Third International Conference on Credit Analysis and Risk Management

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Edited by

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and Hong Qian

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INTRODUCTION

A SUMMARY OF THE THIRD INTERNATIONAL CONFERENCE ON CREDIT ANALYSIS AND RISK MANAGEMENT

AUSTIN MURPHY[1]

The Third International Conference on Credit Analysis and Risk Management was held on August 21-22, 2014, in Rochester, MI, at Oakland University, whose Enterprise Risk Analysis Institute in the Department of Accounting and Finance founded the conference series in 2011. The conference was as informative, useful, and enjoyable as the prior two. The chapters in this book summarize some of the presentations and discussions that occurred in the 2014 conference.

Terry Benzschawel, Global Bond Portfolio Analysis Director at Citibank, led off the conference with a fabulous review of past trends in credit analysis that provided substance for forecasting future directions for this vital financial science. The first chapter is devoted to his writing on this presentation.

Subsequent chapters by various authors summarize presentations on numerous topics. These include an investigation into the actual risks associated with money market funds, a credit card loss analysis, an overview of macroeconomic credit risks in emerging markets, a sovereign bond trading strategy, models of collateralized debt obligations, loan screening with credit transfer, credit risk with off-balance-sheet obligations, counterparty risk, a model of bank credit risk with contagion, internal liquidity management issues, general models of estimating default risk, hedging debt portfolios, a new measure of debt systematic risk, losses upon default, Basel III analysis, and the effect of sovereign risk on domestic corporate credit spreads.

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There were also many other informative seminars, including ones given by three other keynote speakers. Kevin Cooper of Ford Motor Credit provided a fascinating talk on credit risk management for automobile loans. Professor Tyler Shumway of the University of Michigan at Ann Arbor supplied a unique analysis of the credit risk involved in the private firm loan market. Kevin Bodie of Comerica Bank supplied great insights into the management of commercial loan risk. A listing of all the conference sessions is provided in Exhibit 1.

The next conference in this series is scheduled for August 27-28, 2015, in Basel, Switzerland. See http://www.oakland.edu/business/creditconf

Exhibit 1 Schedules for the Third International Conference on Credit Analysis and Risk Management*

Thursday, August 21, 2014

1p.m. - 2:00 p.m.	**Credit Risk Models: Past, Present, and Future (Introductory Keynote Speaker Terry Benzschawel, Citibank)**
2 p.m. – 2:30 p.m.	Industry Characteristics and Debt Contracting (Alon Kalay and Gil Sadka, Columhia Business School)
	Introducing the Exchange Traded Pieced Loan (Richard Bussman, Central China Normal University)
2:45 p.m. – 3:15 p.m.	Proper Computation of Credit Exposures under the Real World and Risk Neutral Measures (Harvey Stein, Bloomberg)
	Systematic Risk and Yield Premiums in Bonds (Austin Murphy, Oakland University)
3:45 p.m. – 4:15 p.m.	The Stochastic Recovery Rate in CDS (Chanatip Kitwiwattanachai, University of Connecticut)
	Sovereign Risk Spreads in Europe (Yan Sun, IMF, and Frigyes Ferdinand Heinz, IMF)
4:30 p.m. – 5:00 p.m.	*The Relation between Counterparty Default and Interest Rate Volatility, and its Impact on the Credit Risk of Interest-Rate Derivatives (Tao Wu, Illinois Institute of Technology)*
	Assessing Credit Risk in Money Market Portfolios (Emily Gallagher, Paris School of Economics)

6 p.m. - 8:45 p.m.	**Dinner with Keynote Speaker Kevin Cooper (Ford Motor Credit) at Oakland University Meadow Brook Hall**

Friday, August 22, 2014

8 a.m. – 9 a.m.	**Day's Opening Keynote Speaker Kevin Bodie (Comerica)**
9:15 a.m. – 9:45 a.m.	Banks' Loan Screening Incentives with Credit Risk Transfer (Marc Arnold, University of St. Gallen) The Credit Risk Premium: Measurement, Hedging, and Prediction (Terry Benzschawel, Citibank)
10 a.m. – 10:30 a.m.	Applying Technology to Enhance Decisioning throughout the Credit Lifecycle (Tara kinner, SAS) Does the Macro-economy Impact Industry Credit Risk: A Study in an Emerging Market (Rimpa Saha, Arunkumar Gopalaswamy, Indian Institute of Technology)
10:45 a.m.–11:15 a.m.	Forecasting Loan Loss Rates using Multivariate Time-Series Models (Hongbing Chen, Stonegate Mortgage) Model for Sovereign Default Risk and Relative Value (Terry Benzschawel, Citibank)
11:30 a.m. – 12:45 p.m.	**Lunch with Keynote Speaker Tyler Shumway (University of Michigan), "Forecasting Defaults of Private Firms"**
1 p.m. – 1:30 p.m.	*Can Balance Sheet Diversification Substitute for the Bank Capital? (Matjaz Steinbacher. Kiel Institute for the World Economy)* Liquidity and Corporate Governance: Evidence from Family Firms (Liang Fu, Oakland University)
1:45 p.m. – 2:15 p.m.	*How Does Government Borrowing Affect Corporate Financing and Investment? (Mark Leary, Washington University*) Credit Risk Measurement, Leverage, and Basel III (Marianne Ojo, North West University, South Africa)

2:30 p.m. – 3:00 p.m.	*Consumer Credit on American Indian Reservations (Peter Grajzl, Washington & Lee University* Credit Risk and Off-balance-sheet Contractual Obligations (Shao Zhao, Oakland University)
3:15 p.m. – 3:45 p.m.	Sovereign Risk and the Pricing of Credit Default Swaps (Matthias Haerri, University of Applied Sciences Northwestern Switzerland) Joining Risk and Rewards (Harvey Stein, Bloomberg)
3:50 p.m. – 4:20 p.m.	*"Forecasting Credit Cards' Portfolio Losses in the Great Recession: a Study in Model Risk" (Sougata Kerr, Federal Reserve Bank of Philadelphia)*
4:30 p.m. – 5:00 p.m.	Merton's Model with Stochastic Recovery (Albert Cohan, Michigan State University) *Two Risk Models for CMOs with Credit Tranching (Dror Parnes, University of South Florida*, and Michael Jacobs Jr. (Price Waterhouse Coopers)

** Sessions in italics indicate live video teleconferencing*.
For more information, see http://www.oakland.edu/internationalcreditconference.

CHAPTER ONE

DEFAULT MODELS: PAST, PRESENT, AND FUTURE

TERRY BENZSCHAWEL[1]

Abstract

The roots of default models can be found in the origins of credit markets, beginning with fundamental analysis, the development of financial ratios, and the emergence of credit rating agencies and agency ratings in the early 1900s. Altman's (1968) z-score model marks the beginning of the modern era, consisting also of applications of the risk neutral pricing framework to credit and the development of Merton-type structural default models and hybrid statistical-structural models. The recently-developed market-implied PD model (Benzschawel and Assing, 2012) bridges the current and post-modern modeling eras. The post-modern period is characterized by development of expert systems and big data methods, whose potential is just beginning to be exploited. Models are presented from a practitioner's viewpoint, focusing on each's accuracy, ease of implementation, advantages and limitations as well as how each has increased our predictive ability with regard to obligor risk and asset relative value. Each level of model improvement requires greater amounts of input data, computational power, and theoretical complexity. Also, despite ongoing improvements in model accuracy and comprehensiveness, all model types continue to find uses among various investor types and for different applications.

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Introduction

As expressed in the motto of the original Dun & Bradstreet credit rating agency, credit is "Man's Confidence in Man" (Downes and Goodman, 1991): the exchange of a liquid asset (i.e., cash) for a documented promise of payments in the future. In general, credit instruments consist of loans, bonds, charge-account balances with commercial firms, and, more recently, credit default swaps and other financial obligations. A common feature of these instruments is that their returns are subject to the risk of default.[2] This report describes the history of methods for analyzing the default risk of credit issuers from its origins in the fundamental analysis of government bond risk to the latest applications of "big data" techniques to predict corporate bankruptcy. Although most previously successful forms of credit analysis continue to play various roles in financial markets, the modern demand for quantitative estimates of default probabilities has resulted in the dominance of risk-neutral and structural credit models for use by broker dealers and investment firms for trading and risk management.

Over the past several decades, models of default risk have evolved from fundamental analysis, agency ratings, and regression-based models to become dominated by structural models and reduced form approaches in their various forms. In addition, evaluations of default model accuracies have transitioned from anecdotal descriptions of predictive success to quantification using methods derived from statistical decision theory. It is important to note that default prediction is a statistical problem; one rarely knows with certainty if a borrower will default prior to the actual non-payment of an obligation. Given the inherent uncertainty in the default process, it appears that after several decades of refinements within modern modelling approaches, we are reaching a limit in our ability to accurately predict default over time horizons of a year or more.[3] That fact, along with limitations of existing frameworks to provide reliable estimates of default risk for sovereign nations, municipalities, financial firms, and private companies, is fueling demand for new classes of credit models. In fact, applications of "expert consensus" and "big data" methods have been proposed to fill that demand, examples of which are described below.

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[2] These now include structured credit products such, as collateralized loan obligations (CLOs), single-tranche CDOs, credit options, and even counterparty credit risk.

[3] For example, the "best" available credit models all capture roughly 60%-70% of firms who will default within the next year within the top 10% of firms that are ranked as riskiest.

Most of the discussion herein concerns the application of quantitative techniques for estimating credit risk and relative value. However, at present, no credit model can serve as an adequate substitute for fundamental analysis in making investment decisions. In fact, a fundamental evaluation of a credit investment should be the final step in the credit vetting process; a process that should also involve analysis using quantitative techniques. Although no current model is adequate to capture the complexity of reality, being ahead of the competition can be profitable. That perspective is useful when considering the development and applications of credit models to problems in credit risk and valuation.

Origins of the Bond Market and Early Credit Analysis

The development of credit analysis is closely linked to the evolution of financial markets, and that relationship is considered briefly in this section.[4] The creation of modern financial assets is generally attributed to the Dutch who, in 1609, invented common stock to finance the Dutch East India Company. The Dutch also established the first version of a central bank at that time (Neal, 1990). By the 1600s, the Dutch already had a government bond market for decades and soon thereafter had all major components of a modern financial system. In 1688, the British invited William of Orange, the Dutch leader, to be their king, and he brought experienced Dutch financiers to England. The Bank of England was subsequently established in 1694 and England went on to have the first industrial revolution and to lead the world economy in the eighteenth and nineteenth centuries (Dickson, 1967).

A century later, Alexander Hamilton, the first U.S Secretary of the Treasury from 1789-1795, worked to establish a modern financial system modeled on Dutch, English, and French precedents. Thus, by 1795, the United States, essentially a bankrupt country before 1789, had strong public finances, a stable dollar, a banking system, a central bank, and bond and stock markets in several cities. And just as the English had succeeded the Dutch in economic and financial leadership, the Americans went on to displace the English as the world's pre-eminent national economy within a century.

For much of the four-century history of modern capital markets, there were few questions regarding credit quality because most bond investing was in the public or sovereign debt of nations and governments, and

[4] An extensive and informative treatment of the historical development of the bond market and credit analysis can be found in Sylla (2002).

investors trusted the willingness and ability of countries and municipalities to honor their commitments. In fact, up until the nineteenth century, only the Dutch, the English, and the Americans, people with representative governments, issued significant amounts of sovereign debt. The development of the railroads in the 1800s fueled the demand for capital in the United States. Early on, this demand for capital could be met with bank credit and stock issues. However, after 1850, railroad corporations grew larger and expanded into territories where few local banks and investors were willing to provide financing. The solution to that problem was the development of a huge market, both domestic and international, for the bonded debt of U.S. railroad corporations. Along with it came the demand for information on the investment quality of those firms

Still, it was not until 1909 that John Moody devised a scale for rating the credit quality of risky obligors, in this case the railroads. By that time, the railroad bond market was a half-century old and the sovereign bond market had been operating for centuries. Thus, both sovereign and corporate bond markets were able to operate without the benefit of agency ratings. How was this possible? Sylla (2002) argues that three important American developments combined to lead to the emergence of bond-rating agencies. These are the credit-reporting (but not rating) agency, the specialized financial press, and the investment banker. The development of each of these institutions is summarized in Figure 1. The agency started by Moody in 1909 represents a fusion of the function of the three institutions that preceded it.

Credit Reporting Agencies

- Letters of recommendation from a known source sufficed until the 1830s
- Lewis Tappan founded the Mercantile Agency in 1841 that sold information to subscribers (became Dun & Bradstreet in 1859) – by 1900, over one million subscribers
- John Bradstreet founded a similar firm in Cincinnati and published the first commercial rating book in 1851
- Merged with Dunn in 1933 to become Dunn & Bradstreet and acquired by Moody's in 1962

Financial Press

- Railroads were America's first big business
- *The American Railroad Journal* began in 1832 and Henry Poor became its editor in 1849
- After the Civil War, Poor and his son published *Poor's Manual of the Railroads of the U.S.,* the recognized authority on railroads
- The Poor company entered the rating business in 1915 and merged with Standard Statistics in 1941 to form Standard & Poor's (S&P), later acquired by McGraw Hill publishers

Investment Bankers

- Bankers who underwrote the deals put their reputations (and capital) on the line in all deals
- The banker was an insider, insisting that companies disclose relevant information, even insisting on being on their boards of directors
- International contacts for capital depended on the bankers reputation (e.g., J.P. Morgan, Kuhn Loeb & Co, Goldman Sachs)
- Resentment rose over bankers access to inside information, rather than banker dominance of corporations

Figure 1. Precursors to the bond rating agency that represent a fusion of functions performed by these institutions prior to the 1900s.

Credit, Credit Risk, and Credit Models

Model-based approaches for estimating credit risk and relative value make some common assumptions and have some common objectives. First, they assume that accurate estimates of the likelihood of default can be derived from information in financial statements, analysts' reports, news services, and market prices. That is, one can build useful models of default. Also, changes in agency credit ratings tend to lag market perceptions of changing credit quality (see below), thereby fueling demand for alternative approaches to estimating default risk. In addition, agency rating scales provide only a ranking of risk and serve to estimate default risk "through the credit cycle," whereas modern investors demand more quantitative and timely estimates of obligors' credit quality. Finally, as shown below, changes in credit quality from equity based models and expert systems can often predict moves in bond yields.

Credit is the provision of access to liquid assets today in return for a promise of repayment in the future. Typically, credit is thought of as the debt that one party owes another. In a credit transaction, there is usually a lender, the provider of credit, and a borrower, also called the obligor or debtor. Most common instruments of credit, particularly with maturities greater than one year, are coupon-bearing instruments called bonds and loans. The simplest debt instrument is one without coupons, called a zero-coupon or discount bond. A diagram of cash flows from the lender to the borrower of a zero-coupon bond appears in Figure 2. The fundamental question in credit analysis is "How much should an investor charge the obligor for lending money to be repaid at a future date?"

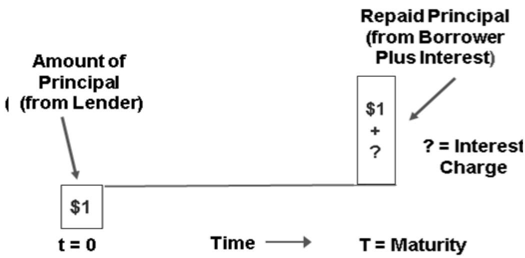

Figure 2. A single risky cash flow of $1 to be received at time T.

Credit risk involves several types of risk, but what separates credit risk from interest rate risk is the potential that an obligor may not make the coupon payments and may fail to pay back the principal. The main risk thought to be associated with credit is default risk.[5] When such a credit event occurs, the due date for repayment of principal is usually accelerated to the date of non-payment and all future coupons are forfeited.[6] The lender has a claim on the borrower's assets for the principal and accrued interest up to that time. Although there is room for legal disagreement about what constitutes default on a financial asset, there is general agreement that it involves several types of credit events (Moody's, 2010). These are:

1. A missed, delayed payment of interest and/or principal;
2. Bankruptcy, administration, legal receivership, or other legal block to the timely payment of interest and/or principal; or
3. A distressed exchange whereby the issuer offers debt holders a security that amounts to a diminished financial obligation, and the exchange has the apparent purpose of helping the borrower avoid default.

In default, lenders rarely receive the full value of principal and interest, and their claims have levels of priority depending on whether the debt is secured, senior, or subordinated.[7] In addition, the recovery value, or, more specifically, the loss given default (LGD), also depends on the firm's industry sector, economic conditions, geography, and other factors.[8] Finally, there is market risk associated with credit investments because the

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[5] In fact, although default risk plays a major role in what drives credit spreads, market risk is likely a greater factor in most changes in the value of credit instruments—see the discussion of credit risk premium below.

[6] Also, there are typically provisions of cross-default, whereby failure to make a specified payment on one obligation triggers defaults on the firm's other debt instruments, even if no payment from those are due at that time.

[7] The position of a given type of debt in the firm's capital structure has legal implications in recovery via the Absolute Priority Rule (Eberhart, Moore, and Rosenfelt, 1990). However, despite legal priority, in practice the strict priority rule is violated routinely. Despite routine violations of the Absolute Priority Rule, the effect of priority on amount recovered in default has been confirmed (Altman and Eberhart, 1994; Fridson, and Garman, 1997). An excellent discussion of the role of seniority in recovery value during default can be found in Schuermann (2005).

[8] In fact, the likelihood of default has been much more well-documented and received greater attention from modelers than has loss given default, but its importance in risk and relative value is coming to be widely recognized, particularly with recent changes in the regulatory environment (i.e., Basel regulations). Although recovery models are not the subject of this report, extensive treatments can be found in Benzschawel (2012) and Benzschawel and Su (2013).

value of a credit instrument may change prior to maturity. Market risk results from changes in interest rates, changes in market liquidity, and the credit risk premium. The credit risk premium, described in detail below, reflects interplay between the willingness of lenders to lend and borrowers' demands for credit.

Historical Default Rates and Recovery Values

Credit rating agencies have been tracking corporate defaults for nearly a century and have been documenting cumulative default rates over time for each initial letter-rating category. To provide a historical perspective on the cyclicality of corporate defaults, Figure 3 displays average annual default rates since 1920 for firms with speculative grade ratings, (i.e., rated below Baa3; see Figure 8 for the credit rating scale) as reported by Moody's (Emery, Tennant, Kim, and Cantor, 2008, and Moody's 2013). The figure reveals that default rates are far from uniform, displaying large spikes and clusters in times of economic stress and periods of little or no default. Also, rarely is a very high default year followed by a very low one; default rates tend to change gradually. Finally, the figure shows that we have just emerged from another cycle of high default rates. Benzschawel and Su (2013) estimate that the annual default rate for 2014 will be just over 2%.

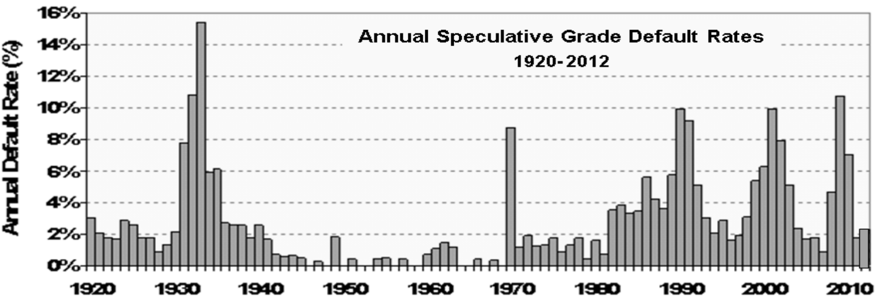


Figure 3. Annual speculative grade (Moody's ratings below Baa3) default rates from 1920-2012.

Other aspects of annual default rates are worth noting, as illustrated by the frequency distribution of annual default rates presented in Figure 4. First, default rates are not normally distributed (i.e., not Gaussian); they are highly skewed toward higher values. Although the average annual default rate is 2.8%, that rate only occurs in about 10% of the years. In fact, during most years, the annual high yield default rate is between 0% and 1%. Historical annual default rates for individual rating categories (not shown) are also skewed. Thus, although one often hears reference to average historical default rates, historical averages are clearly not appropriate measures of their central tendency.

Although measuring and modeling the default rates on risky debt has a long history, the amount recovered in default has received much less attention. This is surprising in that the recovery value in default plays an equal part with default probability in losses from default on risky assets. The expected loss given default, EL, depends on both default and recovery. That is,

$$EL = PD * (1 - RV) \text{, (1)}$$

where PD is the probability of default and RV is the recovery value in default. Despite the fact that expected loss depends on both recovery value and default probability, when estimating portfolio losses, managers commonly assign PDs based on a model, but assume a constant RV. In recent years, major credit rating agencies have reported statistics on recovery values in default because subsequent research has greatly increased our understanding of recovery value and our ability to construct predictive models.[9]

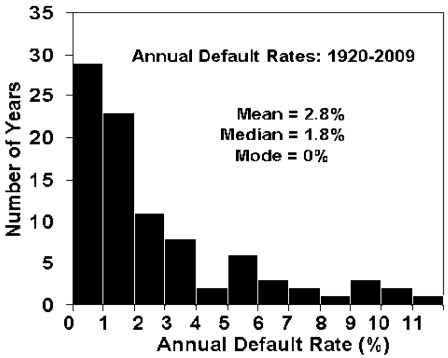


Figure 4. Annual value-weighted default rates, 1920-2008.

[9] For examples, see Verde (2003); Varma and Cantor (2004); Vazza, Aurora, and Miller (2007); and Emery, Ou, and Tennant (2010).

The earliest calculations of historical bond prices just after default averaged roughly 40% of face value (Hickman, 1958; Altman and Nammacher, 1984; Altman and Kishore, 1996). In fact, those early studies provide the basis for the oft-used constant value of 40% recovery of face value by market practitioners. However, the left panel of Figure 5 reveals the wide range of recovery values observed for defaulted firms. Moreover, the shape of the distribution of recovery rates is highly skewed and even bimodal. Also, it appears that neither the mean recovery rate of 40% nor the median of 34.5% are very good predictors of the recovery rate for any single case and that the most common amount recovered in default is about 20%.

The business cycle has also been shown to have a significant influence on recovery in default. That is, results reported by Frey (2000a, b) indicate that recoveries are lower in recessions than during expansions, which was later corroborated by Altman, Brady, Resti, and Sironi (2003). For example, the middle and right panels of Figure 5 display average annual default rates and recovery values, respectively, for senior unsecured debt. In the middle panel, the bars indicate default rates and the connected circles show recovery rates on an inverted scale on the right side. Clearly high and low extremes in recovery rates occur during low and high default periods, respectively. The dependence of recovery on default is demonstrated more clearly in the right panel of Figure 5, which plots average annual recoveries against average annual default rates.

Figure 6 shows that the amount recovered in default depends on other factors as well. These include the seniority of the debt in the capital structure (left panel), industry sector (middle), and agency rating prior to default (right). The interdependencies of all these factors and the relative lack of historical data on recoveries have made it difficult to generate accurate estimates of recovery value in default. Thus, despite the crucial role of recovery value on expected losses in default, very few well-tested models of recovery value have been proposed.[10] Issues regarding recovery value are presented herein to illustrate an existing problem for which newer types of model, such as crowd sourcing and big data, offer potential for greatly improving our ability to accurately estimate expected losses on credit portfolios.

[10] These include Moody's LossCalc (Dwyer and Korablev, 2008), S&P's Ratings Direct (Standard and Poor's, 2008), and Citi's E-3 Ensemble Model (Benzschawel and Su, 2013).

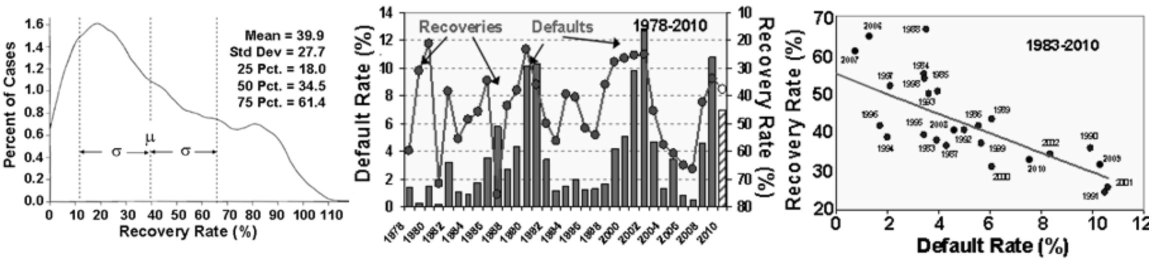
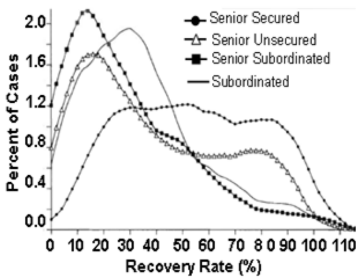


Figure 5. Left: Frequency Distribution of Recovery Rates for Bonds and Loans, Moody's 1970-2003; Middle: Annual Default Rates (Bars) and Recovery Rates (Circles; Inverted Axis); and Right: Scatterplot of Annual Recoveries versus Defaults.



Sector Name	SIC code (4 digit)	SIC code (2 digit)	Average (%)	Std. Dev. (%)	Count
Agriculture / Mining	0199-1499	01-14	53	26	107
Construction	1500-1799	15-17	47	27	110
Food / Tobacco / Clothing	2000-2299	20-22	53	31	106
Clothes / Wood / Furniture	2300-2599	23-25	43	27	65
Paper / Printing	2600-2799	26-27	38	27	150
Chemicals / Rubber	2800-3099	28-30	44	30	136
Leather / Stone / Metal	3100-3499	31-34	44	30	156
Machinery / Electronics	3500-3699	35-36	45	30	134
Transportation Equipment	3700-3799	37	40	31	127
Manufacturing (Misc.)	3800-3999	38-39	40	29	55
Land Transportation	4000-4499	40-44	44	22	54
Transport / Pipelines (Other)	4500-4799	45-47	33	19	284
Communications	4800-4899	48	37	30	371
Utilities	4900-4999	49	58	33	229
Wholesale Trade	5000-5199	50-51	42	33	89
Retail Trade	5200-5999	52-59	49	29	266
Depository Financial	6000-6099	60	33	30	144
Nondepository Financial	6100-6199	61	63	27	150
Securities / Broker Dealer	6200-6299	62	9	2	294
Insurance / Real Estate	6300-6799	63-67	39	29	149
Travel / Entertainment Services	7000-7999	70-79	53	29	244
Services (Misc.)	8000-8799	80-87	62	22	431

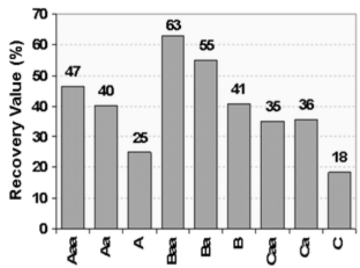


Figure 6. Diagram of median log default probabilities from Citi's HPD model as a function of agency rating category (lower axis) and five-year CDS spread (top axis) illustrating the mapping between HPD score and inferred credit rating or CDS spread.

Early Credit Models: Fundamental Analysis, Agency Ratings, and Financial Ratios

To begin the discussion of credit models, consider first the origins of quantitative credit analysis as embodied in fundamental analysis, including agency ratings and the initial applications of financial ratios to default risk.

Fundamental Analysis. Fundamental credit analysts examine in detail a firm's balance sheet, income statement, management, position within its industry, and future prospects. On that basis, they form opinions regarding whether a firm's credit is improving, deteriorating, or stable, and possibly if its debt is trading rich, cheap or is priced fairly. For example, financial analysts typically consider a firm's past records of:

- Assets,
- Earnings,
- Sales,
- Products,
- Management, and
- Market positioning.

From that analysis, they predict future trends in those indicators and their implications for firms' success or failure. They may even make qualitative judgments about firms' default risk relative to other firms and whether or not firms' assets are fairly priced.

Fundamental analysis is a well-established and critical aspect of investment strategy and will continue to be so. Despite its usefulness, fundamental analysis has many limitations. Figure 7 lists some advantages and disadvantages of fundamental analysis. An advantage of fundamental analysis is that it can provide a close and in-depth monitoring of a firm's activities and provide a detailed assessment of its management. Analysts are also forward looking in that they attempt to project the prospects of the firm in the context of its industry and the economic environment. Fundamental analysis is particularly useful for avoiding credit spread "blow-ups" and for early identification of financial problems. Furthermore, analysts can identify potential event risk, such as leveraged buyouts, equity buybacks, mergers, etc., events that are often challenging for model-based approaches.

Advantages

- Close and in depth monitoring of firm's activities
- Useful for avoiding "blowups" and defaults
- Can identify potential "event risk" (LBO, equity buybacks, etc.)
- Forward looking

Disadvantages

- Only single analyst's opinion
- Difficult to quantify
- Intermittent, incomplete, and inconsistent coverage of universe of firms
- Don't always respond to market movements and events
- Analysts are expensive

Figure 7. Advantages and limitations of fundamental analysis.

Nevertheless, analysts' views of a firm's prospects often differ and, even at the same advisory company, a new analyst's opinion of a given firm may differ from that of his or her predecessor. In particular, analysts' views can be difficult to quantify; they rarely assign firms' probabilities of default or a spread value of richness or cheapness, tending to prefer qualitative assessments. Fundamental analysts typically do not provide daily opinions, so it is not always clear that one has his latest opinion and an analyst may not respond in a timely way to market moves or events. Also, coverage of a firm may be intermittent; an analyst may leave, and coverage of a firm or industry may be suspended. In fact, there is necessarily incomplete coverage of a large number of firms issuing debt, so tracking analysts' performances can be difficult. Finally, analysts are "expensive," particularly relative to model-based approaches.

Credit Rating Agencies. Credit agencies began analyzing firm default risk in the 19th century. As listed in Figure 1, Lewis Tappan founded the Mercantile Agency in 1941 and the forerunner of Dunn and Bradstreet, Inc. was organized in Cincinnati, Ohio, in 1849 to provide investors with independent credit investigations based on fundamental analysis. At that time, information of firms' credit quality was particularly scarce, and firms found that they could issue debt more cheaply if it had been reviewed by a respected credit agency. Still, it was not until 1909 when John Moody developed the credit rating scale, which he first applied to characterize the relative riskiness of railroad bonds.

Moody's credit rating scale appears along with those of its major competitors, Fitch and Standard and Poor's (S&P), in Figure 8.[11] The

[11] It is difficult to overemphasize the contribution of the agency rating scale to the development of credit markets and to credit modeling efforts. Not only did it allow quantification of judgments about firms' credit qualities, thereby aiding issuers and

major features of rating scales are well known; credits rated AAA/Aaa by S&P/Moody's are of the highest quality, and bonds in all categories down through BBB-/Baa3 are called investment-grade because they have very little near-term risk of default. Typically, investors in investment-grade bonds are concerned with either managing liability or collecting steady income from coupons while monitoring their exposure to mark-to-market risk from changes in credit spreads. Bonds rated below BBB-/Baa3 are called speculative grade or high yield bonds. High yield bonds are typically held in different investment funds than investment-grade bonds and traded by different individuals within the same investment firms. Also, high yield bond investors typically seek higher yields, speculating on price appreciation and on decreases in firms' default risk over time.

Number Code	S&P / Fitch	Moody's	Yield Book	PD Range From	PD Range To	PD Range Avg	Interpretation	Class
0			a4	0	0	0	Risk-Free	Investment Grade
1	AAA	Aaa	a3	0	0.03	0.03	Highest Quality	
2	AA+	Aa1	a2+	0.03	0.05	0.04	High Quality	
3	AA	Aa2	a2	0.05	0.06	0.06		
4	AA-	Aa3	a2-	0.06	0.08	0.07		
5	A+	A1	a1+	0.08	0.10	0.09	Strong Payment Capacity	
6	A	A2	a1	0.10	0.16	0.13		
7	A-	A3	a1-	0.16	0.23	0.19		
8	BBB+	Baa1	b3+	0.23	0.37	0.28	Adequate Payment Capacity	
9	BBB	Baa2	b3	0.37	0.61	0.50		
10	BBB-	Baa3	b3-	0.61	0.84	0.73		
11	BB+	Ba1	b2+	0.84	1.1	0.96	Likely to Fulfill Oligations; Ongoing Uncertainty	High Yield
12	BB	Ba2	b2	1.1	1.3	1.2		
13	BB-	Ba3	b2-	1.3	1.6	1.4		
14	B+	B1	b1+	1.6	2.1	1.8	High Risk Obligations	
15	B	B2	b1	2.1	2.8	2.4		
16	B-	B3	b1-	2.8	3.4	3.2		
17	CCC+		c3+	3.4	4.0	3.7	Current Vulnerability to Default	
18	CCC	Caa	c3	4.0	6.3	4.2		
19	CCC-		c3-	6.3	14	9.4		
20	CC	Ca	c2	14	31	21	In Backruptcy or Default, or Exhibits Other Shortcomings	Distresse
21	C	C	c1	31	67	45		
22	D	D	d	67	100	100		

Figure 8. Credit rating scales from S&P, Fitch, and Moody's along with Citigroup's Yield Book risk categories and average one-year default probabilities by rating category from Citi's HPD model.

investors, but also it enabled historical tracking of defaults and credit spreads by generating ratings for use by subsequent generations of credit modelers.

Bonds' initial agency credit ratings appear to order well their long-term default risk. For example, Figure 9 shows cumulative default rates by year as a function of initial agency rating on linear (left plot) and logarithmic (right panel) default axes. The graphs indicate clearly that bonds in each lower rating category (see Figure 8 for the ordering) have subsequently higher cumulative default rates across the entire 30-year time period. Also, the logarithmic plot shows a very regular vertical spacing of cumulative default curves by rating category. Notice in the right panel of Figure 9 that after about 7-10 years, curves for all rating categories are parallel. That is, marginal default rates settle in, but at rates that are higher for each successively lower-rated category.

The pattern of yield spreads by maturity for each agency rating category also indicates, at least on average, general agreement between agency ratings and investors' perceptions of credit risk. To demonstrate this, consider first the top left panel of Figure 10, which displays a typical bond with promised annual coupons, *c*, paid at semi-annual intervals and a bullet payment at maturity. The equation at the lower left in Figure 10 specifies how the yield on a bond is determined as the single annual discount rate, *y,* which serves to equate the sum of discounted cash flows to the current market price. That equation can be used to derive the curves in the plot at the right in Figure 10. That graph displays, for each letter-rating category, average yield curves as a function of maturity fit to US Treasury bonds and corporate bonds in Citigroup's Broad Investment Grade (BIG) and High Yield Indexes.[12] The lowest yields are for US Treasury bonds (UST), which serve as a benchmark for comparison with the riskier corporate bonds, whose average yield curves are higher for all rating categories and at all maturities. In particular, as bonds go down the credit quality scale (i.e., as agency ratings get lower), magnitudes of yields at each maturity increase monotonically; the lower the agency rating, the higher the yield. Finally, notice that for almost all risk categories, the yield curves are upward sloping; they increase with maturity. However, for the riskiest bonds (i.e., the ones rated triple-C), the curve is inverted, with yields for bonds having short maturities higher than longer maturity ones. In fact, this pattern, while not always present, is typical and is generally assumed to indicate that the marginal risk of high-default obligors decreases over time.[13]

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[12] Citigroup Index Group (2013) describes the criteria for inclusion of bonds in the corporate indexes.

[13] That is, if a risky obligor with default probability $p_{0,1}$ survives one year , the one-year probability between years 1 and 2, $p_{1,2} < p_{0,1}$. But see Berd, Mashal, and Wang (2004) for an alternative interpretation.

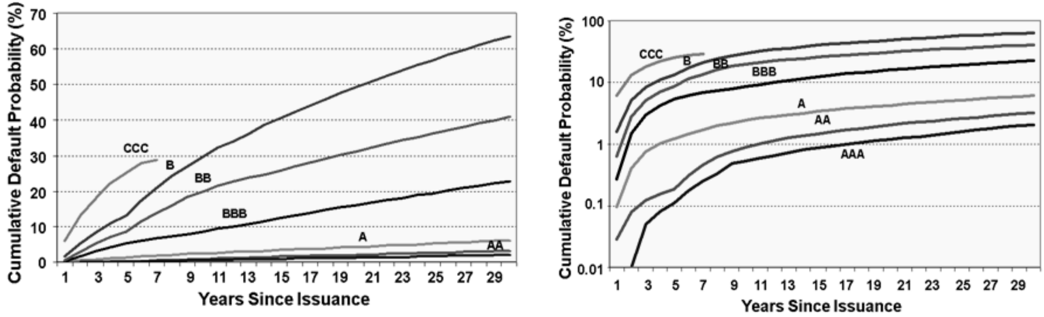


Figure 9. Cumulative default rates by time since issuance and initial rating category on linear (left) and logarithmic (right) axes.

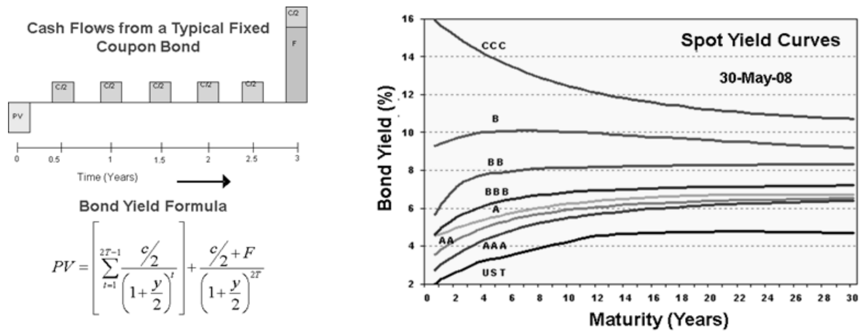
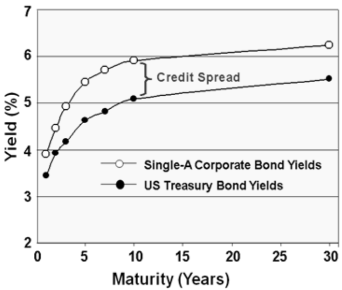


Figure 10. Left: Cash flows from a semi-annual fixed coupon bond and a formula for its yield; Right: par yield curves by agency credit rating.



The present value, *PV*, of a bond with maturity, *T* for:

US Treasuries $PV = \left[\sum_{t=1}^{2T-1} \frac{c/2}{\left(1+\frac{r_{0.5t}}{2}\right)^t}\right] + \frac{c/2+100}{\left(1+\frac{r_T}{2}\right)^{2T}}$

Corporates $PV = \left[\sum_{t=1}^{2T-1} \frac{c/2}{\left(1+\frac{r_{0.5t}+s}{2}\right)^t}\right] + \frac{c/2+100}{\left(1+\frac{r_T+s}{2}\right)^{2T}}$

Credit Spread

Where *PV* is the price of bond with coupons (*c*), r_t is the term structure of US Treasury spot yields at 0.5 year intervals, and *s* is the yield spread of the bond to US Treasuries.

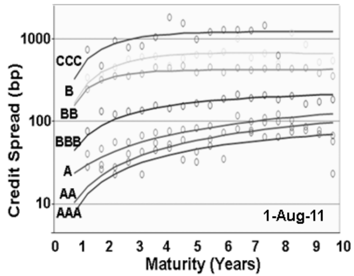
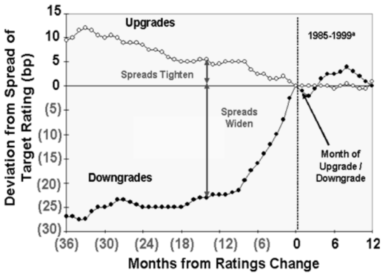


Figure 11. Left: Yield curves for US Treasuries and for single-A corporate bonds; Middle: Formula for calculating yield spreads to Treasuries; and Right: Yield spreads-to-Treasuries by rating**.**



Portfolio Construction Rules:

1. 100 Credits
2. Uniform Ratings from Single-A to Single-B+
3. Average Rating: Triple-B-
4. Maturities from 4 to 12 years
5. Sector / Issuer Maximum: 20%/2%

RANDOM**: Pick Bonds at Random**

GREEDY**: Select Highest Yielding Bonds First**

CONSERVATIVE**: Select Bonds with Lowest Expected PDs from the KMV Model first**

Defaults per Portfolio

	Random	Greedy	Conservative
1994	0.00	0.00	0.00
1995	0.00	0.00	0.00
1996	0.00	0.00	0.00
1997	0.25	1.47	0.00
1998	0.11	0.40	0.00
1999	0.95	3.26	0.00
2000	0.70	0.22	0.00
2001	0.46	1.67	0.00
2002	2.68	4.82	0.00
Mean	0.57	1.32	0.00

Figure 12. Left: Average credit spreads are at agency rating averages in the month of change; Middle and Right: 500 Annual identically-rated portfolios constructed using different rules have different average default rates per portfolio.

The price of a bond is typically quoted in terms of yield spread: the increment in yield over the yield of a Treasury bond of similar maturity (or the term structure of credit spreads) required to match the market price of a bond with a coupon. The bond's spread serves to isolate the price of its credit risk and is typically quoted in basis points (where 1bp is 1/100 of 1%) of yield increment relative to Treasuries (or some other reference such as the London Interbank Borrowing Rate – LIBOR). The left panel of Figure 11 illustrates the credit spreads of hypothetical triple-A corporate bonds of various maturities as the differences in yields between those bonds and US Treasuries of similar maturities. The concept of a credit spread has become an important measure for describing the relative riskiness of bonds.

In addition to the positive features of agency ratings, there are also some well-documented limitations. Consider first the left panel of Figure 12 from Benzschawel and Adler (2002). They tracked differences between spreads of over 2,500 downgraded bonds and over 2,000 upgraded bonds to the average spreads of their future rating categories before and after ratings' changes. The chart shows average differences for upgrades and downgrades separately. For upgrades, spreads start to tighten two- to three-years prior to the upgrade, arriving at the average spread during the month of upgrade. For downgrades, spreads start to widen only nine-months prior to downgrade, but are also at the spread of the target-rating category at the month of downgrade. The middle and right hand panels of Figure 12 show results of a study by McDermott, Skarabot, and Kroujiline (2003, 2004), who constructed portfolios each year from 1994 to 2002 using identical rules for agency ratings' distributions, maturities, and industry sectors, but different selection rules:

1. RANDOM: Select bonds at random as long as they satisfy the rules (i.e., the benchmark).
2. GREEDY: Select the highest yielding bonds first.
3. CONSERVATIVE: Select the bonds with the lowest expected PDs from Moody's KMV model first.

Multiple portfolios of 100 corporate bonds were selected each year from the bonds in Citi's BIG and High Yield Indexes. The right panel of Figure 12 shows the average number of defaults per portfolio by year and the overall average. Note that according to agency criteria, all of those portfolios should be equally risky. Clearly, that is not the case. Selecting the highest yielding bonds as in the "Greedy" method produced over twice the number of defaults per portfolio as the "Random" method. Conversely, the "Conservative" method, picking safe credit according to the KMV model (described below), avoided all defaults, thereby also demonstrating its ability to outperform agency ratings at predicting default risk (or safety in this case).

The development of agency credit rating scales have proven critical to the expansion function of modern credit markets over the last century. Some positive features of agency ratings appear in the left column of Figure 13, with limitations presented in the right column. For example, the agencies have developed consistent rating methodologies, they cover a wide range of corporate, municipal and sovereign issuers, and they have collected and shared publically their detailed data on bond defaults since the 1920s. Furthermore, agency ratings have proven useful, at least on average, as indicators of credit risk and relative value. Nevertheless, as listed in the right portion of Figure 13, agencies are slow to react to credit events. On average, the market recognizes changes in credit quality months, and even years, prior to ratings changes—that is typically, changes in agency ratings trail changes in credit spreads. Also, although the rating agencies have long histories and present average default rates by year and credit quality; Figure 3 and Figure 4 illustrate that default rates are highly dependent on the credit cycle and rarely are they at their mean values. Finally, subscriptions to agency ratings are expensive and, as will be shown below, are inferior to other types of models in ordering bonds by default risk.

Advantages

- Ratings by Moody's, S&P, and Fitch are reliable and generally correct when made
- The agencies cover a wide spectrum of debt issuers
- Provide accurate long-term rankings of default probabilities
- Agreement, on average, between market spreads and rating

Disadvantages

- Agencies are slow to react to credit events
- Reluctant to change a rating, often erring on the conservative side
- Subscriptions are expensive
- Rating changes tend to trail changes in credit spreads
- Use of average historical defaults ignores effects of the credit cycle on default rates
- Other models perform better at predicting defaults

Figure 13. Advantages and limitations of agency ratings.

Despite the limitations of agency ratings, it is difficult to overstate their importance in the development of financial markets, not only in the United States, but globally. One is hard pressed to identify a major corporate or sovereign bond issuer who has found it unnecessary to have an agency credit rating. Furthermore, agency credit ratings have been written into legislation, loan agreements, pension targets, and fund indentures. Although the rating agencies have been criticized as being slow to react to credit changes and to have overstepped their expertise for the rating of structured credit products, no other credit scoring system has had comparable acceptance over such an extended period. In fact, the agency rating is arguably the most successful credit model in existence.

Financial Ratio Analysis

The first reference to ratio analysis can be traced to Euclid, who described its benefits and properties in 300 B.C. (Heath, 1956). However, the application of ratio analysis in finance originated much later, its origins being traced to the late nineteenth century.[14] A financial ratio (or accounting ratio) is a quotient of two numbers where both numbers are taken from an enterprise's financial statements. The earliest reference to a financial ratio is the "quick ratio," attributed to Rosendale (1908), but Horrigan (1968) claims that James Cannon, a pioneer of financial statement analysis, was using ten different ratios as early as 1905, and Foulke (1961) suggests that the current ratio may have emerged as early as 1891.[15] In any case, the use of financial ratios for credit analysis developed rapidly with the introduction of the first ratio criterion for risk, the 2-to-1 current ratio, and inter-firm comparisons and relative ratio criteria. Despite this, few analysts used financial ratios prior to World War I, and those who did were inclined to use only the current ratio. The passage of the Federal income tax code in 1913 and establishment of the Federal Reserve System in 1914 increased demand for financial statements and improvement in their analysis. Wall (1919) responded to this need with his now classic study of seven different financial ratios for 981 firms, stratified by industry and location.

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[14] See Horrigan (1968) for a detailed history of the development of ratio analysis. Additionally, Brown (1955) provides a more detailed description of the early history of financial ratio analysis.

[15] The quick ratio is a measure of a firm's liquid assets relative to its current liabilities.

A rapid development of different ratios took place during the 1920s and that proliferation continued until the 1960s.[16] There are now many financial ratios linked to financial risk, and several of the most widely used ratios are listed in Figure 14. Although quantitative, financial ratios are typically viewed as part of fundamental analysis because, until relatively recently, their relationship to default was not explicitly specified. Fisher (1959) and Beaver (1966) were the first to attempt to systematically evaluate the relationship between financial ratios and corporate failure, and Beaver identified many of the ratios that we view as important today. In fact, that effort by Beaver can be said to have provided the bridge between classical and modern periods in credit risk analysis.

- Quick Ratio (Liquid Ratio):
  - **The ability of a company to use its cash or quick assets to extinguish or retire its current liabilities immediately**

$$\text{Quick Ratio} = \frac{\text{Cash + Marketable Securities + Accounts Receivable}}{\text{Current Liabilities}}$$

- Return on Equity (ROE):
  - **The rate of return on the ownership interest of the common stock**

$$\text{Return on Equity} = \frac{\text{Net Income}}{\text{Average Shareholders Equity}}$$

- Debt Ratio (Leverage):
  - **The percentage of a company's assets that are provided via debt**

$$\text{Debt Ratio} = \frac{\text{Total Debt}}{\text{Total Assets}}$$

- Operating Margin (Profitability):
  - **The ratio of operating divided by net sales**

$$\text{Operating Margin} = \frac{\text{Operating Income}}{\text{Net Sales}}$$

Figure 14. Advantages and limitations of agency ratings.

[16] In fact, Lincoln (1925) already discusses and illustrates 40 different financial ratios.