Pricing Reinsurance Contracts on FDIC Losses

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This paper proposes a pricing model for the FDIC's reinsurance risk. We derive a closed-form Weibull call option pricing model to price a call-spread a reinsurer might sell to the FDIC. To obtain the risk-neutral loss-density necessary to price this call spread we risk-neutralize a Weibull distributed FDIC annual losses by a tilting coefficient estimated from the traded call options on the BKX index. An application of the proposed approach yield reasonable reinsurance prices.

I. INTRODUCTION

In 1991, the Federal Deposit Insurance Corporation Act authorized the Federal Deposit Insurance Corporation (FDIC), "to obtain private reinsurance covering not more than 10 percent of any loss the Corporation incurs with respect to an insured depository institution" (12U.S.C.A1817(b)(1)(B)). Such authorization allows the FDIC to enter into financial contracts with the private sector that price and share bank default risk. The options paper produced by the FDIC (FDIC, 2000) view reinsurance as one way "to use market information to differentiate risks without imposing a particular funding structure on insured institutions." Finally, the Federal Deposit Insurance Reform Act of 2005 permits the FDIC to charge every bank a premium based on risk. Given the significance of such a possible dramatic move toward market pricing of bank risk, it becomes essential to understand the elements of the reinsurance pricing, where a reinsurer provides excess-of-loss coverage to the FDIC. This paper responds to such a need and develops a pricing model for excess-of-loss reinsurance risk.

From a contingent claims point of view, an excess-of-loss reinsurance contract represents a portfolio of call options written on the aggregate loss level of the FDIC. Effectively, the reinsurer sells the FDIC a call-spread where the reinsurer will have to cover losses above a strike level but its commitment is capped by a stated coverage level. In this paper, we obtain a closed form pricing expression for the call-spread under the assumption that the underlying FDIC losses follow a Weibull distribution. We assume that the reinsurer uses the risk neutral distribution of losses to price the reinsurance risk. However, the reinsurer only observes the FDIC's historical (statistical) loss distribution. We show that the reinsurer can obtain the risk neutral density by exponentially tilting the FDIC's statistical loss distribution by a coefficient obtained from the traded options markets. We explain how this exponential tilt may be seen as an approximation to a more general tilt that scales the cash flows by the conditional expectation of the market pricing kernel.

The use of exponential tilts is broadly consistent with much of the current literature that incorporates risk aversion using either constant market prices of risk (Heath, Jarrow and Morton (1992), Heston (1993)) or constant relative risk aversion utility functions (Naik and Lee (1990)). Our specific contribution lies in showing how one may obtain the coefficient of exponential tilting by putting together an analysis of the underlying risk and information from selected traded options markets that relate to the underlying risk. The resulting method is potentially widely applicable in pricing risks embedded in loan defaults, mortgage refinancing, electricity and weather derivatives, and catastrophic losses to give a few examples. Common to the pricing of these risks is the absence of a liquid options market and the presence of high quality statistical data.

Our approach can also be related to the literature estimating the risk-neutral and statistical densities to make inferences about the implied risk-aversion coefficients (see, for example, Jackwerth (2000); Ait-Sahalia and Lo (2000); Ait-Sahalia, Wang, and Yared (2001); Coutant (2001); Bakshi, Kapadia, and Madan (2003); Bliss and Panigirtzoglou (2004)). Collectively, these papers focus on the entire distribution of the underlying assets values. However, catastrophe reinsurance contracts, such as the reinsurance of the FDIC's losses, have zero payoff in the center of distributions and pricing these instruments requires focusing on the tail of the distribution of the underlying asset values. Hence, we add to this literature by utilizing extreme value theory that characterizes the tail distributions of positive random variables like loss levels and estimate the tilting applicable to the tail events rather than the entire distribution of the outcomes.

To estimate the statistical distribution of the FDIC's annual losses on bank failures, we follow Jarrow, Madan and Unal (2007), who analyze the distributional properties of the losses in bank failures of the 1986–2000 period. They show that the two-parameter Weibull distribution best characterizes the FDIC's loss distribution in about 1,300 bank failures. Lucas, Llaassen, Spreij, and Straetmans (2001) also propose the use of Weibull density from a theoretical perspective to capture the distribution of loss rates. We estimate the statistical parameters of the Weibull distribution for annual losses incurred by the FDIC during 1986–2000.

To infer the applicable tilt coefficient in the traded options markets we examine the prices of deep out-of-the-money calls on bank equity (BKX) index and estimate the implied risk neutral distribution in this market. We next estimate the statistical Weibull distribution of the BKX index and infer the constant tilting coefficient implied by the statistical and risk neutral distributions. We risk-neutralize the FDIC's statistical loss distribution with the level of tilting implied in the BKX index. Our findings provide a range of values for the FDIC's reinsurance risk from which one can assess the reasonableness of the reinsurance prices.

As a check on our method, we compare our estimated reinsurance prices with those of MMC Enterprise Risk (MMC). In a report submitted to the FDIC, MMC provides two rough price estimates FDIC might have to pay to a private insurer to purchase a call-spread (MMC, 2001, p. 21). Our calculations show that MMC estimates are in the vicinity of our price-estimates and thus reflect a risk neutral pricing rather than a statistical one.

The paper is organized as follows. Section II defines the excess-of-loss reinsurance contract on FDIC losses. Section III presents the underlying framework for our risk neutralization strategy. Section IV estimates the implied risk aversion in the options market. Section V shows the application of reinsurance pricing. Section VI concludes the paper.

II. PRICING AN EXCESS-OF-LOSS REINSURANCE CONTRACT

An excess-of-loss reinsurance contract is a portfolio of call options written on the aggregate loss level, L, of the insurer. The first call option is written by the reinsurer on the insurer's aggregate loss level at a strike K. As the buyer of this call, the insurer incurs losses up to K but receives from the reinsurer the loss amount L exceeding the strike K. However, the reinsurer's coverage of losses above the strike is not unlimited and payments are capped at $K + B$, where B is the stated coverage level. This condition implies that the insurer simultaneously sells the reinsurer a call option struck at $K + B$. This second call caps the reinsurer's payout at the coverage level B. Taken together, this portfolio of two call options implies that the reinsurer sells the insurer a call-spread.

For a coverage level of B the loss contingent payoff to the call-spread, $CF(L)$, at year end can be expressed as:

$$\begin{aligned} CF(L) &= \text{Min}(\text{Max}(L - K, 0), B) \\ &= \text{Max}(L - K, 0) - \text{Max}(L - (K + B), 0) \end{aligned} \tag{1}$$

The first call option in Equation (1) represents the call option the reinsurer sells the insurer written on the insurer's aggregate loss level, L, at a strike K. The second option ensures that the reinsurer's coverage of losses above the strike is capped at $K + B$.

Specifically, the price of this call-spread w, given an annual continuously compounded risk-free interest rate of r is given by

$$w = \lambda e^{-r} \int_0^\infty CF(L)q(L)\, dL. \tag{2}$$

We assume that we are dealing with an aggregate pool of losses in which there is always some payout annually and therefore that the statistical probability of a loss arrival, λ, is one. By the equivalence of risk neutral probabilities to the underlying statistical probabilities it follows that one may assume the risk neutral λ is also one.

To price the call spread, the reinsurer needs to identify a relevant risk-neutral probability distribution for the annual loss levels, $q(L)$. This density describes the current market price of loss contingent bonds that pay one-dollar face in a year on the contingency that particular loss levels are attained. We assume that the Weibull describes the limiting behavior of scaled maximal losses drawn from random variables with an upper bound. In the present context the potential loss levels are bounded above by the size of insured deposits in place and hence such a distribution might be the right choice. Indeed, Lucas, Llaassen, Spreij, and Straetmans (2001) use Weibull to describe extreme tail behavior of credit losses in terms of portfolio characteristics. In addition, Jarrow, Madan, and Unal (2007) show that Weibull is a better fit than Normal, Frechet, and Beta distributions for the FDIC's historical losses. These considerations lead us to proceed with the Weibull model as a candidate for the risk neutral density of losses $q(L)$.

We provide in Appendix A the closed-form expression for the price of the call option $\mathrm{Max}(L - X, 0)$ with strike X written on the loss level L, which is distributed Weibull. It follows that a reinsurer can obtain the theoretical expression for the call-spread, given in Equation (2), as the difference between the two call options with strikes K and $K + B$ written on loss levels that is Weibull distributed.

It remains to identify the parameters of the Weibull risk neutral distribution of losses. In many markets where there is a liquid market in options on the underlying risk these parameters may be estimated by calibrating the model to market data on option prices. For many contracts on loss levels one does not have active option markets directly on the underlying loss level. However, there is often good data on the statistical loss experience and we may estimate the statistical loss distribution that we call $p(L)$. The focus of the rest of the paper is on strategies for constructing $q(L)$ from a knowledge of $p(L)$.

III. RISK NEUTRALIZATION STRATEGY

We recognize that the question of risk neutralizing a statistical distribution may not arise under certain conditions. For example, in the case of catastrophic loss insurance, Cummins, Lewis, and Phillips (1999), Froot (1996), and Doherty (1997) argue that catastrophe risks caused by natural disasters are uncorrelated with the market portfolio and hence no change of measure is needed. In other words, prices of contingent claims on such risks equal statistically expected payoffs discounted at the risk free rate. In contrast Atlan, Geman, Madan and Yor (2006) recently show that merely being uncorrelated with the market portfolio is insufficient to justify the absence of a change of probability for the risk in question. Our approach, by estimating the tilt, accommodates a zero tilt as a special case.

The Exponential Tilt

Our strategy for risk neutralizing a statistical loss distribution models the expectation of the pricing kernel conditional on the risk at hand. We suppose that the quoted prices for claims of this type are free of arbitrage. In general, the no-arbitrage property is equivalent to prices being equal to discounted expected payoffs under a change of probability from the statistical one to a new probability measure termed the risk neutral probability (Harrison and Kreps (1979)). Somewhat more formally, the price, w, of a claim to a state contingent cash flow $c(\omega)$ can be written as the discounted at the risk-free rate of return, r, of the expected cash flow, where expectation is taken at the risk-neutral measure, E^Q

$$w = e^{-r} E^Q[c(\omega)] \tag{3}$$

Defining by $g(L)$ the projection of the density of Q with respect to the statistical measure P onto the information filtration of the loss level L one may alternatively write that

$$E^Q[c(L)] = E^P[g(L)c(L)],$$

where $c(L)$ is the payoff to a claim contingent on the loss level L. It follows that the risk neutral loss density $q_L(L)$and its statistical counterpart $p_L(L)$ are related by

$$q_L(L) = g(L)p_L(L). \tag{4}$$

We now focus attention on modelling g that is a positive function of the real valued variable L. Under the principles of exponential tilting one takes $g(L)$ to be a normalized exponential tilt and hence

$$q_L(L) = \frac{e^{\alpha_L L}}{\int_0^\infty e^{\alpha_L L} p_L(L) dL} p_L(L) \tag{5}$$

From an incomplete market's point of view, the pricing kernel to be used is no longer uniquely determined and is individual specific as well. As explained in Cummins, Lewis, and Phillips (1999), the actuarial approach to pricing catastrophic insurance employs utility functions of risk-averse agents to construct the risk-neutralized density. The use of exponential tilts has a long history in finance and insurance (see, for example, Esscher (1932); Sondermann (1991); Gerber and Shiu (1994, 1996); Embrechts (1997)).

The risk neutralization strategy of Equation (5) is completed on determining the exponential tilt coefficient α_L. We define the measure change density $y_L(L)$ by

$$y_L(L) = \frac{q_L(L)}{p_L(L)} \tag{6}$$

and note that for this risk neutralization we have

$$\alpha_L = \frac{\partial \ln(y_L(L))}{\partial L}. \tag{7}$$

TILT COEFFICIENTS FOR NON-TRADED RISKS

We begin by noting that tilt coefficients are estimable for risks associated with liquid options markets. An analysis of the time series for the risk at hand yields the statistical distribution while from traded options we obtain the risk neutral density following Breeden and Litzenberger (1978). Given both densities, the tilt coefficient may be estimated by regression methods. This subsection derives a relationship between tilts appropriate for non-traded risks and those observed in the options markets.

We refer to the non-traded risk under study as the risk of loss level L. The objective is to tilt the statistical loss distribution of the loss L and price a contract written on L. Let S denote the level of some financial index with a liquid options market that is related to the loss risk, in the sense that the conditional distribution of losses L given the index level S is nontrivial. Suppose that the joint density of the loss level L and some financial index S, $h(L, S)$, is such that the conditional density of L given S, $\psi(L|S)$, depends on S, i.e.

$$h(L, S) = p_s(S)\psi(L|S) \tag{8}$$

where $p_S(S)$ is the statistical density of the financial index S.

The statistical density of the loss level may then be computed as

$$p_L(L) = \int_0^\infty p_S(S)\psi(L|S)\, dS. \tag{9}$$

We suppose that the major source of priced risks are all captured by the financial risk S that is traded for this purpose. The additional factor uncertainties driving the conditional law of L given S we suppose are not priced and hence we take the conditional law of L given S to be unchanged. The only measure change we entertain in our risk neutralization is the change in the law of S.

A change of probability on S to $q_S(S)$ thus induces a change in the risk neutral probability of L by

$$q_L(L) = \int_0^\infty q_S(S)\psi(L|S)\, dS. \tag{10}$$

Taking the ratio of (10) to (9) we observe that

$$y_L(L) = \int_0^\infty y_S(S)\psi(S|L)\, dS, \tag{11}$$

where $y_S(S)$ is the measure change density for S, defined as

$$y_S(S) = \frac{q_S(S)}{p_S(S)}. \tag{12}$$

In analogy with Equation (7) we define the tilt coefficient in the market for the financial index S by

$$\alpha_S = \frac{\partial \ln y_S(S)}{\partial S}. \tag{13}$$

Our objective is to relate α_L to α_S by a further analysis of Equation (11). Observe that $y_L(L)$ is an average of $y_S(S)$ taken with respect to the conditional probability density $\psi(S|L)$. By the mean value theorem, assuming continuity of y_S, there exists a function

$$S = \phi(L) \tag{14}$$

such that

$$\int_0^\infty y_S(S)\psi(S|L)\, dS = y_S(\phi(L)). \tag{15}$$

The function $\phi(L)$ is simply defined by an application of the mean value theorem as derived from Equation (15) whereby $\phi(L)$ is the value of S such that y_S evaluated at this point agrees with the average value of this function as integrated on the right hand side of Equation (15) with respect to the conditional law of S given L.

The relation between the measure change functions $y_L(L)$ and $y_S(S)$ then follows from Equations (11) and (15)

$$y_L(L) = y_S(\phi(L)). \tag{16}$$

The exponential tilt in L, given in Equation (7) is measured by the logarithmic derivative of $y_L(L)$ and we evaluate this as

$$\frac{\partial}{\partial L}\ln(y_L(L)) = \phi'(L)\frac{\partial}{\partial S}\ln(y_S(\phi(L)) \tag{17}$$

$$\alpha_L = \phi'(L)\alpha_S. \tag{18}$$

Hence the exponential tilt appropriate for the loss level is the options tilt (α_S) computed at $\phi(L)$ scaled by the sensitivity $\phi'(L)$.

Estimating α_L

The exponential tilt coefficient for a non-traded risk, α_L, is estimated in two stages. First, a simple model for the measure change function $y_S(S)$ in the options market provides the estimate of α_S. Next, the tilt adjustment ϕ' is obtained using a regressions model for the conditional distribution of S given L. Hence, the tilt coefficient for loss levels is estimated using Equation (18).

It is customary to employ out-of-the-money call and put options in inferring risk neutral densities following Breeden and Litzenberger (1978), as these are the more liquid options relative to in-the-money options. Hence, for strikes below the current spot one uses puts, while for strikes above the spot we use calls. On recovering $y_S(S)$, one may graph its logarithm against S and if this is linear across the entire range of values for S the slope is the estimate for α_S .

However, one typically observes a sharp nonlinearity such that $y_S(S)$ is U – shaped as is its logarithm with a minimum near the level of the current spot (see, for example, Carr, Geman, Madan and Yor (2002), or Jackwerth (2000)). Hence, the tilt coefficient is positive when $S > S_0$ or for out-of-the-money call options and negative for $S < S_0$ or for out-of-the-money put options. In general one might expect losses to be either positively or negatively related to the financial index. For example, in the case of hurricanes losses would be positively related to an index of property values. In this case, the tilt coefficients embedded in call options written on the property value index would be relevant. In contrast, farm losses are inversely related to the price index of crops produced thus requiring tilt coefficients estimated from the put side.

When the financial index and the loss levels are options on a common underlier, then the possibilities are a bit more complex. For example, in the case of our application the losses incurred by the FDIC can be viewed as a portfolio of put options written on bank assets. The bank stock index on the other hand is a portfolio of call options written on the same underlier. In this case the direction of the relationship is negative on account of movements in the value of the underlying bank assets, in which case tilt coefficients embedded in put options are relevant. However, to the extent that movements in bank asset volatility are the driving factor one has a positive relationship between losses and the level of the index. Hence, the call options are relevant contracts to imputing the tilt coefficients.

We allow for differential tilts on the call and put side and entertain the simple measure change function

$$y_S(S) = a_P e^{-\alpha_P S} 1_{S<S_0} + a_C e^{a_C S} 1_{S>S_0}. \tag{19}$$

where a_P, a_C are the tilt coefficients applicable to the put and call side respectively, which are uniquely determined from the normalizing constant assuming continuity of y_S at S_0.

To determine the coefficients of exponential tilting α_P and α_C from the traded options market, we can estimate $p(S)$ from the time series of asset returns and $q(S)$ from the prices of options that are written on these assets. The implied tilting coefficients, α_C and α_P can be estimated from the following regression:

$$\log\left(\frac{q(S)}{p(S)}\right) = \log(a_C) + \alpha_C S + \varepsilon_C, \quad S > S_0 \tag{20}$$

$$\log\left(\frac{q(S)}{p(S)}\right) = \log(a_P) - \alpha_P S + \varepsilon_P, \quad S < S_0 \tag{21}$$

where the error terms, ε_C and ε_P are deterministic errors of approximation in the functional forms. Were the densities $q(S)$ and $p(S)$ estimated non-parametrically, the estimation errors would filter through into the error terms ε_C and ε_P. However, if the densities on the left hand side are estimated parametrically then ε_C and ε_P primarily reflect the departure of the functional form for the ratio of $q(S)$ to $p(S)$ from an exponential function in S.

To estimate $\phi'(L)$, we determine $\phi(L)$ from Equation (15) on first evaluating the expectation of $y_S(S)$ given L. This computation requires a specification for the conditional density of S given the loss level L. At a general level the conditional density of S given L could constructed by sorting the data with respect to the level of L and then observe the histogram of S at each level of L. Such an exercise would reveal the structure of nonlinearities present in describing the mean and higher moments of the distributions of S as functions of the level of L. The execution of such an approach requires a large amount of data permitting, for example, a precise estimate of the mean of S given the level of L. When data availability is not so large and the range of values for L to calculate the mean of S is wider one may adopt a local linear approximation in each set of sorted L values. These local linear approximations may be pieced together to discover the functional form. With even less data one must conjecture the functional form over ever wider ranges of L.

For this purpose one may begin with a simple linear regression model:

$$S = \alpha + \beta L + \varepsilon \tag{22}$$

with ε distributed normally with mean zero and a volatility of σ_ε. This could then be enhanced to accommodate other functional forms as seen appropriate from an analysis of patterns in the residuals.

We substitute Equation (22) into Equation (19) for S and evaluate the conditional expectation given L to get the left hand side of Equation (15). However, we approximate by ignoring the shift in the functions on the put side or $S < S_0$ for positive β and large L and likewise we ignore the shift in the functions on the call side or $S > S_0$ and negative β.

On this calculation we obtain the approximation for Equation (11) and for positive β that

$$y_S(\phi(L)) = y_L(L) \approx e^{\alpha_C(a+\beta L)+\frac{1}{2}\alpha_C^2\sigma_\varepsilon^2} \tag{23}$$

while for negative β we have

$$y_S(\phi(L)) = y_L(L) \approx e^{-\alpha_P(a+\beta L)+\frac{1}{2}\alpha_P^2\sigma_\varepsilon^2} \tag{24}$$

Taking logarithmic derivatives of Equations (23) and (24) we have that

$$\alpha_L = \alpha_C \beta \mathbf{1}_{\beta>0} + \alpha_P|\beta|\mathbf{1}_{\beta<0}. \tag{25}$$

Comparing Equation (25) with (18) we observe that the tilt adjustment $\phi'(L)$ equals the absolute value of the slope estimate from the regression Equation (22). If the regression model relating S to L is expanded to include nonlinear terms then to preserve the nature of a local exponential tilt one must differentiate this nonlinear functional dependence in a neighborhood of the loss level of interest and work with the slope of the resulting linear approximation as the required tilt adjustment. From this perspective it is recommended that one take the best linear approximation in the first place.

IV. WEIBULL IMPLIED EXPONENTIAL TILT IN THE OPTIONS MARKET

The tilt in the options market is obtained by first constructing the statistical distribution of the stock price at a maturity matching the option maturity. Second, we estimate the risk neutral distribution at a traded option maturity. To maintain consistency with our focus on pricing tail events, we choose the Weibull as the functional forms for both these densities. Finally, the tilt follows on regressing the logarithm of the ratio of the two densities on the level of the stock price as per Equations (20) and (21). The details for the density estimations are explained in the following two subsections.

The Statistical Stock Price Density

The measure change function given in Equation (19) allows for separate tilt coefficients for stock prices below and above the current spot. We therefore study separately the statistical density on these two sides. We focus attention on returns over a prespecified horizon and let S be the final stock price while S_0 denotes the initial stock price.

We define the excess return as a positive random variable with values in the interval $[1, \infty)$ by letting

$$R_u = \frac{S}{S_0}, \quad S > S_0 \tag{26}$$

$$R_d = \frac{S_0}{S}, \quad S < S_0. \tag{27}$$

For such a positive random variable, bounded below by unity, the shifted Weibull distribution is an appropriate extreme value density reflecting finite moments of all orders. For the statistical density we suppose the density of R_u, R_d have the specific Weibull forms with parameters c_u^S, a_u^S and c_d^S, a_d^S with the generic form

$$f(R) = \exp\left(-\left(\frac{R-1}{c}\right)^a\right)\frac{a(R-1)^{a-1}}{c^a} \tag{28}$$

We estimate from time series data on daily returns, using tail returns (for example, the upper or lower quartile of returns), the statistical parameters for both the upside and downside by maximum likelihood.

For a comparison with the risk neutral density, we have to construct statistical returns at the option maturity from the estimated daily return distribution. However, in making a comparison with risk neutral densities there is a horizon mismatch, as risk neutral densities are observed over much longer horizons than a single day. One possibility is to construct long horizon returns from daily returns using the hypothesis of identically and independently distributed returns (i.i.d.). However, such a strategy is contrary to evidence on dependence in returns as demonstrated by autocorrelations in squared returns (Engle (1982)).

We recognize, instead, that uncertainties pertaining to the distant future are rising as we move forward in time and employ instead a scaling hypothesis. Under this hypothesis, we model the return at a horizon of N days as having the distribution of $\sqrt{N}$ times the daily return distribution, or define the return over N days, R_N to be in law

$$R_N - 1 \overset{\text{law}}{=} \sqrt{N}(R-1) \tag{29}$$

The variance then grows linearly with N as it would were we to add independent and identically distributed, but unlike the situation with addition of independent random variables, skewness and excess kurtosis remain constant in N. For the case of adding i.i.d. variables, skewness falls like $\frac{1}{\sqrt{N}}$ and excess kurtosis falls like $\frac{1}{N}$ as shown in Konikov and Madan (2002). In the sense of the higher moments, the uncertainty is maintained at a higher level than would be the case with summing independent and identically distributed random variables.[1]

Thus, it follows from Equations (29) and (28) that the Weibull density for R_N is

$$f(R_N) = \exp\left(-\left(\frac{R_N - 1}{c\sqrt{N}}\right)^a\right)\frac{a(R_N-1)^{a-1}}{(c\sqrt{N})^a} \tag{30}$$

and with parameters $c\sqrt{N}$, a.

The Risk Neutral Stock Price Density

The risk neutral stock price density for upside and downside returns are also taken to be in the Weibull family with parameters denoted by c_u^{RN}, a_u^{RN} and c_d^{RN}, a_d^{RN} respectively. These parameters are to be estimated by calibrating the model

[1]Alternatively, one may appeal to the work of Sato (1999) who shows that the class of all limit laws of arbitrarily scaled sums of independent but not necessarily identical random variables are the laws at unit time of a scaled process of independent and generally inhomogeneous increments. This observation makes such processes relevant to the modeling of financial returns that may easily be seen as the limit of the sum of a large number of independent effects.

prices developed under the specific Weibull density to the prices of the out-of-the-money call and put options. For this task, following Proposition 1, we develop the Weibull call option pricing formula for up and downside returns using the Weibull density.

For a call option of maturity t the call option value, cv,

$$cv = e^{-rt} \int_{\frac{K}{S_0}}^{\infty} (S_0 R - K) \exp\left(-\left(\frac{R-1}{c}\right)^a\right) \frac{a(R-1)^{a-1}}{c^a} dR. \tag{31}$$

Note that in Equation (31), we do not impose the condition that the discounted stock price is the current stock price as we do not assert that the Weibull density applies for all levels of the stock price, but only applies in the upper right tail where the specified calls are in the money. Traditional option pricing models model the entire distribution of the underlying asset and hence must enforce the spot forward arbitrage condition requiring that

$$S_0 e^{rt} = \int_0^{\infty} S_t q(S_t)\, dS_t \tag{32}$$

or that the financed stock purchase has a zero price. Since we focus on the Weibull model for just the tail of the distribution, and use it to price out of the money calls and puts on the up and down side, we do not have a condition integrating across the entire range of stock prices. In fact, we impose no distributional hypothesis at all, in the center of the distribution, or the near money density.

Performing the requisite integration we obtain that

$$cv = e^{-rt} \left[S_0 \left(P_2 + c\Gamma\left(1 + \frac{1}{a}\right) P_1 \right) - KP_2 \right] \tag{33}$$

$$P_2 = \exp\left(-\left(\frac{\frac{K}{S_0} - 1}{c}\right)^a\right) \tag{34}$$

$$P_1 = 1 - gammainc\left(\left(\frac{\frac{K}{S_0} - 1}{c}\right)^a,\ 1 + \frac{1}{a}\right) \tag{35}$$

We propose to estimate c_u^{RN}, a_u^{RN} using out-of-the-money calls struck at tail strikes trading in the market.

On the down side we have to evaluate the put option value pv,

$$\begin{aligned} pv = & \ e^{-rt}\int_{\frac{S_0}{K}}^{\infty}\left(K-\frac{S_0}{R}\right)\exp\left(-\left(\frac{R-1}{c}\right)^a\right)\frac{a(R-1)^{a-1}}{c^a}dR \\ = & \ Ke^{-rt}\exp\left(-\left(\frac{\frac{S_0}{K}-1}{c}\right)^a\right) \\ & - S_0e^{-rt}\int_{\frac{S_0}{K}}^{\infty}\frac{1}{R}\exp\left(-\left(\frac{(R-1)}{c}\right)^a\right)\frac{a(R-1)^{a-1}}{c^a}dR \end{aligned} \tag{36}$$

The last integral is evaluated numerically. We estimate the parameters c_d^{RN}, a_d^{RN} using downside tail strikes trading in the market.

V. PRICING THE FDIC'S REINSURANCE RISK

The FDIC retained MMC Enterprise Risk (MMC) to determine the feasibility and the costs of private sector reinsurance arrangements. In a report submitted to the FDIC, MMC provides two rough price estimates for reinsuring the aggregate annual losses of the FDIC (MMC, 2001, p. 21). The specific estimates are such that the annual premium on a \$2 billion coverage at a one basis point (less than one chance in 10,000) risk level is \$4 million. A second price estimate states that the annual premium on a higher risk level of one percentage point (one chance in 100) with \$0.5 billion dollar coverage is \$10 million.

We illustrate our methodology for risk neutralizing a statistical distribution by pricing the claims quoted on by MMC. Additionally, we price the aggregate loss distribution of the FDIC and quote on the level of aggregate premiums required from the banking system as a whole.

Statistical Loss Distribution on Bank Failures

Our focus is to capture the distribution of annual aggregate losses on bank failures covering the period 1986–2000. The aggregate annual loss levels of the FDIC are displayed in Table 1. Although we could increase sample observations by including years dating back to 1930s we find this manner of expanding the sample undesirable because these dated periods are not reflective of risks faced by the FDIC today. Given the relatively small sample size we estimate by the method of moments the statistical parameters c and a.

From the sample mean μ and standard deviation σ of the FDIC's annual loss experience we invert for the shape parameter a the following:

$$1+\frac{\sigma^2}{\mu^2}=\frac{\Gamma\left(1+\frac{2}{a}\right)}{\Gamma\left(1+\frac{1}{a}\right)^2}. \tag{37}$$

Table 1: FDIC Annual Loss Levels

Year	Loss (in \$Billions)	Number of Bank Failures
1986	1.775	145
1987	2.023	203
1988	6.921	280
1989	6.199	207
1990	2.785	169
1991	6.148	127
1992	3.675	122
1993	0.646	41
1994	0.179	13
1995	0.085	6
1996	0.038	5
1997	0.005	1
1998	0.234	3
1999	0.841	7
2000	0.039	6

Source: Failed Bank Cost Analysis, 1986–2000, Division of Finance, FDIC.

Equation (37) is derived from Equations (44) and (45). The estimate for c follows from the Equation for the mean (44) given an estimate for a.

From Table 1 we observe that the annual unconditional mean and standard deviation of annual loss levels between 1986–2000 is $\mu = \$2.106$ billion and $\sigma = \$2.497$ billion, respectively. Substituting these values in Equation (37) and using method of moments, we obtain the statistical parameters for the Weibull distribution as $c = 1.9317$ and $a = 0.8472$.

Option Tilts on the BKX Index

To approximate the appropriate tilt coefficient we assume that the reinsurer examines market risk preferences on an asset that best reflects the aggregate bank risk. One proxy for such an asset is the PHLX / KBW Bank Index (BKX). BKX is a capitalization-weighted index composed of 24 geographically diverse stocks representing national money center banks and leading regional institutions. The index is evaluated annually by Keefe, Bruyette & Woods to assure that it represents the banking industry. The index was initiated on October 21, 1991 and options started trading on September 21, 1992. We note that the bank index can be viewed as a portfolio of call options written on the assets of the underlying banks. On the other hand the FDIC losses constitute a portfolio of put options payouts on this same underlying asset base. Thus we expect a relationship between the two, that may be positive or negative. We also note that FDIC losses are associated with small and large bank failures whereas the index just covers the large banks. To the extent that small banks hold different portfolios from the large banks with risk components that need to be priced our use of the BKX index may not price all the relevant risks.

In measuring the degree of exponential tilting in the options market for the bank index, BKX we must decide the region of strikes appropriate for relating these tilt coefficients to those of our loss levels. As explained in Equation (11) we need to assess the concentration of the conditional density of the index given large loss levels. There are two effects to consider. First, it may be the case that loss probabilities rise in a down market and this can bring larger losses associated with a downward move in the index. Second, the magnitude of losses may be driven by higher bank asset volatility, with bank asset values stable, and in this case larger losses would be associated with higher equity levels.

We assess the degree of exponential tilting that occurs in pricing out-of-the-money equity call and put options at the 1, 5, and 10 percent risk levels. We do this analysis by estimating the statistical and risk neutral densities in the upper and lower tail of the returns, denoted by $p(S)$, and $q(S)$ respectively, and estimate the regression Equation given in Equations (20) and (21) for values of S in both tails of the statistical distribution.

We use time series data on the BKX for 1500 days ending on September 28, 2001 to obtain the statistical distribution and data on index options for every second Wednesday of each month over the year beginning in October 2000 and ending in September 2001 to estimate the risk-neutral distribution. To estimate the statistical parameters of the Weibull density we first compute the upside returns as described in the previous section. We sort these returns and extract the top and bottom 25% of returns. The Weibull model is estimated by maximum likelihood on large positive returns to yield the statistical parameters for the BKX index. The estimated parameters are $c_u^S = 0.0345$, $a_u^S = 2.5324$ and $c_d^S = 0.0335$, $a_d^S = 2.7593$.

The risk neutral parameters are estimated by calibrating model prices (Equations (33) and (36)) to the call and put option prices with maturity of around two months with the five largest and smallest strikes trading in the market for this maturity. The calibration is done for one day in each month from October 2000 to September 2001. The results are presented in Table 2 for the BKX index, where the average $c_u^{RN} = 0.0645$, $a_u^{RN} = 0.9413$ and $c_d^{RN} = 0.0612$, $a_d^{RN} = 0.6824$.

Next, the regression Equations (20) and (21) are estimated where the logarithm of the ratio of the risk neutral density to the scaled statistical density regressed on the price level in the range between 1% to 0.01% return levels in two months. The resulting slope coefficients are the associated levels of exponential tilting on the upper and lower tail of the return distribution. The results are presented in Table 3 along with the mean levels of tilting for the BKX. We observe that the mean levels of tilting to losses on the upside in BKX is 0.1739, while the corresponding figure for the downside is −0.6387.

Table 2: Risk-Neutral Weibull Parameter Estimates on Extreme 2-Month BKX Call and Put Options

Date	Maturity	cdrn	adrn	curn	aurn
Oct. 2000	0.1804	0.0563	0.6465	0.0821	1.1453
Nov. 2000	0.1968	0.0627	0.7004	0.0176	0.4245
Dec. 2000	0.1779	0.0636	0.6932	0.0272	0.5128
Jan. 2001	0.1781	0.0665	0.6701	0.0540	0.6997
Feb. 2001	0.1779	0.0527	0.6749	0.0659	0.9728
Mar. 2001	0.1779	0.0342	0.4549	0.0914	1.0725
Apr. 2001	0.1753	0.0736	0.6703	0.0867	0.9985
May 2001	0.1945	0.0632	0.7057	0.0680	0.9862
Jun. 2001	0.1753	0.0365	0.6122	0.0524	1.0211
Jul. 2001	0.1945	0.0538	0.6794	0.0734	1.1855
Aug. 2001	0.1917	0.0406	0.6049	0.0637	1.1206
Sep. 2001	0.1563	0.1303	1.0758	0.0913	1.1556
Mean Level	0.1814	0.0612	0.6824	0.0645	0.9413

Estimating the Tilt Adjustment

As described in section II tilts obtained from the options markets need to be adjusted before they can be used to tilt the statistical loss distribution. The proposed tilt adjustment requires the estimation of the regression Equation (22).

To estimate the slope coefficients for the conditional distribution of the level of the index given the loss level, one ideally needs the relationship between the BKX Index and FDIC's annual loss levels. Because the BKX exists after 1992, a

Table 3: Exponential tilt coefficients for out-of-the-money put and call options on the BKX index

Date	Maturity	Put Options	Call Options
Oct. 2000	0.1804	−0.6403	0.1348
Nov. 2000	0.1968	−0.6183	0.2533
Dec. 2000	0.1779	−0.6392	0.2588
Jan. 2001	0.1781	−0.6498	0.2415
Feb. 2001	0.1779	−0.6298	0.1747
Mar. 2001	0.1779	−0.6846	0.1841
Apr. 2001	0.1753	−0.6597	0.2026
May 2001	0.1945	−0.6177	0.1596
Jun. 2001	0.1753	−0.6292	0.1135
Jul. 2001	0.1945	−0.6138	0.0732
Aug. 2001	0.1917	−0.6608	0.1152
Sep. 2001	0.1563	−0.6216	0.1763
Mean Level	0.1814	−0.6387	0.1739

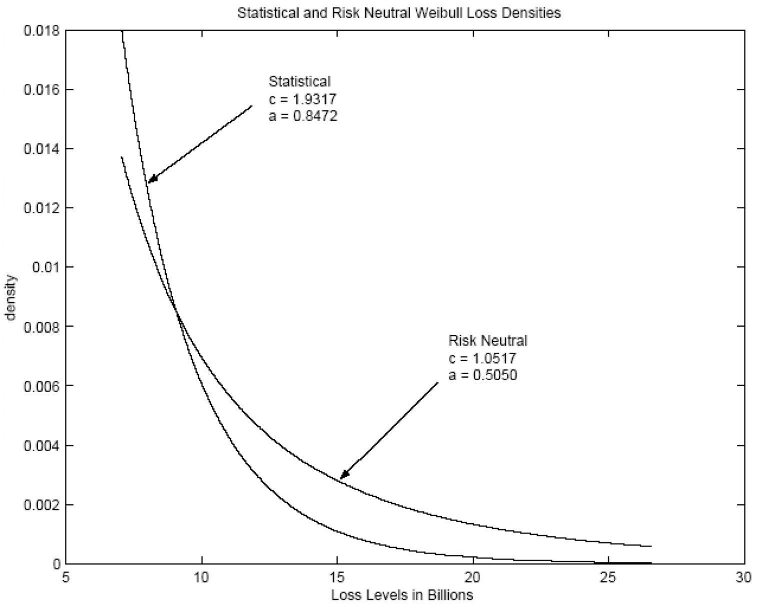

Figure 1: Weibull Statistical and Risk Neutral Distributions for Annual Fund Loss Levels. The risk neutral distribution is obtained by exponential tilting the statistical density using Bank Index option market tilt coefficient.

regression exercise would only have eight observations. To increase the sample, we use the annual levels of NASDAQ Bank Index between 1981 and 2001. The correlation between the BKX index and the NASDAQ Bank Index for the monthly data for the period September 1992 to September 2001 is 0.93.

The resulting regression for Equation (22), where we regress the NASDAQ bank index on the level of F DIC losses over the period 1981–2001. yields the result $\alpha = 1165.43$, $\beta = -0.1698$, with respective standard errors of 191.31, 0.0675 and an R^2 of 28.76%. We therefore employ in accordance with Equation (25) the β scaled put side tilt and use $\alpha_L = 0.6387 * 0.1698 = 0.1085$. Hence, we tilt the statistical distribution of the FDIC's losses by this coefficient to obtain the risk neutral distribution.

The Value of the Call-Spread

We can price the call spread now by using the tilt coefficient of 0.1085 to tilt the statistical distribution and obtain the risk-neutral distribution. We estimate the price of a call spread in the context of a reinsurance quote estimate given to the FDIC. Although the strike levels are not specifically indicated in the report we can easily estimate the implied strikes given the parameters of the statistical Weibull density.

Note that the probability of a loss amount exceeding the strike is given by

$$P(L > K) = \theta = 1 - F(K) \tag{38}$$

For the Weibull cumulative distribution function,

$$F(K) = 1 - \exp\left[-\left(\frac{L}{c}\right)^a\right] \tag{39}$$

Equation (38) is written as

$$-\log(\theta) = \left(\frac{K}{c}\right)^a \tag{40}$$

Hence, the strike is expressed as

$$K = c(-\log(\theta))^{\frac{1}{a}} \tag{41}$$

Substituting the estimates of c, a, and the risk level, θ, in Equation (41) we obtain $K_1 = \$11.72$ billion and $K_2 = \$26.56$ billion for the high risk and low risk cases, respectively. We note that these estimates of strike levels, implied by the quoted prices, can be considered reasonable because they are well within the current \$30 billion FDIC deposit insurance fund level.

To risk neutralize the statistical loss density of the FDIC we need to exponentially tilt it by the level observed in the pricing of BKX put options scaled by the β coefficient of the regression (22), 0.1085. We recognize that exponentially tilted Weibull densities are not themselves in the Weibull class. As an alternative approach, we alter the risk neutral density such that the derivative of the logarithm of the risk neutral density accounts for the altered tilt. Specifically, using Equation (5) the estimated tilting is basically the difference between the derivative of the logarithm of the risk neutral and statistical densities,

$$\frac{d\log q(L)}{dL} - \frac{d\log p(L)}{dL} = 0.1085$$

We evaluate the derivative of the logarithm of p at the two strikes of 11.72 and 26.56 to be $-.3638$ and $-.2871$. This provides us two Equations

$$\left.\frac{d\log q(L)}{dL}\right|_{11.72} = -0.2553$$

$$\left.\frac{d\log q(L)}{dL}\right|_{26.56} = -0.1786$$

from which we can simultaneously solve for the parameters c and a of $q(L)$ to obtain $c = 1.0442$ and $a = 0.6054$. Using these values for the risk neutral parameters we price the two call-spreads to obtain the values

$$w(.01,\ .5) = 6,157,387$$
$$w(.0001,\ 2) = 1,394,000$$

These prices compared with those of the MMC estimates appear to indicate over-pricing by MMC to the order of approximately \$4 million in each case.

We can place these estimates in perspective by pricing the call-spread statistically. In other words, assuming risk neutrality we can use the statistical mean \$2.106 billion and standard deviation \$2.497 billion as our working Weibull distribution and estimate the actuarially fair prices. Under this assumption, using Equation (49), the call-spread is valued statistically at \$4.5 million and \$150, 000 for 1% and 0.01% risk levels, respectively. Note that the statistical prices establish the lower bound for the reinsurance price risk. Thus, we observe that MMC estimates reflect some level of tilting in pricing rather than assuming risk neutrality on the part of the reinsurer.

VI. CONCLUSION

This paper proposes a parsimonious approach to formulating a risk neutral distribution from an estimated statistical distribution associated with an underlying uncertainty. As a result, contingent claims on the uncertainty can be priced via the statistical density. To obtain the risk neutral density we employ a renormalized exponential tilt of the statistical density, a method often used in the literature. Our contribution lies in explicitly relating the level of this exponential tilt to those observed in related options markets that serve as a sufficient statistic for the uncertainty at hand.

More specifically, we focus attention on uncertainties related to tail loss events and develop for the purpose, option pricing models using the Weibull extreme value distribution. These are employed to obtain closed form expressions for reinsurance contract pricing.

Our application focuses on pricing FDIC's reinsurance risk. We envision the reinsurer to be facing the FDIC's statistical loss experience, which we estimate to be Weibull distributed with mean \$2.106 billion and standard deviation \$2.497 billion. We propose that the reinsurer risk-neutralizes this distribution by a tilt coefficient obtained from the traded call option prices on the BKX index. Application of the call-spread pricing expression derived in the paper yields the reinsurance price estimates. When we compare these prices to estimates provided by the MMC we observe that MMC prices are consistent with our estimates in that they embed tilting on the part of reinsurer.

VII. APPENDIX

Derivation of the Weibull Call Option Model

Note that for strike X we can express the payoff to a call option written on the loss level L as follows:

$$C(X) = \int_X^\infty (L - X) f(L)\, dL, \tag{42}$$

where the Weibull probability density function is given by

$$f(L) = \exp\left(-\left(\frac{L}{c}\right)^a\right) \frac{aL^{a-1}}{c^a}. \tag{43}$$

with mean μ and standard deviation σ

$$\mu = c\Gamma\left(1 + \frac{1}{a}\right) \tag{44}$$

$$\sigma = c\sqrt{\Gamma\left(1 + \frac{2}{a}\right) - \Gamma\left(1 + \frac{1}{a}\right)^2} \tag{45}$$

where $\Gamma(x)$ is the gamma function. Hence, Equation (42) can be written as,

$$C(X) = \int_X^\infty L \exp\left(-\left(\frac{L}{c}\right)^a\right) \frac{aL^{a-1}}{c^a} dL - X \exp\left(-\left(\frac{X}{c}\right)^a\right). \tag{46}$$

The first term is simplified as follows:

$$\int_X^\infty L \exp\left(-\left(\frac{L}{c}\right)^a\right) \frac{aL^{a-1}}{c^a}\, dL = \frac{a}{c^a} \int_X^\infty L^a \exp\left(-\left(\frac{L}{c}\right)^a\right) dL \tag{47}$$

Performing the integration we obtain in terms of the incomplete gamma function and discounting it at the risk-free rate of r, we have

$$C = e^{-r}\left[c\Gamma\left(1+ \frac{1}{a}\right)\left(1 - gammainc\left(\left(\frac{x}{c}\right)^a,\ 1 + \frac{1}{a}\right) - X \exp\left(-\left(\frac{X}{c}\right)^a\right)\right)\right] \tag{48}$$

Hence, the value of the Weibull call option, with parameters c and a, written on the loss level L with strike X is given by

$$C = e^{-r}[L^* W_1 - X W_2]$$

where

$$L^* = c\Gamma\left(1 + \frac{1}{a}\right) \tag{49}$$

$$W_1 = 1 - gammainc\left(\left(\frac{x}{c}\right)^a,\ 1 + \frac{1}{a}\right) \tag{50}$$

$$W_2 = \exp\left(-\left(\frac{X}{c}\right)^a\right) \tag{51}$$

and L^* is the expected loss level under the risk-neutral measure, Γ and gammainc are the gamma and incomplete gamma functions.

We note the Weibull call option formula has a similar structure to the Black-Scholes option pricing formula. The present value of the strike is multiplied by the Weibull risk neutral probability that the call is in the money. L^* is the risk neutral expected loss level and is multiplied by W_1, which is the probability of the call being in the money under a suitably adjusted measure.

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