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Advanced Financial Risk Management:

Tools and Techniques for Integrated Credit Risk, Market Risk, Liquidity Risk and Interest Rate Risk Management

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Part 3: Risk Management Techniques for Credit Risk Analytics

Chapter 17
Credit spread fitting and modeling

Chapter 16 provided an extensive introduction to reduced form credit modeling techniques. In this chapter, we combine the reduced form credit modeling techniques with the yield curve smoothing techniques of Chapter 5 and related interest rate analytics in Chapters 6 through 14. As emphasized throughout this book, we need to employ the credit models of our choice as skillfully as possible in order to provide our financial institution with the ability to price credit risky instruments, to calculate their theoretical value in comparison to market prices, and to hedge our exposure to credit risk. The most important step in generating this output is to fit the credit models as accurately as possible to current market data.

If we do this correctly, we can answer these questions:

- Which of the 15 bonds outstanding for Ford Motor Company is the best value at current market prices?
- Which of the 15 bonds should I buy?
- Which should I sell short or sell outright from my portfolio?
- Is there another company in the auto sector whose bonds provide better risk-adjusted value?

Answering these questions is the purpose of this chapter. We continue to have the same over-all objective: to accurately measure and hedge the interest rate risk, market risk, liquidity risk and credit risk of the entire organization using the Jarrow-Merton put option concept as our integrated measure of risk.

Introduction to Credit Spread Smoothing

The accuracy of yield curve smoothing techniques has taken on an increased importance in recent years because of the intense research focus among both practitioners and academics on credit risk modeling. In particular, the reduced form modeling approach of Duffie and Singleton [1999] and Jarrow [1999, 2001] has the power to extract default probabilities and the "liquidity premium" (the excess of "credit spread" above and beyond expected loss) from bond prices and credit default swap prices.

In practical application, there are two ways to do this estimation. The first method, which is also the most precise, is to use the closed form solution for zero coupon credit spreads in the respective credit model and to solve for the credit model parameters that minimize the sum of squared pricing error for the observable bonds or credit default swaps (assuming that the observable prices are "good numbers," a subject to which we return later). This form of credit spread fitting includes both the component that contains the potential losses from default and a "liquidity premium" like that in the Jarrow model we discussed in Chapter 16. It also allows for the model to be "extended" to exactly fit observable bond market data in the same manner as the Heath, Jarrow and Morton interest rate models of Chapters 6 through 9 and the Hull and White/Extended Vasicek term structure model discussed in Chapter 13.

The second method, which is used commonly in academic studies of credit risk, is to calculate credit spreads on a "credit model independent basis" in order to later study which credit models are the most accurate. We discuss both methods in this chapter. We turn to credit model independent credit spreads first.

The Market Convention for Credit Spreads

Credit spreads are frequently quoted to bond buying financial institutions by investment banks every day. What is a credit spread? From a "common practice" perspective, the credit spreads being discussed daily in the market involve the same kind of simple assumptions like the yield to maturity and duration concepts that we reviewed in Chapters 4 and 12. The following steps are usually taken in the market's conventional approach to quoting the "credit spread" on the bonds of ABC Company at a given instant in time relative to a (assumed) risk-free curve like the U.S. Treasury curve:

1. Calculate the simple yield-to-maturity on the bond of ABC Company given its value (price plus accrued interest) and its exact maturity date.
2. Calculate the simple yield-to-maturity on the "on the run" U.S. Treasury bond with the closest maturity date. This maturity date will almost never be identical to the maturity date of the bond of ABC Company.
3. Calculate the "credit spread" by subtracting the risk free yield to maturity from the yield to maturity on the ABC Company bond.

This market convention is simple but very inaccurate for many well-known reasons:

- The yield to maturity calculation assumes that zero coupon yields to each payment date of the given bond are equal for every payment date—**it implicitly assumes the risk free yield curve is flat**, but if credit spreads are being calculated for credit risky bonds with two different maturity dates, a different "flat" risk free curve will be used to calculate the credit spreads for those two bonds because the risk free yield to maturity will be different for those two bonds.
- The yield to maturity calculation usually implicitly assumes **periods of equal length** between payment dates (which is almost never true in the United States for semi-annual bond payment dates)
- The **maturity dates on the bonds don't match** exactly except by accident
- The **payment dates on the bonds don't match** exactly except by accident
- The **zero coupon credit spread is assumed to be flat**
- Differences in coupon levels on the bonds, which can dramatically impact the yield to maturity and therefore credit spread, are ignored
- Often, timing differences in bond price information are ignored. Many academic studies, for example, calculate credit spreads based on bond prices reported monthly. Since the exact timing of the pricing information is not known, it is difficult to know which date during the month should be used to determine the level of the risk free yield curve
- Call options embedded in the bond of ABC Company are often ignored, because they can't be calculated independently of the credit model used. The value of a call option on a bond that is "10 years, non-call five" depends on the probability that the issuer will default in the first five years before the call option can be exercised, for example.

The market convention for fitting credit spreads is very simple, but these problems with the methodology are very serious problems. This kind of inaccuracy is no longer tolerated by traders in fixed income derivatives like caps, floors, swaps, swaptions, and so on based on the Libor curve. We discuss issues with the Libor curve in some detail below. Better analytics for credit spread modeling are now moving into the market for corporate, sovereign, and municipal bonds as well and for very good reason—if you don't use the better technology, you'll be "picked off" by traders who do.

A Better Convention for Credit Model-Independent Credit Spreads

The credit spread calculation that is the market convention has only one virtue—it is simple. We start by proposing a better methodology for analyzing the credit spread of one bond of a risky issuer that avoids most of the problems of the market convention. This methodology continues to assume, however, that the credit spread for each bond of a risky issuer is the same at all payment dates.

We can derive a more precise calculation of credit spread on a "credit model independent basis" if we use the yield curve smoothing technology introduced in Chapter 5. This method has been in commercial use since 1993.[1] Assume there are M payments on the ABC Company bond and that all observable non-call U.S. Treasuries are used to create a smooth, continuous Treasury yield curve using the techniques we described in Chapter 5. Then the continuous credit spread x on the ABC bond can be constructed like this:

1. For each of the M payment dates on the ABC Company bond, calculate the continuously compounded zero coupon bond price and zero coupon yield from the U.S. Treasury smoothed yield curve. These yields will be to actual payment dates, not scheduled payment dates,

[1] This method has been a standard calculation of the Kamakura Risk Manager enterprise-wide risk management system since 1993.

because the day count convention associated with the bond will move scheduled payments forward or backward (depending on the convention) if they fall on weekends or holidays

2. Guess a continuously compounded credit spread of x that is assumed to be the same for each payment date.
3. Calculate the present value of the ABC bond using the M continuously compounded zero coupon bond yields y(i) + x, where y(i) is the zero coupon bond yield to that payment date on the risk free curve. Note that y(i) will be different for each payment date but that x is assumed to be constant for all payment dates.
4. Compare the present value calculated in Step 3 with the value of the ABC bond (price plus accrued interest) observed in the market.
5. If the theoretical value and observed value are within a tolerance e, then stop and report x as the credit spread. If the difference is outside the tolerance, improve the guess of x using standard methods and go back to Step 3.[2]
6. Spreads calculated in this manner should be confined to non-callable bonds or used with great care in the case of callable bonds.

This method is commonly used by many of the world's largest financial institutions. It can be easily implemented using the "solver" function in common spreadsheet software.

Deriving the Full Credit Spread of a Risky Issuer

Even the improvement listed above for reporting credit spreads ignores the fact that the credit spread is a smooth, continuous curve that takes on the same kind of complex shapes as yield curves do. In order to capture the full credit spread curve, we need to accomplish the following tasks:

Yield curve smoothing needs to be extended to include inputs like the observable prices of coupon-bearing bonds, not just zero coupon bond prices

Credit spread smoothing analogous to yield curve smoothing has to be implemented

Potential problems with the data of risky issuers need to be understood and interpreted with caution. We focus here on issues in the London interbank offered market and in the single name credit default swap market.

Differences in credit spreads by issuer, maturity date and observation date need to be explained and understood

We take on each of these tasks in turn.

Yield curve Smoothing with Coupon-Bearing Bond Price Input

In Chapter 5, we included the maximum smoothness forward rate approach in our comparison of 23 different smoothing techniques, both in terms of smoothness and "tension" or length of the resulting forward and yield curves. In each of our worked examples, we showed how to derive unique forward rate curves and yield curves based on the same set of sample data. This sample data assumed that we had observable zero coupon yields or zero coupon bond prices to use as inputs. At most maturities, this will not be the case and the only observable inputs will be coupon-bearing bond prices. In this section, we show how to use coupon-bearing bond prices to derive maximum

[2] Chapter 1 of van Deventer and Imai's Financial Risk Analytics illustrates one method commonly used for this purpose.

smoothness forward rates and yields. The same approach can be applied to the 22 other smoothing techniques summarized in Chapter 5.

Revised Inputs to the Smoothing Process

In Chapter 5, we used the following inputs to various yield curve smoothing approaches:

Actual Input Data		
Maturity in Years	Continuously Compounded Zero Coupon Yield	Zero Coupon Bond Price
0.000	4.000%	1.000000
0.250	4.750%	0.988195
1.000	4.500%	0.955997
3.000	5.500%	0.847894
5.000	5.250%	0.769126
10.000	6.500%	0.522046

For the remaining parts of this series on basic building blocks of yield curve smoothing, we assume the following:

- The shortest maturity zero coupon yield is observable in the overnight market at 4%
- The 3 month zero coupon yield is observable at 4.75% in the market for short term instruments, like the U.S. Treasury bill market
- The only other observable instruments are 3 coupon bearing bonds with the following attributes:

Figure 1

Optimization for Risk-Free Bond Smoothing			
	Additional Inputs for Smoothing		
Bond Number	1	2	3
Bond Name	Bond 1	Bond 2	Bond 3
Coupon	4.60%	5.40%	6.30%
Years to Maturity	1.1	3.25	9.9
Actual NPV	100.30	99.00	99.70

Note that we are expressing value in terms of observable "net present value," which is the sum of "price" and "accrued interest." It is the total dollar amount that the bond buyer pays the bond seller. We ignore the arbitrary accounting division of this number into two pieces ("accrued interest" and "price") because they are not relevant to the smoothing calculation. We assume all three bonds pay interest on a semiannual basis. In doing the smoothing calculation in practice, we would use exact day counts that recognize that "semiannual" could mean 179 or 183 days or some other number. For purposes of this example, we assume that the two halves of the year have equal length.

Note also that the yield to maturity on these bonds is irrelevant to the smoothing process. The historical "yield to maturity" calculation embeds a number of inconsistent assumptions about forward rates among the three bonds and other observable data, as we discussed earlier in this chapter. To use "yield to maturity" as an input to the smoothing process is a classic case of "garbage in/garbage out."

Valuation Using Maximum Smoothness Forward Rates from Chapter 5

The first question we ask ourselves is this: how far off the observable net present values is the net present value we could calculate using Example H Qf1a (where we constrained the forward rate curve to be flat at the 10 year point) in Chapter 5?

To make this present value calculation, we use the coefficients for the 5 forward rate curve segments from Chapter 5. Recall that we have 5 forward rate curve segments that are quartic functions of years to maturity:

$$f_i(t) = c_i + d_{i1}t + d_{i2}t^2 + d_{i3}t^3 + d_{i4}t^4$$

The coefficients that we derived for the base case in Example H were these coefficients:

Figure 2

Coefficient Vector		Values
c1		0.04
d11		0.074458207
d12		2.29303E-16
d13		-0.63327238
d14		0.853048721
c2		0.036335741
d21	=	0.133086359
d22		-0.35176891
d23		0.304778043
d24		-0.0850017
c3		0.127299577
d31		-0.23076899
d32		0.194014109
d33		-0.0590773
d34		0.005962133
c4		-0.51565953
d41		0.626509818
d42		-0.23462529
d43		0.036175898
d44		-0.00197563
c5		0.879043488
d51		-0.48925259
d52		0.10010343
d53		-0.0084546
d54		0.000255891

We can then use these coefficients in this equation to derive the relevant zero coupon bond yield for each payment date on our three bonds. The yield function in any yield curve segment j is

$$y_j(t) = \frac{1}{t}\left[y^*(t_j)t_j + c_j(t-t_j) + \frac{1}{2}d_{j1}(t^2-t_j^2) + \frac{1}{3}d_{j2}(t^3-t_j^3) + \frac{1}{4}d_{j3}(t^4-t_j^4) + \frac{1}{5}d_{j4}(t^5-t_j^5) \right]$$

We note that y* denotes the observable value of y at the left hand side of the line segment where the maturity is t_j. Within the segment, y is a quintic function of t, divided by t. Using this formula, we lay out the cash flow timing and amounts for each of the bonds, identify which segment is relevant, calculate the zero coupon yield and the relevant discount factor using the formulas from Part 10 of our blog:

Figure 3

			Using Example H Qf1a		
Bond Number	Years to Payment	Cash Flow	Yield Curve Segment Number	Zero Yield	Discount Factor
1	0.1	2.3	1	4.358165	0.995651
1	0.6	2.3	2	4.860950	0.971256
1	1.1	102.3	3	4.434453	0.952392
2	0.25	2.7	1	4.750000	0.988195
2	0.75	2.7	2	4.729628	0.965150
2	1.25	2.7	3	4.377519	0.946751
2	1.75	2.7	3	4.517091	0.923995
2	2.25	2.7	3	4.940777	0.894789
2	2.75	2.7	3	5.356126	0.863041
2	3.25	102.7	4	5.588093	0.833924
3	0.4	3.15	1	4.912689	0.980541
3	0.9	3.15	2	4.584244	0.959581
3	1.4	3.15	3	4.370700	0.940645
3	1.9	3.15	3	4.629099	0.915804
3	2.4	3.15	3	5.077060	0.885282
3	2.9	3.15	3	5.448956	0.853833
3	3.4	3.15	4	5.614631	0.826217
3	3.9	3.15	4	5.585261	0.804266
3	4.4	3.15	4	5.443462	0.787012
3	4.9	3.15	4	5.279120	0.772072
3	5.4	3.15	5	5.158666	0.756867
3	5.9	3.15	5	5.113988	0.739541
3	6.4	3.15	5	5.150395	0.719193
3	6.9	3.15	5	5.258530	0.695699
3	7.4	3.15	5	5.421918	0.669501
3	7.9	3.15	5	5.621647	0.641395
3	8.4	3.15	5	5.839378	0.612315
3	8.9	3.15	5	6.059341	0.583167
3	9.4	3.15	5	6.269693	0.554687
3	9.9	103.15	5	6.463464	0.527354

If we multiply each cash flow by the relevant discount factor, we can get the theoretical bond net present value from the coefficients derived in Example H of Chapter 5:

Figure 4

	Additional Inputs for Smoothing		
Bond Number	1	2	3
Bond Name	Bond 1	Bond 2	Bond 3
Coupon	4.60%	5.40%	6.30%
Years to Maturity	1.1	3.25	9.9
Actual NPV	100.3	99	99.7
Example H QF1a NPV	101.953547	100.715178	100.694080
Pricing Error	1.653547	1.715178	0.994080

The table shows that the zero coupon yields that we used in the smoothing process produced incorrect net present values. As we shall see below, the problem is not the maximum smoothness forward rate technique itself. It is the inputs to the smoothing process at the 1, 3, 5 and 10 year maturity in our input table:

Figure 5

Actual Input Data		
Maturity in Years	**Continuously Compounded Zero Coupon Yield**	**Zero Coupon Bond Price**
0.000	4.000%	1.000000
0.250	4.750%	0.988195
1.000	4.500%	0.955997
3.000	5.500%	0.847894
5.000	5.250%	0.769126
10.000	6.500%	0.522046

Given these inputs, our smoothing coefficients and NPVs follow directly as we have shown above and in Chapter 5. We now improve our valuations by changing the zero yields used as inputs to the process.

Iterating on Zero Coupon Yields to the Smoothing Process

We know that the 4% yield for a maturity of zero and the 4.75% yield for 0.25 year maturity are consistent with observable market data. That is clearly not true for the 1, 3, 5 and 10 year zero yields because (a) there are no observable zero coupon bond yields at those maturities and (b) bond prices in the market are trading at net present values that are inconsistent with the yields we have been using at those maturities so far. We now pose this question:

> *What values of zero coupon bond yields at maturities of 1, 3, 5, and 10 years will minimize the sum of squared pricing errors on our three observable bonds?*

We can answer this question using a powerful enterprise-wide risk management like Kamakura Risk Manager (see www.kamakuraco.com) or even by using common spreadsheet software's non-linear optimization ("solver") routines. Using the latter approach, we find that this set of inputs eliminates the bond pricing errors:

Figure 6

Actual Input Data		
Maturity in Years	Continuously Compounded Zero Coupon Yield	Zero Coupon Bond Price
0.000	4.000%	1.000000
0.250	4.750%	0.988195
1.000	5.912%	0.942591
3.000	6.138%	0.831815
5.000	6.078%	0.737946
10.000	6.384%	0.528157

The forward rate curve coefficients for maximum smoothness forward rate smoothing that are consistent with these inputs are given here:

Figure 7

Coefficient Vector		Values
c1		0.040000
d11		0.064352
d12		0.000000
d13		-0.182575
d14		0.216590
c2		0.039117
d21	=	0.078478
d22		-0.084757
d23		0.043444
d24		-0.009429
c3		0.047700
d31		0.044147
d32		-0.033261
d33		0.009113
d34		-0.000847
c4		0.126353
d41		-0.060723
d42		0.019174
d43		-0.002539
d44		0.000124
c5		0.052668
d51		-0.001776
d52		0.001490
d53		-0.000181
d54		0.000007

The table below confirms that the sum of the cash flows multiplied by the relevant discount factors from this revised set of coefficients produces bond net present values that exactly match those observable in the marketplace:

Figure 8

	Additional Inputs for Smoothing		
Bond Number	1	2	3
Bond Name	Bond 1	Bond 2	Bond 3
Coupon	4.60%	5.40%	6.30%
Years to Maturity	1.1	3.25	9.9
Actual NPV	100.30	99.00	99.70
Theoretical NPV	100.30	99.00	99.70
NPV Errors	0.00	0.00	0.00

This simple example shows that using bond prices as input to the smoothing process is only a small step forward from using zero coupon bond yields. It goes without saying that there is no need to use an arbitrary functional form, like the Nelson-Siegel approach, that is neither consistent with the observable bond prices nor optimum in terms of smoothness. It continues to mystify us why that technique is ever employed.

For the remainder of this chapter, we will use bond prices as inputs. What if the bonds are issued by a firm with credit risk? How should the analysis differ from the case when the issuer of the bonds is assumed to be risk free? We turn to that analysis in the next section.

Credit Spread Smoothing Using Yield Curve Smoothing Techniques

In this section, we show that it is incorrect, sometimes disastrously so, to apply smoothing to a yield curve for an issuer with credit risk, ignoring the risk free yield curve. We show alternative methods for smoothing the zero coupon credit spread curve, relative to the risk free rate, to achieve far superior results. Smoothing a curve for an issuer with credit risk without reference to the risk free curve is probably the biggest mistake one can make in yield curve smoothing and we show why below.

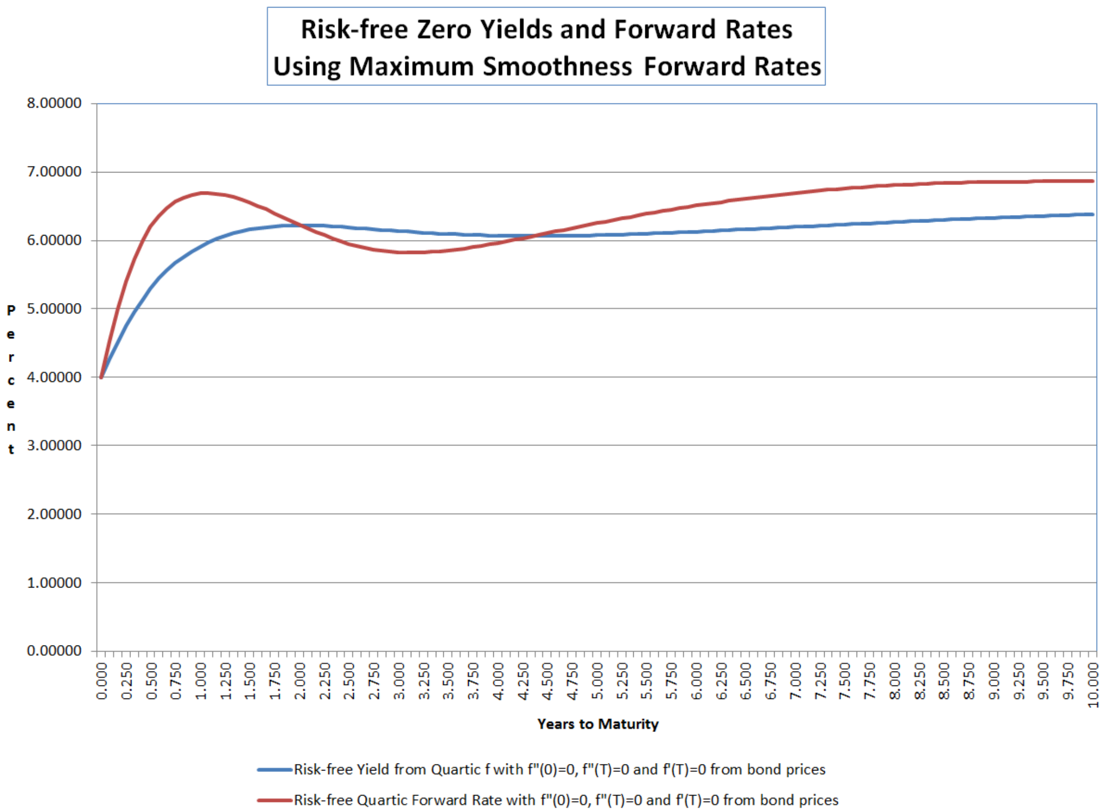
Setting the Scene: Smoothing Results for the Risk Free Curve

We start first by assuming that there is a risk-free bond issuer in the currency of interest. Prior to the 2007-2010 credit crisis, this assumption might have been taken for granted, but given current concerns about sovereign risk we make the assumption here that the government yield curve is truly free of credit risk. We use the data from the previous section for our risk-free curve.

We smoothed the risk free yield curve for two reasons: first, so we can derive pricing for other risk-free transactions than those with observable prices, and, second, so we can derive a high quality credit spread for ABC Company. The ABC yield curve will allow us to make a new financing proposal to ABC Company that is consistent with observable credit risky bonds of ABC Company.

The zero coupon bond yields and forward rates for the risk-free government bond curve derived in the previous section are graphed here:

Figure 9



We now use this information to derive the best possible credit spreads for ABC Company.

A Naive Approach: Smoothing ABC Yields by Ignoring the Risk Free Curve

We start by first taking a naive approach that is extremely common in the yield curve literature: we smooth the yield curve of ABC Company on the assumption that we don't need to know what the risk free curve is. This mistake is made daily with respect to the U.S. dollar interest rate swap curve by nearly every major financial institution in the world. They assume that the observable data points are so numerous that the results from this naive approach will be good, and then they blame the yield curve smoothing method when the results are obviously garbage. In truth, this is not one of Nassim Taleb's black swans—it's an error in finance made by the analyst, and the mistake is due to incorrect assumptions by the analyst rather than a flaw in the smoothing technique.

We show why in this example. We assume that these zero coupon bonds are outstanding issues of ABC Company with observable net present values:

Figure 10

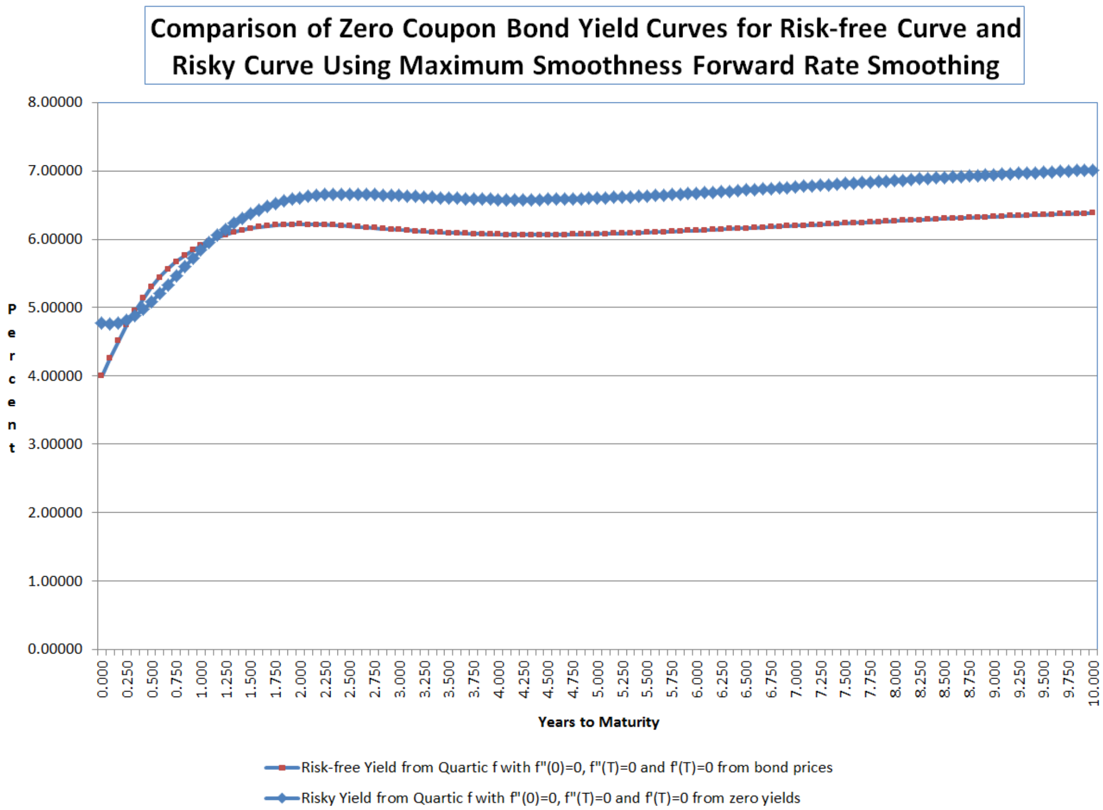
Input Data for Risky Yield Curve Creation				
Maturity in Years	Risk-free Zero Yield	Observable Credit Spread	Risky Zero Yield	Zero Coupon Bond Price
0.100	4.317628	0.450000	4.767628	0.995244
2.750	6.164844	0.490000	6.654844	0.832761
3.250	6.114068	0.500000	6.614068	0.806576
3.400	6.101630	0.510000	6.611630	0.798680
9.400	6.353080	0.620000	6.973080	0.519198
9.900	6.378781	0.630000	7.008781	0.499639

The risky zero yield is derived using continuous compounding from the (assumed) observable zero coupon bond price. Derivation is similar if the observable data were risky coupon bearing bonds of ABC Company. We know what the risk-free zero coupon yield is from the smoothing of the risk-free curve in the prior section and in Chapter 5. The observable credit spread is simply the difference between the observable ABC Company zero coupon yield and the risk free yield that we derived above on exactly the same maturity date, to the exact day. We now want to smooth the risky yield curve, naively assuming that the risk-free curve is irrelevant because we have six observable bonds and we think that's enough to avoid problems.

We make the additional assumption that the credit spread for a very short maturity is also 45 basis points, so the assumed "zero maturity" yield for ABC Company is the risk-free zero yield of 4.00% plus 0.45%, a total of 4.45%. We apply the maximum smoothness forward rate technique to these zero coupon bonds, exactly as in Chapter 5. If instead ABC bonds were coupon bearing, we would have used the approach for coupon bearing bonds like we did at the start of this chapter.

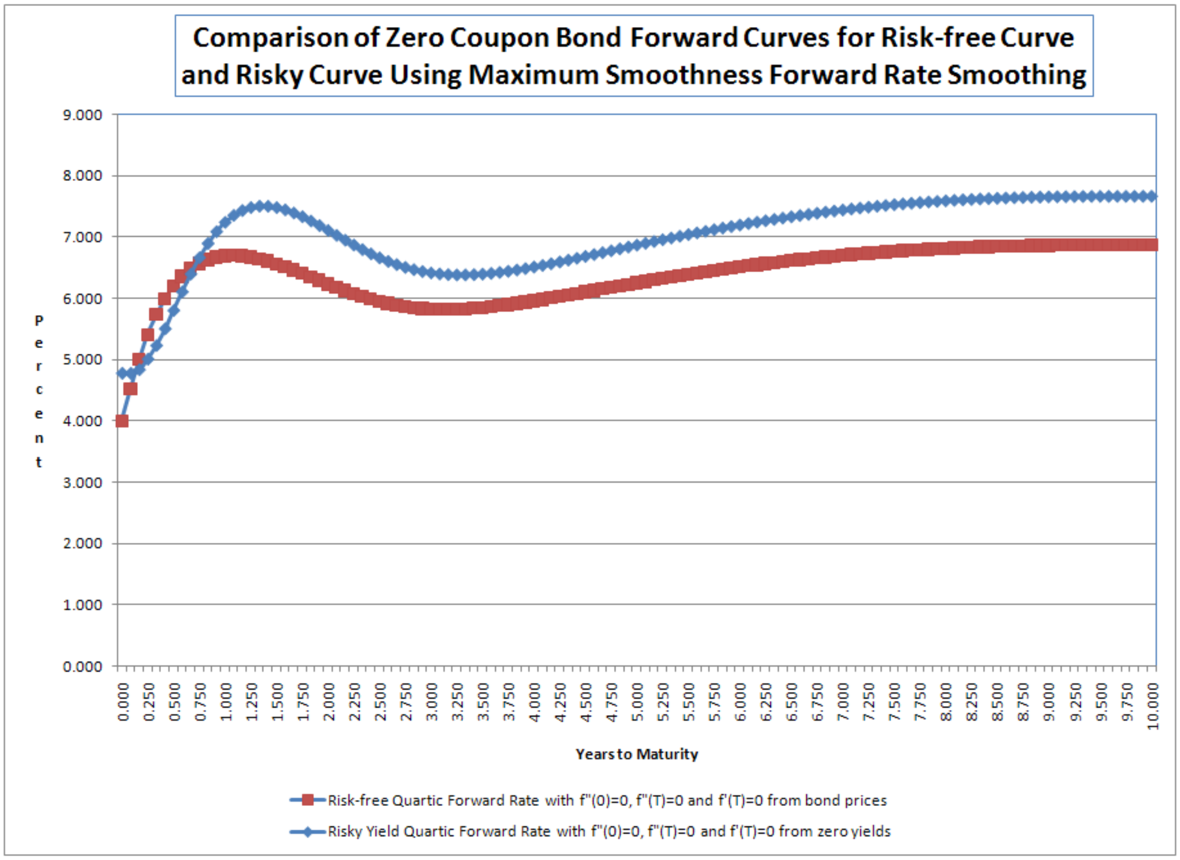
We compare the zero coupon yield curve that we derive for ABC Company with the zero coupon yield curve for the government in this graph:

Figure 11



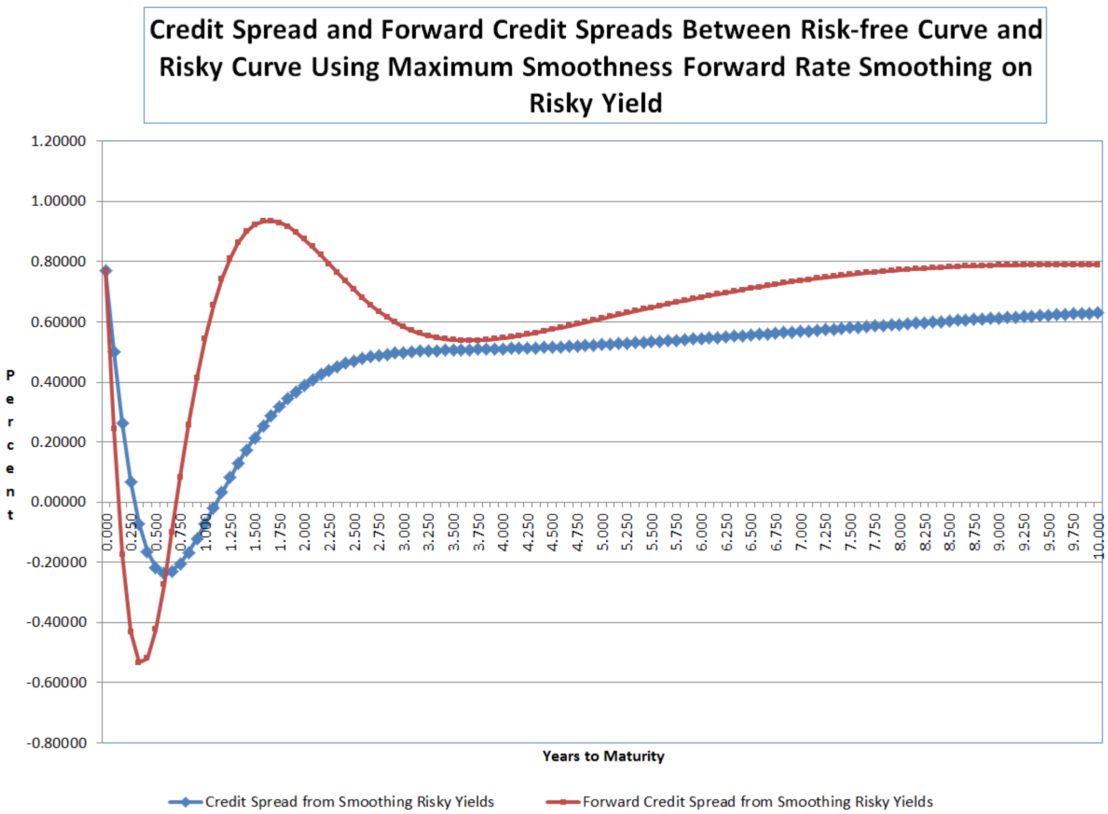
We can immediately see that we have a problem. ABC Company's fitted yield curve, which ignored the government curve, causes negative credit spreads on the short end of the yield curve, because the ABC yield curve is less than the risk-free zero coupon yield curve.

When we compare the forward rates from the two curves, we can see this problem more clearly:



Taking one more view, we plot the zero coupon credit spread (which is the difference between the ABC Company zero yields and government yields) and the credit spread forwards (the difference between the ABC Company forward rates and the government forward rates) in this graph:

Figure 13



The darker line is the zero coupon credit spread. It is volatile and goes negative in the maturity interval between 0.25 years and 1.25 years. The problem with the credit spread forwards makes these issues even more obvious. The forward credit spreads go negative by approximately 50 basis points. This means that any transactions for ABC Company in this interval will be grossly mispriced.

What does the analyst do now? Most analysts are like the football coach whose team loses because the coach had a bad game plan-the coach blames the quarterback. In this case, most analysts would blame the smoothing method, but in fact the problem is caused by the analyst's decision to ignore the risk free curve. We show how to fix that now.

Fitting Credit Spreads with Cubic Splines

A natural alternative to smoothing the yields of ABC Company is to smooth the zero coupon credit spreads. One should never commit the unimaginable sin of smoothing the differences between the yield to maturity on an ABC bond with N years to maturity and the simple yield to maturity on a government bond that also has something close to N years to maturity. The mistakes embedded in this simple calculation were outlined above. The fact that this mistake is made often doesn't make the magnitude of the error any smaller. We make two choices in this section. First, we again assume that the credit spread at a zero maturity for ABC Company is the same 45 basis point spread that we see on the shortest maturity bond. Second, we choose to use a cubic spline to solve for the ABC credit spread curve and we require that the observable credit spreads and actual credit spreads be equal.

Each credit spread curve segment will have a cubic polynomial that looks like this:

$$c(t) = a + b_1 t + b_2 t^2 + b_3 t^3$$

where t is the years to maturity of that instantaneous credit spread. In Chapter 5, we showed how to fit cubic splines to any data. In that chapter, it was zero coupon yields. In this section, we're fitting to zero coupon credit spreads.

We arbitrarily choose to use knot points of zero, 0.25 years, 1, 3, 5 and 10 years. These are the same knot points we used for risk-free curve smoothing. We could have just as easily used the observable yields and maturities in the chart above. In that case, all that credit spread smoothing does is to connect the observable credit spreads: 45 basis points at a zero maturity, 45 basis points at 0.1 years, 49 basis points at 2.75 years, and so on.

We use the risk-free curve knot points and iterate until we have an (almost perfect) match to observable credit spreads:

Figure 14

Risky Zero Yield	1	2	3	4	5	6
Maturity in Years	0.100	2.750	3.250	3.400	9.400	9.900
Actual Zero Spread	0.450%	0.490%	0.500%	0.510%	0.620%	0.630%
Theoretical Zero Spread	0.450%	0.489%	0.504%	0.506%	0.623%	0.628%
Yield Errors	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sum of Squared Yield Errors times 100,000,000						0.46

The match can be made perfect by changing parameters in the optimization routine. The zero coupon credit spreads that produce this result are as follows:

Figure 15

Actual Input Data		
Maturity in Years	Zero Coupon On the Run Spreads	Zero Coupon Bond Price
0.000	0.450%	1.000000
0.250	0.449%	0.988195
1.000	0.428%	0.955997
3.000	0.499%	0.847894
5.000	0.498%	0.769126
10.000	0.628%	0.522046

The zero maturity is not shaded because it is not part of the iteration. We have assumed that the zero maturity credit spread is the same 45 basis points as the observable data for 0.1 years to maturity. Once we have the spline parameters as in Chapter 5, we can plot zero coupon credit spreads and zero coupon forward credit spreads. The results are plotted later in this section.

We now turn to maximum smoothness forward credit spreads.

Maximum Smoothness Forward Credit Spreads

In this section, we apply the maximum smoothness forward rate approach of Chapter 5 to forward credit spreads, not forward rates. The forward credit spreads are simply the difference between the ABC Company forward rates and the government yield curve forward rates. When we recognize that relationship, the approach in Chapter 5 can be used with extremely minor modifications. We iterate on zero coupon credit spreads instead of zero coupon yields.

When we do that iteration, we get an almost perfect fit. A perfect fit just requires tweaking the tolerance in the iteration routine:

Figure 16

Risky Zero Yield	1	2	3	4	5	6
Maturity in Years	0.100	2.750	3.250	3.400	9.400	9.900
Actual Zero Spread	0.450%	0.490%	0.500%	0.510%	0.620%	0.630%
Theoretical Zero Spread	0.450%	0.489%	0.504%	0.507%	0.621%	0.629%
Yield Errors	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sum of Squared Yield Errors times 100,000,000						0.23

The zero coupon credit spreads which produce this happy result are given here:

Figure 17

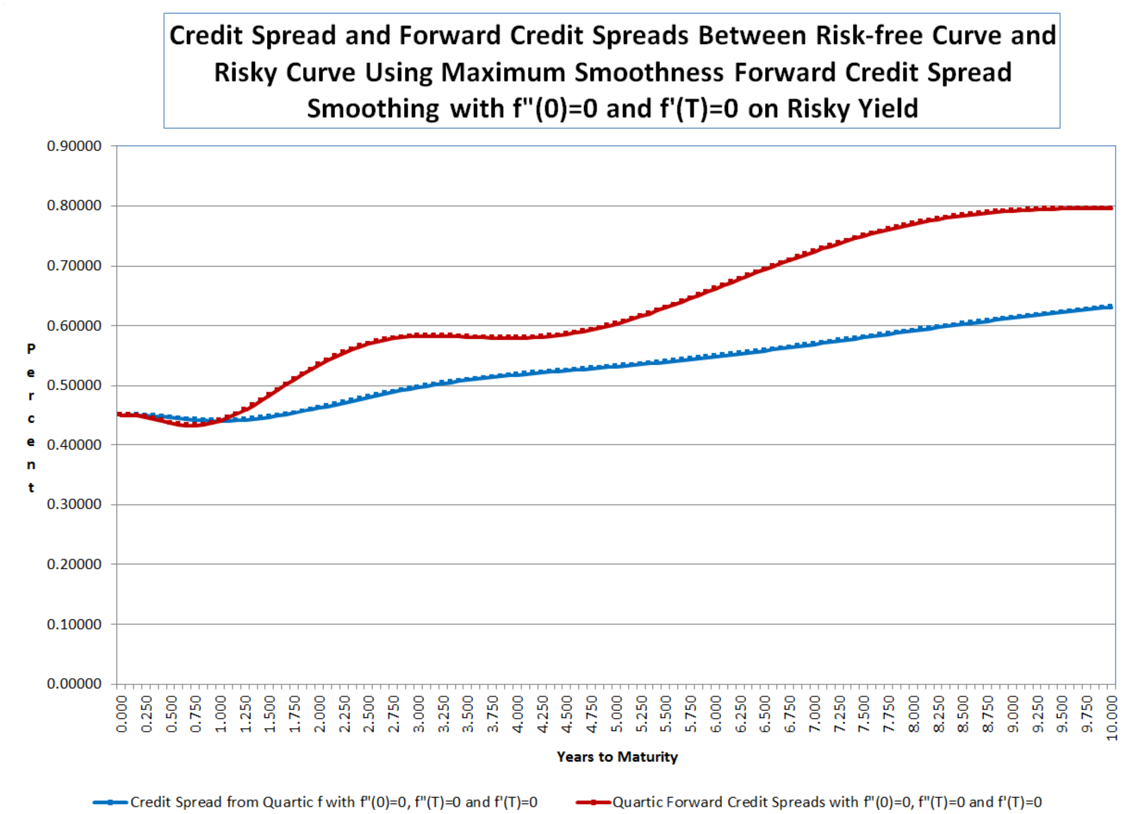
Actual Input Data for On the Run Risky Zero Yield Credit Spread Forwards with f"(0)=0

Maturity in Years	On the Run Zero Coupon Yield Spread	Zero Coupon Bond Price
0.000	0.450%	1.000000
0.250	0.449%	0.998878
1.000	0.440%	0.995609
3.000	0.497%	0.985202
5.000	0.532%	0.973752
10.000	0.631%	0.938840

Again, the zero maturity spread of 45 basis points is not part of the iteration as above.

We can plot the zero coupon credit spreads and forward credit spreads that result:

Figure 18

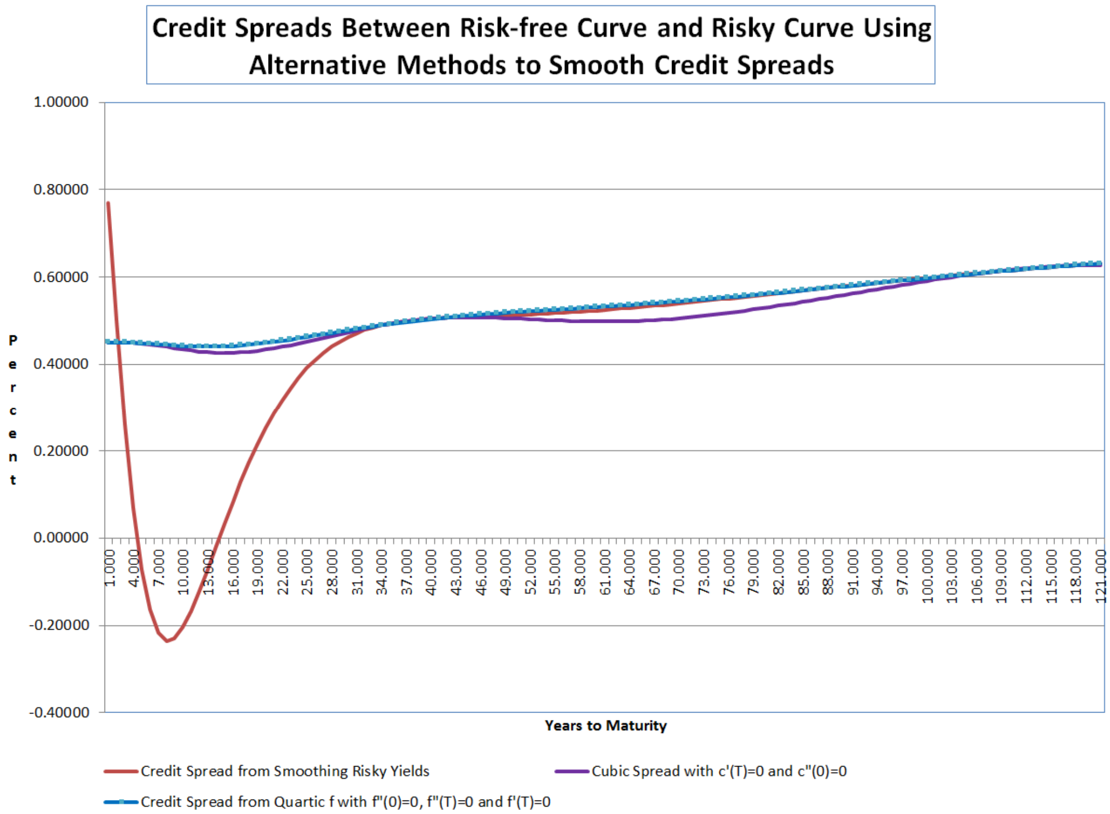


The resulting credit spread curve is very well-behaved and the forward credit spread is smooth with only modest variation. This confirms what we asserted in the naive example: there is no problem with maximum smoothness forward rate smoothing. The early negative credit spreads resulted from the analyst's error in ignoring risk free rates.

Comparing Results

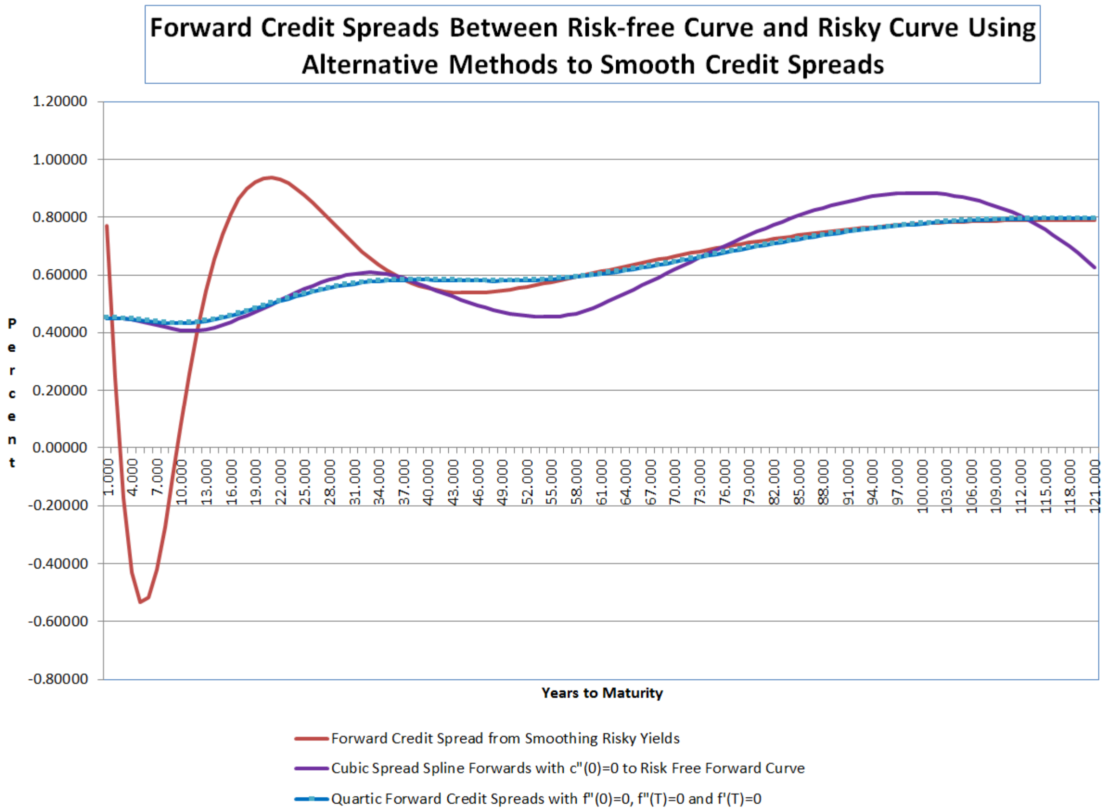
We can compare our three examples by looking first at the credit spreads from risky yield smoothing, cubic credit spread smoothing, and maximum smoothness forward credit spread smoothing:

Figure 19



Most analysts would assert that the maximum smoothness forward credit approach is superior because the resulting zero coupon credit spread curve is smoother. The same is true, by definition, for forward credit spreads:

Figure 20



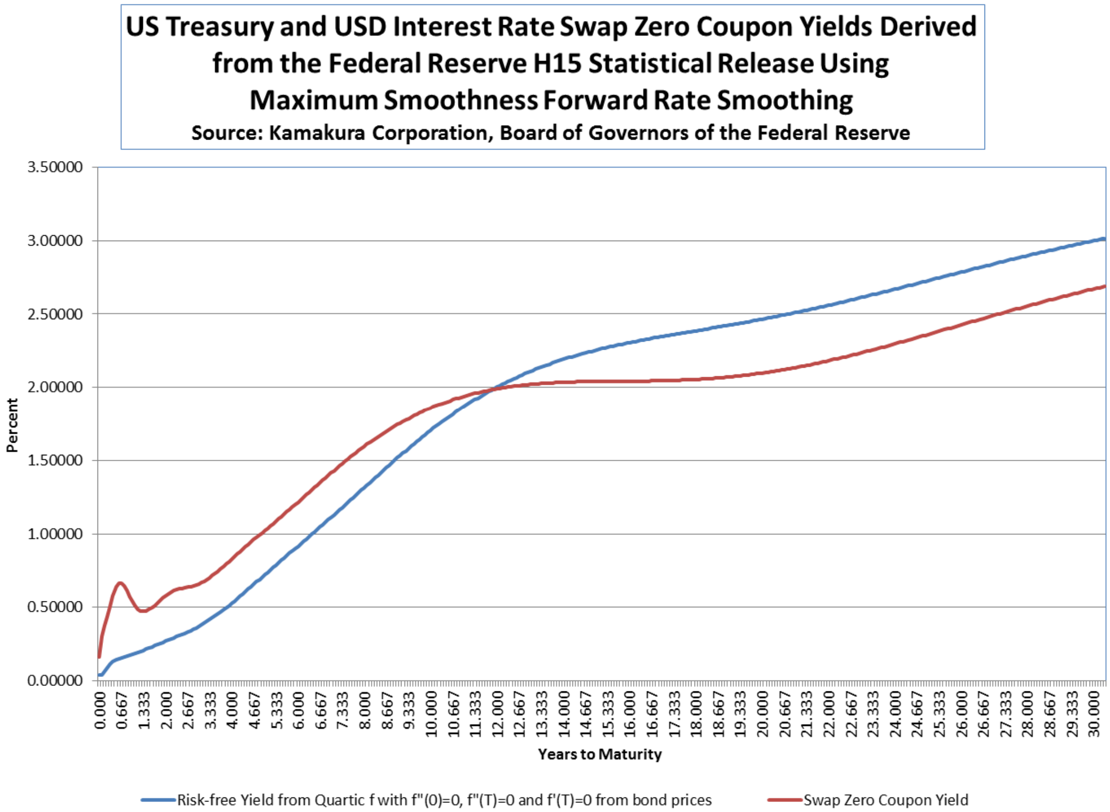
These results make it obvious that standard yield curve smoothing techniques can be applied to the zero coupon credit spread curve. The performance of alternative techniques is essentially identical to the performance of the same techniques applied to zero coupon yields themselves.

In the next two sections, we discuss how data problems can impact credit spread smoothing using any smoothing technique. We start with the case of the London Interbank Offered Rate (Libor) and interest rate swap curve.

Data Problems with Risky Issuers: The Case of Libor

There are two problems that immediately confront an analysis who is seeking a smooth credit spread curve between the U.S. Treasury curve and a combination curve composed of 1, 3 and 6 month Libor rates and the interest rate swap quotations for longer maturities. This graph plots the zero coupon bond yields that are produced when one applies the maximum smoothness forward rate technique to the U.S. Treasury curve and, as we have outlined above, the same technique to the credit spreads between the Libor-swap curve and the Treasury curve. There is a distinct "kink" in the Libor-swap zero coupon bond yields as shown clearly in this graph using data for June 7, 2012 reported by the Federal Reserve in its H15 statistical release:

Figure 21



Many analysts will blame this kink on the yield curve smoothing technique, but it is actually the result of a mistake by the analyst. The analyst has made a common but serious mistake by assuming that Eurodollar deposits and interest rate swaps are homogeneous and can be appropriately considered to be part of the "same curve." In fact, Eurodollar deposits are much more risky, with a potential loss to the depositor of 100% of principal. Interest rate swaps, by contrast, involve no exchange of principal at maturity and even a mark to market loss during the life of the swap is required to be collateralized. For this reason, the kink recognizes the "regime switch" from a high credit risk level on the short end of the curve to a lower credit risk regime on the long end of the curve. At 30 years, the interest rate swap yield is below (has a negative spread) the U.S. Treasury yield and has been for more than two years as this book is going to press. Again, this is a data issue and not a smoothing issue.

The second data issue with the Libor-swap curve is more serious and more disturbing: corruption and market manipulation. As of press time, three major lawsuits alleging manipulation of U.S. dollar Libor are pending in the U.S. courts and investigations are underway in Japan and Europe. Market participants have been fired and a leading bank is cooperating with the investigation. The authors have analyzed patterns of Libor indications compared to third party estimates of funding costs and default risk and believe that the allegations of Libor manipulation are likely to be proven true.

For this reason, using the Libor curve as a basis for risk management and using the Libor specific "Libor market model" is fraught with danger.

Data Problems with Risky Issuers: The Case of Single-Name Credit Default Swaps

Similar problems are rampant in the market for single name credit default swaps. The May 2012 sight of JPMorgan Chase, wallowing in a credit default swap position from which it cannot exit, raises many questions. One of the key questions is a particularly simple one: is the arena for credit default swap trading a market place or a mud pit? We sadly conclude that the answer is "mud pit" and outline some of the very many steps that are necessary for credit default swap arena to become a market place. Without these reforms, the CDS mud pit is likely to suffer the same fate as collateralized debt obligation-total irrelevance.

JPMorgan's May 8, 2012 announcement of $2 billion in losses turned the spotlight on the arena for credit default swaps, a security that doesn't hold up well under bright lights. We focus on single name credit default swaps, not the credit default swap index market in which JPMorgan has suffered its losses. The reason for our focus is also simple: the CDS index market is built on the foundation of the single name CDS market. If the single name CDS market is a mud pit, so is the index market.

What do we mean when we ask if the CDS market is a mud pit? We are in essence asking the following questions:

- Is there a transparent and open transmission of traded prices, bids and offereds in real time by reference name like there is for common stocks and options?
- Is there reliable reporting of trade volume in real time like there is for common stocks and options?
- Is there sufficient competition in the market to prevent market manipulation by a concentrated set of dealers, like there is for common stocks?
- If the market is highly concentrated, is there sufficient regulatory scrutiny to prevent rampant market manipulation?
- Is there sufficient regulatory scrutiny to prevent CDS trading on inside information?

Sadly, the answer to all of these questions is no. The unfortunate answer to another key question is "yes"--that question is "Has there been tacit cooperation among market participants and data vendors to preserve the status quo in the CDS mud pit?" We briefly deal with each of these questions in turn.

Is there a transparent and open transmission of traded prices, bids and offereds in real time by reference name like there is for common stocks and options?

In spite of changes in reporting by the Depository Trust & Clearing Corporation (www.dtcc.com) in recent years, the single name CDS bids, offereds, and traded prices are tightly controlled by a small cadre of dealers, market data vendors, and DTCC itself. The data is not freely available on a website like Yahoo or Google. While one broker who distributes CDS data does time stamp bids, offereds and trades in its data service, they are the exception, not the rule, and they see a relatively small market share of total activity. The primary product offered by the largest CDS data vendor does not distinguish between bids, offereds, and traded prices. Moreover, the data service typically lists CDS spreads for 2,000 corporates and sovereigns even though there have never been more than 1,000 reference names traded in a given week since DTCC began reporting trade volume (but not bids, offereds, or traded prices) since the week ended July 16, 2010.

Is there reliable reporting of trade volume in real time like there is for common stocks and options?

No. DTCC has this information, but it makes trade volume available on a weekly basis with a 3 business day lag, starting with the week ended July 16, 2010.

Is there sufficient competition in the market to prevent market manipulation by a concentrated set of dealers, like there is for common stocks?

No. In a recent blog, using the standard measures of market concentration by the Department of Justice and volume data from the Office of the Comptroller of the Currency, we showed that the market for credit default swaps has been "highly concentrated" since its inception. For the full text, see this link:

http://www.kamakuraco.com/Blog/tabid/231/EntryId/371/The-Credit-Default-Swap-Market-and-Anti-Trust-Considerations.aspx

The European Commission announced on April 29, 2011 that it was launching two anti-trust investigations into the CDS market:

http://europa.eu/rapid/pressReleasesAction.do?reference=IP/11/509&format=HTML&aged=0&language=EN&guiLanguage=en

If the market is highly concentrated, is there sufficient regulatory scrutiny to prevent rampant market manipulation?

No. In fact, a courageous journalist recently described how to manipulate the credit default swap market in this post from three years ago:

http://www.marketrap.com/article/view_article/91172/did-the-markit-group-a-black-box-company-partially-owned-by-goldman-sachs-and-jp-morgan-devastate-markets

Is there sufficient regulatory scrutiny to prevent CDS trading on inside information?

No. The SEC launched the first action alleging insider trading in 2009, but it was ultimately unsuccessful:

http://www.sec.gov/news/press/2009/2009-102.htm

The fact that insider trading is a serious problem was highlighted by this announcement from the UK's Financial Services Authority in 2011:

http://www.bloomberg.com/news/2011-03-25/fsa-said-to-review-credit-default-swaps-in-market-abuse-probe.html

That leads us to perhaps the most saddening question of those posed above:

Has there been tacit cooperation among market participants and data vendors to preserve the status quo in the CDS mud pit?

Yes. Perhaps the most egregious form of cooperation is the effort to preserve the impression that there is active trading in a large number of reference names when in fact there is not. For a review of trading volume reported by the DTCC, see the following links:

All Reference Names:

http://www.kamakuraco.com/Blog/tabid/231/EntryId/365/CDS-Trading-Volume-for-1-090-Reference-Names.aspx

U.S. Banks:

http://www.kamakuraco.com/Blog/tabid/231/EntryId/366/Credit-Default-Swaps-and-Deposit-Insurance.aspx

Sovereigns:

http://www.kamakuraco.com/Blog/tabid/231/EntryId/368/Sovereign-Credit-Default-Swap-Trading-Volume.aspx

Sub-Sovereigns and Municipals:

http://www.kamakuraco.com/Blog/tabid/231/EntryId/367/Municipal-Credit-Default-Swap-Trading-Volume.aspx

Breathless reporters or rating agencies claim "Dell's CDS widen 42%" when, in fact, there were only 9.6 gross trades per day and 1.75 non-dealer trades per day in Dell during the week ended May 25, 2012, according to DTCC:

http://finance.yahoo.com/news/fitch-solutions-dells-cds-widen-120600373.html

Reporters need a story, and the CDS mud pit provides material. Rating agencies need a product that is not a rating, and the CDS mud pit provides one. CDS data vendors couldn't sell CDS data if it were well known that (a) 81.68% of trades in the DTCC trade warehouse were trades between dealers or (b) more than 50% of the reference names for which data were reported by the vendor had NO trades in a given week, on average.

For these reasons, whenever one sees a credit default swap quotation, it should be regarded with an extremely high degree of suspicion. Credit default swaps do not have the depth of trading, transparency or integrity to provide a legitimate basis for credit spread smoothing.

Determinants of Credit Spread Levels

Let us accept as reality the risk that the publicly available credit default swap quotes have been manipulated. What factors have had an impact on the level of CDS spreads quoted? Jarrow, Li, Mesler, and van Deventer examine this issue in detail (see RISK Magazine, September, 2007).

Jarrow, Li, Mesler and van Deventer ("JLMV") argue that corporate credit spreads, as measured in the credit default swap market, depend not only on expected losses but also on market liquidity, institutional restrictions, and market frictions. The difference is a credit risk premium. This credit risk premium is justified theoretically using a simple economic model, and this credit risk premium is validated empirically using credit default swap spreads.

It is still common to hear traders argue that observable spreads in the credit default swap market are equal to the product of the default probability for the underlying credit times the loss given default. But, this simple trader's argument obviously ignores supply and demand considerations in the market for credit insurance. Indeed, if CDS spreads only reflect expected loss with no risk premium, then why would institutional investors be willing to be providers of credit insurance in the CDS market? The Jarrow model reviewed in Chapter 16 recognizes this phenomenon explicitly with its provision for a "liquidity premium."

Consistent with financial theory, and contrary to the simple trader's argument, researchers have consistently found that bond spreads and credit default swap quotations are higher than historical credit loss experience for those particular credits. These results are usually obtained by comparing credit spreads, derived by the smoothing techniques above, with either actual or projected default risk and recovery. Empirically, a credit risk premium appears to exist.

Nonetheless, the simple trader's argument is still common in the industry. Consequently, the purpose of this section is two-fold. First, to help dispel the trader's argument, we explain in simple terms and using standard economic theory why credit spreads should exceed expected losses (the default probability times loss given default). Second, given the existence of a credit risk premium, we then provide a statistical model for estimating credit spreads in the credit default swap market that uses other explanatory variables (in addition to default probabilities and losses given default) to capture credit risk premium. The statistical model performs quite well. The estimation is performed using a large database of credit default swap prices provided by the broker GFI. We accept the GFI data "as is" with no adjustments for possible data manipulation by market participants.

The Credit Risk Premium - the Supply and Demand for Credit

The degree of competition among lenders for a particular financial instrument varies dramatically with the attributes of the instrument and the attributes of the lenders. A hedge fund trader recently commented:

> ""Bond prices in the market place anticipate ratings changes with one exception. When a firm is downgraded to 'junk,' a very large number of institutions are compelled to sell immediately. This causes a step down in bond prices of large magnitude, unlike any other change in ratings."

This statement reflects market segmentation, generated by heterogeneity in lenders' risk aversion, trading restrictions, and private information. Implicitly this quotation says that the number of potential lenders to a "junk" credit is much less than the number of potential lenders to an investment grade credit, even if the default risk for these companies are the same. There is less demand for the financial liabilities of the junk credit, and spreads therefore must widen. In the limit, a small and risky business may have only one lender willing to lend it monies. In this case, the fact that the lender is a monopoly supplier (with their own risk aversion, private information, and institutional constraints) has at least as much impact on the level of the spread as does the default probability or loss given default of the borrower.

Consider an example. On the demand side, as a company's true one-year default probability increases, its need for funds increases. It needs more funds because, as the default probability rises, its revenues are declining and its expenses are increasing. Conversely, when the company has strong cash flows, it has very low default risk and it has little need for additional funds.

On the supply side, when the company is a strong credit, the potential supply of funds to the company is very large. More lenders are willing to participate in loans to the company. This is due to the heterogeneity of lenders' risk aversion, private information, institutional constraints, and transaction costs. Indeed, those lenders that are very risk averse, or who are not privy to private information concerning this company's cash flows, are willing to lend because the risk is low and private information is less relevant. Also, any institutional investment restrictions regarding junk lending will not be binding. As the company becomes more risky, the number of lenders drops, due to the desire to avoid risk by an increasing number of lenders and related concerns regarding private information about the borrower's prospects. Institutional constraints (as mentioned above) will also kick in at an appropriate level. The maximum potential supply of funds drops steadily until, in the limit, it reaches zero.

Equilibrium is NOT where the supply of funds *as a function of the one-year default probabilities* exactly equals the funding needs. This is because there are other considerations to an economic equilibrium in the credit risk market. For example, loss given default is a relevant and missing consideration in the determination of a borrower's risk, as are third party bankruptcy costs (e.g. legal fees) and transactions costs incurred in the market for borrowed funds. From the borrower's side, a financial strategy that retains the option to seek additional funds at a later date holds a real option of considerable value and this option provides a reason not to borrow the maximum at any moment in time. These missing considerations make the analysis more complex than this simple example indicates, but the downward sloping nature of the supply curve for lenders' funds will still hold. That is, as the credit risk of a borrower increases, the volume of available loans declines.

An individual lender, realizing the downward sloping nature of the aggregate supply curve, will decide on the volume of their lending based on their marginal costs and revenues. Marginal cost includes the expected loss component of the credit spread plus the marginal costs of servicing the credit. The expected loss component, equal to the default probability times loss given default, depends on the lender's private information regarding a borrower's default probabilities and potential loss given default.

Marginal revenue represents the lender's *risk adjusted* percentage revenue per additional dollar of loan. Due to risk aversion,[3] the risk adjusted marginal revenue curve will be downward sloping. To induce a risk averse lender to hold more of a particular loan in a portfolio, increasing idiosyncratic risk, the lender must be compensated via additional spread revenue. Alternatively, and independent of risk aversion, if the lender's loan volume is sufficient to affect the market spread (i.e. the lender is not a price taker), then the marginal revenue curve will be downward sloping based on this consideration alone. For either reason, as the loan volume increases, the percentage revenue per dollar of additional lending declines.

Standard economic reasoning then implies that the lender will extend loans until their risk adjusted marginal revenue equals their marginal cost. Ignoring for the moment market frictions (the difference between marginal costs and the expected loss), we see that, for the marginal dollar lent, the marginal

[3] It might be argued that lenders – banks – are risk neutral and not risk averse. However, it can be shown that risk neutral lenders, subject to either regulatory capital constraints and/or subject to deadweight losses in the event of their own default, will behave as if they are risk averse (see Jarrow and Purnanandam [2005]).

credit spread equals the expected loss (PD*LGD). Next, adjusting for market frictions, on the margin, the marginal credit spread equals (marginal costs + PD*LGD). But, the observed credit spread reflects the *average spread per dollar loan*, and not the marginal spread. Since the marginal revenue spread curve is downward sloping, the average revenue spread per dollar loan exceeds the marginal revenue spread curve. Thus, the observed credit spread per dollar loan is given by:

Credit spread = (average-marginal revenue spread + marginal costs + PD*LGD).

The first component is due to risk aversion and or market liquidities, i.e. the fact that the supply curve for loans is downward sloping. The second component is due to market frictions - the marginal costs of servicing loans. The third component is the expected loss itself.

This simple economic reasoning shows that a trader who argues that the CDS quote equals the default probability times the loss given default is really assuming an extreme market situation. The extreme market situation requires that the first and second components of the credit spread (as depicted above) are zero. The first component is zero only if the supply curve for loans is horizontal. That is, there is an infinite supply of funds at the marginal cost of credit – markets are perfectly liquid and there is no credit risk premium. And, the second component is zero only if there are no costs in servicing loans. These are unrealistic conditions, and their absence explains why the simple trader's argument is incorrect.

JLMV argue that there are two methods available to determine the drivers of credit risk spreads. The first method is to build an economic model, akin to that described above, and fit the model to observed credit risk spreads. The second is to fit a statistical model. A statistical model is often useful when building an (equilibrium) economic model is too complex. And, furthermore, a statistical model can be thought of as an approximation to the economic model.

As suggested by the discussion in the previous section, building a realistic equilibrium model for credit spreads with lender heterogeneity in risk aversion, private information, and institutional restrictions, is a complex task. Furthermore, such a construction is subject to subjective assumptions regarding lender preferences, endowments, institutional structures as well as the notion of an economic equilibrium. To avoid making these subjective assumptions, which limit the applicability of the model selected, and, in order to obtain a usable model for practice, JLMV elect to build a statistical model for credit risk spreads instead.

The JLMV statistical model uses various explanatory variables, selected to capture the relevant components of the credit spread, as discussed in the previous section. In particular, JLMV seek explanatory variables that will capture the credit risk premium, market liquidity, institutional constraints, and expected losses. Before discussing these explanatory variables, it is important to first discuss the functional form of the explanatory variables fit to the data.

Previous authors (see, for example, Campbell et al [2002], Collin-Dufresne et al [2000], Huang et al [2003], and Elton et al [2001]) fitting a statistical model to credit spreads typically use a linear function to link the credit spread to explanatory variables via ordinary least squares regression. Implicit in the linear regression structure, however, is the possibility that, when the model is used in a predictive fashion, the statistical model may predict negative credit spreads. Negative credit spreads, of course, are inconsistent with any reasonable economic equilibrium as long as the risk free curve is truly risk free.

If one were in Greece in 2012, for example, it would be a serious mistake to consider the credit curve for the Hellenic Republic to be a risk free curve.

The solution to this problem is simple. One only needs to fit a functional form that precludes negative credit spreads. Fitting a linear function to ln[credit spread(t)] is one such transformation. Another transformation is to use the logistic function,

$$credit\_spread(t) = \frac{1}{1+e^{-\alpha-\sum_{i=1}^{n}\beta_i X_i}}$$

where alpha and beta for *i = 1,…n* are constants and X_i for *i = 1,…n* are the relevant explanatory variables.

Unlike the natural logarithm, the logistic formula has the virtue that predicted CDS spreads always lie between 0 and 100%. And, similar to the use of the natural logarithm, one can estimate the alphas and betas in the logistic formula by using the transformation, (-ln[(1-credit spread[t])/credit spread[t]]) to fit a linear function in the explanatory variables via ordinary least squares regression. This linear function can be thought of as Altman's Z-score, for example. Alternatively, one can use a general linear model for the derivation. In this post, we use the logistic regression approach to model credit risk spreads.

The broker GFI supplied the CDS quotes used in the JLMV estimation. Their database included daily data from January 2, 2004 to November 3, 2005, which includes more than 500,000 credit default swap bid, offered, and traded price observations. This was a particularly benign period in U.S. economic history, a brief period of calm prior to the 2007 to 2010 credit crisis. Bid prices, offered prices and traded prices were all estimated separately. In the JLMV data base, there were 223,006 observations of bid prices, 203,695 observations of offered prices, and 19,822 observations of traded prices. Traded CDS prices were only 1/10th as numerous as the bid and offered quotations, consistent with the concerns about market manipulation discussed above. CDS quotes where an upfront fee was charged were excluded from the estimation because conversion of the upfront fee to a spread equivalent requires a joint hypothesis about the term structure and relationship of default probabilities and credit spreads, and that is what we are trying to derive in this post. The JLMV data set pre-dates the change in ISDA credit default swap convention which made up-front fees the standard, not the exception.

The explanatory variables that JLMV used to fit CDS prices include the credit rating, estimated default probabilities, and company specific attributes. Two types of estimated default probabilities were used: one from the Jarrow - Chava reduced form model that we discussed in Chapter 16, and the second from a Merton type structural model which we review in Chapter 18. All of these estimates were obtained from version 3.0 of the Kamakura Risk Information Services default probability service. The CDS maturities, agency ratings, and all of the individual macro-economic factors and company specific balance sheet ratios that are inputs to the Jarrow-Chava reduced form model were also included as inputs. These macro variables and company specific factors are listed below. These macro- and microvariables are intended to capture the credit risk premium, market liquidities, institutional constraints, and market frictions as previously discussed.

47 variables were found to be statistically significant in predicting CDS spreads. For bid prices, the explanatory variables included:

- 7 maturities of KRIS version 3.0 Jarrow - Chava default probabilities
- KRIS version 3.0 Merton default probabilities
- Dummy variables for each rating category
- A dummy variable indicating whether or not the company is a Japanese company
- 10 company specific financial and equity ratios (see Jarrow and Chava [2004] for a list of the relevant variables)
- Dummy variables for each CDS maturity
- Dummy variables for senior debt
- Dummy variables for the restructuring language of the CDS contract
- Selected macro-economic factors (see Jarrow, Li, Matz, Mesler, and van Deventer [2006] for details)

The best fitting JLMV relationship for each of the three series (bid, offered and traded) explained more than 80% of the variation in the transformed CDS quotations. The best fitting relationship also explains more than 90% of the variation in the raw CDS quotations (after reversing the log transformation explained above). The t-scores of the explanatory variables ranged from 2 to 236. The five-year maturity Jarrow - Chava default probability had the highest t-score among all the different maturity default probabilities included. The Japanese dummy variable was statistically significant with a t-score equivalent of 133 standard deviations, indicating that CDS spreads on Japanese names are much narrower than the otherwise equivalent non-Japanese name. Company size had a t-score equivalent of 100 standard deviations from zero, implying that CDS spreads are narrower for large companies, everything else constant. The JLMV statistical model fit CDS market prices quite well, validating the existence of credit risk premium in CDS prices.

JLMV found that Merton default probabilities explained 12-28% of the variation in the transformed CDS quotes. Ratings explained 36-42% of the transformed CDS quotes. The Kamakura Risk Information Services version 3.0 Jarrow - Chava default probabilities and all of their explanatory variables explained 56-61% of the transformed variables. The super hybrid approach, which includes all factors, explained 81-83% of the variation in the transformed CDS quotes.

Conclusions

Credit spreads are driven by the supply and demand for borrowed funds, and not just the default probability and loss given default. This is true for all borrowers from retail to corporate to sovereign. When fitting a statistical model to corporate sector CDS spreads, hazard rate default probabilities and their inputs dominate ratings, and ratings dominate Merton default probabilities, in their ability to explain movements in CDS quotes. A super hybrid approach provides the best over-all explanatory power for CDS quotes. In the next chapter, we compare this modern approach to credit risk assessment to legacy approaches that have been used over the last century.