Credit Modeling Innovations

A number of conceptual innovations have been central to the transformation of credit risk theory and practice over the past 25 years. The most significant of these contributions are reviewed in this article.

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IN THE 1960S a young academic named Ed Altman turned his attention to improving the rigor of credit risk analysis. Focusing on accounting statements, he developed a weighted average of five financial ratios, which he called a Z-score.[1] The five ratios and the weights were chosen to maximize the resulting index's discriminatory power in predicting default over the one and two years following the date of the statements.

In effect, Altman brought rigorous statistical techniques to the task of defining a credit quality index. In practice, a Z-score was generally supplemented by more qualitative factors like absolute market size, market growth prospects, the level and trend in a firm's

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market share, the existence of legal or logistical barriers to entry for competitors, and threats from new technological possibilities. Over the past 40 years, various manifestations of the Altman Z-score have continued to play an important role in fundamental credit analysis.[2]

Credit Migration Approach

Just as Ed Altman's analysis was a rigorous extension of traditional approaches to credit risk assessment, so the credit migration approach builds on historical data for credit ratings. A transition matrix displays all rating classes in the headers for both the columns and the rows. The elements of this matrix indicate the probability that an obligor starting a period with a rating corresponding to the row will end the period with the rating corresponding to the column. The largest probabilities tend to lie along the diagonal, indicating the high likelihood that a firm's rating will be unchanged during the period.

In its simplest form, this approach makes the aggressive assumption that the probability of a firm migrating to another rating is the same for all firms in a given rating class. For multi-period analysis, it is possible to introduce momentum factors for one or more periods if the data is available to support this level of detail. In this case, entities that migrated in the previous period or periods are deemed to have different future transition probabilities than those with ratings that have been stable. In addition, it is possible to apply different transition matrices depending on the projected state of the economy.

Extending the transition approach to modeling multiple holdings requires some means of imposing correlations on the migration behavior. The approach implemented by CreditMetrics involves simulating the value of each firm's assets against a grid that maps simulated asset values to corresponding credit ratings. This mapping preserves the migration probabilities of the applicable transition matrix. Historical correlations among each firm's equity-value changes are used as proxies for asset correlations, and these are imposed on the simulation process. Future cash flows are then discounted in each simulation based on rates appropriate to the credit rating implied for each instrument in that scenario. Repeating this simulation many times produces an estimated distribution of future portfolio values from which a credit value-at-risk (CVaR) estimate can be derived.

The KMV Approach to the Merton Model

In 1974, Robert Merton pointed out that the legal structure surrounding a limited liability corporation implies that debt holders have effectively written a put on the firm's assets to the benefit of the equity holders. The strike price for this put is the book value of the liabilities. If the market value of the unleveraged assets falls below the book value of the liabilities, the equity holders have the option to "put" the assets to the debt holders. This effectively limits the downside loss of the equity holders, simultaneously leaving them with unlimited upside potential—identical to the payoff of an asset owner with a put option.

Unfortunately, the market value of a firm's assets is not observable. The market value of the equity can be observed, but it reflects the value of the assets in excess of the liabilities plus the value of the implicit put option on those assets. From the option market, however, it is possible to observe the implied volatility of the equity value. The combination of the value of equity and the volatility of that value makes it possible to derive estimates for both the level and the volatility of the value of the firm's assets. The distance of the current asset value from the default point (the value of the liabilities) and the volatility of the asset value supports a calculation of how likely it is that the asset value will drop low enough to trigger a default. This is the basis

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for estimating an expected default frequency or EDF. Furthermore, since the asset values are estimated explicitly, their observed correlations can be calculated directly rather than imputing correlations based on changes in equity values.

The Merton Model approach is a significant departure from traditional credit analysis techniques. Rather than examining fundamentals directly, the intent is to extract the implication of the combined analysis of the market as it is manifested in a firm's stock price. Initially, traditional credit analysts were almost universally skeptical of attempts to deploy the Merton Model in practice. While that skepticism has softened in recent years, it remains quite common. Nevertheless, most balanced assessments deem the approach to be broadly successful. Proponents argue that the model captures credit deterioration in specific entities much sooner than traditional credit analysis tools. Skeptics counter that market-based assessments such as the Merton Model produce too many predictions of deterioration that fail to materialize. With defaults being so infrequent, producing conclusive evidence is far from easy. Nevertheless, a great many practitioners argue that the discriminatory power of the approach makes it both effective and efficient. Most would agree that analysis based on this type of approach should at least be used as a supplement to traditional micro-credit analysis. At a minimum, it can serve as an early warning of situations that warrant special attention prior to a normally scheduled review date.

The Actuarial Approach

In practice, the actuarial approach is synonymous with Credit Suisse First Boston's CreditRisk+ paradigm. This model does not delve into the anatomy of a default; rather, the stochastic element is the default rate itself. Default happens randomly based on past history of behavior, and economic causality (leverage ratio, asset volatility, etc.) is ignored, which is why the approach is termed "actuarial." As the name suggests, the approach is borrowed from the insurance industry, where it is customary to look at the frequency and severity of the actual loss experience and construct a risk premium out of it rather than pry into the "economics" of each type of loss. Default is assumed to be a low-frequency event driven by a Poisson distribution[3], the intensity parameter of which is computed from actual loss history.

CreditRisk+ requires only a few inputs. They are the mean default rate for the obligor, the volatility of the same, and facility exposure (it takes loss given default, or LGD, as a fixed item). Additionally, portfolio segments or factors (also called sectors) need to be specified. These can be divided by industry/geography classifications, but there can also be macro variables, for example, in the case of a retail portfolio. Each facility can belong to a single sector or multiple sectors. An obligor like Merck could belong partly to German pharmaceuticals and partly to U.S. pharmaceuticals. Sectors can be specific (meaning that the risk belonging to it can be diversified away) and systematic (meaning that obligors belonging to a sector will display correlated default behavior).

It is important to understand that, unlike in the case of CreditMetrics, pair-wise correlation between obligors is an *output* of the model rather than an *input* to the model. It is driven by sector volatility as the primary input. Two obligors that do not have a sector in common will have zero default event correlation. In other words, obligors in each sector are pair-wise correlated depending on their level of participation in that sector. Obligors across sectors are uncorrelated. Ten years ago, when this model was developed, full-blown Monte Carlo simulation of a portfolio was impossible. But in its original mathematics done in closed form, CreditRisk+ had heavy dependence on the assumption of default rates being small. It was unsuitable, therefore, for non-investment-grade portfolios.

More recent Monte Carlo-based versions have rectified this shortcoming. Also, the assumption of the Poisson distribution meant that each facility could default multiple times. Though this was considered a drawback, in the case of retail loans (credit cards, auto loans, mortgages) this is not altogether unrealistic, as people do go into and out of default behavior based on the vagaries of economic life (unemployment, divorce, illnesses, etc.). However, if desired, in the Monte Carlo version, Bernoulli can easily take the place of Poisson as the preferred frequency distribution and restrict defaults to "one strike and out" for comparison.

Once considered passé, the classic CreditRisk+ paradigm in its various reincarnations is staging a robust comeback. This is especially true with versions using Monte Carlo simulations that are more general and flexible than the original polynomial formulation, occasionally including innovations such as stochastic recovery rates and correlated sector variables. This is happening against the backdrop of a rising popularity for reduced-form models, of which CreditRisk+ might, in fact, be seen as an example[4], and amid a discounting of the importance of transition matrices long considered the real showpiece of the CreditMetrics framework.

It has been argued by CreditRisk+ aficionados that the transition matrices capture a relatively trivial part of the credit story, as the transitions typically have low probability and correlation. Supporters argue further that the real cause for concern is the dramatically changing credit spreads that can happen with *no change* in the credit rating.[5] This philosophy has received a further boost in the emerging markets (in the Middle East, Eastern Europe, and Latin America) as well as within certain institutions in Western Europe, where Basel II has served as a catalyst for overhauling the credit processes in the light of modern quantitative methods. CreditRisk+ serves as a great first step for ambitious institutions desirous of going beyond regulatory compliance while getting additional mileage out of the work already done for Basel II. This is because CreditRisk+ has less onerous input requirements based on more *observable* and straightforward metrics, which is not true of its elegant rival CreditMetrics.

Retail Credit Scoring

Although lenders have been evaluating credit risk throughout recorded history, the introduction of today's massive computer power and extensive data resources has enabled virtually real-time credit risk analysis to take place. This applies both to approval of customer-initiated credit requests and to determining the "next best product" to sell to retail customers based on credit and other relationship factors.

Many in the industry will recall Barnett Bank, one of the largest banks in Florida until its acquisition by NationsBank (now Bank of America). Around 1988 Barnett Bank was already experimenting with what, over time, would become automated retail scoring technologies. The scorecards used initially within Barnett were simple manual expert-based "rules" that established an overall score for a retail applicant. Some of the more notable criteria included in these scorecards were:

- Length of employment.
- Length of time at the current address.
- Education level.
- Renter or owner.
- The ratio of monthly fixed debt service to monthly income.
- The ratio of monthly rent or mortgage payments to monthly income.

The specific ground rules became increasingly customized as banks realized that pooled data was sometimes too general to capture the idiosyncratic risks and rating philosophy manifested in an institution's own experience and historical time series.

- Number of revolving lines open.
- Number of bureau inquiries in last 90 days.
- Proof of income.
- History of timely payment of obligations.
- Co-signor/guarantor.

For indirect auto credits, other considerations included such things as channel and vehicle type. These were deemed relevant for recovery value and default propensity, since some higher-risk customers were prone to come through particular "channels."

Although many more criteria were used, filling in the form would, based on answers to the criteria, result in a "score" for the customer. If the score was high, the retail credit was considered good; if the score was too low, the credit was considered higher risk. Even at this early stage, the bank's goal was to price higher-risk credits differently and to monitor actual versus target volume in different risk categories. While commonplace today, this approach was unusual at the time. Clearly, riskier credits were generally priced higher, but the granularity of the pricing schemes applied by Barnett offered much finer resolution than its competition. Other banks still looked primarily at secondary forms of collateral or co-signors to minimize expected losses.

Over time, this basic approach become less focused on expert input and relied more heavily on public and proprietary data collection combined with statistical estimation of default and loss probabilities. The specific ground rules became increasingly customized as banks realized that pooled data was sometimes too general to capture the idiosyncratic risks and rating philosophy manifested in an institution's own experience and historical time series.

Profitability Analysis

Today, pricing retail and corporate credit on a risk-adjusted basis is commonplace. Profitability systems are being widely deployed as competitive tools to ensure that relationships are well modeled and adding value. These systems evaluate the net income contribution and risk-capital consumption of various products by geography, branch, and lender. Conducting profitability analyses at a very granular level has become not only possible, but competitively necessary. For example: What region is earning the most money from indirect auto lending? Within the region, which branches are performing best? Within those branches, which lenders are doing the best and why? Outside of these higher-performing regions and branches, are we meeting our hurdle rate of return? If not, can this performance be improved or should we exit indirect lending in certain locations?

Extensions to Small Business Lending

Not only are such analyses critical to remaining competitive in the highly commoditized retail-lending sector, but similar techniques have increasingly been applied to small and medium-sized enterprise (SME) lending. Such analysis ranges from bankruptcy prediction models through simple discriminant analysis—such as Altman's Z-score described above—to more advanced models using a variety of regression and other statistical methods. While such techniques are typically fine for large portfolios with many credits, more sophisticated and customized scorecards are often needed for low-default portfolios, portfolios with little or no data (e.g., emerging markets), and portfolios with unique characteristics where past data is either nonexistent or of questionable relevance.

Models and Judgment

As the application of these various risk-based scoring and classification models has expanded, so has the stability and understanding of the methodology. Calibration techniques have improved, and systematic backtesting has become standard practice. Models provide an excellent benchmark not only for credit ratings but also for risk-based pricing at a very granular level. Banks are applying risk-based pricing not only to single transactions, but also in light of structural aspects of facilities and of entire banking relationships. These trends are revolutionizing bank and customer profitability analysis, altering the competitive landscape, and offering more liquidity to the marketplace.

Despite these advances, time has demonstrated that experience still matters. The blind application of purely statistical models is not a satisfactory approach. Models must be subject to constant review and their results must be supplemented with expert judgment. The goal of credit modeling must be to support expert judgment—not to replace it. That said, effective, expert judgment needs to be open to the much richer and more sophisticated information generated by the models. Sometimes the sensible blending of sophisticated model results with experienced judgment is lost in a no-man's land between quants and traditional credit analysts. And that is a situation to be avoided at all costs. ❖

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Notes

1. Altman's original ratio was tailored to public industrial companies and involved the following five financial ratios: 1) EBIT/Total Assets, 2) Net Sales/Total Assets, 3) Market Value of Equity/Total Liabilities, 4) Working Capital/Total Assets, and 5) Retained Earnings/Total Assets. The Z-score was defined as: Z-score = 3.3 x A + .999 x B + 0.6 x C + 1.2 x D + 1.4 x E.

2. Indeed, Dr. Altman, now in his mid-60s, continues his research and remains a widely quoted expert on credit risk issues.

3. The Poisson distribution is modified to be a Poisson-Gamma or a negative binomial distribution so that default rate volatility data can be matched better than by Poisson assumptions alone.

4. See, for example, *Credit Portfolio Management* by Charles Smithson, Wiley Finance, New York, 2002, p. 141.

5. This argument is elaborated in the chapter entitled "CreditRisk+" by Tom Wilde in *Credit Derivatives and Credit Linked Notes*, Satyajit Das, ed., Wiley Frontiers in Finance, Singapore, 2000, pp 589-629.