RATIONALE AND RESULTS WITH THE LFC CAT BOND PRICING MODEL

By Morton N. Lane, Ph.D.

Cat bond pricing presents theorists with both an opportunity and a challenge. The opportunity is that for the first time ever, investors have been presented with explicit probability statistics about the likelihood of full repayment at maturity. They receive these probability estimates at the time of issue. Other fixed income securities may allude to likely default statistics, via a letter rating, but none, prior to the advent of cat bonds, did this with precision. Indeed, the rating agencies themselves used different metrics to arrive at their letter ratings, therefore representing different things. In spite of this, the traded market often uses the letter ratings interchangeably as surrogate ranges of default probability. The opportunity then is to observe transaction prices and examine them relative to precise statistics provided at issue.

The challenge of cat bonds is that by rights, the prices that are observed should be lower than they are. Capital asset pricing model theories suggest that any asset that diversifies an investment portfolio away from systemic market risk is desirable. Investors if they are efficient should want diversifying assets, which cat bonds represent, in large quantities. In theory, the price should be driven lower by investor demand to the point where they are just compensated for expected losses and the risk free rate. In the 10 years that the embryonic cat bond market has existed, observed prices have never approached those low levels. Observed prices have always given the investor a premium. So much for theory.

The object of this paper is to take advantage of the empirical opportunity of cat bond pricing and to provide some insights into the challenge they present to theory. Primarily, the paper is a record of several years experience in observing
cat prices using a model which we label the LFC (Lane Financial) model. The paper will trace the beginnings of this model’s development, its continued explanatory powers as well as its shortcomings. The objective is not to promote the model as superior to any other, but simply to record the usefulness of any model when viewing prices and analyzing markets.

Expected Loss

It is generally agreed that the price of risky instruments consists of two components, above and beyond the default free time value of money. Those two components are contained in the spread above the risk free rate in cat bonds, or corporate bonds for that matter. The first component is there to compensate the investor for expected loss. The second is there to compensate the investors for unexpected loss. This compensation for unexpected loss is, in the context of insurance often referred to as the load. In the finance context it is often referred to as the expected excess return. Most of the controversy about pricing concerns the unexpected loss reward, but even the first component, expected loss, should generate some discussion.

Expected loss is the probability-weighted sum of the possible outcomes that the bond can take on. In a bond that has only two possible outcomes, full repayment or full default loss, with probabilities \( p_0 \) and \( p_1 \) respectively, expected loss (EL) is given by the formula

\[
EL = 0*p_0 + (1)*p_1 = p_1 \quad \text{also } p_0 = 1-p_1
\]

Clearly this can be generalized to the case of many possible loss outcomes \( L_i \) where the possible loss outcomes are \( i = 0,1,\ldots,n \). With probability \( p_i \) the expected loss formula becomes

\[
EL = \sum p_i L_i \quad \text{all } i
\]

The question that the simple formula provokes for investors is: Are they indifferent to the distribution of possible outcomes of \( p_i \)'s? In the binary case for example, is an investor indifferent between two bonds with the same coupon (or spread over LIBOR) and same expected loss. Is the investor indifferent between say a bond with a 2% probability of 50% loss of principal, and a bond with a 50% chance of a 2% loss of principal? Both bonds have the same expected loss, of 1%. If the answer to the question is, yes, he should be indifferent and expected loss may provide an adequate risk measure. As long as there is some hesitation about which bond is preferred or if the answer is that it would depend on the price, then the investor is implicitly saying he has a preference function that looks beyond expected loss to other aspects of distribution of outcomes. This is true even in the context of adding to an existing portfolio of bonds where the size of each bond can be controlled.

Looking beyond expected loss, the central tendency (mean) measure of bond loss outcomes, to other measures of the distribution of outcomes brings us to that component of price that compensates for unexpected loss. Intuitively the investor will be biased against large loss outcomes. Bonds with small loss possibilities will be preferred to bonds with large ones, all else being equal. Weight the possibilities with probabilities, however, and the biases and indifference points become more difficult to assess.

Unexpected Loss

The most common measure of range of outcomes around the mean is the standard deviation. In the case of binary bonds with full limit losses the formula for standard deviation is

\[
\text{Standard Deviation} = \sqrt{p_0*p_1}
\]

In the two examples where the losses are 50% or 2% with probabilities 2% or 50% respectively, the formulas change slightly to

\[
\text{Standard Deviation} = .50*\sqrt{p_0*p_1} = 7%
\]

and

\[
\text{Standard Deviation} = .02*\sqrt{p_0*p_1} = 1%
\]
Clearly, in our very simplified example even though the expected loss measure is identical, the standard deviation is very different. The 1% standard deviation says the (unexpected) loss outcomes are likely to be quite close to the mean. In the case of an extreme loss of 50%, even though it has a lower probability, the standard deviation is higher at 7%. Standard deviation, therefore, expresses something about the spread of outcomes and one theory of pricing has it that the compensation for unexpected loss should be related to this measure. For example, that theory of pricing might suggest that the compensation for unexpected loss should be, say, 40% of the standard deviation. Then the prices of the two instruments should be,

Price of low-probability-of-large-loss-bond
= Expected Loss + 40% of Std Dev
= 1% + 0.40 * 7%
= 3.80%

Price of higher-probability-of-small-loss-bond
= Expected Loss + 40% of Std Dev
= 1% + 0.40 * 1%
= 1.70%

In other words, this theory of pricing says the investor will be indifferent if the bonds in our example are priced at 3.80% over LIBOR and 1.70% over LIBOR. The 2.80% and the 70 basis points are measures of load (insurance context) or expected excess return (finance context). They compensate for unexpected loss in a consistent fashion.

The concept that price is equal to “expected loss plus a fraction of the standard deviation” is theoretically very respectable. In the case of insurance it was developed by Rodney Kreps in the early 1990’s. He also showed that the exact fraction of standard deviation to be used was a function of many variables including interest rates. In the finance world, the fraction is analogous to the famous Sharpe Ratio. Prof. Sharpe measured the expected excess return of capital market instruments against their volatilities (standard deviations) over and above the risk free rate. The parallelism of the two approaches is beguiling and many (see, for example, Wang2) have tried to reconcile the approaches. However, Sharpe worked in a mark-to-market traded world where return distributions are, if not normal, close to log normal. Insurance is different. It tends to be characterized by very asymmetric distributions of loss. It raises the question: Is standard deviation a good measure of unexpected loss in an asymmetric world?

**Frequency and Severity**

In examining cat bond prices three very distinct observations caused us to look beyond the Kreps and/or Sharpe models. First, fitting observed prices to the model produced some quite erratic price predictions. The model did not describe the real world very well. Second, for all the respectability that standard deviation has as a measure of risk, we have yet to see it listed in the prospectuses of any of the cat bonds heretofore brought to market. If it is so important why is it not spelled out? Third, what the investor documents did provide is measures of the likelihood of some-loss and the likelihood of total-loss. If those are the measures provided isn’t it empirically likely that those are the measures of risk that the investor looks to for compensation for unexpected loss?

The probability of some loss is known variously as the “attachment probability” or the “probability of first dollar loss”. More succinctly, it is the inverse of the “frequency” of loss. It describes all those occasions when a loss could happen. In a binary bond the probability of one loss is the probability of any loss. In a more general case it is the sum of the probabilities of all possible losses.

\[ \text{Frequency of loss} = \sum_{i} p_i \quad \forall i > 0 \]
\[ = (1-p_0) \quad \forall i > 0 \]

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Alternatively,

\[
\text{Probability of First Dollar Loss (PFL)} = \sum_{i} p_i = (1-p_0)
\]

Investors are both informed and concerned about the frequency or likelihood of loss. In the case of cat bonds this is done with precision. In the case of corporate bonds they are informed via the Rating Agencies. A Standard and Poor’s rating says something about the frequency with which bonds of a particular letter rating default. (Incidentally, this is in contrast to Moody’s ratings which say more about expected loss.)

But if the frequency of loss is important, so is the magnitude of loss, if and when a loss occurs. Something about the magnitude of loss can be gleaned from the other statistic that is usually contained in cat bond prospectuses, the probability of exhaustion or more accurately, probability of total loss. If the probability of total loss is close to the probability of first loss then the investor can infer that the severity of loss is high - in others words if there is any loss it is likely to be total. If, on the other hand, the probability of exhaustion is very low in absolute terms, or low relative to the probability of first loss, then it is quite possible that the loss will be less than total. In the case of defaulted corporate bonds there is usually some residual value of assets and, on average, the loss (over the full economic cycle) has been about 60%. Similarly, for credit default swaps the residual value will be less than total. These observations are empirically based. In the case of cat bonds, empirical measures of severity are few and far between but in model terms they are given precisely.

A better measure of severity of loss is conditional expected loss. It answers the question: If there is a loss, how big is it expected to be? In the world of credit it is referred to as loss given default. Actual loss given default is an empirically observable ex-post measure of severity. An ex-ante measure is expected loss given default or expected loss conditional upon some loss. In the discrete probability algebra we have been using, the conditional expected loss is

\[
\text{Conditional Expected Loss (CEL)} = \sum_{i} [p_i/(1-p_0)]*L_i \quad \text{all } i > 0
\]

Notice that

\[
\text{CEL} = \sum_{i} [p_i*L_i]/(1-p_0)
\]

\[= \text{EL/PFL} \]

In other words, the severity measure is easily discernable from the expected loss estimates and frequency measures given in every prospectus.

**LFC Model**

The preceding analysis has given reasons why there should be a load added to expected loss in pricing cat bonds. Furthermore, it has been argued that the load should take account of the shape of the distribution and that frequency and severity of loss is a more plausible set of measures than standard deviation. The remaining question is how the investor market evaluates or incorporates these measures. At this point, the LFC model requires something of a leap. It is asserted that frequency and severity are traded off in a power type relationship.

\[
\text{Load} = \gamma * (PFL^\alpha) * (CEL^\beta)
\]

Therefore

\[
\text{Price} = \text{EL} + \gamma * (PFL^\alpha) * (CEL^\beta)
\]

This load formula is an application of the Cobb-Douglas production that students of economics used to characterize the trade-off between labor and capital in production of goods and services. Here, use of the model conveys the idea that investors trade off between frequency of loss and severity of loss. Given equal likelihood of loss it is certain that investors would prefer (want less compensation for) lower severity. Conversely, with identical severities rational investors would
prefer lower frequency. The question is how a little more frequency will be traded for a little less severity. That is purely and simply an empirical question. Furthermore, it is only answerable if prices, frequency and expected severities are observable. Such is the case with cat bonds.

Before turning to the empirical question, however, it is worth pausing to establish that even though the LFC model appeared from nowhere it is related to other approaches. For example, if \( \gamma = 0.40, \alpha = 0.5 = \beta \) then

\[
\text{Price} = \text{EL} + 0.4 \times (\text{PFL}^{0.5}) \times (\text{CEL}^{0.5}) \\
= \text{EL} + 0.4 \times (\text{PFL} \times \text{CEL})^{0.5} \\
= \text{EL} + 0.4 \times (\text{EL})^{0.5}
\]

and \((\text{EL})^{0.5}\), for small \(p\), is approximately equally to the standard deviation. In other words, an empirical fit with the power coefficients equal to 0.5 would be a special case and a good validation of the Kreps model.

There is another case that is of interest. Consider,

\[
\text{Price} = \text{EL} + \gamma \times (\text{PFL}^{\alpha}) \times (\text{CEL}^{\beta}) \\
= \text{PFL} \times \text{CEL} + \gamma \times (\text{PFL}^{\alpha}) \times (\text{CEL}^{\beta}) \\
= (\text{PFL} \times \text{CEL}) \times [1 + \gamma \times (\text{PFL}^{\alpha-1}) \times (\text{CEL}^{\beta-1})] \\
= \text{EL} \times [1 + \gamma \times (\text{PFL}^{\alpha-1}) \times (\text{CEL}^{\beta-1})]
\]

In other words, price is a multiple of expected loss. However, the multiple is an inverse function of frequency and severity. If severity were constant between deals then the price multiple would change with probability of first dollar loss. This is important since we know this to be true. Lower rated corporate bonds (that by definition) have a higher chance of default actually do trade at lower multiples of expected loss than say AAA rated bonds. What the above formula suggests is that in addition to frequency, severity can also have an influence on the multiple. Very often investment bankers promote cat bonds on the basis of their multiple. It is gratifying that the LFC model would again present those multiples as special cases.

The Empirical Analysis

Several attempts were made to fit various functions to observed cat bond prices in 1997, 1998 and 1999. Those attempts are recorded on the Lane Financial LLC web site under the titles, *A Year of Structuring Furiously; Price, Risk and Ratings for Insurance Linked Notes and Risk Cube; Price, Risk and Ratings (Part II)*. While now only of archeological interest, these papers do record the thought process by which the LFC model evolved. The first specific attempt to capture the trade off asserted in that evolution of thinking was presented in a paper entitled *Pricing Risk Transfer Transactions* at the A.F.I.R.’s meeting in June 2000. The main empirical results of the paper, together with subsequent regressions, are shown in Table 1. The 2000 fit involved using the issue price and probability statistics of all the bonds issued in the twelve months prior to analysis. Eleven bonds were available for analysis, but by considering the tranches of each bond separately sixteen observations were used in the regression. Each tranche of a multiple tranche bond was available for the investor to accept or reject without having to take tranches jointly. Hence, each piece could be viewed as an independent price observation for regression purposes.

The results of the 2000 analysis were encouraging. The estimated parameters were plausible and indeed with alpha and beta close to one half, the parameters had some resonance with, although greater precision than, standard deviation type measures. The regression statistics themselves were reasonable, but, truth to tell with such a small sample base, not all that reliable.

The regression analysis was repeated in 2001, and those results are also shown in Table 1. Again, sixteen observation points were used, although now on the securities issued during the preceding year, 2000.

What is noticeable between 2000 and 2001 is that the importance of the severity measure (CEL) is diminished. The power coefficient fell from .574
It is a pattern that is accentuated in all subsequent regressions shown in Table 1. Interpreting this is hazardous, but two explanations are possible. First, that the investors did not in fact consider severity of outcome as important as the frequency of loss. That is certainly intuitive given experience of corporate bonds where investors rely heavily on ratings which are usually interpreted as frequency measures. The second possible explanation is that the range of securities offered did not show much differentiation in severity of outcome so that the regression statistics on severity are not significant. Probably the correct answer contains elements of both. Certainly, it was true that as bonds became more standardized they tended to have similar severity profiles, as it is assumed exists in corporate bonds. Actually one never really knows the profiles in corporates since the ex ante numbers are never given with corporate bond offerings. Instead, rating agencies measure the ex post experience with severity of an actual loss and then mentally apply that average measure to all bonds.

While a smaller severity coefficient might be expected intuitively, there is no intuition that would justify a negative coefficient. It stretches credulity that prices should be lower when higher severity is present, all else being equal. But that is unfortunately the picture that emerges from Table 1 for the quarterly regressions of 2001-2.

Of Cycles and Seasons

The regressions of 2000 and 2001 suffered from one obvious defect. The data was based on issues that were scattered throughout the calendar year. An issue in January might experience quite different market conditions from an issue the following December. The underlying reinsurance market might have softened or hardened in the meantime. Certainly, the reinsurance market was weakening in 1999 and may have strengthened slightly during 2000. But during the year events can cause quite dramatic swings in pricing. The French storms at the end of 1999 provide one illustration. The events of 9/11/2001 provide another extreme example.

As a result, model fits were not picking up these cycle changes. In fact, the choice of annual data meant that the cycle effect was average and thereby muted. What was needed was simultaneous pricing of securities, so that any trade-offs inherent in investor markets were captured at a single point in time. On cue early in 2001 the beginnings of a secondary market emerged. The value of secondary market information was described in an LFC note Stirrings in the Secondary Market March 2001. Underscoring the importance of the secondary markets, a session was also added at the last moment to the agenda of the Bond Market Association’s first meeting on Insurance Linked Securities later that month. Most insurance practitioners had some difficulty with the concept of a secondary market and certainly did not see much value in it. Insurance is, after all, written and the consequences suffered or enjoyed. The idea of trading out of a position if circumstances changed is not something that had been possible in the traditional market. “Write and ride” the risk was the insurance equivalent of “buy and hold” for investors, except the investors typically did not buy and hold.
Notwithstanding, the emergence of a secondary market, thin as it was, provided for the first time the possibility of simultaneous pricing of outstanding securities. The results of these regressions are seen quarterly during 2001-2002. They display the disquieting feature that the severity coefficient is either negative or close to zero, i.e. irrelevant to secondary prices. Several possible explanations are in order. First, that severity is not in fact a large determinant of price. More likely, however, is that the secondary prices are picking up some seasonal price shifts, but the regression is not.

A cat bond issued for twelve months pays a premium equally throughout the year. Exposure, however, is not evenly spread throughout the year. As Fig 2 shows, with any wind risk so far securitized there is a season to the exposure. An investor buying a bond with embedded US hurricane risk in January and trying to sell it six months later should not expect half the premium. He has not born half the risk. As Fig 2 shows, 90% of US hurricane risk falls in the months of August, September and October. A holder of the risk during those months will want to be paid 90% of the premium. This will be reflected in the secondary market prices. That seller who wanted out after six months is likely to receive a price which will give him little more than a financial return. As he has born no significant cat risk he will receive little or no significant cat premium.

Thus, seasonality clearly affects secondary market prices. But it means that regressions done using issue probabilities of loss will not capture the revised of-the-moment estimates. Bonds with embedded seasonality must be ignored or their expected loss, etc., estimates adjusted. In the LFC experiments during 2001-2002 and shown in Table 1 the practice was to drop (based on a pure judgment call) deals with strong and immediate seasonalities. It was also practice to drop deals with immediate maturities where small differences in price have big consequences.

What the results show is that selectively dropping deals is not an adequate response to seasonal issues. Even though making the seasonal adjustments is difficult, some is necessary to get at the statistical truth. Swiss Re has recently put out a piece to aid with this adjustment and John De Caro at Cochran Caronia has been writing about the issue for some time. It will be interesting to see how the regressions perform when both seasonal adjustments and secondary market prices are used. Although, empiricists should be warned, that while single peril bonds are relatively easy to adjust, seasonally adjusting multi-peril, or multi year bonds is not a trivial exercise. Furthermore, the seasonal adjustment that must be made is not only change to expected loss. With multiple occurrence indemnity bonds in particular, when losses occur, 3 See Special Report; Seasonality and the Pricing of Cat Bonds, Swiss Re, August 2003.
even if they do not specifically affect the bond, they may affect how close the bond is being affected by subsequent occurrences. In other words, the frequency or probability of attachment will need to be adjusted, in addition to the expected loss.

The promise that precise prices and precise probability statistics allow for excellent explanations of pricing are still there, but the exercise brings with it its own problems. Incidentally, this is not just an LFC model problem; these comments apply to any of the empirical models that are freely discussed. The Kreps Model and the Kreps and Major model ⁴ all need to be adjusted in the same way. In an ideal world the issuers would update their loss-estimates statistics quarterly, say, and these would be regressed against secondary market prices of outstanding securities. But we are not there yet.

**Earthquake-only Cat Bonds**

Cat bond that specifically do not have a seasonality component are those that cover earthquake. At the present time there are hardly enough outstanding issues to regress from secondary prices, but regressions can be fitted over all issued earthquake bonds. In a privately commissioned recent report on earthquake-only bonds LFC generated the last set of results in Table 1. They show that once again the pricing of initial issues is mainly dependent on the frequency measure but that the severity measure is a significant component of price trade-offs. This analysis contains all earthquake bonds issued since 1997 including two early securitizations SR1 and SR2 which are somewhat anomalous to the more recent issues. They are included for completeness, as are four securities with significant earthquake risk.

The earthquake regression does not have a seasonality component but it is not contemporaneous data. Cyclical pressures will not be captured nor isolated in the regression.

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<th>Anticipated Prices from LFC Fitted Regression Model</th>
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* Based on the Earthquake only model 2003.

**Usefulness of Models**

Notwithstanding the empirical problems confronting analysts, models even with their bad fits can be very useful. One illustration of that is shown in Figure 1. It shows the results of using the latest earthquake-only regression from Table 1 and applying the model in-sample to fitted securities. If pure statistics explained prices, then there would be a random pattern of discrepancies between model price and actual price. In fact as Figure 1 shows, if the results are arranged by zone of coverage, interesting patterns emerge. Clearly, nearly all the California quake zone covers, with the exception of SR1 and SR2, trade at a discount to the model price. In other words, the actual market demanded a higher price than the model would suggest. In contrast, the Japanese earthquake zone covers traded at

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a premium to what the model suggested. Evidently there is something else at play between the zones. We suggest that the something is supply and demand. California is a source of a great number of issues. Investors therefore can have too much concentration of California risk. Japan on the other hand is in short supply for the balanced portfolio writer and its issues get bid to a premium. A corollary to all of this is that new issues from zones in even rarer supply will get even better treatment by the market. Taiwan is an example of that. Even though it has a very unusual structure and even though it was not rated it traded at a premium to model.

Without a model, such insights are harder to obtain. LFC has used similar approaches to discern cheapness and dearness of particular securities, and to determine where anticipated issues might come to market. See Tables 2 and 3 for a more complete chart of the range of prices. Even if the predicted price is different from the actual price, the tables can be used as a key to search for the reason for discrepancies. Often investors will overlook features that the rest of the market has picked up – premiums and discounts to model can be the first clue to unusual structural features.

Concluding Remarks

Opportunity and challenge were the themes that opened this paper. Precise prices for a new asset class (cat bonds) and the provision of precise statistics promised unique insights into the mind of the risk bearing market. That opportunity has been made available, but has yet to be fully exploited. Problems of contemporaneous pricing and of seasonally adjusting expected loss estimates remain. Nevertheless, model fitting with all its imperfections is useful and revealing. As the market gets bigger and deeper it is expected that these insights and fits will become more and more useful.

In closing, it is worth noting that the use of empirical models such as the LFC model is an example of what used to be called “normative” economics. It is an examination of what is, rather than what ought to be (“positive economics”). As such empirical models often fall short of the high goals of a full and rational explanation of investor behavior. Perhaps the most intriguing way in which these empirical models fall short is that they do not recommend “arbitrage free” prices. This is equally true for LFC, the Kreps and the Kreps and Majors approaches to explaining observed prices. Essentially, it is possible under any of the empirical approaches to create synthetic securities that are cheaper than a combination of existing securities, thereby affording the opportunity for arbitrage profit. Despite the lack of evidence of great arbitrage activity in the secondary market there is evidence that issuers are taking advantage of such opportunities in their pronounced issuance shift from single peril bonds to multi-peril bonds (see Arbitrage Algebra for Multi-Peril ILS on the website or upcoming in the Journal of Risk Finance for a discussion). In the future, the empirical analysis of prices must be cognizant of these arbitrage phenomena as well as the features captured in the analysis to date. The opportunity is there but the challenges are growing and stimulating.
Table 3

### Implications of LFC Pricing Model in terms of its Components

\[
\text{Price} = \text{EL} + \text{gamma} \times (\text{PFL} \times \text{alpha}) \times (\text{CEL} \times \text{beta})
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#### PRICE = EL + LOAD

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#### MULTIPLE

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