

Measuring Credit Spread Risk: Incorporating The Tails

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MEASURING CREDIT SPREAD RISK: INCORPORATING THE TAILS

Rachel Campbell and Ronald Huisman

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Abstract

It is widely known that the small but looming possibility of default renders the expected return distribution for financial products containing credit risk to be highly skewed and fat tailed. In this paper we apply recent techniques developed for incorporating the additional risk faced by changes in swap spreads. Using data from the US, UK, Germany, and Japan, we find that the risk faced from large spread widenings and tightenings is grossly underestimated. Estimation of swap spread risk is dramatically improved when the severity of the fat tails is measured and incorporated into current estimation techniques.

Keywords: Market Risk, Value-at-Risk, Extreme Value Theory, Parametric Distributions, and Backtesting

¹ All errors pertain to the authors.

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1. Introduction

Credit risk management has become an increasingly important area of financial risk management, highlighted by the enormous surge in credit derivatives. A survey by the British Bankers Association (BBA) estimated the global credit derivatives market in 1999 to be \$586 billion, by 2000 the market had grown to around \$893 billion¹, and at the year-end of 2001 the market has been estimated to have mushroomed to an incredible \$1.2 trillion. Indeed forecasts for 2002 estimate a market of over \$1.5 trillion. The recent global financial crisis, the need for credit protection, as well as the potential to enhance loan-based credit portfolio yields and the returns on bank capital have spurred demand for credit derivatives.

Accurate assessment of credit risk depends on methods to accurately measure and control the potential or expected losses resulting from default. This includes estimation of the credit exposure, the probability of default, and the fraction of the market value being recovered at default. Credit spreads, the difference between the risky bond and a risk-free alternative, should therefore reflect the amount of credit risk faced. These spreads change over time due to, for example, varying market conditions, changes in the credit ratings of issuers, or changes in the expectations regarding the recovery rate. Traditional quantitative credit risk models assume that expected changes in spreads are normally distributed, but empirical evidence shows that they are more likely to be skewed and fat tailed. This results in the expected loss distribution for credit portfolios to be highly skewed and severely fat tailed. Among others Subrahmanyam, Ho Eom, and Uno [1998] show this for Japanese yen swap spreads and Phoa [1999] provides evidence using Australian dollar swap spread data. In both papers it is argued that incorporating the apparent fat tails is crucial in order to

correctly measure credit risk. Phoa applies Extreme Value Theory (EVT) to parameterise fat tailed Fréchet, Weibull, and Gumbel distributions in order to measure the maximum expected daily widening in swap spreads on the Australian dollar. However, the method used by Phoa to assess the amount of tail fatness (the tail index) is known to be biased. Phoa deals with this fact by showing results for two different tail index estimates. Recent developments in EVT have lead to the development of an unbiased tail index estimator, which has proven to work successfully in measuring the tail index, and therefore is also able to capture the additional downside risk in Value at Risk estimates for stocks and exchange rates².

In this paper we apply the technique mentioned above to model the tails of the distribution of expected changes in swap spread. Using data from US, UK, German, and Japanese 10 year swap and government bond rates, we provide evidence of the apparent tail fatness in the empirical distributions of the changes. Furthermore, it is shown that the approach outperforms the normal distribution in measuring the risk faced by large widenings or tightenings of credit spreads. The plan of the paper is as follows. Section 2 focuses briefly on credit spreads. In section 3, we discuss the data and provide sample statistics. Section 4 introduces tail index estimation and presents the results. Section 5 concludes.

2. Credit Spreads

The expected credit loss is measured by the drop in value due to the possibility of default, λ , over a time interval t and can be expressed simply as the probability of default multiplied by the proportion of the position not recovered; as shown below in equation (1)².

$$ECL = (1 - f)(\lambda \Delta t)P_t \quad (1)$$

Where f is a fraction representing the recovery rate and P is the price of a risk free bond at time t . The credit spread for a given maturity may be written in terms of yields, y , as in equation (2), where λ is again the probability of default over the same period as the maturity of the risky bond, P^* , and the risk free bonds,

$$y^* - y = (1 - f)\lambda \quad (2)$$

The credit spread therefore represents the probability of default multiplied by the proportion not recovered. Indeed using equation (2) the term structure of default probabilities can be inferred from the term structures of risky and risk free bonds, in a similar manner to Jarrow and Turnbull [1995]². The term structure of credit spreads (and shocks to credit spreads) is indeed non-trivial. From the credit spread we can determine much of the risk involved in credit risk. Indeed it is this factor which is used as the crucial element in credit risk management. For example for the next periods estimate of the expected credit loss we can substitute in the credit spread as the markets' expectation of default and recovery. When multiplied by the credit exposure (average price is at the 50% confidence level), we have an estimate for the expected credit loss, similar to that given in equation (1), however now in terms of the credit spread.

$$ECL = (y^* - y)P^{0.50}_t \quad (3)$$

If however an estimate of the unexpected credit loss is required we multiply the price of the risk free asset instead by the worst credit exposure at a chosen confidence interval, c . For risky debt the credit exposure is the principal, so P^c_t simplifies to the assets' Value-at-Risk for a given confidence level. For products like derivatives it is only when the derivative contract is in the money that potential credit risk arises, so

we also need to multiply by the probability of being in the money at time t , denoted by probability m .

$$UCL = m(y^* - y)P^c_t \quad (4)$$

This approach to estimating unexpected credit loss however does not take into account the risk associated with changes in the size of the credit spread, credit spread risk, or changes in the probability of default and the recovery rate. So unless this is incorporated into the worst case CaR estimate³ it is vital that scenario analysis is used to track the sensitivity of the CaR measure to either credit spread risk or changes in default and recovery rates. Changes in the credit spread, (credit spread risk) is therefore the risk involved with changes in the size of the credit spread. This can have implications for worst case scenario analysis of credit risk for fixed income products, as well as for pricing credit derivative products where the credit spread is a determining factor for the value of the derivative.

In the following section we provide empirical evidence of the probability distribution of credit spread changes, so that sensitivity analysis used in worst case-scenario analysis for credit risk management, and in the pricing and hedging of derivatives products on credit spreads can be more accurately determined.

3. Historical Credit Spread Tightenings and Widenings

To estimate the distribution of shifts in credit spreads for a variety of countries, we employ daily data for the US, UK, Germany and Japan from Datastream over the period January 1990 until January 2000. The credit spread prices the additional risk over a base asset such as the Treasury bill rate. We therefore use 10 year Government

Bond yields for the respective countries as the base asset. The swap rate is commonly taken as a proxy for the AA credit rate, since the swap market is significantly deeper and more liquid than that for corporate bonds⁴. We therefore also use the 10 year Datastream Swap Rate, which is a value-weighted index of the middle yield on U.S. swaps. The swap spread (credit spread) is the swap rate less the yield on the current 10-year Government Bond. As a word of caution it may not always be appropriate to use the Treasury yield as the risk-free rate since Treasuries are more liquid and repo at lower rates. It may therefore be more appropriate to use a swap rate as the risk-free rate. A further limitation is that in using a constant-rating series we are not able to reflect spread shifts which result from rating migrations.

The summary statistics for the daily shifts in credit spreads are given in table 1. We can see that the average daily shift is extremely small with standard deviations ranging from 6.2% for Germany, to 8.8% for the UK. The distribution of credit spread shifts in Japan is highly skewed, and all countries credit markets exhibit significant excess kurtosis.

INSERT TABLE 1

Deviations from normality will result in the probability of large movements in credit spreads to be higher than stipulated under the assumption of normally distributed returns. The assumption of gaussian innovations generates a smaller probability of extreme movements, so the assumption of normality is likely to underestimate the credit spread risk of either large tightenings or widenings in credit spreads. The degree of misspecification is of course vital for accurate estimation in risk management for both credit risk, and worst-case scenario analysis. The histogram of shifts in swap spreads is given for the US in figure 1 against the probabilities

assuming normality. We do indeed observe a greater than normal probability of extreme movements in credit spreads, exemplifying the small but looming potential for increases in default risk to have severe implications on the size of credit spread risk.

INSERT FIGURE 1

Of course the prevalence of skewed distributions could also result in an alternative probability for large downward shifts in the swap spread than for upward shifts, so we shall look at both tails of the distribution of shifts in swap spreads. A simple approach to modelling the additional tail fatness in distributions is by parameterising the student-t distribution with degrees of freedom in accordance with the tail estimate of section 2. This approach follows the approach of Huisman, Koedijk and Pownall [1998] in their VaR-x approach, however instead of focussing directly on Value-at-Risk estimation, here we focus on quantile estimates. These quantile estimates can then be directly incorporated into scenario analysis for Credit-at-Risk analysis, or indirectly, when pricing far out-of-the-money credit risk derivatives.

4. Tail Index Estimation

Recent developments in the application of Extreme Value Theory to risk management enable us to provide a good estimate of the tail index of the distribution of daily movements in credit spreads. Tail index estimation is the specification of the degree with which the tail of a distribution exhibits tail fatness, and was first introduced by Hill [1975]. The tail index measures the speed with which the distribution's tail approaches zero; the fatter the tail the slower the speed and the lower the tail index given. The tail index has the attractive feature that it is equal to the number of existing moments of the distribution, and thus can be used to parameterise the student-t

distribution. Hence the link to the fatter tailed Student-t distribution, which nests the normal distribution as a limiting case. We use a modified version of the Hill estimator, developed by Huisman et al [1997] to estimate the tail index, which has been modified to account for the bias in the Hill estimator. Specifying k as the number of tail observations, and ordering their absolute values as an increasing function of size, we obtain the tail estimator proposed by Hill. This is denoted below by γ and is the inverse of α , (5).

$$\gamma(k) = \frac{1}{k} \sum_{j=1}^i \ln(x_{n-j+1}) - \ln(x_{n-i}) \quad (5)$$

As pointed out by Phoa (1999) in practical applications of the Hill estimator an uncomfortable trade-off exists between variance and bias. This occurs through the use of fewer observations as we move further out into the tails of the distribution, so that although the estimate is less biased (reflects more fully the tail of the distribution) the variance of the estimate increases. The bias of the Hill estimator is therefore a function of the sample size used for the estimate, and is shown in figure (2) for the US swap spread data⁵.

INSERT FIGURE 2

Following the methodology of Huisman et al. [1997], we can use a modified version of the Hill estimator [1997] to correct for the bias in small samples. A bias corrected tail index is therefore obtained by observing the bias of the Hill estimator as the number of tail observations increases up until κ , whereby κ is equal to half of the sample size:

$$\gamma(k) = \beta_0 + \beta_1 k + \varepsilon(k), \quad k = 1 \dots \kappa \quad (6)$$

The optimal estimate for the tail index is the intercept β_0 . And the α estimate is just the inverse of this estimate. This is the estimate of the tail index that we use to parameterise the Student-t distribution. Recent applications of this approach for estimating market risk have been shown to work well for a variety of financial time series⁶. We have estimated the tail estimates using the alpha HKKP estimator for the four countries, and the estimates for both tails, the left tail and the right tail respectively are given in table 2.

INSERT TABLE 2

Since all the series exhibited excess kurtosis it is not surprising that the alpha estimates used to parameterise the student-t distribution generate much fatter tailed distributions than under normality. We also observe that the alpha estimate for the left tail alone for all the series is slightly smaller than the estimate using both tails, and the right tail of the distribution only. This provides evidence of a greater probability attached to credit spread tightenings than to credit spread widenings. This may result from the fact that sharp rises in Treasury yields appear more frequently than sharp falls⁷. We therefore analyse the quantile estimates for the downward and upward shifts in credit spreads separately, using the tail index estimator for the respective tail. In figure 3 we have plotted the quantile estimates using the two approaches for quantiles ranging from 7.5% to 92.5% in the right and left tails of the distributions respectively.

INSERT FIGURE 3

More extreme cases the assumption of normality severely underestimates the size of the potential shift in the credit spread shift. Indeed this is the case for all the series, which we analysed, and the results for the quantile estimates for potential daily tightenings and widenings are given in tables 3 and 4.

INSERT TABLES 3 & 4

The probability of credit-spread tightenings has historically been slightly larger than similar sized upward movements. However all the results provide evidence of severe underestimation of the potential changes in large movements of credit spreads. Indeed the fatter tailed student-t distribution parameterised by the alpha tail index estimator provides basis point movements for monthly, yearly, 5, and 10 yearly events much more in line with those having been observed in recent years. It would therefore appear to be much more prudent to use these larger estimates in risk management techniques and derivative pricing and hedging strategies incorporating credit spread risk.

5. Conclusions

Estimation of credit-spread risk is not only important for pricing and hedging credit derivatives but also for accurate risk management. Small but looming possibilities of default however render the expected return distribution for financial products containing credit risk to be non-normal. To correctly assess the true probability of large movements in credit widenings and tightenings we apply recent techniques developed to incorporate additional downside risk resulting from non-normalities in managing market risk to data on swaps and swap spreads. The downside of our results is that for unexpected events the assumption of normality results in credit spread risk in many countries' credit markets to be grossly underestimated. Estimation of swap and credit spread risk for such events is dramatically improved when the severity of the additional downside risk is measured and incorporated into current estimation techniques. These results are not only crucial for improving credit risk management but also in pricing out-of-the money credit derivatives.

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Table 1

Summary Statistics

The table gives the summary statistics for daily shifts in credit spreads over the period January 1990 – January 2000.

CREDIT SPREAD	US	UK	GERMANY	JAPAN
OBSERVATIONS	2610	2610	2610	2610
AVERAGE DAILY SHIFT	-5.747E-06	-2.797E-04	1.226E-04	-1.782E-04
STANDARD DEVIATION	0.076	0.088	0.062	0.069
SKEWNESS	-0.052	0.015	-0.042	-0.344
KURTOSIS	7.224	9.352	7.353	28.723

Table 2

Alpha Estimates

The table gives the alpha estimates for daily shifts in credit spreads over the period January 1990 - January 2000, using the HKKP estimator.

	US	UK	GERMANY	JAPAN
ALPHA (BOTH)	3.848	3.423	3.550	2.939
KAPPA	1305	1305	1305	1305
ALPHA (LEFT)	3.957	3.035	2.803	2.735
KAPPA	603	618	732	582
ALPHA (RIGHT)	4.506	3.835	4.230	3.561
KAPPA	701	686	572	723

Table 3***Credit Spread Tightenings – Quantile Estimates***

The table gives the quantile estimates for daily shifts in swap spreads over the period January 1990 – January 2000, assuming normality and the student-t distribution, with degrees of freedom parameterised by the alpha estimates for the left tail as described in Table 3.

MONTHLY EVENT 4.76%	EMPIRICAL	NORMAL	STUDENT-T (α_L)
US	-12.0	-12.7	-11.7
UK	-13.0	-14.7	-12.3
GERMANY	-9.0	-10.4	-8.3
JAPAN	-9.0	-11.5	-9.0
YEARLY EVENT 0.397%	EMPIRICAL	NORMAL	STUDENT-T (α_L)
US	-29.6	-20.2	-26.6
UK	-35.0	-23.4	-32.2
GERMANY	-24.7	-16.5	-22.8
JAPAN	-31.9	-18.3	-25.1
5-YEARLY EVENT 0.079%	EMPIRICAL	NORMAL	STUDENT-T (α_L)
US	-37.0	-24.1	-41.4
UK	-57.4	-27.8	-55.8
GERMANY	-32.5	-19.7	-41.1
JAPAN	-62.9	-21.8	-46.0
10-YEARLY EVENT 0.040%	EMPIRICAL	NORMAL	STUDENT-T (α_L)
US	-53.4	-25.6	-49.7
UK	-58.9	-29.5	-70.4
GERMANY	-35.9	-20.9	-52.7
JAPAN	-69.7	-23.1	-59.4
20-YEARLY EVENT 0.019%	EMPIRICAL	NORMAL	STUDENT-T (α_L)
US	-	-27.0	-59.5
UK	-	-31.2	-88.7
GERMANY	-	-22.1	-67.7
JAPAN	-	-24.4	-76.7

Table 4**Credit Spread Widenings – Quantile Estimates**

The table gives the quantile estimates for daily shifts in swap spreads over the period January 1990 – January 2000, assuming normality and the student-t distribution, with degrees of freedom parameterised by the alpha estimates for the right tail as described in Table 3.

MONTHLY EVENT 4.76%	EMPIRICAL	NORMAL	STUDENT-T (α_R)
US	12.9	12.7	12.0
UK	14.0	14.7	13.5
GERMANY	10.0	10.4	9.7
JAPAN	10.0	11.5	10.3
YEARLY EVENT 0.397%	EMPIRICAL	NORMAL	STUDENT-T (α_R)
US	26.3	20.2	25.8
UK	33.5	23.4	31.0
GERMANY	23.6	16.5	21.3
JAPAN	26.3	18.3	24.6
5-YEARLY EVENT 0.079%	EMPIRICAL	NORMAL	STUDENT-T (α_R)
US	29.9	24.1	38.5
UK	43.7	27.9	48.7
GERMANY	29.9	19.6	32.5
JAPAN	38.4	21.8	39.8
10-YEARLY EVENT 0.040%	EMPIRICAL	NORMAL	STUDENT-T (α_R)
US	31.9	25.6	45.4
UK	52.2	29.6	58.8
GERMANY	31.0	20.9	38.7
JAPAN	40.4	23.2	48.7
20-YEARLY EVENT 0.019%	EMPIRICAL	NORMAL	STUDENT-T (α_R)
US	-	27.0	53.3
UK	-	31.2	70.7
GERMANY	-	22.0	45.8
JAPAN	-	24.4	59.2

Figure 1

Histogram of Daily Spread Shifts

This figure gives the quantile estimates for daily shifts in swap spreads over the period January 1990 – January 2000. We compare the empirical distribution to that under the assumption of normality.

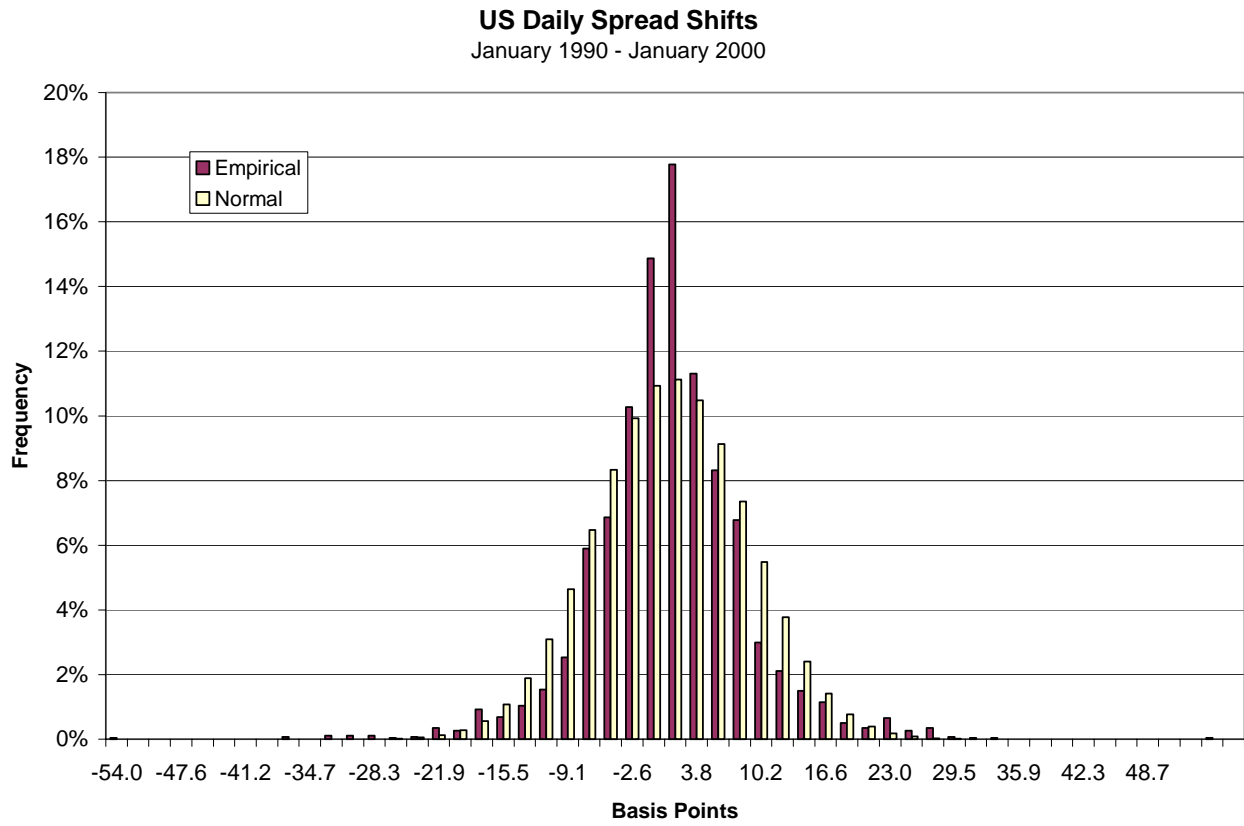


Figure 2

Hill Tail Index Estimator

This figure gives the bias in the Hill estimator as the sample size m increases for the tail index estimation as given in equation (8). Daily shifts in US swap spreads over the period January 1990 – January 2000. We compare the empirical distribution to that under the assumption of normality.

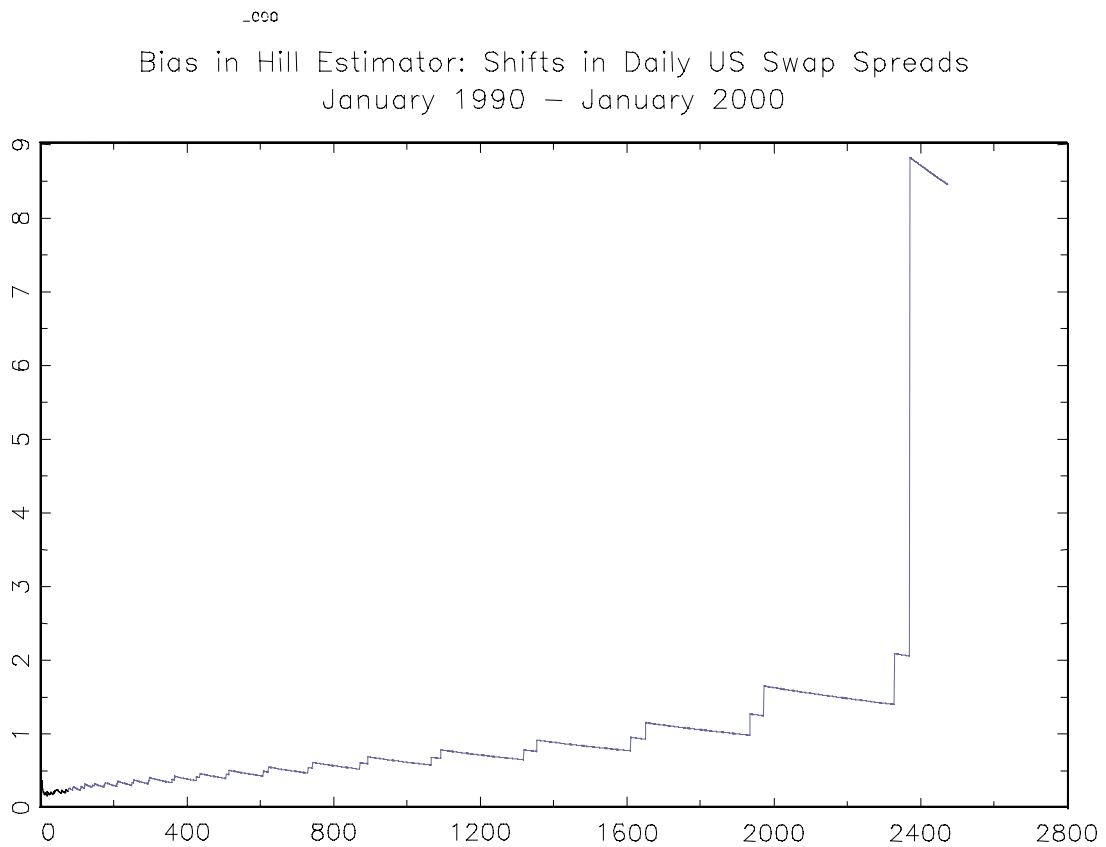
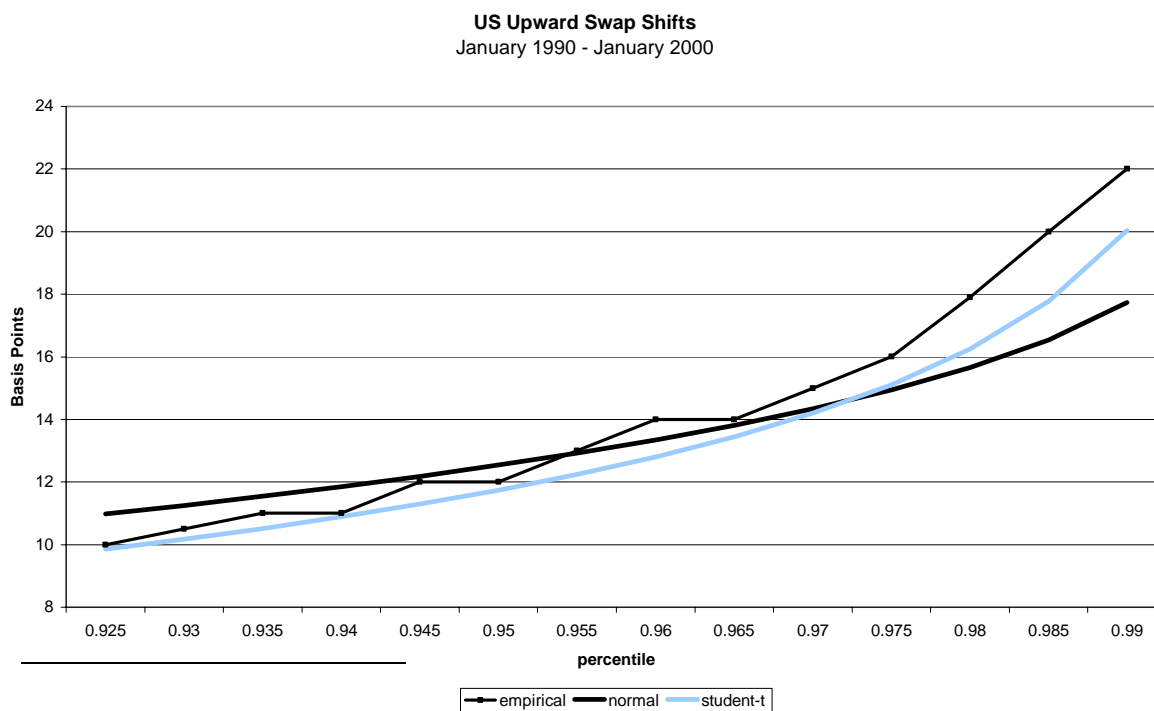
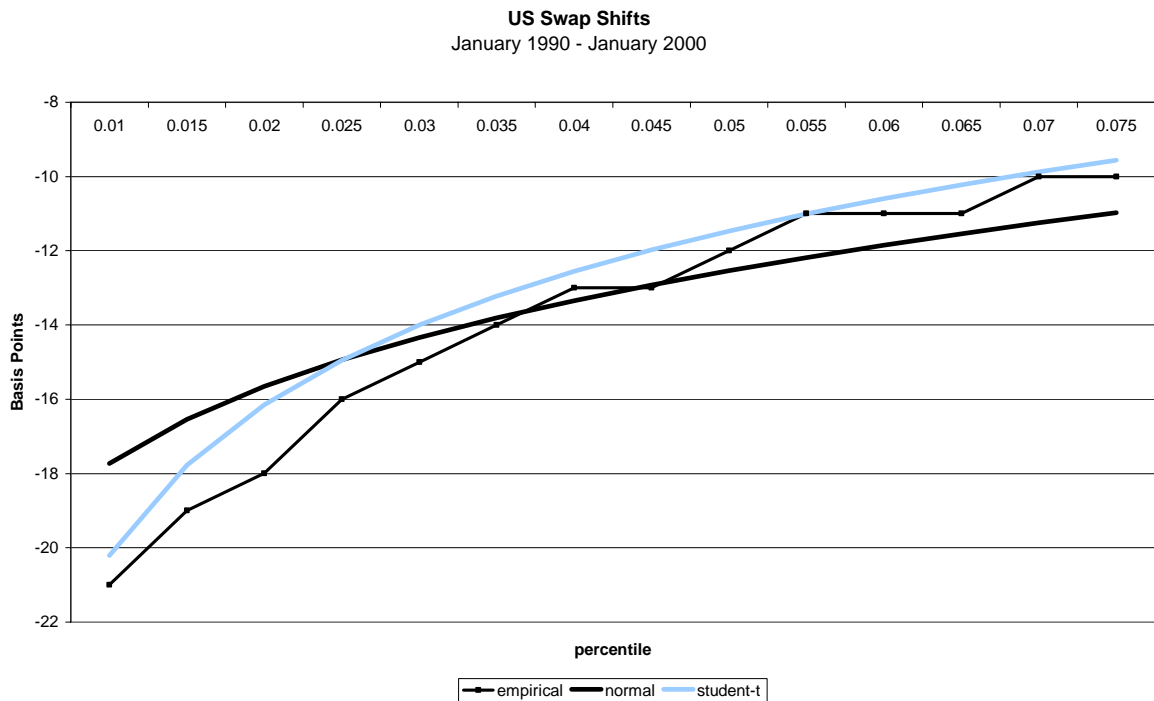


Figure 3

Quantile Estimates using Alternative Parametric Distributions

This figure gives the quantile estimates for daily shifts in swap spreads over the period January 1990 - January 2000, assuming normality and the student-t distribution, with degrees of freedom parameterised by the alpha estimates for the left tail as described in Table 3.



Endnotes

- 1 Credit Risk Survey, BBA [2000].
- 2 See Huisman, Koedijk, Kool, and Palm [2000], Pownall and Koedijk [1999], and Huisman, Koedijk, and Pownall [1998]
- ³4 Jarrow and Turnbull [1995] provide a consistent methodology for pricing and hedging derivative securities involving credit risk, assuming no arbitrage and complete markets.
- ⁴5 Even though a confidence level (commonly 95%) is taken for the distribution of the underlying asset, it is not commonly assumed for the distribution of shifts in the credit spread, however it is a simple exercise to incorporate this directly into the estimate using a bivariate distribution.
- 6 The Datastream Value-weighted index of the middle yield on U.S. corporate bonds index for example with which includes all maturities and investment grade credit ratings could have been used, however the market is much less liquid with only weekly data available for the same sample period.
- ⁶7 A similar pattern emerges for all the series studied.
- ⁷8 See Huisman, Koedijk & Pownall [1998] for an application to US stocks and Bonds, and Pownall & Koedijk [1999] for Asian stock markets, as well as Campbell, Eicholtz & Huisman [2000] for the US and Dutch real estate markets.
- ⁸9 See Phoa [1999].

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