A Comment on Market vs. Accounting-Based Measures of Default Risk

K·M·V

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Overview

Default occurs when a firm fails to service its debt obligations. When defaults occur, lenders typically suffer losses. Accordingly, borrowers pay lenders a spread over the default-free rate of interest proportional to their default probability.

Before the fact, there is no method to discriminate unambiguously between borrowers who will default and those who will not. Ex ante, that is, we can only make probability assessments of the prospects of default.

The typical borrowing firm has a default probability of 2%, over the ensuing year. Thus, there is a 98% complementary probability of that firm not-defaulting. Default is a deceptively rare event.

A naive lending approach would seem to be, simply, to assume firms will not default. After all, 98% of the time they don't. However, the consequent losses would bankrupt such a naive lender in short order.

The successful lender must discriminate between small default probabilities. For example, the odds of a AAA firm defaulting are only about 2 in 10,000 per year. A single-A firm has a 5 times higher probability of default. A CCC, the bottom of the agency scale, has 200 times the odds of default of a AAA, but still only about 4%.

The strictly subjective judgments of old are no longer an adequate basis for discriminating among firms' default prospects. The measurement of default probabilities is rapidly evolving into a science. There are two critical ingredients to competitive default probability measurement: data and models. Models are the means by which data are transformed into default probabilities.

Data pertinent to estimating default probability arise from two sources: financial statements and market prices of firms' debt and equity. Presently, far more use is made of financial statements than prices in estimation of firm default probability. Statements are, inherently, reflections of what happened in the past. Prices, by contrast, are forward looking. Prices are formed by capital providers as they anticipate the future prospects of the firm. Prices contain, thereby, ex ante information. The most accurate default measurement derives from models employing both sources. There is a limit, of course, to the information that can be extracted from statements or prices.

The most functional models are grounded in theory that works. Unfortunately, there is not much theory in economics, macro or micro, that works. Most models are ad hoc, i.e. they lack structure that reflects the causative linkage among the included variables. Even so, ad hoc models have considerable predictive power. But, alas, we cannot determine why they work. Ad hoc models are destined to remain undecipherable "black boxes", even to their designers.

The conclusion advanced here is simple. When available, we want to use market prices in default prediction, for they add substantial predictive "power". Moreover, we want an integrating model whose conceptual structure is readily understandable and appealing to experienced intuition. And finally, the model's conformity to actual default experience must be rigorously tested.

Models using market prices are no more expensive to deploy than those using only financial statements. Moreover, market prices can be economically refreshed as often as you like, e.g. daily, whereas models employing only financial statement data have an irreducible quarterly lag.

On the other hand, when estimating the default probability on private firms, we only have statement data. We must do the best we can with statement data. The model needs to deal with firms whose capital structure is at variance with the norm. For example, when examining the possible impact of a recapitalization, we will want to obtain an accurate estimate of the new default probability. These requirements lead us to a model based on causation rather than correlation.

Therefore, with private firms, we prefer a model whose conceptual structure is the same as that for public firms. Indeed, the conceptual model developed by KMV is the primary focus of this discussion. From it we can comprehend the value added by equity prices to the predictive power of statements alone. Moreover, its robustness in coherently appraising firms whose financial ratios deviate from the norm can be assessed. The conceptual model, accordingly, places private and public borrower default assessment on common ground in bank credit portfolio management.

The Problem

Lending requires resolution of two fundamental questions: (1) what is the likelihood of default; and (2) what will be lost if default occurs? The "probability of default" derives from the dynamic fortunes of the borrower corporation. Default occurs when the borrower's resources are depleted to such an extent that a promise to pay cannot be met.

The "loss given default" depends, primarily, upon security and seniority. More generally, the facility agreement bears significantly on the prospects of loss should default occur. The loss given default expectation is, then, highly facility dependent. Although loss given default is an important source of uncertainty in lending, the dominant source of uncertainty, and thereby risk, is the default probability itself. This comment will focuses on measurement of the probability of default.

The anticipation of default by KMV's models is expressed as a probability distribution. The distribution has expected and unexpected parameters (or mean and standard deviation, in the parlance of conventional statistics). The role of loss given default is to transform the default distribution into a loss distribution, or "loss function".

The principal challenge of lenders is to characterize, ex ante, the default distribution of each borrower. And then, to follow the dynamic evolution of the default distribution: to monitor for quality degradation. There are three primary sources of input to this process: (1) subjective appraisals; (2) financial statement data; (3) market prices of the borrower's debt and equity.

In the old days, subjective appraisals dominated the means of discrimination among borrowers. Serious financial statement analysis had to await the development of auditing, computers, and models, all quite recent developments. Market prices, as inputs to the process, are only now entering the practice of default measurement. So, the question as to the incremental benefit from market prices requires demonstration.

Market prices do not fit readily into ad hoc models of default prediction that have been trained on financial statement data. One reason is that financial accounting has not evolved into a coherent conceptual picture of the economics of a firm, especially when distress threatens default. Indeed, uncertainty is not even definable in the prevailing financial accounting paradigm.

Market prices are formed by investors in anticipation of a firm's future cash flows. The present value of cash flows, i.e. price, is obtained by discounting for the uncertainty of the cash flows. Thus, market prices have a measure of uncertainty embedded in them. (By contrast, financial statements are an agglomeration of past transactions; they contain no embedded discount rate). But, the discount rate embedded in an issuer's stock price is not directly applicable to the same issuer's bonds. Debt is a prior claim, relative to equity, on the cash flows generated by the firm's assets. Accordingly, the appropriate discount rate is systematically lower for debt.

In sum, the most accurate measurement of default probabilities requires the use of prices, equity prices most particularly. KMV has evolved a conceptually appealing model that uses equity prices when available, and otherwise just financial statements. This covers all the bases: publicly traded firms and privates as well.

A Market Based Measure of Default Risk

Expected Default Frequency, EDF, from KMV's CREDIT MONITOR system, is a measure of the probability that default could occur over the ensuing year (or other time horizon, out to five years, specified by the user). Default is the event of a borrower missing any scheduled payment.

EDF is different from expected loss. The expected loss is the EDF times the loss given default. Default is a characteristic of the borrower. Loss given default is a characteristic of the borrowing facility.

EDF contains information extracted from market prices, plus financial statement data. That is, EDF depends upon the behavior of the price of the borrower's common stock.

KMV's conceptual model advances an explicit causative condition of default. It says, in effect, that *borrowers default when their available resources have been depleted below a critical level*. The task is to find the causative links between measures of "resources", "depleted", and "when". As evolved, EDF requires four critical variables:

1. MARKET VALUE OF ASSETS.

2. VOLATILITY OF FUTURE ASSET VALUES.

3. "SHAPE" OF THE DISTRIBUTION OF FUTURE ASSET VALUES.

4. FACE VALUE OF OBLIGATIONS REQUIRING SERVICING.

GRAPH 1 depicts the relationships among the model's variables (there are actually six of them, but the asset growth rate, variable 5, holds little discriminating power, and the time horizon, variable 6, can be specified by the analyst). The variables have a causative relationship with each other, shown in the graph. The trade-off among all variables can be readily estimated, unlike ad hoc models that lack causative specification.

We obtain an estimate of the market value of assets, <u>*variable #1*</u>, by adding up the estimated market value of all liabilities, including equity. For publicly traded firms, we observe the equity's market value. Unfortunately, few firms with publicly traded equity have traded debt. For those that do, timely quotes are difficult to obtain. Instead, an alternative approach is adopted.

- The riskiness of equity results, necessarily, from the firm's underlying assets and its leverage. By the application of derivative asset pricing theory (a generalization of the options pricing theory of Black, Scholes and Merton), empirically observed equity riskiness can be decomposed into its constituent asset risk and leverage components. That is, when we estimate the riskiness of debt and know its par value, we can deduce its market value. The riskier the equity, the lower the market value of the debt in relation to its par value.

From this methodology an estimate of asset risk falls out. It is widely known that stock prices reflect the riskiness of the issuer's equity. The options approach to interpreting stock prices, by carving away the effect of leverage, makes it possible to measure the issuer's underlying asset riskiness, <u>*variable #2*</u>.

<u>*Variable #3*</u>, the shape of the distribution of future asset values is difficult to measure. Moreover, it cannot be assumed. For default measurement, the likelihood of large negative events is critical.

- We obtain the "shape" of distribution of asset returns in the region of distress from data on historical default and bankruptcy frequencies. Our measurements, from over 1200 incidents of default or bankruptcy, reveal that distress is considerably more likely than from an assumption of normal density (i.e. that a "log normal" process is generating the cash flows). With historical data, we are able to estimate the probability density in the region of distress quite accurately. See *GRAPH 2* for the default incidence we have discovered, shown quarterly, since 1973.

Unlike agency ratings, the time horizon used by EDF is explicit. It needs to be specified by the user. For use in early warning, we set the time horizon to one year, across all firms. Indeed, CREDIT MONITOR displays one year EDFs. In pricing a particular exposure, the requisite EDF should correspond to the exposure's tenor.

The face value of debt requiring servicing, *variable #4*, depends also on the choice of horizon. At one year, the requisite quantity is, by accounting definition, the observable level of current liabilities. At a longer horizon, we cumulate the debt servicing requirement to that horizon. For example, as the date a balloon payment on a term loan approaches, the EDF rises. If successfully refinanced with another term loan, the EDF falls. Thus, the EDFs over a series of years going forward, display a pattern that reflects the time-table of debt coming due (as well as asset riskiness and leverage.)

The model's parameters are combined by arithmetic, not regression. The probability of default, EDF, is the shaded area in *GRAPH 1*. Thus, unlike an ad hoc model, there is a causative structure underlying EDF. And, it is simple. The implementation problem lies in accurate determination of the model's four key parameters. The quality of the implementation is reflected in the model's default prediction "power," i.e. the ability ex ante to discriminate between good and bad loans.

Obtaining Discriminating "Number"

Assessment of Predictive Power

What do we mean by predictive power? Here, as usual, we have both a theoretical problem and an empirical one.

Consider a policy of never lending to firms below, for instance, B-. There is opportunity cost, however, in not lending to firms excluded by that policy which do not default. Thus, the ratio of defaults avoided to opportunity cost incurred is one theoretical approach to measuring default predictive power of these models.

KMV has collected an extensive library on defaulted companies. We analyze over 1200 companies that have defaulted, or entered bankruptcy. These defaults occurred in a population of some 60,000 company-years with data in COMPUSTAT. About 200 of the defaulting firms were rated, or nearly 2% of the 10,000 rated-company-years sub-population. With this data we can test the predictive power of various models.

GRAPH 3 displays five years of monthly EDFs prior to the dates of default for over 1200 companies, non-rated and rated. Default dates are aligned at the right. The number on the vertical scale, on the left, is the probability of default, EDF.

The level of EDFs is sloping upward, toward progressively higher default likelihood, as the date of default draws closer. The steepness of the slope sharpens as the date of default approaches. The median company's EDF one year prior to default, from GRAPH 3, is nearly 6%. This contrasts with the lowest S&P rated companies, CCC-, whose median EDF is about 4%. Concurrently, the median company in the whole population, of defaulters and non-defaulters taken together, has an EDF around 1.5%.

The subset of defaulting companies from GRAPH 3 that had agency ratings is plotted in GRAPH 4. Only about 15% of the entire non-financial US population has ratings. There are several striking features:

- The median EDF for defaulting firms that were rated reached 2% nearly three years before default occurred. The median rating only reached that level of probability (ie. BB-/CCC+) a couple of months prior to default. This suggests a median lead time of EDFs over S&P ratings approaching 3 years.

- Based on median values, there is a *five-fold* difference in default probability between EDFs and S&P's ratings one year prior to default.

- By two years prior to default, the 75th percentile EDF (ie. highest quality quartile of defaulting firms) crossed over the 25th percentile S&P rating (ie. lowest quality quartile of the defaulting firms). Thus, two years prior to default, the distribution of EDFs is only 25% overlapped with S&P ratings.

EDF has considerable sensitivity below 0.2%, as well. That is, the preceding may, incorrectly, suggest that because EDF is sensitive at the high-distress end of the scale, it may not perform as well among the highest quality firms. *GRAPH 5*, generated by CREDIT MONITOR, provides the IBM anecdote, and this picture is not atypical. EDF "kicked up" to a probability level not reached by S&P until nearly two years later. Interestingly, IBM's quality has rapidly declined to the point where it is riskier than the median, the 50th percentile company in the entire US population. In February '91, IBM was at the 99.99th percentile; no companies were higher in quality.

There is considerable variability through time in default expectations. *GRAPH 6*, generated by CREDIT MONITOR, displays this variation. The median company, at the peak of the credit cycle (January '91) had an EDF of 2.3%. At the prior cycle-trough (August '89), the median low was 1.2%, 110 basis points lower in default probability. By May '93, the median company's EDF had returned, coincidentally, to 1.2%.

It should be apparent that default estimates that are mid-credit-cycle averages are of limited value. Pricing and portfolio management models require default estimates that are credit-cycle sensitive. Otherwise, originators would be over-charging at credit-cycle lows and under-charging at cycle highs. Restated, an originator will be at a significant disadvantage to a competitor with a cycle- sensitive pricing model.

In sum, EDF can be effectively employed as a lending policy threshold, in early warning, in pricing, and in portfolio management models. It is consistently better than S&P ratings in discrimination and lead-time. And the difficult task of adjusting ordinal default ranks to the period of the credit-cycle is *not* left entirely to the intuition of the user.

Next, we address the opportunity cost. What is the frequency distribution of firms that did not default when their measured EDFs reached a given level?

We form the ratio of defaults avoided at each policy cut-off (discussed in Section IV A above) to its corresponding opportunity cost. Dubbed "power curves", we plot the ratio from the lowest quality end of the spectrum to the highest. This contrasts EDFs to ratings in both relevant dimensions. EDF remains the winner, see *GRAPH 7*.

A simple measure of superiority of EDF cannot be easily summarized in a single metric. First, defaults avoided and opportunity cost are not of equal importance. Second, it is easier to act on a declining quality AA than a single-B: AAs can be refinanced far more readily than single-Bs.

Ordinal vs. Cardinal

Most conventional credit analysis sorts companies into an "ordinal" default rank. For both valuation and portfolio analysis, however, we require "cardinal" numbers. That is, real numbers, not letters without inherent numerical meaning. We need to know more than that a company is, for example, a BBB+. We need to know that its default probability is, say, 28 basis points, at the one year horizon. The first step in obtaining this linkage, from ordinal to cardinal, derives from KMV's empirical analysis of historical default frequencies. Still, this alone will not suffice. That is, setting the price for an exposure based on the average value during the credit cycle is not adequate.

GRAPH 8 displays the rise and fall of S&P's BBBs over the past five years, as measured by CREDIT MONITOR. The three broken lines are, from top to bottom, the 25th, 50th, and 75th percentiles in the cross-section of companies rated BBB by S&P. The vertical scale is the default probability, linearly scaled. As of August 1993, there were 205 companies with BBB ratings, including both the pluses and minuses. The 50th percentile, the median, has varied from 43 to 13 basis points over the last five years. This implies that the compensatory spread for the median BBB should have nearly tripled, trough to peak of the credit cycle.

In other words, not only do pricing and portfolio models require "cardinal" numbers, they need to be cycle-adjusted. The importance of adapting pricing to the credit cycle is difficult to over-emphasize.

The overall credit cycle in the US (or anywhere) is not easily measured. CREDIT MONITOR, however, obtains an excellent "picture" of it by aggregation of all publicly traded firms in the population. That is, without imposing any macro structure, *GRAPH 9* displays the waxing/waning of the cycle in the US, as a whole. Contrast this picture with that of Sweden, which is, these days, immersed in a very serious credit crunch, *GRAPH 10*. (Note the differences in horizontal scales.)

To emphasize the point, *GRAPH 11* displays only the 10th percentile, toward the worst end of the spectrum in the US, on a linear scale (versus the natural log of GRAPHs 9 and 10.) From the peak of 1350 basis points of default probability, the recent level of 600 basis points represents a whopping decline! Thus, from the perspective of EDF, the credit dimension of the economy has been improving since early in 1991.

CREDIT MONITOR's EDFs are cardinal. KMV makes use of this feature to rescale PRIVATE FIRM MODEL quarterly. CREDIT MONITOR, also, inherently takes the credit cycle into account. Accordingly, the output from KMV's default models, both public and private, can be used directly in valuation and portfolio analyses.

GRAPH 8 also reveals another important message about BBBs. The 25th percentile (top line on GRAPH) EDF reached a high of 87 basis points during the last five years. The low of the 75th percentile (lowest line) EDF during the five years was 6 basis points. In other words, there is enormous variation in EDFs among BBBs. The horizontal lines on *GRAPH 12* (under the broken lines connecting squares) span the 5th to the 95th percentiles for BBBs as of July 1992. From the perspective of EDF, BBBs are highly variegated.

From the perspective of EDF, the AAAs of *GRAPH 12* are clearly separated from BBBs. The small triangle of dots at the far left does not overlap BBBs. Similarly, CCCs, the very flat triangle to the far right, are almost distinct from BBBs. All other rating classes are overlapped. That is, a single-A is about as likely to be a BBB or a AA as it is a single-A. AAAs, BBBs, and CCCs are nearly unambiguous. The in-between classes are "fuzzy".

There are 19 different gradations at S&P, including the pluses and minuses. S&P's precision could be, therefore, no greater than 1 in 19. As suggested above, there appears to be evidence for only three *unambiguous* clusters. We suspect that the resolution of EDFs may be nearer 1 in 100. Banks, typically, use fewer than ten gradations, of which three may be non-performing. Most important, both S&P and EDF are considerably more discriminating than most bank grading systems.

The "Freshness" of Default Estimates

From the perspective of predictive power, EDF is a technological advance. When the economics of acquiring EDFs is considered, the margin of value added increases further. Very important, EDFs can be re-estimated frequently and inexpensively. Indeed, EDF technology makes "explicit" debt portfolio management feasible. Previously, it could require a calendar quarter to revise all default estimates in a bank's portfolio. With EDFs, it is feasible to reform the input requirements for a portfolio management model every day. Default estimation is required for valuation, ie. establishing the economic price of the credit.

The frequency with which default estimates can be revised for either use depends upon: (1) the frequency with which data is refreshed, (2) the feasibility of obtaining data, and (3) the time and cost required to produce the estimates.

Statement data on publicly traded firms is refreshed quarterly in the US. In some cases private firm statements can be refreshed monthly. However, for private firms, no market prices can be observed. Information from statements is the only source for estimating the conceptual model's variables.

By contrast, share prices are refreshed with every recorded trade and are observable a few seconds later. Since prices are inherently ex ante, they require no pro forma adjustments. Thus, prices can be entered into CREDIT MONITOR, and a few milliseconds later, a refreshed EDF emerges. EDFs on all publicly traded firms can be re-estimated every few minutes, if need be. There are more than twelve thousand publicly traded firms in the major western trading nations (all of which KMV will be soon covering). These firms may account for three-quarters of all corporate productivity in these nations, and a considerably larger fraction of corporate borrowings.

Compared with pro formas of human origin, EDFs are inexpensive to obtain. It is expensive to recast pro formas for every portfolio exposure even quarterly, setting aside the issue of discriminating power. If portfolio analysis is to be conducted frequently enough to be of value, perhaps weekly, then the principal estimation burden must rest with models, not humans.

Thus, market price based estimators of default are valuable for three reasons: discriminating power, freshness, and cost. This conclusion stops short, however, of the desired result. How can companies without traded equity be analyzed? The preceding analysis suggests our direction. We bring them into the same conceptual context as the public companies.

Private Borrowers

Credit management in banks entails dealing with both privates and publics. Private firms default for the same reasons as public firms. Their default risk can be understood in precisely the same conceptual context as public companies. In other words, the problem in analyzing a private company is how to determine the variables described previously (asset market value, asset risk, level of obligations) without stock prices.

The problem can be viewed from an alternative perspective. Any method for measuring default risk can be "distilled" down to information about these three variables. If a method works it is because it tells us something about asset risk, asset value, or the level of obligations.

Pursuing this line of research has led to the PRIVATE FIRM MODEL. The model estimates the firm's equity value and risk, from statement data, and then transforms them into asset value and risk. Obligations are determined in the usual way directly from financial statement items, starting with current liabilities in the instance of the one year horizon.

Most important, the model's predictive power is already impressive. *Graph 13* compares the default predictive power of PRIVATE FIRM MODEL with that of the public company model in Credit Monitor. It displays admirable discriminating power, despite the lack of market data.

KMV has developed a number of models for rating private companies, including ad hoc fitted models similar to popular existing approaches. These have been used as "race horses" to provide competition for the PRIVATE FIRM MODEL during the development process.

The extra default prediction power of the public company model comes from having the actual equity valuation. Alas, there is no good substitute for knowing equity prices. Fortunately for the evaluation of private companies, equity risk, which plays a central role in the analysis, can be estimated quite well from statement data alone.

Whereas the shape of the asset value distribution (variable #3 in Graph 1 above) can be measured for public companies, no such data exists for privates. The model uses for privates the same function derived from public company experience. This is one illustration of the benefit of treating private companies commensurately with publics. Another is that Credit Monitor can be used to periodically recalibrate PRIVATE FIRM MODEL's ordinal ranks into cardinal numbers.

Another benefit is that the estimated private company model provides a point of departure for analyzing the effect of capital structure changes. Because the basic framework is causal, rather than fitted, it can be used credibly to assess the result of divestitures, recapitalizations, and so forth.

In sum, PRIVATE FIRM MODEL represents an analytically coherent model of default risk with substantial default prediction power, even by comparison with the public company model. It is a means for integrating the risk assessment of private and public companies within a debt portfolio.

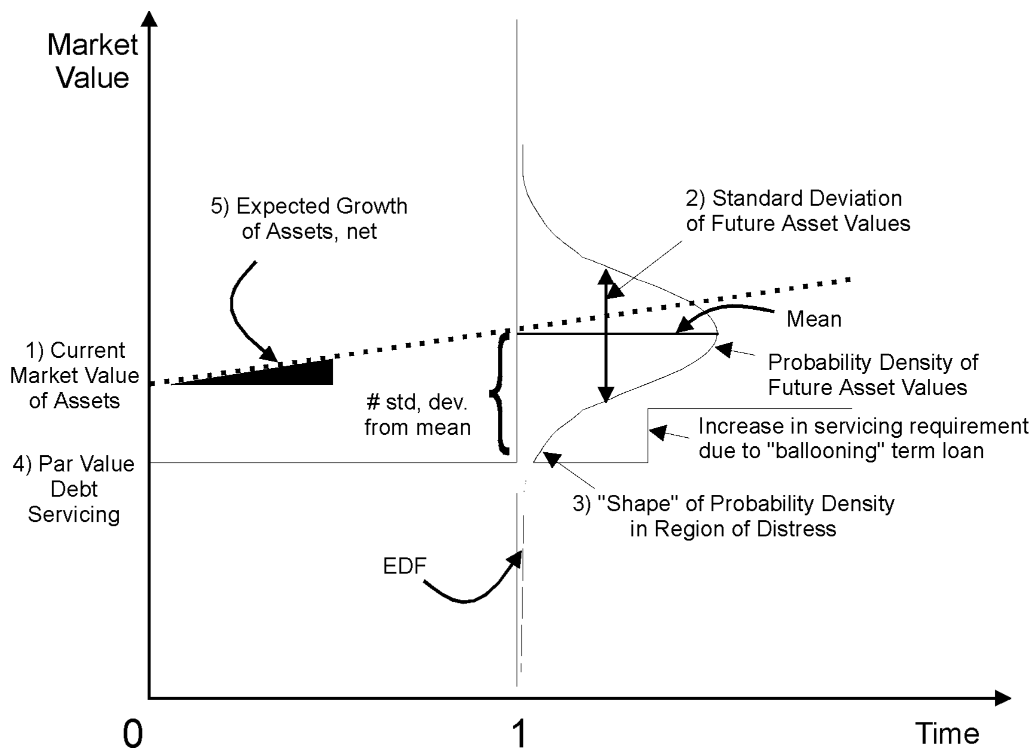
A Postscript

The point of departure for this comment is that market based, timely, and powerful default risk assessment is critical to economic lending. The comment, then, describes KMV's conceptual approach to measuring default probabilities, and discussed its implementation in practice to both public and private companies. It emphasized the need for cardinal versus ordinal risk measures. It also discussed the need for a fast, efficient, and broad scale measure in order to be applicable to *the monitoring and management of loan portfolios*.

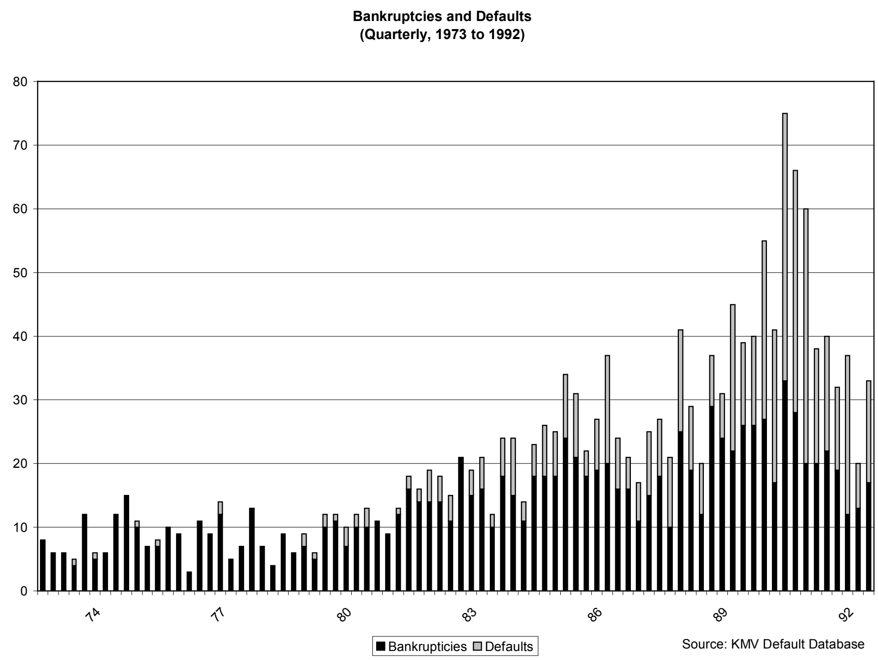
Why should one be concerned about the application to loan portfolios? There is increasing awareness that the real issue in front of lenders, both bank and non-bank, is portfolio management. Valuation is important. Diversification is important. However, the only context in which they become actionable is that of a specific portfolio: how much to hold; how much to sell; how much to buy . . . while getting the price right.

The requirements for portfolio analysis go beyond default risk estimation alone. The relationship between default risks must also be measured; i.e., loss correlations. The technology which has been discussed here is ultimately of little use if it does not lend itself to the determination of correlations as well. In fact, this technology provides a means, perhaps the only feasible means, for determining loss correlations.

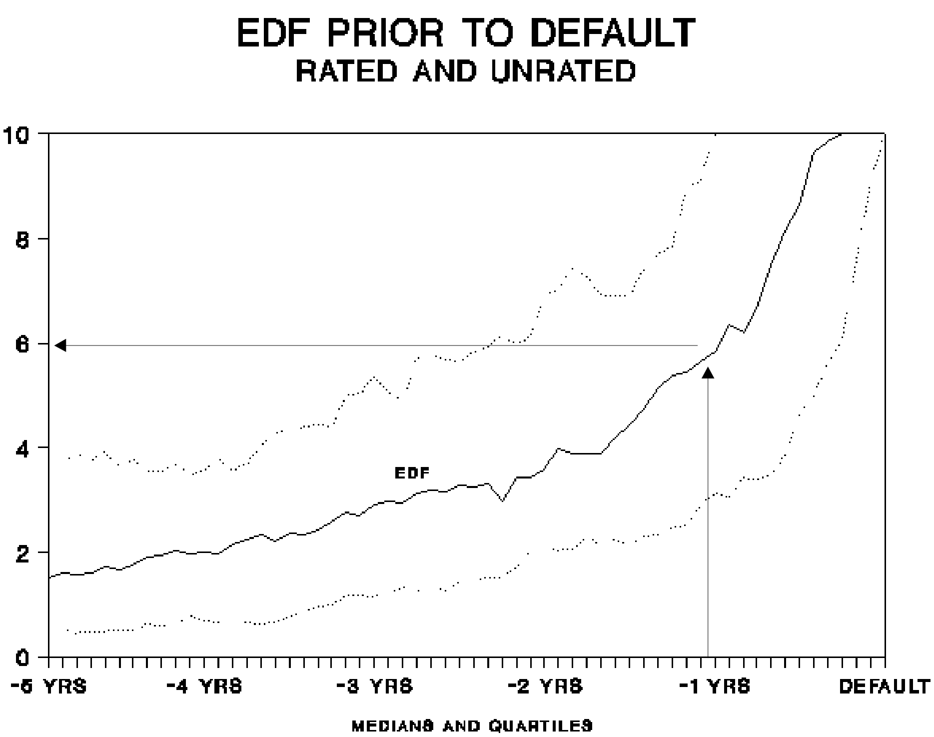
The riskiness of bank portfolios has never been appreciated more than it is today. The way to manage that risk lies in maximizing diversification relative to return opportunities. The default risk measurement techniques developed at KMV provide a path towards that objective.



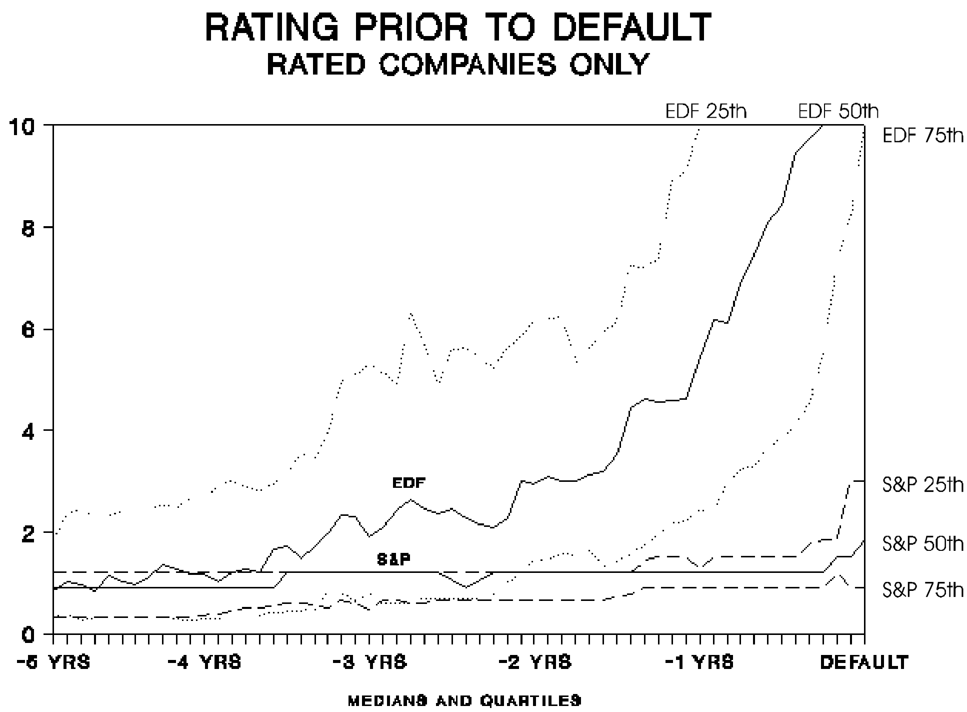
Graph 1



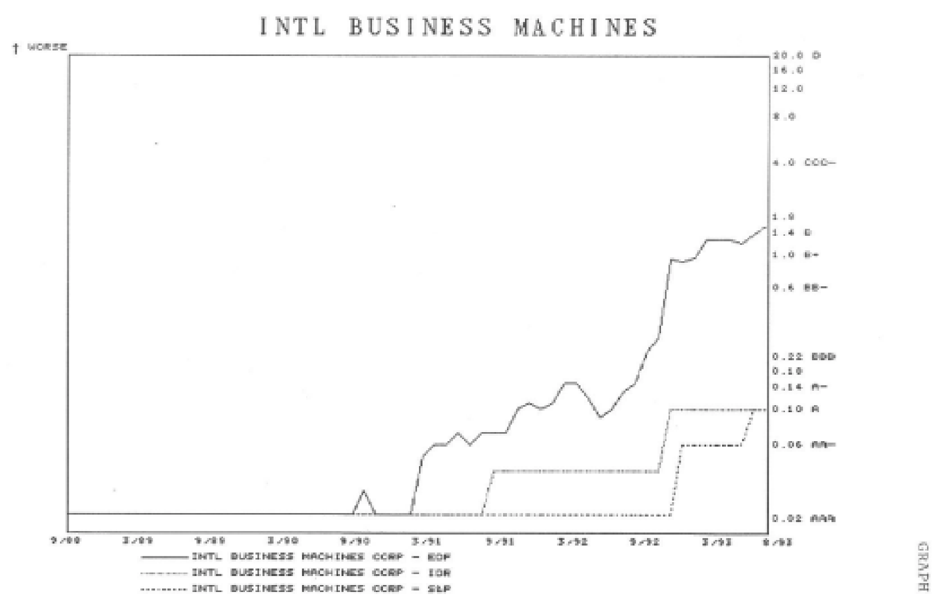
Graph 2



Graph 3



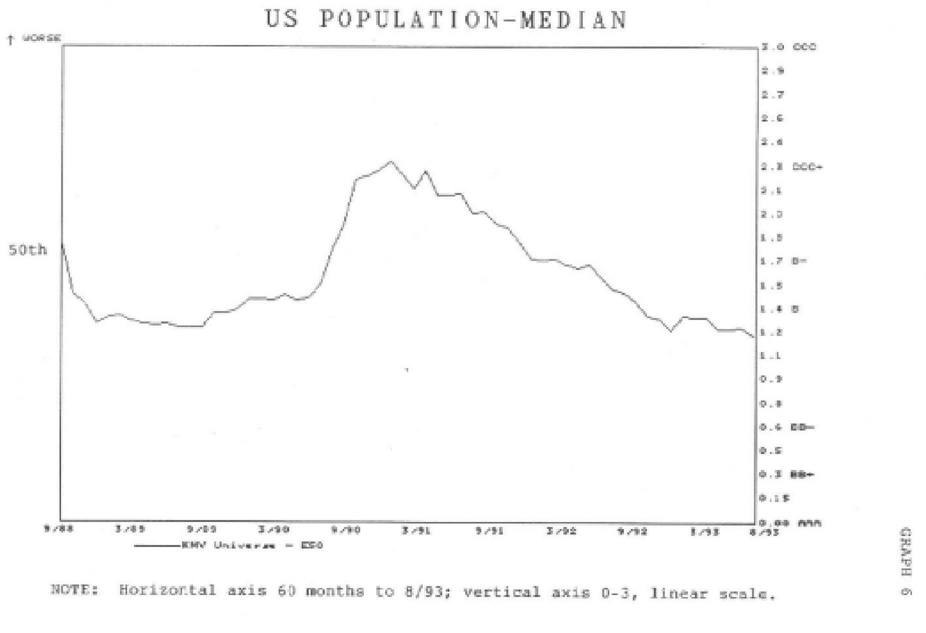
Graph 4



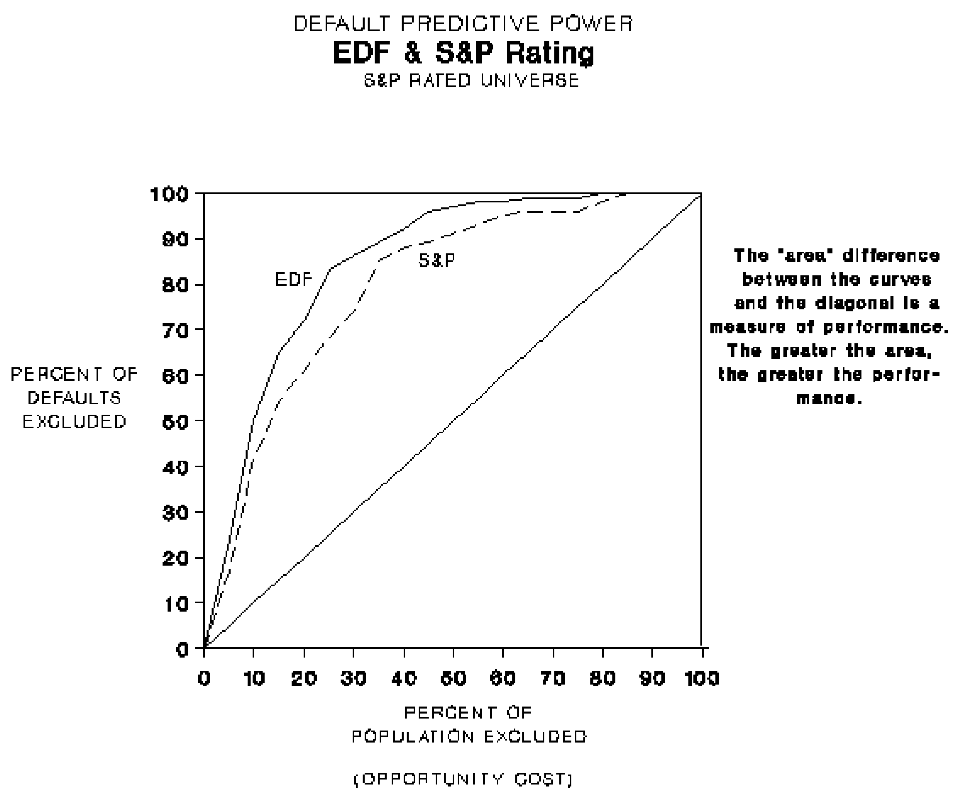
Key: The darkest and most volatile line is EDF. The intermediate line is KMV's rating analogue regression model, IDR. The lowest line, dashes, is S&P's rating.

As of August 31, 1993, KMV's EDF had IBM at 158 BP, (single B). This compares to Compaq at 35 BP, up from 28 BP on 12/31/92 and Apple at 153 BP, up from 16 on 12/31/92.

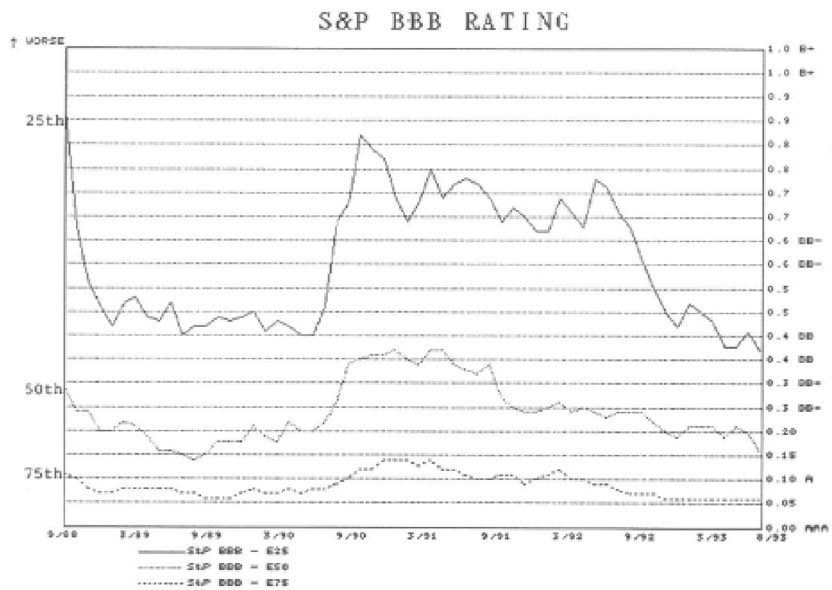
Graph 5



Graph 6



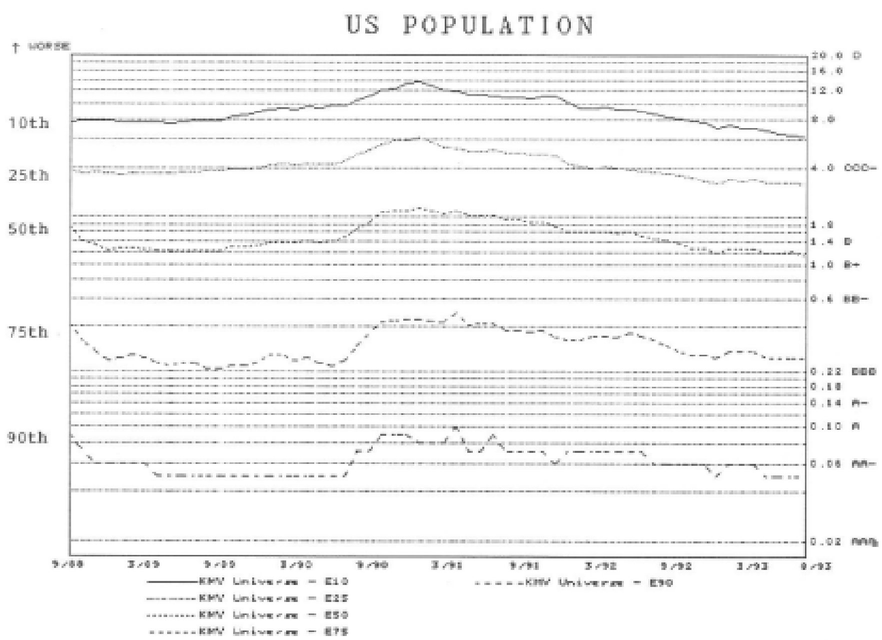
Graph 7



GRAPH 8

NOTE: Horizontal axis 60 months to 8/93; vertical axis 0-1, linear scale.

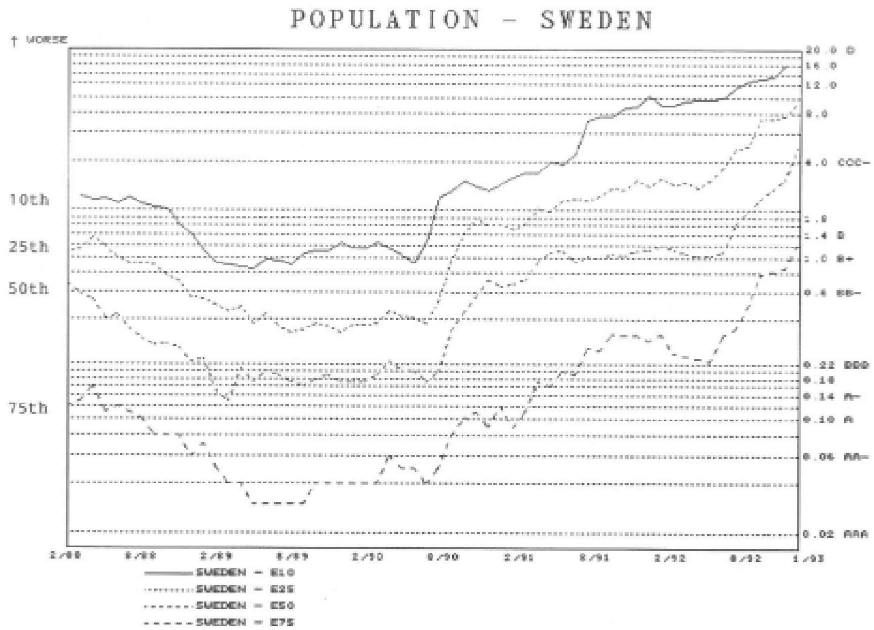
Graph 8



GRAPH 9

NOTE: Horizontal axis 60 months to 8/93; vertical axis 0-20, log scale.

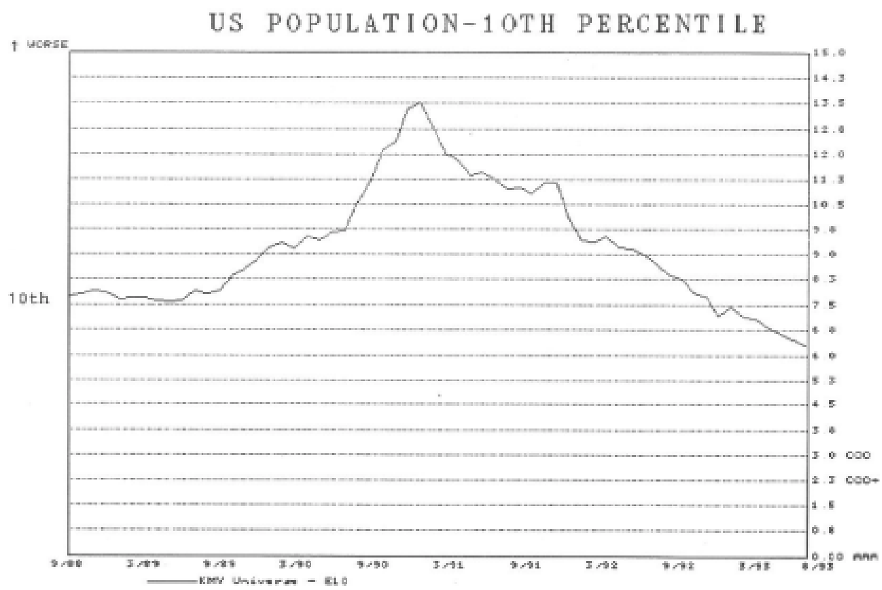
Graph 9



NOTE: Horizontal axis 60 months to 1/93; vertical axis 0-20, log scale.

GRAPH 10

Graph 10

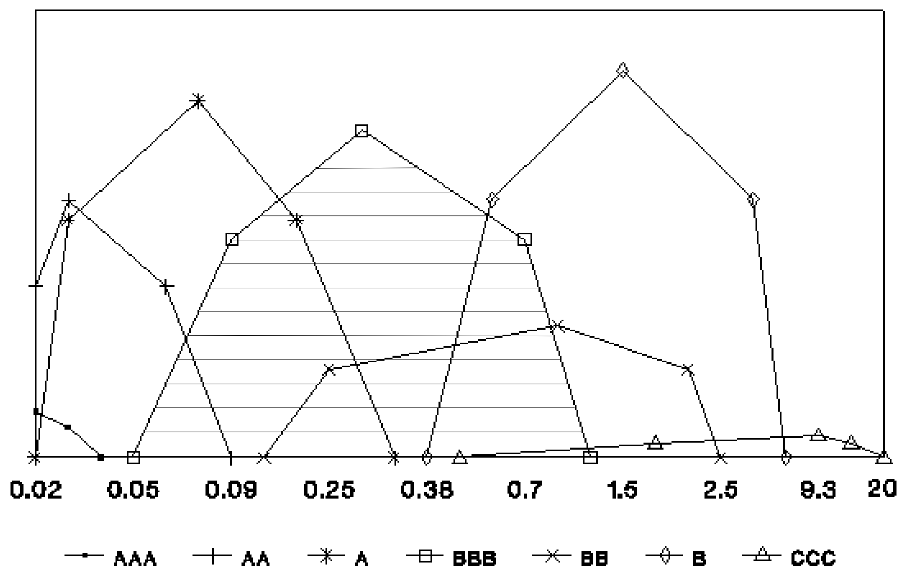


NOTE: Horizontal axis 60 months to 8/93; vertical axis 0-15, linear scale.

GRAPH 11

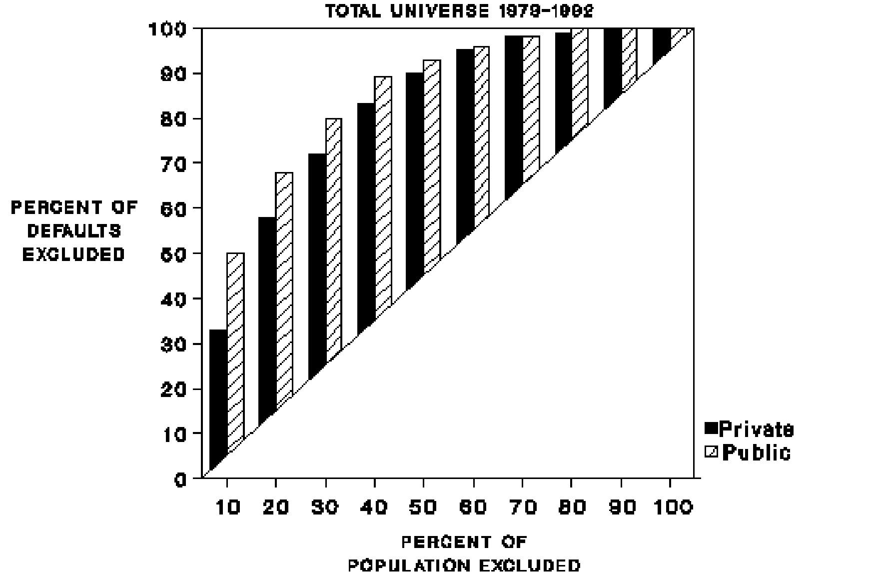
Graph 11

FREQUENCY DISTRIBUTION OF EDFS
BY DEBT RATING CATEGORY



Graph 12

DEFAULT PREDICTIVE POWER
EDF, Private vs. Public
TOTAL UNIVERSE 1979-1992



Graph 13