

Implied Credit Ratings

Kamakura Public Firm Models, Version 4.1

March 2009

Kamakura Risk Information Services public firm default probabilities were launched in November 2002, followed by the KRIS Sovereign Default Service in 2008. The KRIS service provides estimates of the full term structure of default probabilities of an individual public firm based upon current public information about the firm, its economic environment, firm-specific financial ratios and equity market inputs. The maturities that are available are 1 month, 3 months, 6 months, 1 year, 2 years, 3 years, and 5 years. The KRIS default probabilities are used by major corporations and financial institutions in Europe, Asia and the Americas for two major purposes: monitoring the risk of single counterparties and monitoring the risk of large portfolios of counterparties whose default risk is highly likely to be correlated.

The KRIS default probability service also contains the implied credit ratings for each of the 22,000 companies in KRIS, i.e. “Implied Ratings.” These implied ratings rely on the joint assumptions that (a) a credit rating was actually granted to the company and that (b) the rating is consistent with the average behavior of the rating agencies over the period for which the implied ratings relationship was derived. In the case of KRIS version 4.1, this period is 1995-2004. A complete description of the calculation of implied ratings is contained in Appendix E to the KRIS Version 4.1 Technical Guide (February 2006). Appendix E was authored by Professor Robert A. Jarrow, Li Li, Mark Mesler and Dr. Donald R. van Deventer and available to KRIS subscribers only.

Background on Deriving Implied Ratings

Many financial institutions and corporations are extremely interested not only in default probabilities for various maturities but also

- (a) estimated rating agency ratings for those institutions that do not have ratings and
- (b) statistical estimates of the probability of various ratings even for those firms that have ratings, in order to assess the probability of a downgrade or an upgrade in the current rating

For category b, there is an intense client interest in knowing the probability of an upgrade from or downgrade to non-investment grade or “junk” status, since the junk/non-junk shift in ratings triggers a large number of investment policy-related buy and sell signals that cause large drops or jumps in bond prices. While many market observers have urged investors to abandon ratings-linked investment policies, a large number of investors are still constrained by these legacy investment rules.

The uncertainty in rating agency behavior is attributable to the long periods of stability in ratings during times of great changes in default probabilities, financial ratios, stock price inputs, and macro economic factors. Until its recent financial difficulties, for example, Citigroup was rated AA- for more than ten years by Standard & Poor’s during a period that

spanned the tech crash in 2001-2002 and a number of difficult periods in the 1990s. As noted in a March 15, 2006 press release from Kamakura Corporation, the Kamakura version 4.1 default probabilities have a 99.00% accuracy in predicting default of rated public companies, compared to an accuracy of only 96.44% for agency ratings. The ROC accuracy ratio for KRIS is well above the predictive capability of public debt ratings at every monthly time horizon measured through 60 months forward. This relative lack of accuracy also contributes to the uncertainty in rating agency behavior.

KRIS Implied Ratings

The ratings data used for the implied rating modeling was the ratings of Standard & Poor's as reported by S&P affiliate Compustat. The Compustat data was supplemented with a separate file from S&P that contains the exact date of the ratings change for all companies rated by Standard & Poor's. The probability of being "not rated" or "rated" is based on 2.2 million monthly observations of rated and non-rated companies in the KRIS default data base from January 1990 to October 2004. The predicted rating, conditional on being rated, is based on 282,000 monthly observations of public debt ratings C or above over the same time period.

There are three primary methods for mapping from default probabilities to ratings.

1. Create a one to one mapping from a specific default probability range to a specific rating
2. Create a probability of a given rating from the observed default probabilities, a variation on Alternative 1 that allows for the uncertainty in knowing the rating from default probabilities alone
3. Estimate the probability of each rating from default probabilities and other inputs, assigning the "mapped rating" to the median rating grade of the full probability distribution of potential ratings conditional on having a rating. This method also predicts the probability of an upgrade and a downgrade. This technique does not use the existing rating as an input, so it is the equivalent of the predicted rating given that the company had had no prior rating or rating history
4. Estimate the probability of each rating from both the existing rating and other inputs like default probabilities. This is the equivalent of predicting the speed at which S&P will move its rating as the default probabilities and other inputs drift from the "normal" range for companies with that debt rating.

This screen print from the KRIS default probability service begins to show why method 1 is too simplistic:

Home Analysis History Ranking Risk Map Correlations Portfolio Private Firm

Distribution by: Rating Go! Model: KDP-jc Country: USA Date: 2005 Feb 4 Term: 5 Year

Distribution by Rating

% From	% To	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	NR	TOTAL
0.00	0.02	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	86	86
0.02	0.05	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	8	8
0.05	0.10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	15	15
0.10	0.20	3	2	4	6	14	5	13	16	9	2	3	1	-	-	-	-	-	-	-	-	-	-	46	124
0.20	0.30	5	-	8	7	31	55	43	52	73	52	28	27	21	9	6	1	-	-	-	-	-	-	290	708
0.30	0.40	2	1	4	8	13	34	31	45	62	47	22	27	34	22	5	5	1	-	-	-	-	-	715	1078
0.40	0.50	-	1	3	7	7	18	12	26	35	17	17	21	31	24	8	6	3	-	-	-	-	-	631	867
0.50	0.60	2	-	1	3	3	4	7	7	16	15	12	21	25	13	7	6	2	-	-	-	-	-	527	671
0.60	0.70	1	-	-	1	3	4	5	5	6	9	6	13	18	13	8	2	1	-	-	-	-	-	420	515
0.70	0.80	-	-	1	-	1	3	1	2	6	6	-	10	9	12	5	2	-	1	-	-	-	-	391	450
0.80	0.90	-	-	-	-	1	2	3	1	5	8	1	4	6	5	6	1	-	-	-	1	-	-	326	370
0.90	1.00	-	-	-	1	-	2	2	2	2	3	4	1	4	9	3	1	1	1	-	-	-	-	258	294
1.00	1.25	1	-	-	3	1	-	-	3	5	2	3	2	12	10	4	3	-	-	1	-	-	-	504	554
1.25	1.50	-	-	-	-	-	-	-	1	3	3	1	2	9	4	6	4	1	-	-	-	-	-	352	386
1.50	1.75	-	-	-	-	-	-	-	1	1	3	2	1	-	3	6	6	1	1	-	-	-	-	221	246
1.75	2.00	-	-	-	-	-	-	-	-	-	1	1	2	3	2	4	2	-	1	-	-	-	-	158	174
2.00	2.50	-	-	-	-	-	-	-	-	-	-	-	-	1	2	7	6	-	1	-	-	1	-	198	216
2.50	3.00	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	3	2	1	-	-	-	-	110	118
3.00	3.50	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	1	-	-	-	-	2	-	67	71
3.50	4.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-	-	-	-	55	57

This “risk map” from KRIS on February 4, 2005 for five year Jarrow-Chava default probabilities shows that at any given time there is considerable overlap of default probabilities within ratings categories. On this day, AAA-rated Pfizer has a five year default probability of 1.18%, well above the average one year loss experience for AAA-rated companies (which is zero from 1981 to 2002). That default probability is high even for lower ratings grades. Pfizer was at severe risk of downgrade because of problems with many drugs in its product line, just like the withdrawal of Vioxx from the market impacted the formerly AAA-rated Merck.

Given a default probability, it is much more realistic and practical to say that there is a probability that the company may have a number of ratings, assign a probability to each one, and “map” to the median rating grade. This is simple but it is possible to do much better. It has often been observed that ratings agencies have a bias in favor of large companies that is much greater than the impact of size on actual rates of default. The ratings for large companies are said to be biased “high” or “good” relative to their actual default experience. In modeling implied ratings, we can use size as a potential explanatory variable and confirm whether or not this is true.

The other thing we know is that actual default rates and estimated default probabilities for all maturities and all ratings grades rise and fall over the business cycle, but ratings generally vary relative little over the course of the business cycle. This means that we need to explicitly incorporate where we are in the business cycle as part of the implied ratings modeling. Potential explanatory variables include the full KRIS 4.1 reduced form

default probability term structure, all of the KRIS 4.1 input variables individually, company size, macro economic factors, and market capitalization and liabilities level variables.

For these reasons Kamakura has derived implied ratings using the third method above. We describe the modeling in the following section. Kamakura is also very interested in forecasting the future ratings of a company using its existing ratings as an input, instead of method 3 where the prediction is done as if the company had no prior ratings history. For this prediction using the existing rating as an input to have meaning, one would make the prediction time dependent, with a different probability distribution for various points in the future. So far, client demand for the latter type of implied rating has been modest, but Kamakura would be pleased to add this second method to KRIS when demand warrants.

KRIS Implied Rating Calculations

Two estimates are provided in KRIS from the mapping of default probabilities to ratings:

1. The probability that a company has any rating higher than D or SD. For many small companies, for example, no rating is assigned no matter how strong their financials are because the company is simply too small to be a public debt issuer.
2. The probability of various ratings, given that we are to assume the company has a rating, without using the knowledge of the current rating.

The probability that the company has a rating is done by defining a 0/1 dependent variable. The variable is assigned a value of 1 if the company has a rating that is C or above. Using logistic regression, by estimating this variable, we are estimating the probability of a company having a rating of C or above. If the probability of having a C rating or above is less than 100%, the remaining probability is the probability of being not rated.

The probability of having a specific rating, say BBB, is done using an estimation technique called ordinal logistic regression. This estimation is done by defining a single variable which takes on an ordinal value for each ratings grade. Using the ordinal ranking of ratings, we define the variable by which AAA is defined as 1, AA+ is defined as 2, AA is defined as 3, etc. down to C. In this case there would be one regression for all ratings grades and the output would be a smoothed probability distribution by rating grade. We pick the median rating grade from the distribution as “most likely” rating conditional on having a rating. In addition, we could also derive the probability of an upgrade and a downgrade from the distribution.

More specifically, ordinal logistic regression can be thought of as a special combination of more traditional 0/1 logistic regressions. The first logistic regression can be thought of as the probability of being rated AAA. The second logistic regression can be thought of as producing the probability of being rated AA+ or better. The probability of being rated AA+ is the probability in the second logistic regression minus the probability of the first logistic regression. Ordinal logistic regression is an efficient methodology for accomplishing this objective, and it tends to produce a very smooth probability distribution of implied ratings.

Implied Ratings were calculated using ordinal logistic regression and the following explanatory variables: the KRIS 4.1 reduced form default term structure of default probabilities and their inputs, including all of the individual macro economic factors, market capitalization and various dummy variables.

30 variables, including the constant term, are used to predict the probability of having a rating of C or above. The ROC accuracy ratio is 0.9303, a fairly good level of accuracy. Company size is more important than any other variable in predicting whether a company has a rating. In addition to market capitalization, having liabilities in excess of \$90 million is a very important factor in predicting whether or not a company is rated.

The best fitting relationship for predicting the probability of various ratings conditional on having a rating was done on a smaller data set; the data set used consists only of those companies with a rating at that point in time. Using ordinal logistic regression, we find the full term structure of reduced form default probabilities and a number of company attributes (especially size, with a z-score of 225) are all statistically significant in explaining rating agency behavior. The huge statistical significance of company size in explaining ratings, even though the impact of size on default probabilities has already been taken into account, is one of the most important causes of error in agency ratings, as the recent credit crisis has confirmed.

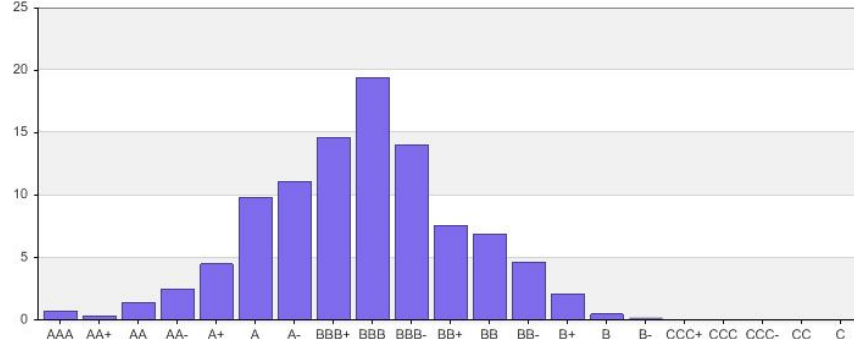
The longer term reduced form default probabilities are more statistically significant than shorter term default probabilities in driving ratings, as one would expect. In all, 31 variables drive rating agency behavior, not just a long term default probability as one might at first expect. One interesting result is that the one year default probability, the primary focus of the Basel II capital guidelines for banks, has less statistical significance in predicting S&P ratings than any other default probability maturity. This shows why it is very difficult to compare default probabilities and ratings---rating agency behavior is driven by many considerations even when the existing rating is not used as an input. Full details of the implied ratings formula and related coefficients are given in Appendix E of the KRIS Version 4.1 Technical Guide, February 2006. This Technical Guide is available only to KRIS subscribers.

Interpreting KRIS Implied Ratings

What is an implied rating? Given the way that predicted ratings have been modeled, we can say this: The implied rating is the rating most likely to be assigned by S&P if (a) the company had not been previously rated and (b) S&P assigned the rating based on company default probabilities and other attributes in the same way that it behaved in rating companies from 1995 to 2004. The case of GE provides a good example of this interpretation. In March of 2009, S&P downgraded GE from AAA to AA+. On March 17, 2009, however, the KRIS Implied Rating for GE was BBB as shown in the following chart.

GENERAL ELECTRIC CO

Most Likely Rating: BBB
S&P Rating: AA+
Probability of:
 Rated 82.95%
 Not Rated 17.05%
 Investment Grade* 64.25%
 Non-Investment Grade* 35.75%
 Upgrade* 0.67%
 Downgrade* 99.03%
 Upgrade to Inv. Grade* N/A
 Downgrade to Junk* 21.71%
 * conditional on having a rating



Dist	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C
Prob	0.7	0.3	1.4	2.4	4.5	9.8	11.1	14.6	19.5	14.0	7.6	6.8	4.6	2.0	0.4	0.1	0.0	0.0	0.0	0.0	0.0
Cum	0.7	1.0	2.3	4.8	9.2	19.1	30.2	44.8	64.2	78.3	85.9	92.7	97.3	99.4	99.8	99.9	100.0	100.0	100.0	100.0	100.0

The implied rating of BBB, compared with the newly refreshed rating of AA+, shows that S&P has been much “kinder” to GE, even after the downgrade, than it has been on average to all of the companies it rated at each month end during the period 1995 to 2004. GE default probabilities, observable credit default swap quotes, and bond spreads all point to the same conclusion.

The KRIS implied ratings have many important uses:

- They are an important supplement to Moody’s and S&P ratings, a “third opinion” so to speak. The opinion is that of S&P itself, as it behaved over the 1995-2004 period, as implemented by Kamakura and driven in large part by Kamakura default probabilities
- They point out where current agency ratings are inconsistent with average rating agency actions over the 1995-2004 period
- They provide early warning of future ratings changes
- They provide an estimate of the probability that a currently unrated company can in fact obtain a debt rating
- They provide a rating for companies that have not been rated by either major rating agency
- They provide an explicit linkage between KRIS default probabilities and the ratings concept, which is useful to managers still in the process of moving from the 100 year old ratings concept to modern quantitative default models that are updated daily.

The remainder of this brochure summarizes the main types of default models available under the KRIS default probability service.

KRIS Public Firm Models: A Summary

Kamakura’s Public Firm Models currently offer four different quantitative approaches to modeling default probabilities: two versions of the Jarrow Chava Model (KDP-jc), the

Merton Structural Model (KDP-ms), and the Jarrow Merton Hybrid Model (KDP-jm). Both the third generation (version 3.0, released in October 2004) and the fourth generation (version 4.1, released January 9, 2006) of the Jarrow-Chava models are available on the web site at the request of the KRIS client base. All of these approaches incorporate information on market prices of firm equity and interest rates, so that current market expectations are fully reflected in the default probability estimates. The availability of multiple Public Firm Models provides subscribers with theoretically sound alternative views on the likelihood a particular firm will default. Version 5.0 of the KRIS models will be released in 2009.

The Jarrow Chava Model

The Jarrow Chava Model is a statistical hazard model that relates the probability of firm default to several explanatory variables. The explanatory variables include firm financial ratios, other firm attributes, industry classification, interest rates and information about firm and market equity price levels and behavior. In this model, firm default can occur randomly at any time with an intensity determined by the explanatory variables. Originally developed by Kamakura's Director of Research, Robert Jarrow, the Jarrow Chava Model provides an objective, statistically reliable method of predicting potential firm defaults. The Federal Deposit Insurance Corporation of the United States announced in December 2003 that it was adopting the methodology incorporated in the Jarrow Chava Model for its Loss Distribution Model for the bank and savings and loan insurance funds. Both the third and fourth generation Jarrow-Chava models incorporate multiple equations for forecasting default at different forward time intervals, conditional on survival to that point in time. These equations share the same inputs but they have different weightings depending on the time horizon. The current and forward conditional default probabilities are combined to derive the full default term structure out to five years.

Merton Structural Model

The Merton Structural Model uses option pricing methods to relate the probability of firm default to its financial structure and information about the firm's market price of equity. The explanatory variables include a measure of the firm's outstanding debt, its market valuation, and information about firm and market equity price behavior. In this model, firm default occurs when the market value of the firm's assets decline below a threshold related to the firm's outstanding debt. Robert Merton, winner of the Nobel Prize in Economic Sciences in 1997, originally developed this model.

Jarrow Merton Hybrid Model

The Jarrow Merton Hybrid Model is a statistical hazard model that relates the probability of firm default to the same explanatory variables as the Jarrow Chava Model, but it also incorporates the default probability of the Merton Structural Model as an additional explanatory variable. In this model, firm default can occur randomly at any time with an intensity determined by the explanatory variables. Kamakura offers this Model to combine the default prediction capabilities of the associated models. Forward default probabilities and the full term structure of default are derived in the same fashion as for the Jarrow-Chava models.

About Kamakura Corporation

Founded in 1990, Honolulu-based Kamakura Corporation is a leading provider of [risk management](#) information, processing and software. Kamakura has been a provider of daily default probabilities and default correlations for listed companies since November, 2002. Kamakura announced the KRIS Sovereign Default Probability Service on May 19, 2008. Kamakura launched its collateralized debt obligation (CDO) pricing service KRIS-CDO in April 2007. Kamakura is also the first company in the world to develop and install a fully integrated enterprise risk management system that analyzes credit risk, market risk, [asset and liability management](#), transfer pricing, and capital allocation. The Kamakura Risk Manager system, now in version 7.0, was first offered commercially in 1993 and has been continually enhanced since then. Kamakura has served more than 185 clients ranging in size from \$3 billion in assets to \$1.6 trillion in assets. Kamakura's risk management products are currently used in 27 countries, including the United States, Canada, Germany, the Netherlands, France, Austria, Switzerland, the United Kingdom, Russia, Eastern Europe, the Middle East, Africa, Australia, Japan, China, Korea and many other countries in Asia.

Kamakura has world-wide distribution alliances with Fiserv (www.fiserv.com), Unisys (www.unisys.com), and Zylog Systems (www.zylog.co.in) making Kamakura products available in almost every major city around the globe.

For more information contact

Kamakura Corporation
2222 Kalakaua Avenue, 14th Floor, Honolulu, Hawaii 96815
Telephone: 1-808-791-9888
Facsimile: 1-808-791-9898
Information: info@kamakuraco.com
Web site: www.kamakuraco.com