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by
Norbert Jobst
Stavros A. Zenios

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The tail that wags the dog: Integrating credit risk in asset portfolios

Norbert Jobst *
Stavros A. Zenios †

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*Fellow, HERMES Center on Computational Finance & Economics, University of Cyprus, and PhD student, Brunel University, UK. norbert.jobst@brunel.ac.uk

†Professor and Director of the HERMES Center on Computational Finance & Economics, University of Cyprus, Director of RiskLab, Cyprus International Institute of Management, Nicosia, CY, and Senior Fellow, Financial Institutions Center, The Wharton School, Philadelphia, USA. zenioss@ucy.ac.cy. This work was completed while he was with Algorithmics Inc. as a Marie Curie Fellow of the European Commission.

Abstract

Tails are of paramount importance in shaping the risk profile of portfolios with credit risk sensitive securities. In this context risk management tools require simulations that accurately capture the tails, and optimization models that limit tail effects. Ignoring the tails in the simulation or using inadequate optimization metrics can have significant effects and destroy portfolio efficiency. The resulting portfolio risk profile can be grossly misrepresented when long run performance is optimized without consideration of the short term tail effects. This paper illustrates the pitfalls and suggests models for avoiding them.

1 Introduction

Credit risk and derivative securities are characterized by a large chance of positive returns and very small probability of large investment losses. The distribution of price returns of these instruments are asymmetric and highly skewed, exhibiting very flat tails on the downside. Of course investors are compensated for assuming the low-probability risk of losses. This is evidenced, for instance, by the total return of the corporate bond indices *viz-á-viz* the US Treasury market as summarized in Table 1 for the eleven-year period from January 1990 to April 2001. On a duration adjusted basis the Merill Lynch Eurodollar index, for instance, realized annualized return of 9.35% with a standard deviation of 4.48%. The Eurodollar index outperformed during this period the US Treasury index, which realized duration adjusted returns of 8.74% with a standard deviation of 4.73%.

Index	**Return (%)**
Merill Lynch Eurodollar	139.68
US Treasury	137.37
US Agency Master (AAA)	142.39
US Corporate domestic	156.34

Table 1: Total return of broad market indices from January 1990 to June 2001.

In a portfolio management context the question is then raised whether the return of the credit risky portfolio adequately compensates for the low-probability, large-losses events. Given the proliferation of corporate bond issues, the constant stream of innovations in credit derivatives, and their increased use in the asset portfolio of financial—and other—institutions, it is only fitting that credit risk pricing models are receiving today widespread attention; see, for instance, Saunders (1999) and Schönbucher (2000). Costly lower-tail outcomes are also having an impact on the practice of enterprise wide risk management as pointed out by Stulz (1996). However, models for integrative risk management in the context of credit risky securities are scant.

In this paper we demonstrate the significance of the tails when shaping the risk profile of credit asset portfolios. We start with the obvious, namely, that properly simulated credit events result into risk profiles with flat tails on downside risk (i.e., losses) and limited upside potential (i.e., gains). But then we proceed with more subtle and important observations:

Observation no. 1. Losses are probabilistic events and without adequate accuracy they may be missed. This is demonstrated in section *"Where is the tail?"*.

Observation no. 2. When the tails are properly simulated they distort substantially the risk-return tradeoffs of portfolios rendering inefficient portfolios that may be considered as efficient when the tails are ignored. This is shown in section *"Tail effects on efficient frontiers"*.

Observation no. 3. To avoid distortions of the efficient frontier we need to optimize appropriate risk metrics and to do so with adequate accuracy. The relevant models are introduced in section *"Optimizing the right risk metric"*.

Observation no. 4. With appropriate modelling the long-term performance goals can be met without suffering catastrophic blows from the tails in the short run. This is demonstrated in section *"Long term performance with short term tails"*.

These observations are supported by empirical analysis carried out using the simulation models developed recently by Jobst and Zenios (2001). In our numerical experiments we simulate 500 economic scenarios and 5000 credit events, for a total of 2.5 million simulation runs. Portfolio models are optimized on samples of five to ten thousand scenarios, drawn from the 2.5 million simulations.

2 Where is the tail?

The causes of loss from credit assets are many and complex in nature. Credit risk can be described as the risk that one of the trading counterparties does not fulfill their obligations on a certain date or at any time beyond. Losses may result from a counterparty default or a change in the market value due to credit quality migration. In general, credit risk for a single instrument may be decomposed into default risk, migration risk, and security specific risks causing idiosyncratic spread changes. Default is the low-probability, large-impact event.

Tools such as CREDITRISK+ form Credit Suisse, CreditMetrics from JP Morgan, Credit Portfolio View from McKinsey & Co, or KMV's Portfolio Manager allow us to gain important insights into credit risks but a number of important aspects are missing. CREDITRISK+, for example, assesses credit risk due to default losses only without taking into consideration the term structure of credit spreads. CreditMetrics allows us to calculate the present value of a portfolio of credit risk sensitive assets dependent on credit risk only. Market risk is not incorporated explicitly. As a result, no other risks apart from credit risk can be assessed for their impact on the valuation of the portfolio.

In a recent paper (Jobst and Zenios 2001) we have shown how some popular pricing models can be extended to the valuation and simulation of portfolios of credit risky and derivative securities. These extensions allow us to estimate the risk profile of portfolios taking into account market and spread risk, and the risks of rating migration, defaults, and recovery. The simulations reveal—and quantify—the flat tails due to credit events. For instance, Figure 1 shows a flat lower tail when credit rating migrations are simulated under the current economic conditions. This tail is absent when simulating only market and spread changes.

The tail in this example is quite pronounced as it was simulated under the current economic conditions—i.e., assuming the term structure of risk free rates and credit spreads remains unchanged. Figure 2 develops the simulation of the same portfolio integrating market and credit spread risk, and then adding the credit events, i.e., credit rating migrations and defaults. The tail is once more evident but not when we look at the 0.95-quantile of the distributions. The .95 quantiles of the two distributions shown in Figure 2 are positive and very close to each other. However, the .99 quantiles have opposite signs and differ by an order of magnitude. There are no losses at the .95 probability level, even when credit events are properly simulated. At the .99 probability level, however, we observe losses of -1.67% when credit events are simulated. This is *Observation no. 1*: Tails are probabilistic events and without adequate accuracy they may be missed. We will see later that this observation has ramifications when choosing an appropriate risk metric for portfolio optimization.

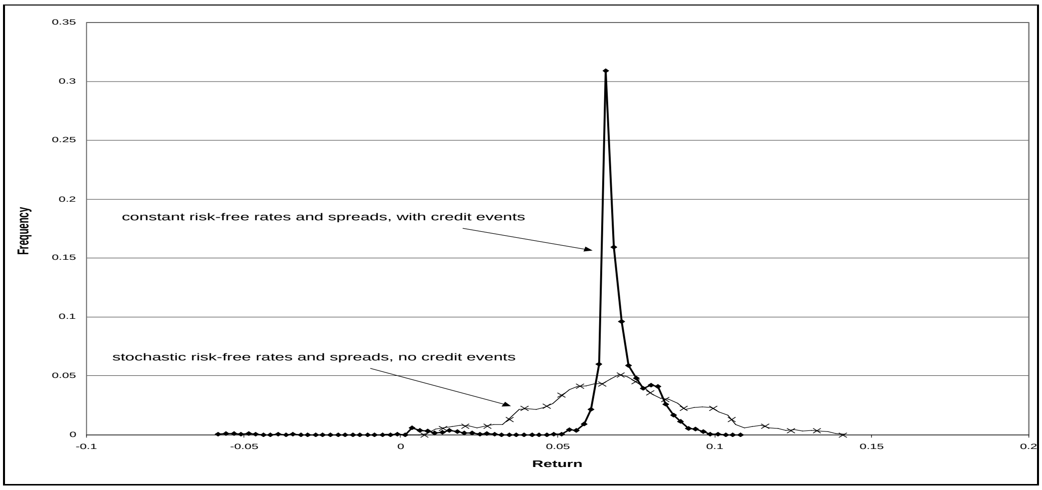

Figure 1: Distribution of returns of a Baa bond portfolio during an eight month risk horizon for (*i*) constant risk free rates and credit spreads with credit rating migrations and default (thick line), and (*ii*) stochastic risk free rates and credit spreads without credit rating migrations or default (thin line).

3 Tail effects on efficient frontiers

We study now the efficient frontiers generated when trading expected return against risk in credit risky portfolios. Ignoring the tails has a significant effect on the efficient frontiers. We simulate first the distribution of returns of 17 bonds rated Baa, *without* credit rating migration and defaults and solve a mean absolute deviation portfolio optimization model (MAD of Konno and Yamazaki 1991) on these simulated data. The efficient frontier of portfolio expected return against its mean absolute deviation is shown by the thin solid line in Figure 3. On the same figure we re-draw (dotted line) the frontier by calculating the expected return and the mean absolute deviation of the optimized portfolios using the distribution of returns *with* credit rating migrations and defaults. Thus we perform an out-of-sample sensitivity analysis of the frontier using tail scenarios that were not included in the scenario sample of the optimization model. There is nothing efficient about the optimized portfolios obtained by ignoring the tails once the tails are properly accounted for. This is *Observation no. 2*: Tails distort the risk-return frontiers rendering seemingly efficient portfolios into inefficient ones.

Running the mean absolute deviation portfolio optimization using the distribution *with* credit events we obtain a frontier which is very close to the out-of-sample frontier and eliminates the inefficient portfolios. This fron-

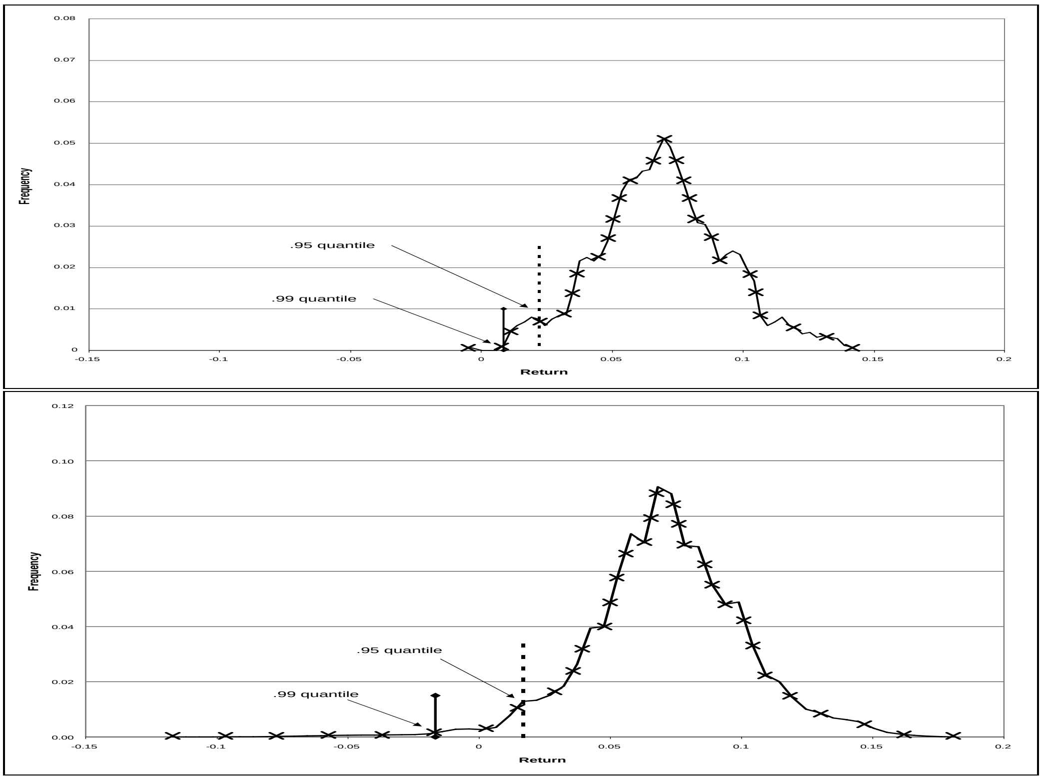

Figure 2: Distribution of returns of a Baa bond portfolio during an eight month risk horizon for stochastic risk free rates and credit spreads. Top figure: without credit rating migrations or defaults. Bottom figure: with credit rating migrations and defaults.

tier is shown by the thick solid line on Figure 3. Does this imply that it is sufficient to simulate accurately the tails and then develop portfolios that optimally trade expected return against risk? The answer is of course affirmative, however the mean absolute deviation risk measure does not properly account for the tails. The distribution of returns of the minimum risk portfolio obtained using the MAD model is shown in Figure 4. We note a small probability of losses in excess of 80% of the portfolio value. These losses are likely to be catastrophic, and when they occur they will most likely—due to bankruptcy—block the portfolio growth to its long term expected return. The long term expected return of the minimum risk portfolio obtained using MAD is 5.5%, but this return will be realized only if the portfolio is not ruined in the short term. This is the same observation made by Stulz (1996) in explaining the discrepancy between the corporate use of derivative securities advocated by theory, and their actual use in practice as revealed by the

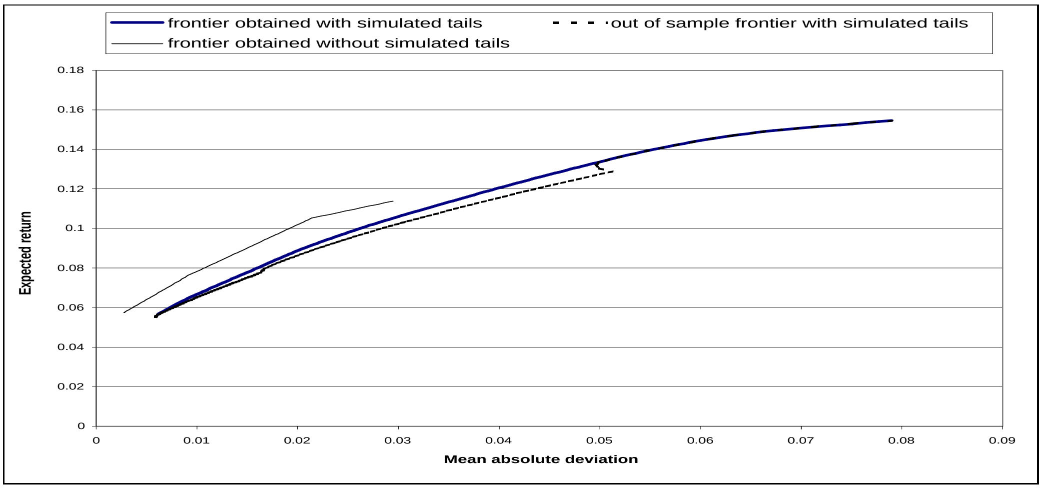

Figure 3: Frontier generated using a mean absolute deviation (MAD) portfolio optimization without simulating the tails due to credit events (thin line), and its out-of-sample performance when credit events are included (doted line). The frontier traced using a MAD model with simulated data of credit events is also shown (thick line).

Wharton surveys (see Bodnar et al. (1998) for the latest survey results).

What then should be done in order to properly account for the tail effects? The answer lies in selecting a risk metric that penalizes appropriately the tail events, and then optimizing the portfolio composition with respect to this metric of risk. We will see in the next section that *Conditional Value-at-Risk* provides a risk metric suitable for integrating credit risk in asset portfolios.

4 Optimizing the right risk metric

Value-at-Risk (VaR) has become an industry standard for measuring extreme events and integrating disparate sources of risk. VaR answers the following question: What is the maximum loss with a given confidence level (say $\alpha \times 100\%$) over the target horizon? Its calculation also reveals that with probability $(1-\alpha)\times 100\%$ the losses will exceed VaR.

Consider a portfolio with value $V(x, \tilde{P})$. This is a function of the holdings $x = (x_i)_{i=1}^m$ of assets in the portfolio, and of the random asset prices $\tilde{P}$. If the current value of the portfolio is V_0 then the losses in portfolio value are given by the *loss function*

$$L(x, \tilde{P}) = V_0 - V(x, \tilde{P}). \tag{1}$$

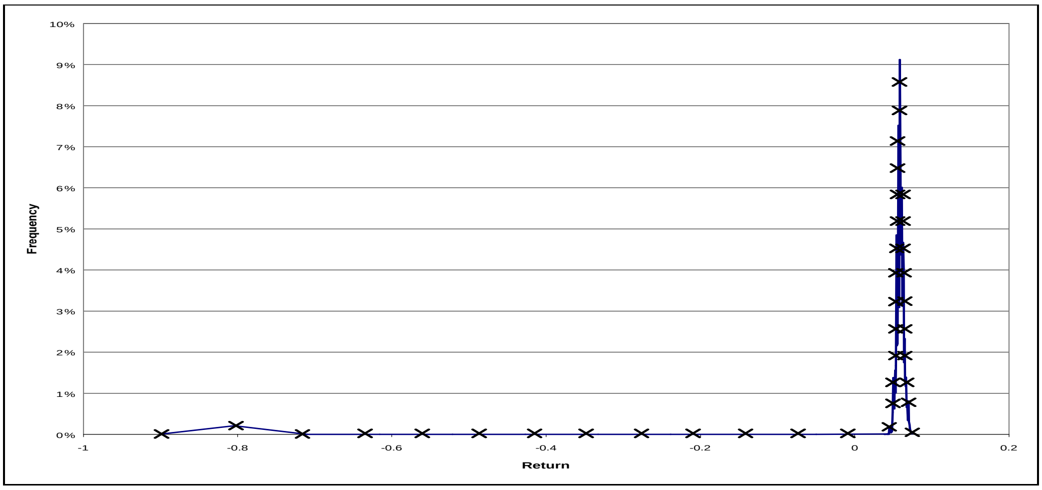

Figure 4: Distribution of returns for the minimum risk portfolio obtained using the MAD model. Note the small probability of negative returns worse that -80%.

The relation between the loss function and portfolio returns is given by

$$L(x, \tilde{r}) = -R(x, \tilde{r})V_0. \tag{2}$$

We assume a discrete scenario setting whereby all random quantities take values from a finite and discrete scenario set indexed by members of a set Ω. That is, $\tilde{P} \in \{P^l\}_{l\in\Omega}$, and the objective probability associated with each scenario $l \in \Omega$ is given by p^l. Under this assumption the probability that the loss function does not exceed some threshold value ζ is given by the probability function

$$\Psi(x, \zeta) = \sum_{\{l\in\Omega | L(x,P^l)\leq\zeta\}} p^l. \tag{3}$$

The Value-at-Risk of the portfolios is then defined as follows:

Definition 4.1 Value-at-Risk. *The Value-at-Risk (VaR) of a portfolio at the α probability level is the left α-quantile of the losses of the portfolio, i.e., the lowest possible value such that the probability of losses less than VaR exceeds $\alpha \times 100\%$. It is given as:*

$$VaR(x, \alpha) \doteq \min \{\zeta \in \mathrm{I\!R} \mid \Psi(x, \zeta) \geq \alpha.\} \tag{4}$$

$\diamondsuit$

The quantile ζ is the left endpoint of the nonempty interval consisting of the values ζ such that $\Psi(x, \zeta) = \alpha$. The dependence of VaR on the confidence level α is sometimes made explicit by referring to α-VaR. Figure 2 illustrates the VaR of the return for a credit risky portfolio of Baa bonds as 1.7% at the .95 probability level, and -1.7% at the .99 probability. There is a 1% chance of losses in excess of -1.7% and a 5% chance that returns will be less than 1.7%.

The VaR measure reveals nothing about the magnitude of the losses outside the given confidence level. Such losses can be catastrophic. Long Term Capital Management is a case in point. Their fund was estimated to have a VaR of only -5% at the .95 probability level. However, a return of -80% in September 1998 wiped off a position of $1.85 trillion and threatened a global meltdown of the financial markets.

A measure of risk that goes beyond the information revealed by VaR is the expected value of the losses that exceed VaR. This quantity is called *expected shortfall*, *conditional loss* or *conditional VaR*, see, e.g., Embrechts, Klüppelberg and Mikosch (2000). For general distributions the conditional VaR is defined as a weighted average of VaR and the expected losses that are strictly greater than VaR. For discrete distributions, and under a mild technical condition that the probability of scenarios with losses strictly greater than VaR is exactly equal to $1-\alpha$, i.e., $\Psi(x,\zeta)=\alpha$, the following definition applies:

Definition 4.2 Conditional Value-at-Risk. *The Conditional Value-at-Risk (CVaR) of the losses of the portfolio is the expected value of the losses, conditioned on the losses being in excess of VaR.*

$$\text{CVaR}(x,\alpha) = \mathcal{E}[L(x,P^l) \mid L(x,P^l) > \zeta] \tag{5}$$

$$= \frac{\sum_{\{l\in\Omega \mid L(x,P^l)>\zeta\}} p^l L(x,P^l)}{\sum_{\{l\in\Omega \mid L(x,P^l)>\zeta\}} p^l} \tag{6}$$

$$= \frac{\sum_{\{l\in\Omega \mid L(x,P^l)>\zeta\}} p^l L(x,P^l)}{1-\alpha}, \tag{7}$$

where the last equality follows from the condition $\Psi(x,\zeta)=\alpha$. ◇

The dependence of CVaR on the confidence level α is made explicit by referring to α-CVaR.

It follows from the definitions that CVaR is always greater or equal to VaR. Both VaR and CVaR are functions of the asset allocation vector x and the percentile parameter α. It is natural to seek to minimize these measures by judiciously specifying the composition of the asset portfolio.

VaR is difficult to optimize when calculated using discrete scenarios. The VaR function is non-convex, non-smooth and it has multiple local minima.

However, CVaR can be minimized using linear programming formulations, see Rockafellar and Uryasev (2000). Consider the minimization of Conditional Value-at-Risk given above by

$$\mathrm{CVaR}(x,\alpha) = \frac{\sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l L(x,P^l)}{1-\alpha}. \tag{8}$$

This function can be expressed as a linear model with the use of auxiliary variables. Let

$$y_+^l = \max\left[0, L(x,P^l) - \zeta\right], \text{ for all } l \in \Omega. \tag{9}$$

y_+^l is equal to zero when the losses are less or equal to the Value-at-Risk, ζ, and it is equal to the excess loss when the losses exceed ζ.

With this definition of y_+^l we write:

$$\begin{aligned}
\sum_{l\in\Omega} p^l y_+^l &= \sum_{\{l\in\Omega|L(x,P^l)\le\zeta\}} p^l y_+^l + \sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l y_+^l \\
&= 0 + \sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l \left(L(x,P^l) - \zeta\right) \\
&= \sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l L(x,P^l) - \zeta \sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l \\
&= \sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l L(x,P^l) - \zeta(1-\alpha)
\end{aligned}$$

Dividing both sides by $(1-\alpha)$ and rearranging terms we get

$$\zeta + \frac{\sum_{l\in\Omega} p^l y_+^l}{1-\alpha} = \frac{\sum_{\{l\in\Omega|L(x,P^l)>\zeta\}} p^l L(x,P^l)}{1-\alpha}. \tag{10}$$

The term on the right is $\mathrm{CVaR}(x,\alpha)$ of equation (8) and it can be optimized using linear programming to minimize the term on the left.

We minimize CVaR subject to constraints on the asset allocation of the form $x \in X$, where X denotes the set of feasible solutions, and the condition that the expected value of the portfolio exceeds some target μ. Using the equivalent definition of CVaR from (10) we write the model as follows:

$$\underset{x\in X}{\text{Minimize}} \quad \zeta + \frac{\sum_{l\in\Omega} p^l y_+^l}{1-\alpha} \tag{11}$$

$$\text{subject to} \quad \sum_{i=1}^{m} \bar{P}_i x_i \ge \mu, \tag{12}$$

$$y_+^l \ge L(x,P^l) - \zeta, \qquad \text{for all } l \in \Omega, \tag{13}$$

$$y_+^l \ge 0, \qquad \text{for all } l \in \Omega. \tag{14}$$

($\bar{P}_i = \sum_{l\in\Omega} p^l P_i^l$ is the expected value of the price of asset i.) Since the loss function $L(x, P^l)$ is linear, see eqn. (1), the model is a linear program. Solution of this model gives us the minimum CVaR* for a given target expected value μ, and the VaR value ζ^* corresponding to the minimum CVaR portfolio. (Recall that CVaR$\geq$VaR and, hence, CVaR$^* \geq \zeta^*$.)

An efficient frontier trading expected shortfall against expected portfolio return is traced by varying the parameter μ. We develop the CVaR efficient frontier of portfolios of Baa bonds, see Figure 5, at the .99 and .95 probability levels. On the same figures we plot the tradeoffs between CVaR and expected return of the optimal portfolios obtained using a MAD model. That is, we take the portfolios of the efficient frontier of Figure 3 and calculate their CVaR. We observe from the two frontiers of Figure 5 (top) that there is nothing efficient about the MAD optimized portfolios when using a risk metric that properly accounts for the tails of the optimized portfolios. It is not sufficient to capture the tails in the simulation phase, as was done in Figure 3. We must also optimize the appropriate risk metric, as was done in Figure 5.

This figure leads to *Observation no. 3*: To avoid distortions of the efficient frontier due to the tail events we need to optimize a risk metric that appropriately penalizes the tails. CVaR provides such a risk metric. Note, however, from Figure 5 (bottom), that the distortions of the frontiers calculated at the .95 probability level are barely noticeable for a wide range of target returns. Echoing *Observation no. 1* we re-emphasize that tail effects can be captured only with adequate accuracy of the models.

4.1 The tail that wags the dog

The risk profile of a portfolio is shaped by the attention paid by the risk manager to the tails. Taking a CVaR perspective on risk management substantially reduces the tails. Figure 6 shows the distribution of returns of the minimum risk portfolio obtained when minimizing CVaR at probability levels .95 and .99. The tail extends up to almost -40% when minimizing CVaR at the .95 probability level, but it shrinks to -10% when minimizing CVaR at the .99 probability level. Both of these losses are substantially lower than the losses in excess of 80% realized when minimizing the mean absolute deviation measure of risk as demonstrated in Figure 4.

Of course the choice of a risk metric has an effect on the upside potential of the portfolio. We note from the distributions of Figures 4 and 6 that the upside potential is reduced as the tails are shrunk. We have the usual tradeoffs between upside potential and downside risk. However, in the context of credit risky securities the downside risk is hidden in the tail and not in the

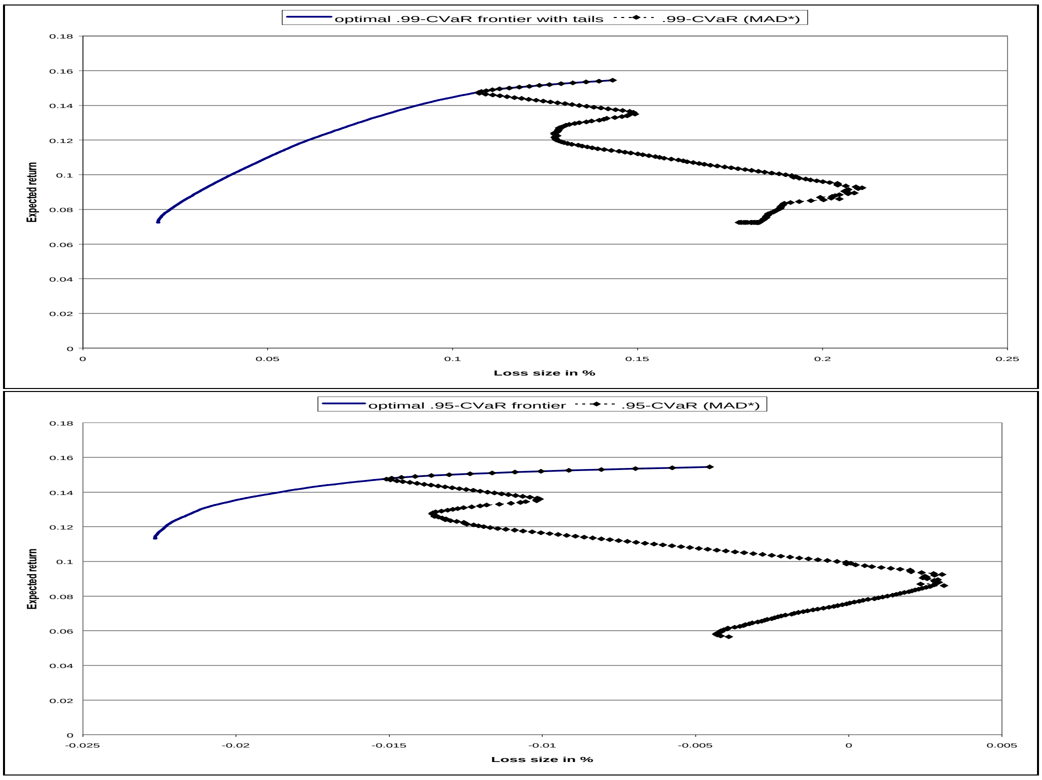

Figure 5: Frontier generated using a CVaR portfolio optimization with credit event simulations (solid line), and the CVaR of efficient portfolios optimized with the MAD model (doted line). Top figure: CVaR estimated at the .99 probability level. Bottom figure: CVaR estimated at the .95 probability level.)

variance or the mean absolute deviation. We see that CVaR has an important role to play in tracing efficient frontiers for the management of credit risk.

4.2 To VaR or to CVaR?

There is some debate among both academics and practitioners whether VaR or CVaR is the appropriate metric for risk management applications. Clearly VaR has an advantage in the practice of risk measurement, where it is considered the industry standard, see, e.g., Jorion (1996). CVaR, on the other hand, appears to be the metric of choice in the insurance industry, see, e.g., Embrechts, Klüppelberg and Mikosch (2000). Axiomatic characterizations of risk metrics—the notion of *coherence* suggested by Artzner (1999) et al.—

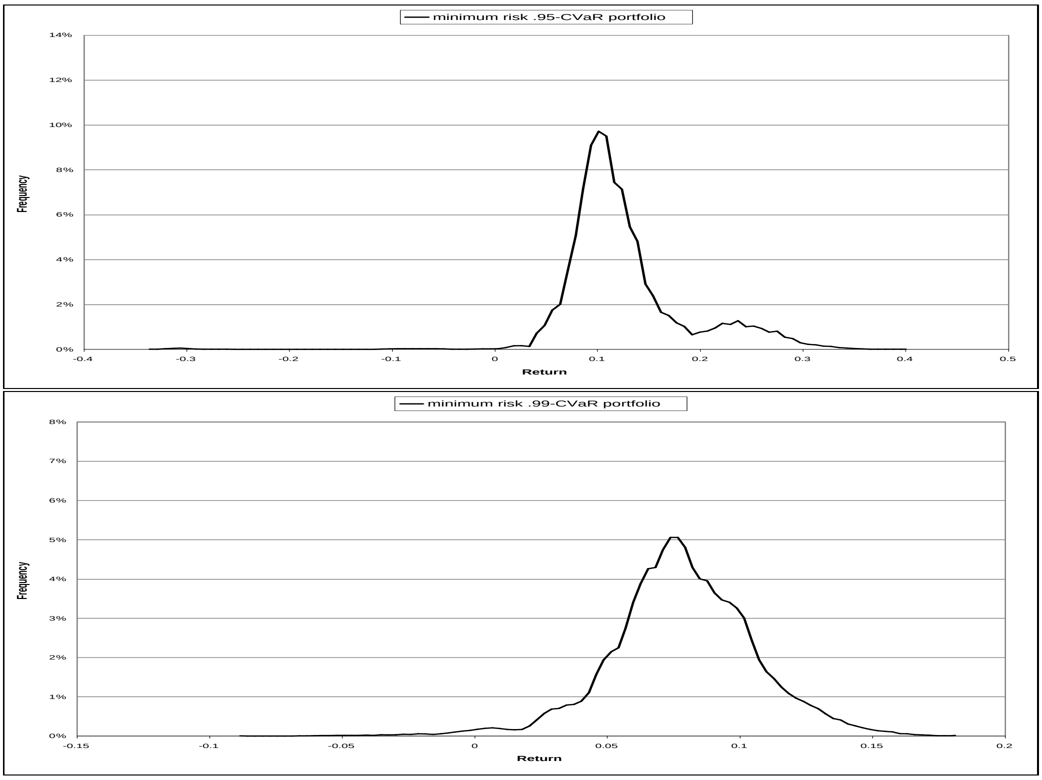

Figure 6: Distribution of returns for the minimum risk portfolio obtained using the CVaR model at the .95 (top) and .99 (bottom) probability levels. Note that the flat tail of negative returns worse than -80%—pronounced in Figure 4 when using a MAD optimization—has been significantly reduced, especially at the higher accuracy of .99 probability.

favors CVaR, which is coherent, over VaR, which is not coherent.

Notions of coherence notwithstanding, the fact that CVaR provides a bound for VaR, and the increasing acceptance of VaR estimates by regulators, has somewhat shadowed the debate. Figure 7 shows the estimated VaR of CVaR optimized portfolios obtained with and without simulations of the tails. As expected CVaR provides an upper bound for VaR. However, this bound need not be tight, especially when the tails are properly simulated. Furthermore, the frontier of VaR against expected returns for the CVaR optimized portfolios need not be efficient. The distortion of the VaR frontier is pronounced when the tails are properly simulated.

The results in Figure 7 clearly make the point that the choice between VaR and CVaR has significant ramifications in the risk management of credit risky portfolios. Given the flat tails witnessed in the simulations of this paper, and the coherence properties of CVaR, we argue that CVaR optimization provides the appropriate risk management framework for credit risky portfolios. The adoption of CVaR criteria for credit risk management by Andersson et al. (2001) was well justified, although their model does not include all the sources of risk incorporated in the simulations of Jobst and Zenios (2001).

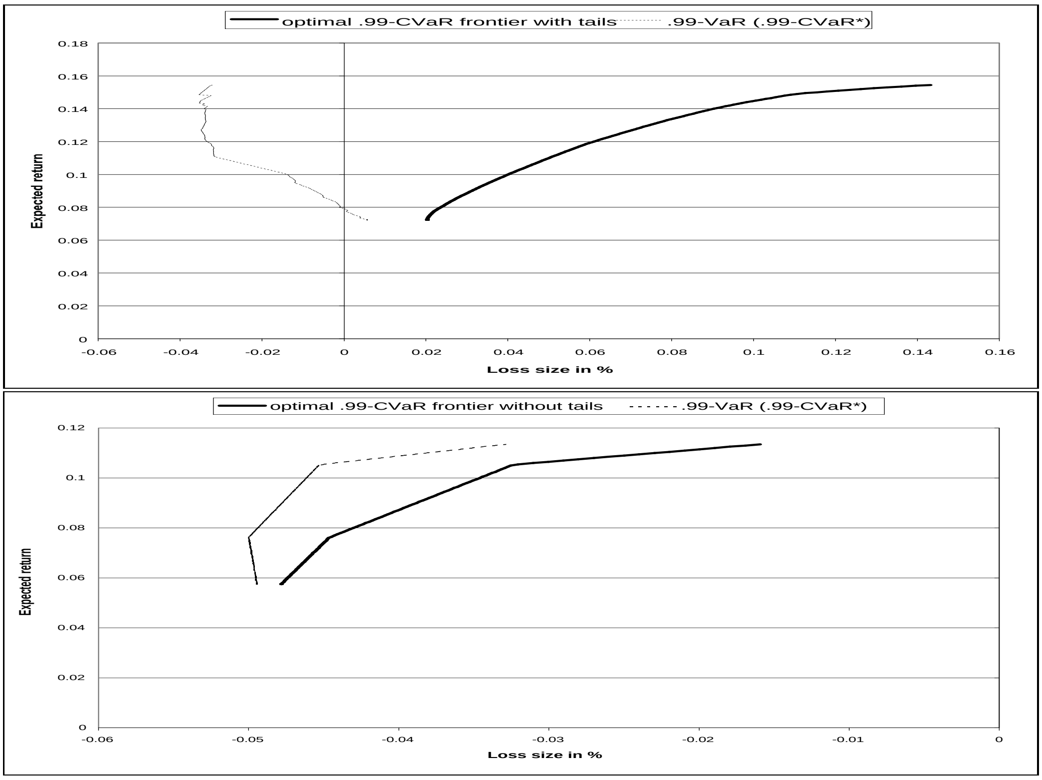

Figure 7: The CVaR efficient portfolios (solid lines) and its estimated VaR (doted lines) with tail effects (top figure) and without tail effects (bottom figure). CVaR estimated at the .99 probability level.

5 Long term performance with short term tails

When optimizing a portfolio performance for the long run, the short term effects are ignored. This has been the tradition in myopic single-period optimization models. Ignoring the short term effects can be catastrophic in the presence of tails. In particular the long-term (expected) potential of a portfolio strategy may never be realized if a tail event in the short run results into bankruptcy. Long Term Capital Management is a case in point. When their fund suffered losses of 80% in September 1998 the New York Federal Reserve orchestrated a bailout. Fourteen banks invested $3.6 billion in return for a 90 percent stake in the firm. The fund eventually recovered its losses and posted positive returns, but the original stakeholders were not there any more.

We look at the short term effects of the tails on the portfolios obtained with the MAD and the .99-CVaR optimization models. We take the minimum risk portfolio from both models at a 12-month risk horizon, and simulate using out-of-sample scenarios the distributions of returns at months 3, 6 and 9. The results for the portfolios obtained by the two models are shown in Figures 8 and 9 respectively.

The expected return of the MAD optimized portfolio over the 12-month period is 5.5%. The worst case losses are of the order of -2% in the first three months, but they jump to -80% at months 6, 9 and 12. The probability of these losses also increases with time—from 0.04% at month 6 to 0.22% at month 12. Although the probabilities are small, these losses are potentially catastrophic. The expected return of the MAD optimized portfolio increases with time, but so does the probability of a catastrophic event that will block the path towards the long term potential.

The expected return of the CVaR optimized portfolio over the 12-month period is 7.2%. The worst case losses of this portfolio remain at around -10% throughout this time period. The probability of losses increases from month 3 to month 9, before it is reduced at month 12 which has been optimized. In any event these losses are not catastrophic, and the long term expected return can be achieved. Not only the CVaR optimized portfolio has higher expected return than the MAD optimized portfolio in the long run, it also has better downside risk profile in the short run.

6 Concluding remarks

This paper has highlighted the pitfalls when one ignores the low-probability costly events of default while integrating credit risky assets into portfolios. The shape of the risk profile of the portfolio is affected substantially by the tails caused by credit events. In order to tradeoff efficiently long term expected return with risks we must recognize that the risks are in the tails. The extreme credit events must be properly simulated with sufficient accuracy. Furthermore, a risk metric must be chosen that accurately captures the impact of the tails. Conditional Value-at-Risk provides such a metric. Its use ensures that long term goals can be met, without suffering catastrophic blows from the tails in the short run. The models developed in this paper for limiting tail effects should also be applicable to portfolios of assets with correlated defaults, such as collateralized loan or debt obligations. This is an area worth exploring.

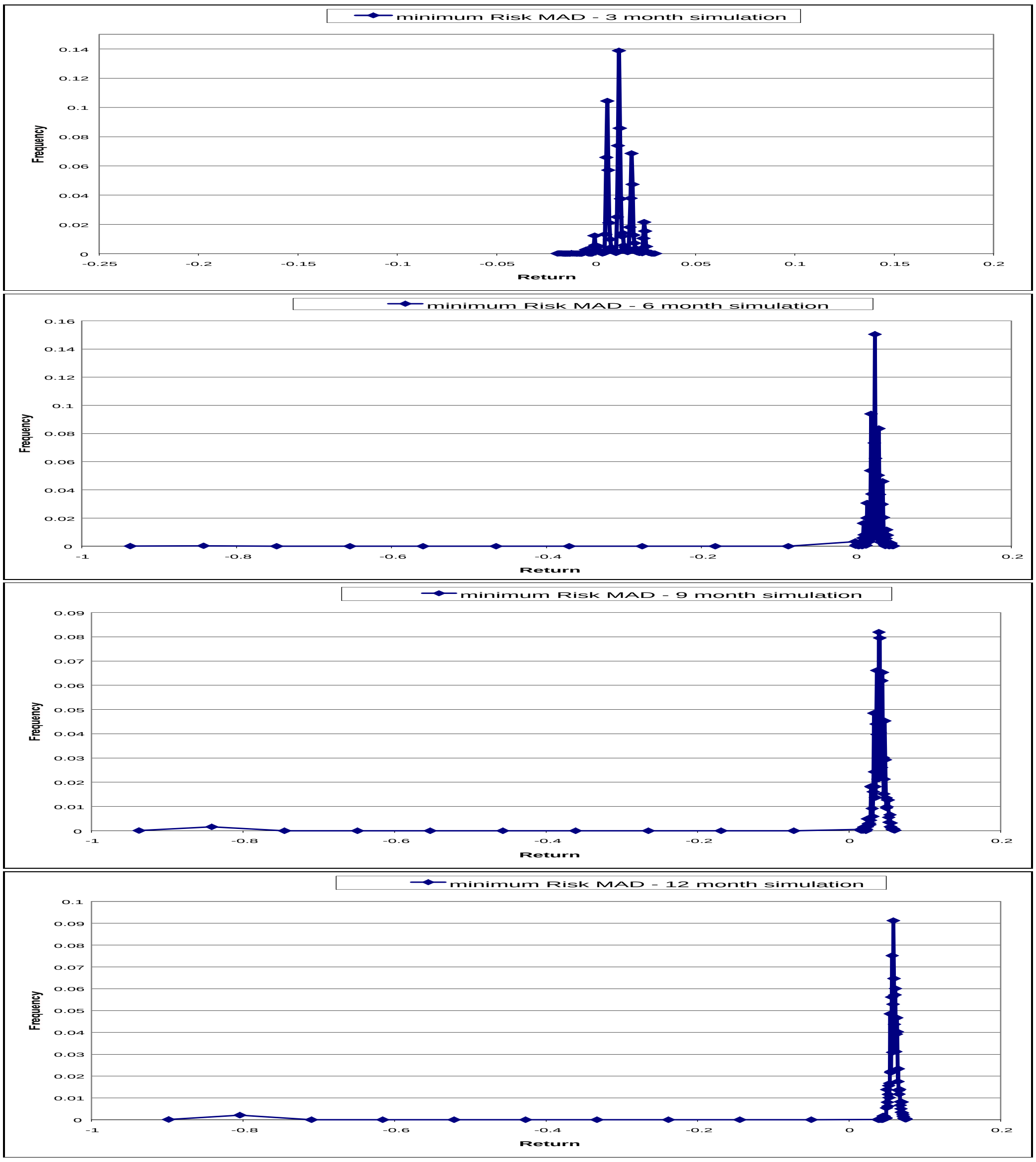

Figure 8: Distribution of returns of the minimum risk MAD optimized portfolio across time, using out-of-sample scenarios. Catastrophic losses are probable after the first three months.

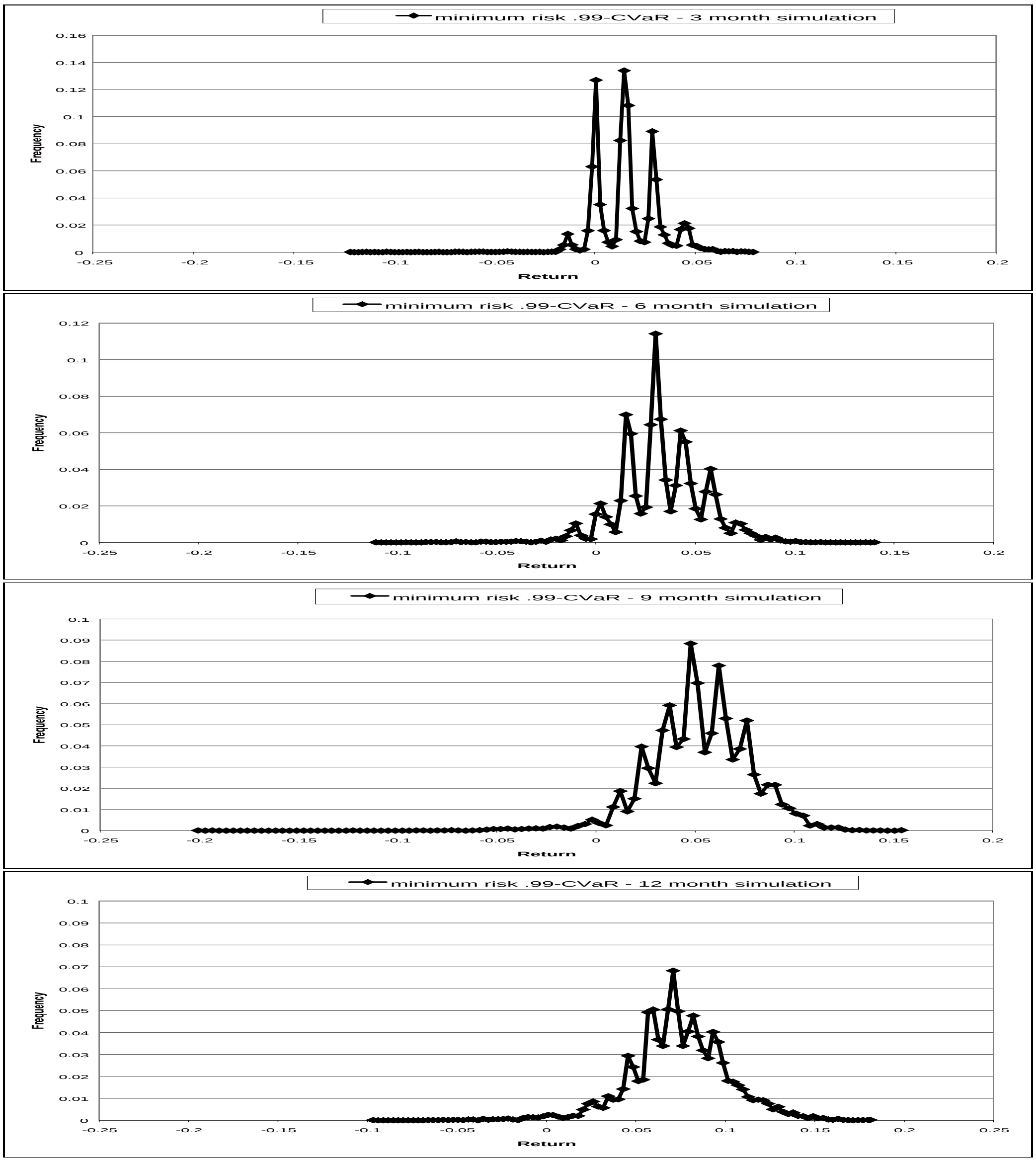

Figure 9: Distribution of returns of the minimum risk CVaR optimized portfolio across time, using out-of-sample scenarios. Worst case returns are limited to around -10% throughout.

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