998
FIRE: Insurance	3620	Utilities: Oil & Gas	278
FIRE: Real Estate	535	Utilities: Water	93
Forest Products & Paper	207	Wholesale	188
Healthcare & Pharmaceuticals	605		

Coupon frequency	Number of debts	Coupon frequency	Number of debts
Commercial paper/Flexible	5	Every 28 Days	17
Daily	2	Monthly	15418
Variable	254	Not Applicable	2049
Accrued	18284	Quarterly	54847
Annual	58622	Semi-Annual	165308
Bi-Annual (Every 2 years)	48	Tri-Annual (3x Year)	21
Bi-Monthly	168	Unknown	127538
Biweekly (2x Month)	1	Weekly	203
Every 49 Days	33		

Debt type	Number of debts	Debt type	Number of debts

Asset Management Quality Rating	11	Mutual Fund	1185
Bank Credit Facility	12405	Master Servicer	2
Bank Financial Strength Rating	1872	Medium-Term Note Program	5972
Bank Note Program	456	Pass-Through	272
Deposit Program	295	Pfandbriefe, Mortgage	2
Deposit Note/Takedown	3990	Pfandbriefe, Public-Sector	2
Insurance Financial Strength Rating	1218	Probability of Default Rating	2201
Collateralized Note	154	Preference Stock	372
Conv./Exch. Bond/Debenture	4902	Preferred Stock	5471
Commercial Paper	4647	Primary Servicer	7
Covered Bonds - Public Sector	3	Regular Bond/Debenture	353179
Issuer Rating	5352	Deposit Rating	2228
Custodial Management Quality Rating	2	Speculative Grade Liquidity	937
Enhanced Equipment Trust	280	Shelf	11754
Equipment Trust	3310	Corporate Family Rating	4259
First Mortgage Bonds	5622	Sec. Lease Oblig. Bond	64
Investment Agreement	6	Surplus Notes	76
Revenue Bonds	9266	Country Ceiling Bank Deposit Rating	127
Short-Term Rating	33	Country Ceiling Rating	127
OSO Rating	537	Lloyd's Syndicate Performance	219
Covered Bonds	1		

Seniority type	**Number of debts**	**Seniority type**	**Number of debts**
Revenue Bonds	4904	Preferred Stock	7697
Junior Preferred Stock	17	Preferred Stock	3
Junior Subordinated	1425	Subordinated	10814
Senior Unsecured	6	Senior Debt for Prospective Shelf	233
Covered Bonds	5	Senior Subordinated	3121
Multiple Seniority	8175	Senior Secured	29801
Not Applicable	18651	Senior Unsecured	357517
Preference Stock	400	Tier III debt	49

Appendix 2

Default type	Resolution type	Bankruptcy type
Bank holiday	Acquired	Bankruptcy
Bankruptcy	Called	Chapter 11
Chapter 7	Cancelled	Chapter 15
Chapter 11	Company taken private	Chapter 7
Conservatorship	Creditors paid in full	Conservatorship
Cross default	Dismissed	Liquidated
Distressed exchange	Distressed exchange	Placed under administration
Grace period default	Emerged from bankruptcy	Prepackaged Chapter 11
Liquidated	Emerged from Chapter 11	Receivership
Loan forgiven	Interest paid in stock	Seized by regulators
Missed principal and interest payment	Liquidated	
Missed principal payment	Liquidation plan confirmed	
Payment moratorium	Made interest payment	
Placed under administration	Made principal payment	
Prepackaged Chapter 11	Merged	
Receivership	Partial distressed exchange	
Seized by regulators	Reorganization plan confirmed	
Suspension of payments		

This table only lists default types, resolution types and bankruptcy types presented in the sample. All items from these three columns may appear for particular debt in any combination (not as it presented by each line in the table)

Industry	Number of debts	Industry	Number of debts
Aerospace & Defense	390	High Tech Industries	960
Automotive	1466	Hotel, Gaming, & Leisure	717
Banking	8466	Media: Advertising, Printing & Publishing	258
Beverage, Food, & Tobacco	1027	Media: Broadcasting & Subscription	603
Capital Equipment	1875	Media: Diversified & Production	257
Chemicals, Plastics, & Rubber	728	Metals & Mining	296
Construction & Building	366	Retail	1190
Consumer goods: Durable	144	Services: Business	246
Consumer goods: Non-durable	496	Services: Consumer	154
Containers, Packaging, & Glass	199	Telecommunications	1110
Energy: Electricity	1533	Transportation: Cargo	630
Energy: Oil & Gas	1569	Transportation: Consumer	106
Environmental Industries	144	Unassigned	250
FIRE: Finance	10589	Utilities: Electric	4242

FIRE: Insurance	3948	Utilities: Oil & Gas	784
FIRE: Real Estate	1437	Utilities: Water	24
Forest Products & Paper	238	Wholesale	171
Healthcare & Pharmaceuticals	785		

Industry	Number of issuers	Industry	Number of issuers
Aerospace & Defense	86	High Tech Industries	235
Automotive	122	Hotel, Gaming, & Leisure	254
Banking	379	Media: Advertising, Printing & Publishing	95
Beverage, Food, & Tobacco	156	Media: Broadcasting & Subscription	173
Capital Equipment	231	Media: Diversified & Production	44
Chemicals, Plastics, & Rubber	136	Metals & Mining	122
Construction & Building	119	Retail	211
Consumer goods: Durable	48	Services: Business	119
Consumer goods: Non-durable	171	Services: Consumer	48
Containers, Packaging, & Glass	71	Telecommunications	272
Energy: Electricity	114	Transportation: Cargo	80
Energy: Oil & Gas	362	Transportation: Consumer	32
Environmental Industries	35	Unassigned	50
FIRE: Finance	154	Utilities: Electric	253
FIRE: Insurance	1070	Utilities: Oil & Gas	93
FIRE: Real Estate	160	Utilities: Water	8
Forest Products & Paper	45	Wholesale	74
Healthcare & Pharmaceuticals	232		

Rating	Number of debts	Rating	Number of debts
A	27	Ba	4
A1	7116	Ba1	640
A2	6843	Ba2	563
A3	4860	Ba3	1366
Aa	15	Baa	11
Aa1	1442	Baa1	2504
Aa2	2943	Baa2	2731
Aa3	5864	Baa3	2032
Aaa	4066	Ca	14
B	2	Caa	76
B1	931	Caa1	385
B2	1265	Caa2	117
B3	1559	Caa3	22

Appendix 3

	3m	6m	1y	2y	3y	5y	7y	10y	20y	30y
1982	11.09%	11.86%	12.27%	12.80%	12.93%	13.01%	13.06%	13.01%	12.92%	12.76%
1983	8.95%	9.27%	9.58%	10.21%	10.45%	10.79%	11.02%	11.10%	11.34%	11.18%
1984	9.92%	10.42%	10.91%	11.67%	11.92%	12.26%	12.42%	12.46%	12.49%	12.41%
1985	7.72%	8.06%	8.42%	9.27%	9.64%	10.12%	10.50%	10.62%	10.97%	10.79%
1986	6.15%	6.30%	6.45%	6.86%	7.06%	7.30%	7.54%	7.67%	7.84%	7.78%
1987	5.96%	6.33%	6.77%	7.42%	7.68%	7.94%	8.23%	8.39%	8.49%	8.59%
1988	6.89%	7.27%	7.65%	8.10%	8.26%	8.48%	8.71%	8.85%	8.91%	8.96%
1989	8.39%	8.48%	8.53%	8.57%	8.55%	8.50%	8.52%	8.49%	8.47%	8.45%
1990	7.75%	7.85%	7.89%	8.16%	8.26%	8.37%	8.52%	8.55%	8.58%	8.61%
1991	5.54%	5.69%	5.86%	6.49%	6.82%	7.37%	7.68%	7.86%	8.00%	8.14%
1992	3.51%	3.66%	3.89%	4.77%	5.30%	6.19%	6.63%	7.01%	7.34%	7.67%
1993	3.07%	3.22%	3.43%	4.05%	4.44%	5.14%	5.54%	5.87%	6.29%	6.59%
1994	4.37%	4.83%	5.32%	5.94%	6.27%	6.69%	6.91%	7.09%	7.49%	7.37%
1995	5.66%	5.82%	5.94%	6.15%	6.25%	6.38%	6.50%	6.57%	6.95%	6.88%
1996	5.15%	5.29%	5.52%	5.84%	5.99%	6.18%	6.34%	6.44%	6.83%	6.71%
1997	5.20%	5.39%	5.63%	5.99%	6.10%	6.22%	6.33%	6.35%	6.69%	6.61%
1998	4.91%	5.02%	5.05%	5.13%	5.14%	5.15%	5.28%	5.26%	5.72%	5.58%
1999	4.78%	4.95%	5.08%	5.43%	5.49%	5.55%	5.79%	5.65%	6.20%	5.87%
2000	6.00%	6.17%	6.11%	6.26%	6.22%	6.16%	6.20%	6.03%	6.23%	5.94%
2001	3.48%	3.45%	3.49%	3.83%	4.09%	4.56%	4.88%	5.02%	5.63%	5.49%
2002	1.64%	1.72%	2.00%	2.64%	3.10%	3.82%	4.30%	4.61%	5.43%	5.43%
2003	1.03%	1.08%	1.24%	1.65%	2.10%	2.97%	3.52%	4.01%	4.96%	5.91%
2004	1.40%	1.61%	1.89%	2.38%	2.78%	3.43%	3.87%	4.27%	5.04%	5.81%
2005	3.22%	3.50%	3.62%	3.85%	3.93%	4.05%	4.15%	4.29%	4.64%	4.99%
2006	4.85%	5.00%	4.94%	4.82%	4.77%	4.75%	4.76%	4.80%	5.00%	4.91%
2007	4.48%	4.62%	4.53%	4.36%	4.35%	4.43%	4.51%	4.63%	4.91%	4.84%
2008	1.40%	1.66%	1.83%	2.01%	2.24%	2.80%	3.17%	3.66%	4.36%	4.28%
2009	0.15%	0.28%	0.47%	0.96%	1.43%	2.20%	2.82%	3.26%	4.11%	4.08%
2010	0.14%	0.20%	0.32%	0.70%	1.11%	1.93%	2.62%	3.22%	4.03%	4.25%
2011	0.05%	0.10%	0.18%	0.45%	0.75%	1.52%	2.16%	2.78%	3.62%	3.91%
2012	0.09%	0.13%	0.17%	0.28%	0.38%	0.76%	1.22%	1.80%	2.54%	2.92%

Interest rates in grey fields were not presented in the initial data and were calculated by the author in the way to preserve the dynamics of rates across maturities and years

Appendix 4

Industry dummy	Moody's industry classification	Number of debts	Total number of debts
Utilities	Utilities: Electric	4242	5050
	Utilities: Oil & Gas	784	
	Utilities: Water	24	
Energy	Energy: Oil & Gas	1569	3398
	Energy: Electricity	1533	
	Metals & Mining	296	
Services	Services: Business	246	4348
	Services: Consumer	154	
	FIRE: Insurance	3948	
Media	Media: Broadcasting & Subscription	603	1118
	Media: Advertising, Printing & Publishing	258	
	Media: Diversified & Production	257	
Consumer goods	Consumer goods: Non-durable	496	890
	Consumer goods: Durable	144	
	Other	250	
Transportation	Transportation: Cargo	630	2202
	Transportation: Consumer	106	
	Automotive	1466	
Real sector	Telecommunications	1110	11337
	Beverage, Food, & Tobacco	1027	
	Healthcare & Pharmaceuticals	785	
	Chemicals, Plastics, & Rubber	728	
	Aerospace & Defense	390	
	Construction & Building	366	
	Forest Products & Paper	238	
	Containers, Packaging, & Glass	199	
	Wholesale	171	
	Retail	1190	
	Capital Equipment	1875	
	FIRE: Real Estate	1437	
	High Tech Industries	960	
	Hotel, Gaming, & Leisure	717	
	Environmental Industries	144	