THE VIABILITY OF HIGH YIELD DEBT AS AN ASSET CLASS

I. Do investors get a fair deal?

$$\text{BEY} = \frac{R_f + D_f(1-\text{Rec}) + D_f\left(\frac{HYC}{2}\right)}{1-D_f}$$

A. HYCoupon-BEY
B. Actual Holding Period Yield-BEY

(Why is there a difference? Liquidity premium, stochastic risk premium)

II. Spread estimation models

A. Altman-Bencingeva

(Are their hypotheses valid??)

B. Fridson-Jönsonn

III. Application to KMV

A. Remedy for weaknesses in estimating market risk premium
B. Simple solution for Adjustments

I. Introduction

I.A Statement of purpose

The high-yield debt segment has witnessed explosive since 1983 reaching a colossal 500 billion dollars in 2000. Even though demand for this asset class might wax and wane in the coming years, it will remain an important part of the world's capital market. **High-yield debt is indeed a separate asset class**, imbued with risk-return characteristics unreplicable by established asset classes such as treasuries and equities [HY 00]. The hybrid nature of the security stems from the fact that the coupon payments limit duration (and thereby volatility) while simultaneously driving returns with the equity component. [HY 00]. Given its low correlation with other asset classes, it becomes especially interesting at a time where market participants' attempts at international diversification are stymied by increasing globalization [HY 00].[1]

Nonetheless, the opinions regarding this value-added benefit of this segment are controversial. The purpose of this document is to research the viability of high-yield debt as an asset class for the UBS private client who is currently invested in his country preferenced balanced portfolio. The information provided in this document will serve a source of knowledge by which one can glean a balanced perspective on the subject matter.

In addition, the reader will gain a general understanding of some credit risk management schemas presently available in the financial community and how they could be applied to the measurement of the aggregate portfolio risk of a constellation of high-yield bonds.

The marketing of such an asset class is also considered.

I.B High Yield Bond Fund Climate 2000-2002

Over the past twenty years, we observe that high-yield debt has performed, with returns net of default, rating migration, and interest rate losses manifesting a compounded annual return spread over 10-year U.S. Treasury bonds of 2.96% [Al Hu 00]. 1998 and 1999, however, were relatively disappointing years for high yield debt.[2] Particularly in 1999, spreads over treasuries were significantly larger, but a concomitant jump in the default rate was registered. Over $23 billion in face value of high yield defaulted in 1999. The 4.15% aggregate default rate was surprising relative to the tame 1.6% level of 1998, and was the first time 4% was surpassed since 1991 [Al Hu 00]. Recovery rate also dropped dramatically to 27.93% across seniorities from its historical level of 40% [Al Hu 00].

[1] One possibility is that the sectors in which high-yield flourishes (ie. casinos, health-care, etc) are uncorrelated with the rest to the economy, in which case equity in these industries would also be a valid alternative, but in many cases, such companies avoid the equities markets due to severe undervaluation. Further, high-yield equity is the riskiest of all market segments due to leveraging and thin liquidity.

[2] Data gleaned for this section is based on the January 2000 study provided by Edward I. Altman [Al Hu 00]. Moody's data on high yield debt was yielded worst results because of inclusion of emreging market debt.

Overall 1999 total returns on high-yield debt were a meager 1.73% [Al Hu 00] but10-year U.S. treasuries performed considerably worst with a negative 8.41% total return. Notwithstanding this relatively admirable performance, future spreads will need to rise or default rates will need to drop if high-yield debt is to remain an attractive asset class compared to equities.

Market participants attribute 1999 sizeable default rate to several factors [source Al Hu 00]:

1) Huge cohort of new issuances from 1997-1999
2) Trend toward earlier default
3) Lower quality issuers
4) Especially vulnerable industries which faced default explosion
5) Flight-to-quality which made coupon payments even more difficult for lower quality issuers
6) Contagion from Russian crisis that made it impossible for distressed companies to get refinancing

The industries and sectors which prominently contributed to the default rate include energy, retailing, communications, health care, leisure/entertainment, and transportation (shipping). We should especially take note of this phenomenon and examine whether sector correlation is anomalous. **Strongly positive default correlations would make sector diversification useless.**

Break-even analysis responds to the question of whether spreads compensated investors for the incurred default risk. To understand break-even analysis, we must first understand the concept of a risk-neutral investor. Such an investor is only concerned with the expected return on his investment, without consideraton for the risk involved. That is, a bet with a 50% chance of a 1000 Franc payoff and 50% of a 200 payoff is just as interesting as a certain 600 payoff. The latter is the certainty equivalent of the bet, and if the investor is not concerned with bet volatility, he will be neutral between the two

$$BEY = \frac{R_f + D_f(1-\mathrm{Rec}) + (D_f * HYC/2)}{1-D_f}$$

alternatives. If the investor is risk-averse, he will demand a premium for the first bet. Such a premium is referred to as a stochastic risk premium. Stochastic risk premiums will be demanded on two occasions: the first when risk neutral investors are faced with new parameters that suggest their expected return might be reduced and, of course, for risk averse investors who must be compensated for the potential sleep they are losing by having taken the bet.

Break-even yield (BEY) is the yield that investors must receive in order to be compensated for actual default rates (D_f) and recovery rates (Rec) [Bencivenga '95 as cited in Al Hu 00]:

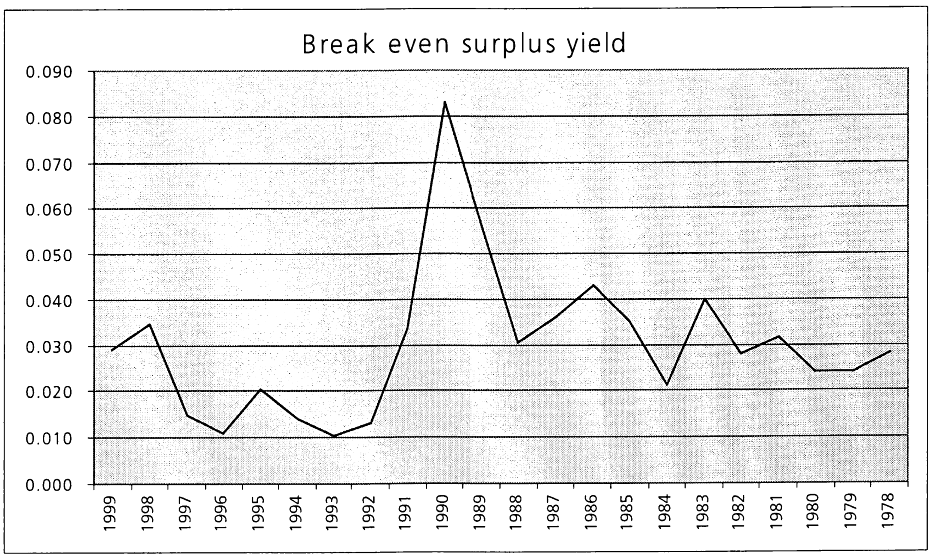
Thus, last year $BEY_{99} = \frac{6.44\% + 4.15\%(1-27.9\%) + (4.15\%)(11.41\%/2)}{1-27.9\%}$

$= 13.41\%$

Actual returns were only 1.73%, which means that investors were over 11.6% below break-even. Hopefully, this trend will not continue in 2000. This break-even analysis assumes that the investor has a portfolio which includes the gamut of high-yield issues available. Although high-yield index funds are currently not

The following graphics depicts the stochastic risk premium over the past twenty years. Were clients paid in extra of the risk taken? A fair bet is one where you are paid for the expected risk of losing your money. If you receive more than the expected risk premium, you are ahead of the game.

Are high yield debt holders receiving such a deal? Not evidently, because stochastic risk premiums do cover the possibility of loss. If these losses were to have occurred then the client would still be able to receive the breakeven yield, and would go away feeling compensated.



The current market environment for high yield bond funds: spreads are being widened by equity market volatility.

April 2000 marked yet another flight-to-safety as investors moved away from volatile high-tech holdings and flooded into government treasuries. The spreads between corporate and government has increased significantly. The lower the quality the debt, the more pronounced the effect.

This implies a risk-aversion shift which will detriment the capacity of lower quality debtors to find financing.[3] Nevertheless, doomsday scenarios aside, the spreads might well be adequate in terms of compensating investors.

Having depicted the market backdrop for high-yield debt, we now move on to investigate various methods for the analysis of (high-yield) portfolio credit risk.[4]

[3] A recent Moody's teleconference on high-yield debt confirmed this observation.

[4] No model is specific to high-yield bond portfolios. Such a specific model would need to be robust to characteristics such as skewness and kurtosis, which may be non-negligible within this asset class.

II. Extant models

II.A **Moody's**

II.A.1 Concept: Static time weighting

The most intuitively straightforward methodology is that of Moody's. Their approach is first to obtain a time-weighted average of the bond ratings that make up the portfolio-- the weighted average maturity (WAM). Next, the fractions (f) which the individual coupon payments represent in the overall portfolio are multiplied by the Moody's cumulative expected losses (CEL) to produce an aggregate expected loss.

Subsequently, the aggregate expected loss is compared to Moody's "idealized" cumulative expected loss rates for a given year, and we are able to assign a rating to the portfolio [MO 99b].

II.A.2 Example

For example, in Appendix 1 we observe the Moody's Bond Portfolio Credit Matrix with a portfolio composed of one ten-year zero-coupon Aaa bond[5], one seven year zero coupon Baa3 bond, and then a mixture of relatively shorter term non-investment quality grade debt.

The WAM $= 3.0\%(2.5)+28\%(3.5)+17\%(4.5)+11\%(5.5)+11\%(6.5)+30\%(9.5)$
$= 5.99 \cong 6$ years

The expected default rate of the portfolio is similarly a time-weighted average of the cumulative default risk of each separate coupon and principal payment.

Risk (Expected aggregate loss) $= \sum_{i=1}^{n} f_i (CEL_i)$

= {%Aaa (9-10 year) in portfolio}*{Aaa-10 year CEL)+ {%Baa3 (6-7 year) in portfolio}*{Baa3-7 year CEL)+...+ {%B1 (6-7) in portfolio}*{B1-7 year CEL)

We use the values from the following table [MO 95a]

[5] One might proffer the objection that the addition of a high quality issuer is inappropriate to the construction of a high-yield bond fund. Nevertheless, given the fact that the Investment Quality Group is conservative in nature and only considers investment grade assets, it was necessary to mix qualities to obtain an overall acceptable rating. The constituency of the portfolio is, however, predominantly high-yield.

Moody's "Idealized" Cumulative Expected Loss Rates (%)

	1	2	3	4	5	6	7
Baa1	0.0495	0.154	0.308	0.4565	0.605	0.7535	0.9185
Baa2	0.0935	0.2585	0.4565	0.66	0.869	1.0835	1.3255
Baa3	0.231	0.5775	0.9405	1.309	1.6775	2.235	2.3815
Ba1	0.4785	1.111	1.7215	2.31	2.904	3.4375	3.883
Ba2	0.858	1.9085	2.849	3.74	4.6255	5.3735	5.885
Ba3	1.5455	3.0305	4.3285	5.3845	6.523	7.4195	8.041
B1	2.574	4.609	6.369	7.6175	8.866	9.8395	10.5215
B2	3.938	6.4185	8.5525	9.9715	11.3905	12.4575	13.2055
B3	6.391	9.1355	11.5665	13.222	14.8775	16.06	17.05

= 0.30(0.0055%) + 0.10(2.3815%)+0.02(1.7215%) + 0.17(2.31%) +...+ 0.01(6.36% + 7.6175 + 8.866 + 9.8395 + 10.5215)

Risk (Expected aggregate loss) = 2.288%

Now, using the WAM, we orient ourselves through the 6-year column until we find a cumulative expected loss that is lower than our aggregate portfolio. We find that 2.235 corresponds to a Baa3 (Baa)[6] rating, and hence our **overall portfolio--despite being 60% junk--is still investment grade.** The fact that junk can be combined with high quality debt to combine an overall investment quality fund is certainly a consideration for private banking.

II.A.3 Discussion

This static WAM approach certainly has the advantage of simplicity, but we must trust Moody's system of "smoothing" the stand-alone values to take into consideration factors such as widening spreads, interest-rate yield curve shifts, and crashes[7]. It would also be helpful for Moody's to explicity state the origin of their "idealized" cumulative expected loss rates and the corresponding standard deviations.

The greatest disadvantage of the Moody's model is the fact that industry and sector correlations are completely ignored. The importance of "concentration risk" will be discussed at a later point. Because the weightings for each ratings bucket ignore issuer identity, one ten-year bond from Aaa issuer A composing 30% of portfolio X is equal to three ten-year bonds issued by Aaa issuer B, C, and D, which also compose 30% of X. Of course, imperfect correlations between the bonds would make the latter case less risky due to the effect of diversification, assuming the absence of counteracting concentration risk.

Further, investors must be educated to understand that the traditional Moody's ratings--despite the same underpinnings--must be understood differently in the case of portfolios. That is, "the stand-alone credit ratings, as Moody's assigns them, are symbols designed to

[6] Baa3 is not used by Moody's for portfolios. Rather, Baa subsumes Baa1,2, or 3.

[7] The people at Moody's insist that their matrix of default probabilites is weighted and "smoothed" to include stress testing and market crashes, however, the evidence is somewhat unconvincing. They further elaborate that they utilize a mixed approach that incorporates Merton-like methodology and even Altman's Z. Altman's Z is a ratio that is linked to balance sheet financial statement entities.

signal a degree of probability that an issuer will pay its debts on time" [MO 99a]. Hence, the investor assumes that under normal circumstances, his debt will be repaid, and in the scarce likelihood of default, only a certain recovery rate will be obtained. The Moody's bond portfolio bearer must understand that default is a given--the ratings are based upon expected aggregate loss, which is a different mathematical and conceptual object.

Moody's has rated a wide variety of high-yield bond portfolio funds worldwide (including recent funds by Nomura-Rockwell[8] and KAMCO).

II.B **CreditRisk +**

II.B.1 Concept

CreditRisk+ presents another relatively straightforward approach to the modelling of portfolio credit risk. An analytical approach is taken, which facilitates speed, avoiding Monte Carlo simulations. The model requires several inputs, which include: exogenously calculated expected default rates, recovery rates (LGD), industry sectors, and the input of econometric risk parameters (time series for default rates and LGDs). Parameters are estimated using external data (Credit Reform from Dunn & Bradstreet)

II.B.2 Graphics/Charts/Tables

II.B.3 Discussion of Pros and Cons

The major shortcoming of CreditRisk+--which many would depict as irremediable--is the fact that sectors are modelled as independent variables. That is, no correlation is taken into account. Given that correlation across industries (sectors) is generally positive, and especially so in the case of strong market downturns, the model would seem to blatantly underestimate portfolio credit risk.

The Private and Corporate Clients Division of UBS has already implemented an improved version of the CreditRisk+ model which allows for the presence of correlations [see Bü Ku 99]. The extended model is called the Corporate Clients Credit Risk Quantifier (CRQ-Tool) and is anticipated to be functional in the near future. UBS users of CreditRisk+ and who will likely have access to the extended model also include CCO-PCC (J. Rickenbacher, M.Wolf) and CCRC (U. Blümli).

West LB uses the same analytics as CreditRisk+, but applies its own parameter estimation.

II.C **Creditmetrics**

II.C.1 Concept

In CreditMetrics, the future portfolio value distribution is generated based on the probabilities that exogenously obtained ratings will change[9]. Given a rating change, the

[8] According to David Vriesinga, Nomura recently used a barbell strategy--high quality in the short-term and long-term--to obtain an investment-grade rating on a fund that was over 70% junk. The authors of the KAMCO fund used a more concentrated debt-quality strategy, and were also granted investment grade status.

[9] Ratings can also be obtained from internal models.

forward yield curve is hypothesized to remain constant[10] [Ja Pe 00]. The synthesis of ratings and forward-curve-discounted value becomes a proxy for portfolio value.

II.C.2 Graphics/Charts/Tables

II.C.3 Discussion of Pros and Cons

It is clear that any given model will be deficient if it is fed faulty parameters. At the same time, it must be recognized that an arbitrary selection of parameters often takes place. In the example of CreditMetrics, if one uses the actual asset idiosyncratic risk, one is often faced with implausibly low overall portfolio volatility [JA PE 00]. Especially in the case of high-yield bond portfolios, one is therefore obliged to guestimate non-systematic risk values as being considerably lower than their empirical values.

As previously mentioned, CreditMetrics assumes that the forward spreads for various rating categories are known and constant. The recent spate of large swings in credit spreads augurs badly for those who rely too heavily upon these assumptions.

Another weakness in CreditMetrics is that correlations between different risk groupings are taken to be zero

II.D KMV

II.D.1 Concept

KMV uses Robert Merton's 1974 model to deduce portfolio value changes based upon equity market capitalizations and leverage levels. This approach is known as the structural approach. Stock price and volatility are key ingredients in the KMV analysis.

Conceptually, KMV (and all other models based upon a Merton methodology) views a firm's equity as an option held by the shareholders of the firm. The latter are entitled to either exercise their option by repaying the debt at its maturity and taking possession of the firm, or abandoning the firm to the debtholders by not repaying the debt.[11]

The KMV/Merton default probability is a function of the number of standard deviations that the value of the firm's assets must drop in order to reach the default point--"Distance to Default":

$$DD = \frac{Asset\_Value - Default\_Value}{\sigma_{ASSETS}}$$

Because equity markets are assumed to be efficient, all market expectations and corresponding risk premiums are embedded into the EDF.[12]

Below we observe the trajectory and EDF distribution for the KMV stand-alone model (and any other structural model).

[10] The fact that the yield curve is independent of rating changes is certainly an oversimplification that can be dangerous in today's increasing corporate spread environment.

[11] The face value of the debt is tantamount to the option's strike price.

[12] Paramount in the risk comparable methodology is the replication of the bond at time 0 with the quasi-Merton model. This calibration is important as it also yields $N(d_2)$ which is the distance to default or first stopping time.

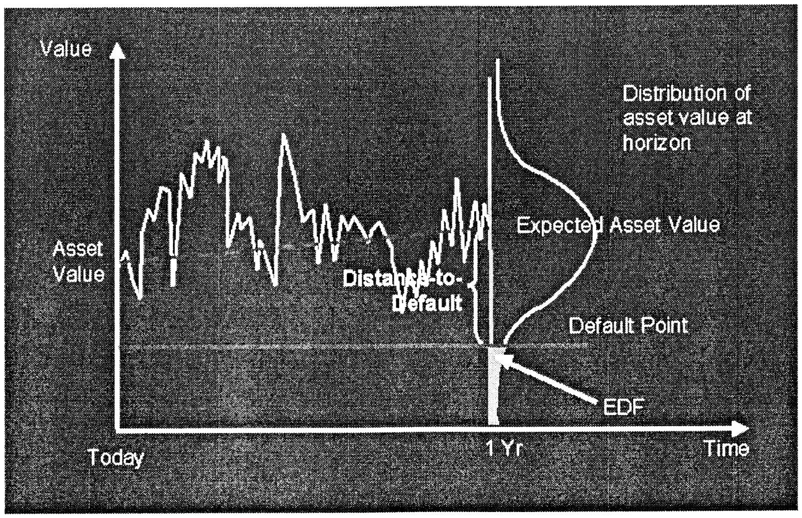


Figure 1: KMV/Merton trajectory [KM 98]

Market risk (shifts in the term structures of spreads, etc.) and credit risk valuations (ie. default probabilities) are both embedded in the EDF. In addition, the severity of loss (Loss Given Default-LGD) is also subsumed in the EDF calculation. As of yet, KMV users have no way of disentangling the portion of risk premium attributed to severity of loss (LGD) from default probabilities.

KMV includes three different rating methodologies: the Matrix (related to Credit Metrics but with no simulations), Book (notional bond values are modeled only for downside risk), and the Risk Comparable approach. The latter is the most famous and is based upon risk-neutral methodology, whereby Standard and Poor's actual historical default values are corrected by a Sharpe ratio-like risk premium. The risk premium and the corporate spread are linearly related.

To obtain covariance data from the private equity firm model, a company is decomposed into fourteen orthogonal factors. Regressions are made on composite industry and composite factors in order to weed out all systematic risk. Each facility is decomposed into various factors which are orthogonal to one another. Facility sensitivities are assigned to different drivers (independent factors).[13] Principal component analysis is used to reduce the dimensionality of the covariance matrix. Driver exposure correlation (global and regional) to all other correlations are especially important in the private firm model. According to KMV expert, medium and large companies have roughly 10% systematic risk.[14]

↳ ANYTIME RISK-NEUTRAL MEASURES ARE USED, WE SHIFT THE PROBABILITIES INTO THE RISK PREMIUM.

Estimating the correlations between assets in defaults is key to an accurate simulation. At the time of this work, KMV did not assign default correlation different from correlation, which naturally presents itself as a danger for the coverage of tail events.

A factor model is employed to measure return correlations between firms (see Appendix 2 for details). Factor models are superior to historical correlation estimates because there is less sampling error. Further, this methodology permits non-listed, private companies to be

[13] For example, if a facility has a 30% sensitiivity to the US country driver, a 100 bp move in the US will add 30 bp to the facility in question.
[14] Stefan Buergi, UBS London

evaluated. The latter are proxied by their size, country, and industry composition [KMV 97] at the top "level" of the model. Two lower levels are also necessary to obtain the first level factor.

The third level is used to localize the company's country in the world through global, regional and industrial factors, This level yields sensitivities which are then regressed upon in the second level to see what the companies sensitivities are to the fact that it is in the land in question. The latter sensitivities are then regressed upon to obtain the company proxy in the first level.

Whenever credit risk specialists deal with risk comparable methodologies, one must be aware of the overriding importance of the role of the risk premium, which is later used to adjust expected default frequencies. All relevant information-including market shocks-is handled via increases in the risk premium, which is none other than a disguised Sharpe ratio (a variant of the aforementioned Distance to Default). (Stress tests would, hence, just include a manipulation of this risk premium, and thus there would be no difference between flights-to-quality and market shocks, which is actually correct from a valuation standpoint. There is no specification for how the risk-premium ratio behaves through time, however, the combination of a static Sharpe ratio with no relevant market fluctuations would certainly underestimate spread risk. **This spread risk would be especially relevant for high yield bond portfolios, and it would be fair to say that without the integration of EDF smoothing techniques or stress tests, KMV will systematically underestimate a high-yield debt portfolio credit risk.**

There is ample evidence that the structural approach dominates statistical or financial statement analysis approaches[15]. It must also be stated that the KMV methodology is more refined than some of its competitors who also implement the Merton model. One to five year EDFs are estimated whereas others only estimate a one-year EDF. For short term pricing, 5-year EDFs can be useful.

Another clear benefit of KMV is the fact that it is designed for the evaluation of aggregate portfolio risk. The actual application of KMV is somewhat complicated and requires preparation. A minimum of five tables must be specified for the portfolio manager to function; other data inputs are supplied automatically by KMV preprocessor.[16]

The aggregate portfolio loss distribution is simulated via Monte Carlo and takes the following form:

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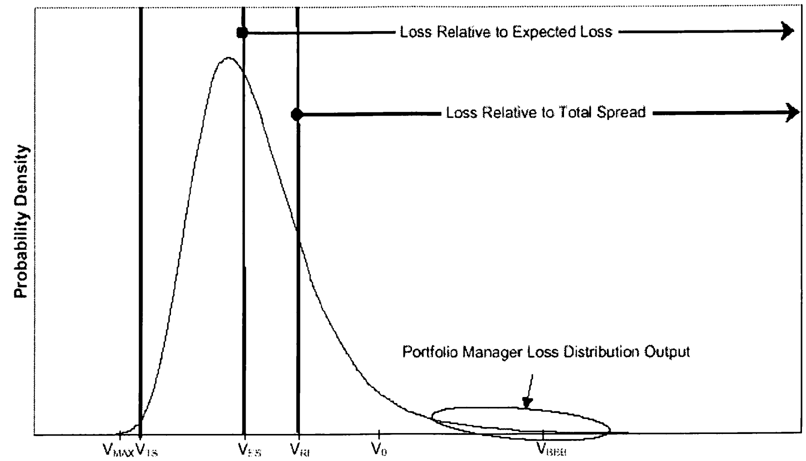
[15] valuation tests that compare the approaches are worthless because structural models are inherently superior, whereas downside tests are considered useful

[16] A short-cut to this official methodology is to simply manipulate premade sample portfolios which include PORTN.dbf and PORTNdy.dbf. These two files are key to running Portfolio Manager and the Credit Monitor's EDF Calc yields necessary 1-5 year EDF data (annualized cumulative values).



The horizontal axis represents the portfolio value distribution at future horizon time "H". The vertical axis depicts the probability of any given realization of a portfolio value. We observe that the distribution is skewed to the left and has fat tails (leptokurtosis). This is due to the fact that during market crashes, increased correlation causes potentially enormous losses. On the other hand, even under the best of conditions (payout of full spread and upgrades of all portfolio constituents), the portfolio value has a ceiling, and most of the time the horizon value will lie near this ceiling.

A great flexibility is offered to the KMV user in terms of choice of parameters. Naturally, simulation quality will be affected by these choices so relevant holding horizon, interest rate curve structures , and downside risk (LGD estimation) must be chosen with care. With respect to downside risk, we use a book valuation of a binomial default or no-default (book value). This data is used later for the simulations. Clearly then, the key to a good simulation is accurate data.

KMV Portfolio Manager outputs the **value distribution** based upon the estimated loss distribution.

This value distribution is obtained through either analytical approximations, calculated loss distributions, and Monte Carlo simulations. Monte Carlo simulations are the most accurate because a wide range of scenarios (20,000 to 100,000) is considered, and because time is not an issue for the purposes of portfolio management, Monte Carlo simulation will always be preferenced.

II.D.2 Discussion of Pros and Cons

Despite the popularity of the model, certain flaws exist and could be dangerous for the measurement risk of a portfolio of high-.yield bonds. Markets are assumed to be efficient. If markets are illiquid and inefficient, we can safely rule out the possibility of accurate predictions based on the KMV approach.

Another non-negligeable weakness of the KMV model is the fact that high dividend pay-out rate simultaneously raises the firms volatility and lowers the company's equity value. Default is thus made to appear more likely.

Factor model R-squareds are capped from 0.10 to 0.65 to avoid noise. Some critiques would say that we are throwing out the baby with the bathwater, because extreme scenarios are thereby avoided. (That is, where a given market driver had a near perfect correlation with a given issue). Nonetheless, this is not a critical fault and can be remedied with stress tests.

Stress tests can also be useful in order to take into account for market risk and global market moves that should also be taken into account for modelling the value of a portfolio of bonds. For example for any given rating class, the composant bonds are not homogoneous and the spread curve is not representative of the entire rating category, but rather just an average. **KMV also ignores the fact that certain industries will clearly be affected more than other in times of market duress.**

II.A.4. **Moody's Public Firm Risk Model**

In response to critics who charged that Moody's static methodology was too focused on the past--financial statements and improvised EDF smoothing--in March 2000--a new modeling approach has been conceived. The approach subsumes contingent claims, financial statement, and macroeconomic variable analysis. Moody's ratings are also included and smoothed to contain specific industrial information. Ratings and financial statement information are processed through a reduced[17] representation statistical model that is non-linear in nature[18] (the Altman Z-score comes from a model that is linear in nature) [MO 00b].

The following variables are essential to the Moody's variation of the ratings and financial statement variables in the public firm model [MO 00b]:

MODEL VARIABLE	DEFINITION	FREQUENCY
Credit Quality	Rating	Credit history if available
Returns on Assets	Net Income/Assets	Annual
Firm Size	Log (Assets)	Annual
Operating liquidity	Working Capital/Assets	Annual
Leverage	Liabilities/Assets	Annual
Market Sensitivity	Stock Price Volatility	Monthly
Equity Growth	Equity Growth Rate	Monthly
Return on Equity	Net Income/Equity	Monthly
Distance to Default	Distance to Default	Monthly

Dsitance to default refers to the number of standard deviations a company's assets must drop before default occurs. This value is the product of Moody's contingent claim approach which is based upon the Merton model which also inspired KMV.

Moody's claims that its inputs into its Merton/Black & Scholes options estimation of the firm's value are more accurate and "optimized" with the additional constraint of imposing minimum data requirements on users. Moody's takes the Distance to Default and maps it onto the historical default probabilities, which effectively transforms the structural model into a statistical one.

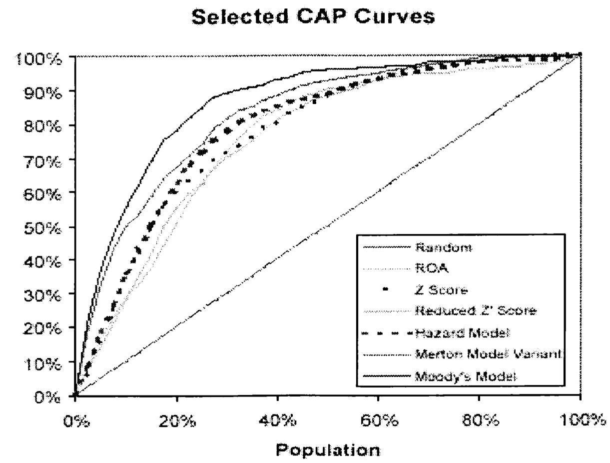
[17] The models are referred to as being reduced form in nature because financial variables are reduced so they can be mapped onto a risk scale. A threshold disguishes between good and bad credits.
[18] The model is described as being a combination of Byesian inference and logistic regressions, a.k.a. artificial neural network.

The non-linear nature of the aforementioned variables is handled by a nested logistic regression, based upon artificial neural networks (ANN). This approach allows for the analysis of highly dimensional and non-linear relationships.

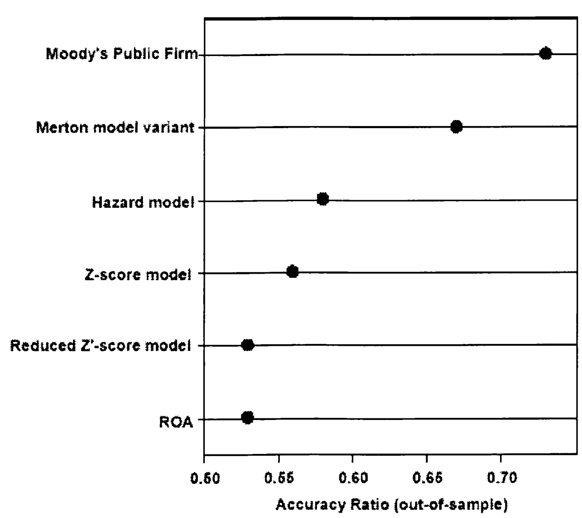
Moody's hybrid model has apparantly stood up well in comparisons to other models including the original Z-score, the improved reduced 1993 Z-score model, a univariate model based on return on assets, a hazard model based on financial data, and a variant of the Merton model based on distance to default [MO 00b].[19] Moody's attributes its success to the extensive use of cross validation made during the modeling process and the probability adjustments used to account for differences in the default rate or the data set used to fit the model and the full universe of public firms [MO 00b]. We should bear in mind that the Moody's model only uses a one year expected default frequency, whereas KMV looks at the respective five year expected default frequencies.

The tests were conducted by Moody's and the benchmark "cumulative accuracy profiles" and "accuracy ratios" are possibly biased to the Public Firm Risk Model[20]. Below we observe the outperformance.

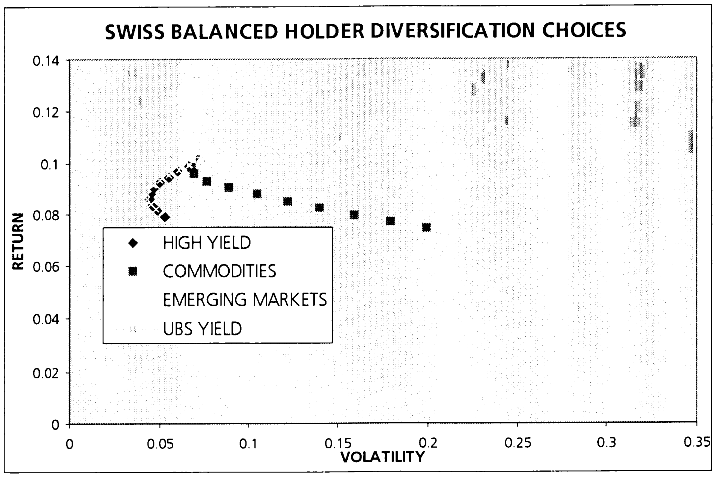
[20] See original text for a detailed explanation of the approaches



Moody's hybrid specifically outperformed the pure Merton variant, which could be likened to a KMV like model. **Clearly, Moody's wants to market its Public Firm model as being the best of all worlds.**



V. Long Term Considerations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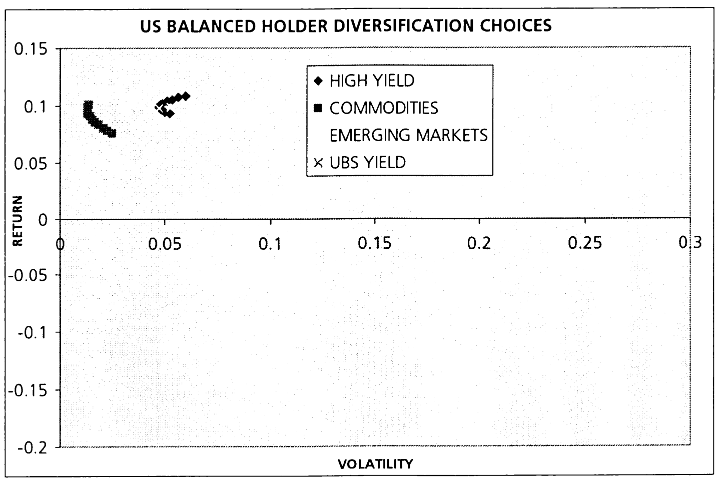
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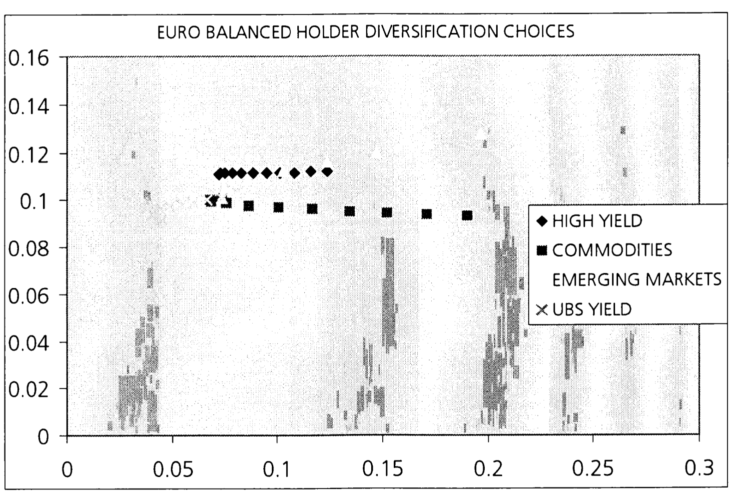
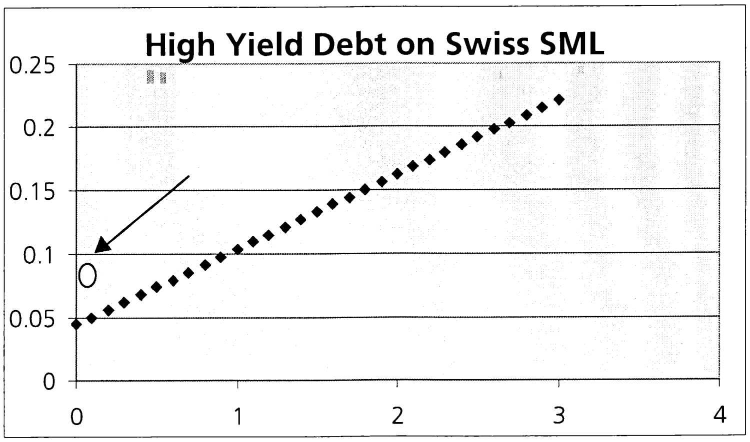
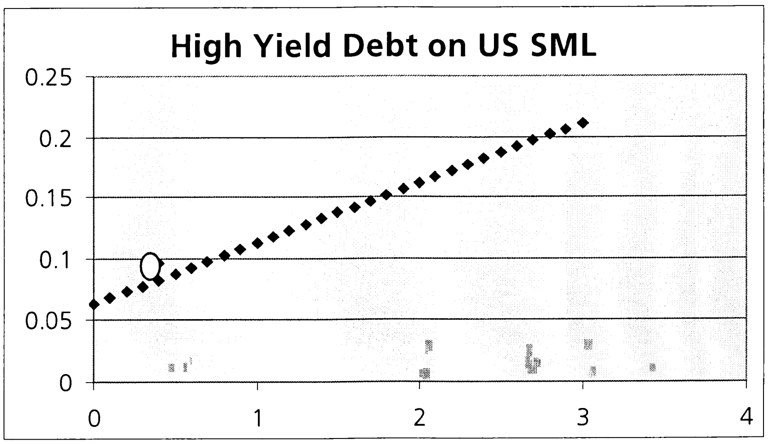
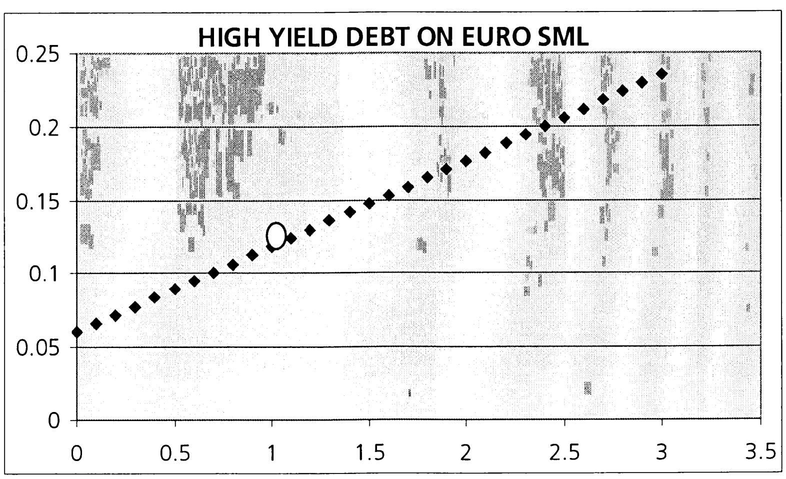

EURO BALANCED HOLDER DIVERSIFICATION CHOICES
HIGH YIELD
COMMODITIES
EMERGING MARKETS
UBS YIELD
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0.05
0.1
0.15
0.2
0.25
0.3







VI:Marketing

Who would benefit most from high-yield bonds? The person that would most profit is one that could time the market and use the premium lag effect to his advantage. But most private clients lack the sophistication to implement this strategy and high commissions would eat up most of the profits.

When the economy booms, then interest rates go up to prevent overheating. This rise in interest rates does not hurt high-yield bonds, but the healthy-economy effect is dominant. Hence high-yield debt is pro-cyclical and would work best with counter-cyclical portfolios such as gold.

There is a limited diversification effect, and the asset class is dominated by equities, which are also pro-cyclical, but have a higher spread relative to treasury bonds. Thus high-yield debt would more than likely not be included in a portfolio of equities, and could be added to a debt portfolio given good diversification.

Such an individual would profit from additional mean-variance efficiency for his portfolio and superior-to-break-even returns.

Given the A fixed-income investor would possibly enjoy extra retur

The approach used to market the high yield would most logically be that of a multisector fund. The previous mean-variance/SML analysis assumes the pure asset class. We take simply a linear combination of this asset class that will be combined with risk free debt instruments. Although the average risk and return will be buffered, this means that the client can hold a larger part of his wealth in this fund, because of its risk free debt composition.

APPENDIX

SWISS SECURITY MARKET LINE REGRESSION

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.077334
R Square	0.005981
Adjusted R Square	-0.000922
Standard Error	0.015041
Observations	146

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.000196	0.000196	0.866385	0.353516
Residual	144	0.032578	0.0002262		
Total	145	0.032774			

	Coefficients	*Standard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00279	0.001278	2.1837157	0.030602	0.000265	0.005316	0.000265	0.005316
X Variable 1	0.053775	0.057773	0.9307978	0.353516	-0.060418	0.167967	-0.060418	0.167967

US SECURITY MARKET LINE REGRESSION

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.448713
R Square	0.201343
Adjusted R Square	0.195797
Standard Error	0.013529
Observations	146

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	1	0.006644	0.006644	36.30276	1.35E-08
Residual	144	0.026355	0.000183		
Total	145	0.033			

	Coefficients	*tandard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*Jpper 95.0%*
Intercept	0.001144	0.001153	0.99263	0.322555	-0.001134	0.003423	-0.001134	0.003423
X Variable 1	0.40001	0.06639	6.025177	1.35E-08	0.268785	0.531234	0.268785	0.531234

EURO SECURITY MARKET LINE REGRESSION

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.607574
R Square	0.369147
Adjusted R	0.364766
Standard E	0.028591
Observatio	146

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regressior	1	0.068882	0.068882	84.26226	4.25E-16
Residual	144	0.117715	0.000817		
Total	145	0.186597			

	Coefficients	*tandard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*Jpper 95.0%*
Intercept	0.000603	0.002423	0.2487	0.803947	-0.004187	0.005392	-0.004187	0.005392
X Variable	1.02942	0.112144	9.179448	4.25E-16	0.807759	1.251081	0.807759	1.251081

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