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EMPIRICAL ANALYSIS OF REAL CREDIT RISK DATA

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ABSTRACT

One important issue related to credit risk is the analysis of rating transitions and default rates. This consists of examining changes in the rating that international organizations give to firms that agree to be inspected. In this paper real credit risk data from the historical Standard & Poor's database are used to calculate the actual cumulative default rate. I calculate the indicator considering both the starting rating class assigned to the firms and the elapsed time in the state before the default. The first part the paper points out that essentials of the credit rating and presents some descriptive statistics of the S&P historical database. Next, the paper shows the cumulative default rates of the financial instruments recorded by means an empirical model. The model considers two fundamental facts that standard reports do not contain. First, I consider the time elapsed in a given class before a rating change. I also consider the rating assessment named NR (No Rating) which represents the biggest class of ratings in the database.

JEL: G11; G21; C11; C33

KEYWORDS: Standard and Poor's Rating Data, Empirical Model; Default Rate; Rating Transitions

INTRODUCTION

This paper deals with computing the Cumulative Default Rate (CDR) through the analysis of rating transitions and considering the time elapsed within a rating class. CDR is one of the most important indicators of credit risk. The computation of CDR is performed by using the biggest database in the world containing real data on credit risk: the historical file from Standard and Poor's company. The paper analyzes the rating history of 298,125 financial instruments that were rated by Standard and poor's in the time horizon January 1, 1981 to December 31, 2008. There are a growing number of people who consider it useful to assign a score to credit. As a result, the number of individuals, businesses and public institutions that have borrowed money from investors rather than banks gets bigger. Moreover, the universe of investors and market players trying to increase their capital by investing in the stock exchange, because of the return earned from good investments, grows ever more. Financial institutions such as banks and insurance companies take a credit risk by granting loans. They also carry debt of other companies or the central governments. Conversely, commercial companies normally assume a credit risk negotiating products in exchange for payment. Therefore, a risk measure of default rates of the financial instruments issued by companies and institutions is compulsory. Literature about modeling methods for credit scoring is wide and plenty, ranging from logistic regression, classification trees, linear programming, neural networks and stochastic processes. Also, banks and rating agencies continuously publish default rates in a huge number of technical reports.

The analysis performed in this paper adds to the existing body of literature by considering the backward time into CDR calculation. Indeed, the CDR evolution depends not only on the starting rating class assigned to the financial instruments analyzed but also on the elapsed time in a given rating class before the default. In addition, it treats in a special way the rating withdrawals that, because of their large number, deserve special attention. The remainder of the paper is organized as follows. The next section describes the essentials of credit rating and the relevant literature. Next I discuss the data and how the database used is organized. Then I explain the empirical model used. The results are presented and discussed in the following section. The paper closes with some ending comments and some suggestion for further research.

LITERATURE REVIEW

Credit risk traces its origin back to 1860 when the authors Poor and Varnum (1860) underlined the lack of quality information available to investors and publicized details of corporate operations. Only in 1975 did the United States Securities and Exchange Commission (SEC) fix a set of rules to paper. John Moody in 1909 proposed a method for credit quality evaluation and the first credit ratings were published in 1916 by Poor's Publishing Company. Afterwards, the work of US Securities and Exchange Commission (1975) integrated the Security Exchange Act of 1934 (the law governing the secondary trading of stocks, bonds and obligations). It set rules about bank and broker-dealer net capital requirements and established that the safety of securities held by entities must reflect in their credit ratings. Domestic and foreign agencies identified as nationally recognized statistical rating organizations (NRSRO) can assign credit ratings.

The works of Basel Capital Accord (2001) reinforced the trend to identify rating agencies. Later, the SEC issued several rules aimed at assigning a proper role of ratings in the securities laws and at identifying formal procedures for labelling and surveying the activities of NRSRO. In particular, see the Sarbanes-Oxley Act (2002), the Credit Rating Agency Reform Act (2006) and the Updates Credit Rating Agency Reform Act (2007, 2008). The latter specifically deals with the rationale for Residential Mortgage-Backed Securities and Collateralized Debt Obligations. These are linked to subprime residential mortgage-backed securities, overall recognized as the first cause of the worldwide financial crisis. Additional details are available on the Website www.sec.gov/divisions/marketreg/ratingagency. Currently ten organizations are designated as NRSRO (five from United States, two from Canada and three from Japan). Moody's and Standard & Poor's are the oldest, most widely respected, and by far the largest among them. They cover about 80% of the global assessment of ratings. More details on the problem of credit risk in general and on the credit risk modeling can be explored, for example, in books by Bluhm et al. (2002), Chacko et al. (2006), Lando (2004), Trueck and Rachev (2009) or in the Websites www.standardandpoors.com and www.moodys.com.

Measures of credit risk are useful because it simplifies the issues of securities and allows purchasers of bonds to identify a qualified measure of the relative credit risk. The higher the measure, the lower the interest rate the issuer must pay to attract investors. In contrast, an issuer with a bad credit risk score must pay a higher interest rate to offset the greater risk assumed by investors. The argument to measure and to manage credit risk by using the history of transitions from one rating to another has been thoroughly studied in literature. The interested reader can refer, for example, to books by Arvanitis and Gregory (2001), Ammam (2002), Duffie and Singleton (2003), Bluhm and Overbeck (2007) or to papers by Finger (2000), Nickell et al. (2000), Bangia et al. (2002), Hu et al. (2002), Christensen et al. (2004), Perry et al. (2008) and Nickerson (2016). In particular Hamilton and Cantor (2006) exposed the Moody's corporate default rate calculation method and discuss the difference between adjusted and not adjusted CDR for rating withdrawals. To acquire more details about other mathematical models for the credit score such as logistic regression, classification trees, linear programming and neural networks the interested reader can refer to Zmijewski (1984), Tucker (1996), Atiya (1997), Hand and Henley (1997) or Vojtek and Kočenda (2006).

DATA DESCRIPTION

This section provides a detailed description of the data used, of the variables involved and other fundamental information. Since the file used for CDR calculation contains a huge number of data points, I manipulate the data as described below. Used data are taken from the S&P rated universe. The database refers to files about entity ratings history, instrument ratings history and issue/maturity ratings history.

The histories of the rating at our disposal cover the period 1922-2008. For statistical reasons, the empirical computation of default rates considers the time horizon from January 1, 1981 to December 31, 2008. This section provides a description of the main variables in the database. Moreover, it provides the values the variables can assume. Let us present the basic terms used by S&P. The term entity (or issuer) includes any issuer or enterprise able to sell pieces of paper that have any monetary value, such as stocks or bonds. The terms *instrument* and *issue/maturity* (or issues) include any individual debt issue by the entities at a particular time and refers to specific maturities and/or programs. The difference between the second and third data file mentioned concerns different numbers and types of respective market identifiers. To calculate the CDR the database has been managed first by merging the files about instrument ratings history and issue/maturity ratings history and then considering the following variables:

The *entity identifier* and the *instrument identifier*. The latter connects with the issuer. It is possible to link one file to other because there are many intersections between them. That means S&P rates not only issuers and stocks/bonds individually but also structured securities and their corporate counterparts as well. The *sector* variable defines the belonging of each record to Global Issuers, Structured Finance, Public Finance and Managed Funds. A record is the basic information needed to carry out the empirical model employed in this paper. Each record, that is each piece of information, represents a first rating assessment or a rating check, at the respective dates, made for the entities and the debt instruments considered. For the Public Finance sector, notice that only United States public companies are included in the database. The *subsector* variable describes the belonging of the entity or the instrument to Corporations, Insurance companies, Financial Institutions, Utilities, Governments (local or regional), Public Finance (U.S.), Servicer Evaluations and Sovereigns. These are usually collectively refereed to with the general term *corporate*. The sub sector variable may also assume six other values that represent a wide range of structured debt issuance with various characteristics. They mainly include consumer debt such as residential mortgage, credit cards, auto, student loan-backed securities and commercial assets such as commercial mortgages, as well repacking of corporate and structured debt securities. Such securities are usually associated with the term *structured finance*. The *region* variable describes the belonging of entities or instruments to Asia-Pacific, Australia/New Zealand, Canada, Emerging Markets, Europe/Middle East/Africa, Latin America or United States. Table 1 shows the total number of entities and instruments long term rated by S&P, depending on their geographical collocation.

Table 1: Number of Entities and Instruments by Region

Regions	Asia	Auszn	Canada	Emerging	Euromidaf	Latin America	USA
Entities	1,378	600	634	2,336	5,177	1,138	14,200
Instruments	14,476	11,902	13,241	19,278	61,631	13,180	155,640

This table shows the number of entities and financial instruments that have a long term rating assessment by Standard and Poor's depending on their geographical collocation.

The total number of rated entities equals 24,928 and that of financial instruments equals 298,125. All records without a long term rating were deleted from the dataset. The number of financial instruments, in all regions, is much larger than that of the entities. So, to keep statistical significance, only instruments are considered in computing the CDR. The *rating* variable represents the long-term credit rating assessed by S&P to entities and instruments. Credit ratings express an opinion of an agency specialized in evaluating credit risk about the ability and willingness of an entity to meet its financial obligations in full and on time. Moreover, they express an opinion about the credit quality of a single debt instrument. The issue credit rating considers the creditworthiness of guarantors, insurers, or other forms of credit improvement on the obligation and takes into account also the currency in which the contract is issued. The *date* variable considers the respective dates (day, month and year) in which the long-term credit ratings have been assessed or audited by S&P. Different rating agencies use different rating systems. Table 2 shows the general summary of the opinions reflected by S&P ratings and the related symbols.

Table 2: Basic S&P Long Term Rating Scale

Rating	Synthetic Meaning
AAA	Extremely strong capacity to meet financial commitments.
AA	Very strong capacity to meet financial commitments
A	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances
BBB	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions
BB	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions
B	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments
CCC	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments
CC	Currently highly vulnerable
C	A bankruptcy petition has been filed or similar action taken, but payments of financial commitments are continued
D	Payment default on financial commitments

This table summarizes the synthetic meaning the opinions of Standard and Poor's about the long-term credit quality of an individual debt instrument. These opinions are classified in decreasing order of credit quality. Symbol AAA represents the highest rating and symbol D the default. Finer long term rating scales can be used. S&P adds notches by introducing for almost all symbols a plus "+" and a minus "-"with the intention to show the relative standing within the major rating categories

The term *investment grade* refers to issuers and issues ranked BBB and above. This term defines entities and instruments with relative high levels of creditworthiness and credit quality. Conversely *non-investment grade* or *speculative* refers to financial instruments for which the issuer has the ability to repay but faces significant misgivings that could change the credit risk. The related ratings are BB or lower. This higher risk of default is offset by a possible larger gain.

One of the most visited rating from an entity or a financial instrument during its rating history is the NR key. An *issuer* or an *issue* designated NR is not rated. In other words, at some point during the rating history, its rating is withdrawn and is removed from consideration. Nevertheless, it is monitored with the aim of capturing a potential default. Ratings are withdrawn when an entity's entire debt is paid off or when the programs are terminated and the relevant liabilities expire or when the issuer leaves the public bond market. The withdrawal can also happen in the process of mergers and takeovers. In addition, withdrawal can happen due to not cooperativeness, especially when a company is in financial difficulties and does not provide all information needed to evaluate the credit rating. Finally, an entity or a financial instrument with NR assessment may mean that no score was asked or that there is little information to make an assessment or that S&P does not intend to classify it for political reasons. The variables used for empirical calculation of the default frequencies and of CDR are: *instrument identifier, rating* and *date.* In other words, the information used for the calculations that follow are the *id* of the instrument, its first long term rating assessment, the matching date and all the other assessments or checks of the long-term rating (NR included) at the respective dates of the same instrument.

Empirical Model

To properly consider rating transitions evolution, it is necessary to introduce the backward time $b(t)$, which is the time elapsed in a given state. Agencies regularly produce reports based on credit risk data that they own. They include: all types of transition matrices, default rates, conditional and unconditional default probabilities and so on. But unfortunately, all these credit risk indicators do not consider the lapsed time within the same rating class before the default. This time is called backward time: $b(t)= t-b$, where b represents the time since the entrance in a given rating class. In other words, the backward time represents the time occurred since the last transition. In the reminder of the paper, to keep statistical significance, data are aggregated and the variables collected. To carry out an empirical analysis the following have been considered: instrument id; long-term rating; assessment date. To make the analysis more readable, as usual, rating classes from CCC to C have been merged, and then the following rating values have been considered:

$$E' = \{\text{AAA, AA, A, BBB, BB, B,CCC, D, NR}\} \tag{1}$$

As noted earlier, given that a NR rating can be generated for both positive and negative reasons, the model proposed provides for a division of the NR class into two subclasses denoted NR1 and NR2, as in D'Amico et al. (2010). In the analysis, a financial instrument takes the value NR1 when NR had come from AAA, AA, A or BBB, while it takes NR2 when NR had come from BB, B, CCC or D. The space set considered here is the following:

$$E = \{\text{AAA, AA, A, BBB, BB, B,CCC-C, NR1, D, NR2}\} \tag{2}$$

In the following a one-quarter timescale is considered. Since data are recorded as month/day/year, the following time transformation is required:

$$t = \left\lceil \frac{4d}{365} \right\rceil \tag{3}$$

where d is a measure in days, $\lceil x \rceil$ represents the lowest integer greater than x and t is the matching quarterly measure.

According to Altman (1989), for each rating category, a pool of issuers having the same starting rating status is formed. Then the eventual defaults of the issuers on a quarterly timescale are observed. In correspondence of each time, a fraction of the pool has defaulted and represents the marginal default rate in that interval. The cumulative default rate is calculated using the relation

$$CDR_i(t;b) = 1 - \prod_{s=1}^{t} \left(1 - \hat{\lambda}_i(s;b)\right),\ i \in \{AAA, AA, A, BBB, BB,\ B,\ CCC-C\} \tag{4}$$

where $\hat{\lambda}_i(b;t)$ is given by the ratio between the number of defaults at time t and the number of survivals at time t-1. Both are calculated conditionally on the occupancy at the current time of the rating class i with a duration in this state equal to b:

$$\hat{\lambda}_i(t;b) = \left(\frac{nr\ \ of\ \ defaulted\ \ at\ time\ t}{nr\ \ of\ \ survivals\ \ at\ time\ t-1} \,|\, b \right),\ i \in \{AAA, AA, A, BBB, BB,\ B,\ CCC-C\} \tag{5}$$

The value of b is computed considering the number of trimesters from the first assessment up to the first rating change with the formula:

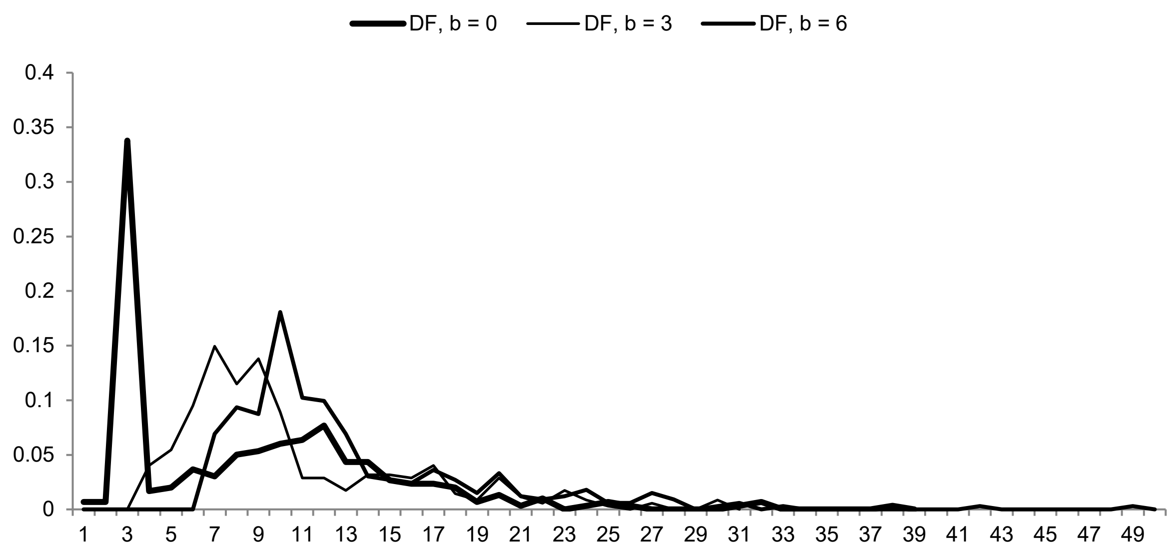
$$b = \left\lceil \frac{d_{fc} - d_{fa}}{365/4} \right\rceil - 1 \tag{6}$$

where d_{fc} is a measure in days the first change of rating from class i and d_{fa} a measure in days the first assessment in the rating class i.

RESULTS AND DISCUSSIONS

This section summarizes results of the calculations in the following graphs. Additional results are available from the author. Figure 1 shows default frequencies of the financial instruments defaulted from the rating AAA and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon equals 50 trimesters. The entrance in the default state includes the entrance in the "bad no rating class", that is in the NR2 rating, as above explained.

Figure 1: Default Frequencies from Rating AAA

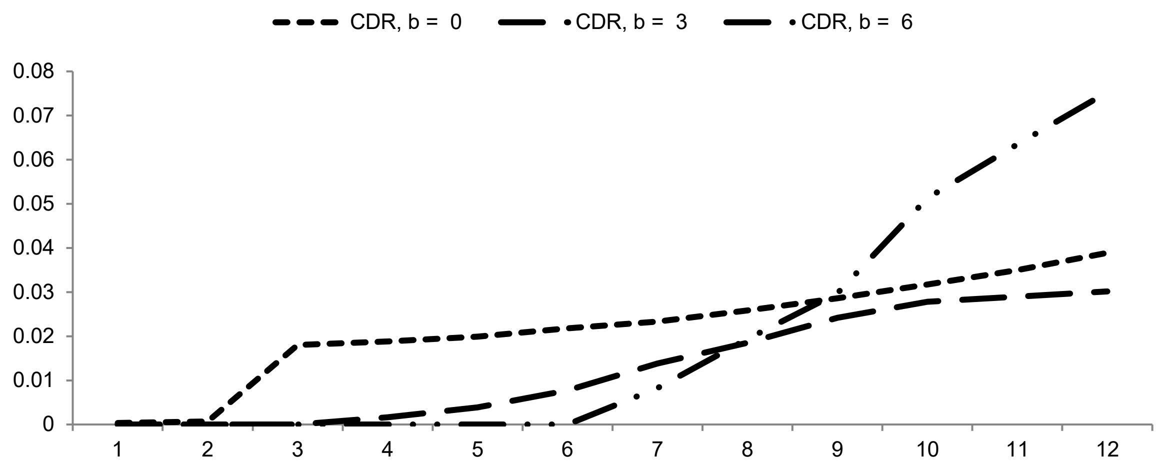


This figure shows Default Frequencies (y-axis) on a time horizon of 50 trimesters- (x-axis) of the financial instruments defaulted from AAA and remaining within the state for 0, 3 and 6 trimesters respectively.

The highest frequencies occur for the financial instruments with entered rating AAA in the same trimester, in which default occurred, as the bold line shows. After the fifteenth trimester, the three lines are close. On the contrary, between the fourth and fifteenth trimester, the frequencies of the instruments defaulted three or six trimesters after the entrance in AAA are higher than those of the instruments defaulted in the same trimester. Figure 2 shows the Cumulative Default Rate of the financial instruments defaulted from AAA and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon equals 12 trimesters.

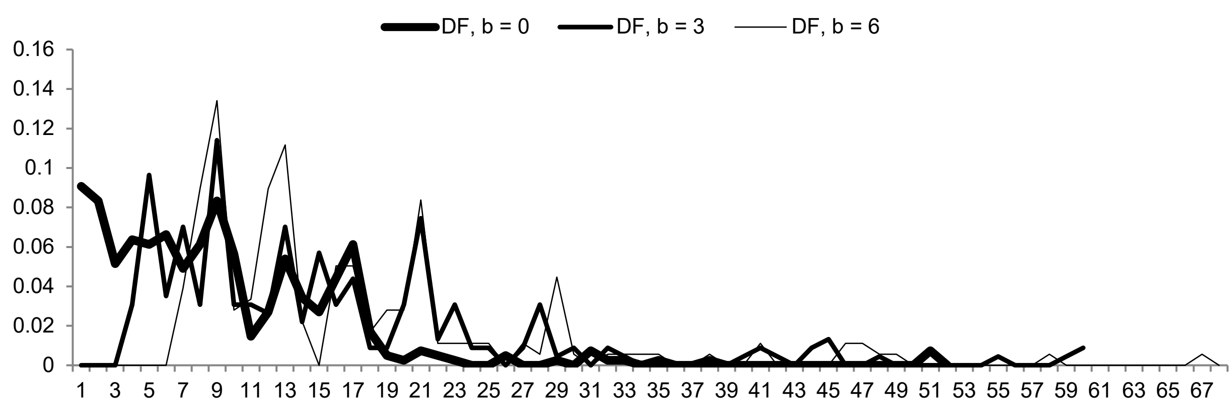
In the first part of the time horizon, up to the ninth trimester, the CDR values of the financial instruments starting from AAA and defaulted in the same trimester (small dotted line) dominate those which defaulted three or six trimesters after they got AAA. After the ninth trimester the highest CDR values occur for the instruments that remaining in AAA for 6 trimesters before defaulting (pointed-dotted line). Figure 3 shows default frequencies of the financial instruments defaulted from the rating BBB and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon equals 68 trimesters.

Figure 2: Cumulative Default Rate from Rating AAA



This figure shows the Cumulative Default Rate (y-axis) on a time horizon of 12 trimesters (x-axis) of the financial instruments defaulted from AAA and remaining within the state for 0, 3 and 6 trimesters respectively.

Figure 3: Default Frequencies from rating BBB



This figure shows the Default Frequencies (y-axis) on a time horizon of 68 trimesters (x-axis) of the financial instruments defaulted from BBB and remaining within the state for 0, 3 and 6 trimesters respectively.

In this case the highest frequencies occur for the financial instruments which entered rating BBB six semesters before (thin line), although the differences are smaller. Throughout the time horizon the three lines are close. Notice the bold line after the nineteenth trimester rapidly gets close to zero. Figure 4 shows the Cumulative Default Rate of the financial instruments defaulted from BBB and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon equals 12 trimesters.

Figure 4: Cumulative Default Rate from Rating BBB

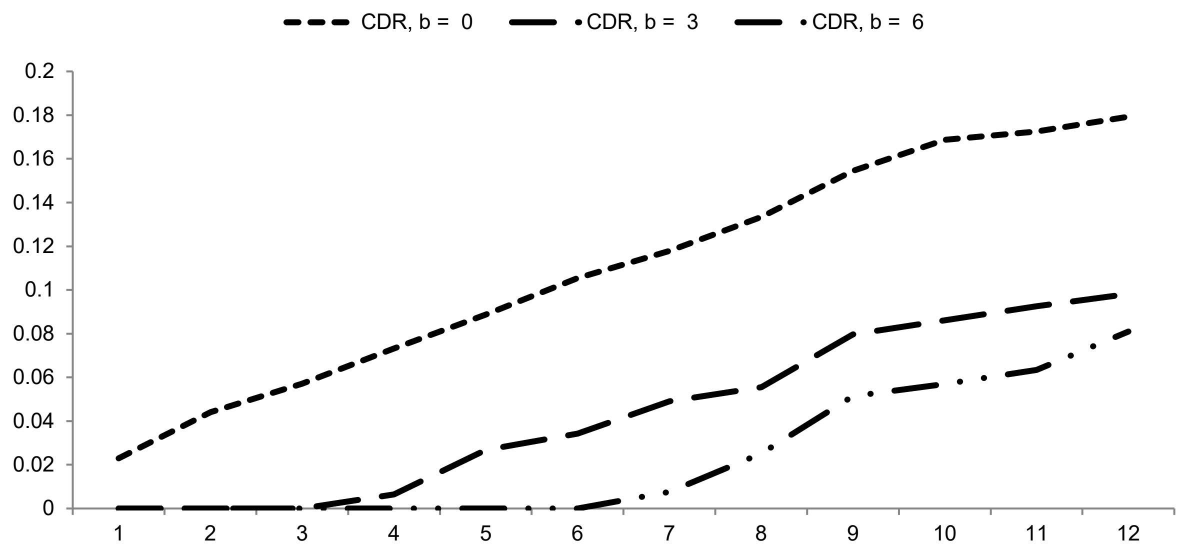
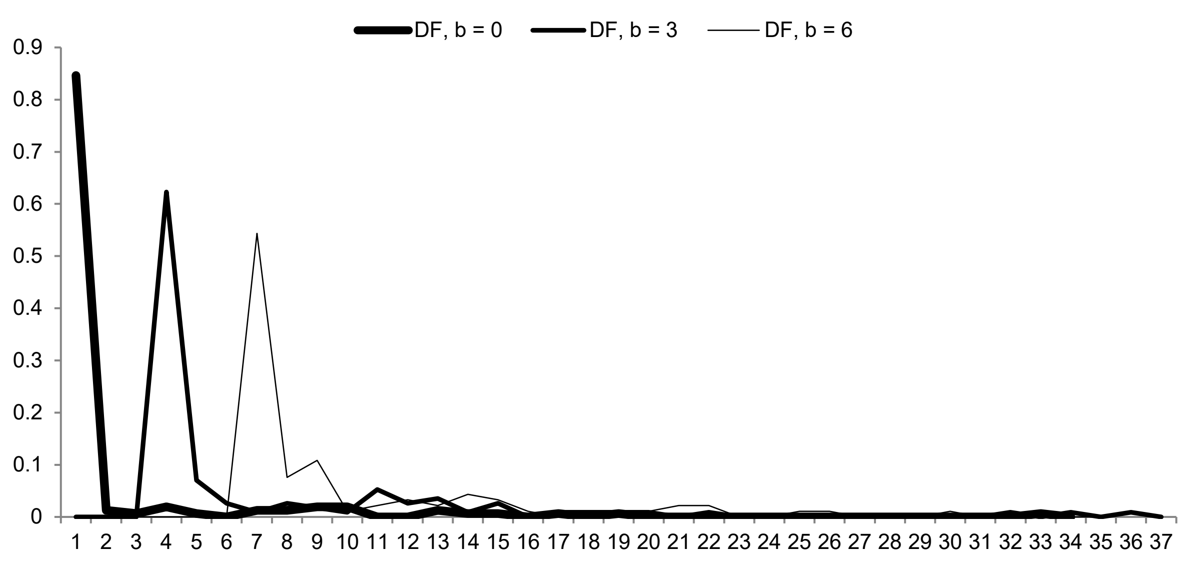


Figure shows the Cumulative Default Rate (y-axis) on a time horizon of 12 trimesters (x-axis) of the financial instruments defaulted from BBB and remaining within the state for 0, 3 and 6 trimesters respectively.

Throughout the time horizon the CDR values of the financial instruments defaulted in the same trimester in which it got BBB (small dotted line) dominate all the others. Figure 5 shows the default frequencies of financial instruments defaulted from the class CCC-C and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon equals 37 trimesters. The three lines show a peak in the early part of the time horizon and rapidly get close to zero.

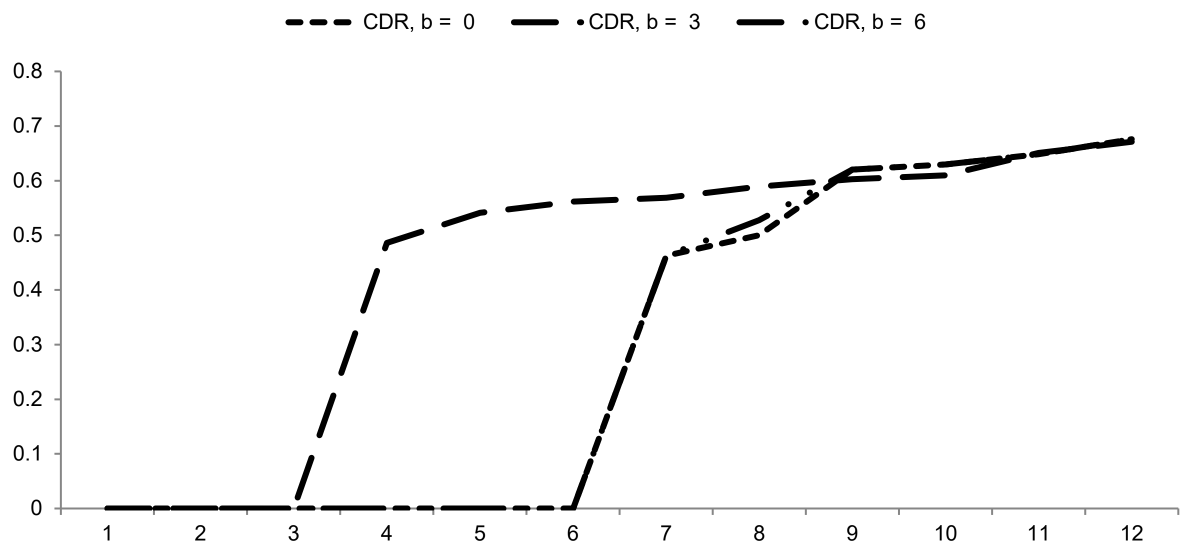
Figure 5: Default Frequencies from Rating CCC-C



This figure shows the Default Frequencies (y-axis) on a time horizon of 38 trimesters (x-axis) of the financial instruments defaulted from CCC-C and remaining within the state for 0, 3 and 6 trimesters respectively.

Figure 6 shows the Cumulative Default Rate of the financial instruments defaulted from CCC-C and remaining within the state for 0, 3 and 6 trimesters respectively. The time horizon is equals 12 trimesters.

Figure 6: Cumulative Default Rate from Rating CCC-C



This figure shows the Cumulative Default Rate (y-axis) on a time horizon of 12 trimesters (x-axis) for financial instruments defaulted from CCC-C and remaining within the state for 0, 3 and 6 trimesters respectively.

The curves have a trend almost similar except the CDR of instruments starting from CCC-C and defaulted in the same trimester (small dotted line) appears shifted towards the previous three quarters. The conclusion is that both Default Frequencies and Cumulative Default Rates frequencies are strongly dependent on the backward values.

CONCLUSION

There are a growing number of people who consider it useful to assign a score to credit. As a result, the number of individuals, businesses and public institutions that have borrowed money from investors rather than banks gets bigger. Moreover, the universe of investors and market players trying to increase their capital by investing in the stock exchange, because of the return earned from good investments, grows ever more. I strongly recommend an accurate analysis of the default frequencies and of the cumulative default rates, both considering the backward time values. This article fills the gap in the literature by examining the quoted credit risk indicators considering how much time the financial instruments remains in a given rating class before the default, that is considering the backward time values. I performed the calculations by using real credit risk data from the S&P historical database. I calculated the CDR through the ratio between the number of defaults at time t and the number of survivals at time t-1. I evaluated both conditionally on the occupancy at the current time of a given rating class with duration in this state equal to the interval time from first assessment up to first rating change.

The results show the CDR is strongly dependent on backward time values. The limitation of the paper concerns the way the credit risk indicators were computed. To keeping statistical significance, I did this by considering all types of debt instruments including corporate and structured finance securities at the same time. Future research might consider separately the defaults of structured finance and corporate instruments. But, unfortunately, the number of such securities distinctly considered would have been insufficient from a statistical standpoint. Also, the analysis considers instruments rated up to December 31, 2008. Much has economically occurred since December 31, 2008. Unfortunately, from 2008 onwards real data are no longer available to me because of a close of the contract with S&P Company.

I would like to highlight the force of the paper because the method I suggested has proved to be successful. Further research will examine the behavior of some stochastic processes such Markov (Jarrow et al, 1997; Israel et al, 2001; Hu et al, 2002) or their generalization such semi-Markov (Vasileiou and Vassiliou, 2013; D'Amico et al, 2014) in following how rating changes deviate by making use of real data. I will compare with the results shown here. In a follow-up paper, I will set up the same data set by using the named stochastic processes to evaluate what better fits the real data.

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