Credit Derivatives Research
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Credit Volatility - A Primer

- **The distribution of credit spreads is complex and neither completely lognormal nor normal**
  The pattern depends on the absolute level of spreads

- **Calculating volatility relies on an assumption of this distribution**

- **Our estimate of historical percentage volatility of TRAC-X Europe is currently around 35%**
  Has been as high as 40%

Introduction

The aim of this technical note is to describe what we mean by volatility in the world of credit as an asset class. We also want to provide a platform for discussion of the issues surrounding trading credit volatility. We will base our analysis on the newly launched TRAC-X Europe index where possible. When we look at credit, we describe the volatility of the asset class as the standard deviation of credit spread changes, either expressed in per cent terms or in basis points. Trading volatility in credit is still at an early stage in comparison to other asset classes (such as equities and interest rates) - where the topic of trading volatility is a well-established one. Moreover, almost all academic literature on volatility refers to equity or interest rate markets. Importantly, some of the key assumptions underlying the models used for trading volatility in equities and interest rates do not hold in credit. The volatility of credit spreads is not easy to model. While we could make an attempt at modelling credit using models that are currently used in equities or interest rates, we think that this is a potentially flawed approach. In our view, volatility of credit spreads remains substantially different from both equity and interest rate volatility, although we will borrow many assumptions and models used in equities and interest rates as a starting point.

The Importance of Distribution

In order to understand credit (spread) volatility it is important to understand what is the distribution of the underlying asset class. Indeed, even to perform a simple volatility calculation we have to assume a certain process for how that particular market behaves. If the model of the market we are using is incorrect, than any conclusions derived from that model are also incorrect. When we refer to option models, we are basically considering how to model the underlying asset class through time. Step one of this process is the distribution of the credit spreads themselves. Hence, the key question

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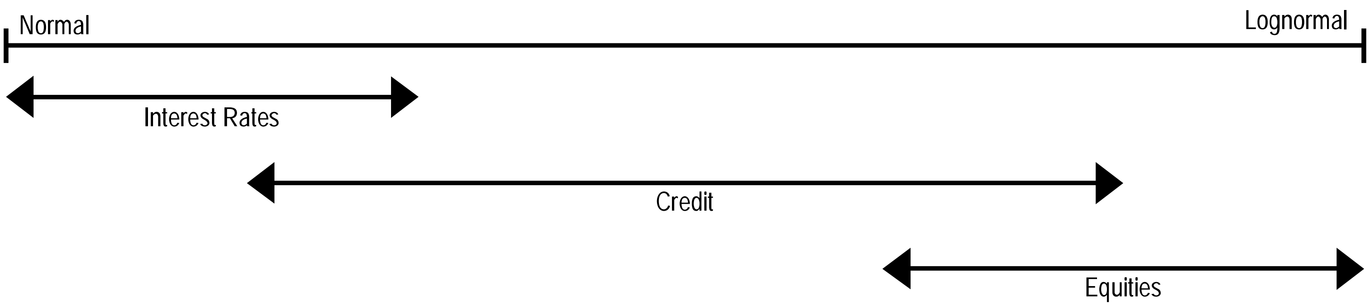
Figure 1: Distribution functions for volatility of different financial asset classes



Source: JPMorgan

becomes: "what distribution of the underlying credit spread time series do we need to use?" - we will see in credit, that the answer to this question may depend on the absolute level of spreads.

As there is no established standard practice in credit, we start by looking at the distribution models used for other financial asset classes. Specifically, we will see what happens when we impose different shapes for the distribution function of volatility for different financial asset classes. In Figure 1, we summarise some of our findings. Importantly for the purposes of this note, we think that the distribution function for credit volatility can be either normal or lognormal. Therefore, credit volatility sometimes appears to behave like interest rates and sometimes like equities. Indeed, at the one end of the spectrum interest rates exhibit a normal distribution function, while at the other end of the spectrum equities exhibit a lognormal distribution function.

Lognormal distributions assume that a certain percentage change up or down is equally likely irrespective of the current level (i.e. an equity price is just as likely to move from 500 to 550 as from 100 to 110). Normal distributions assume that a certain absolute change up or down is equally likely whatever the current level (i.e. an interest rate is just as likely to move from 2% to 2.2% as 4% to 4.2%).

We start by looking at the distribution of volatility in interest rates. In Chart 1, we assume a lognormal distribution and we plot per cent daily yield changes versus per cent yields for Japanese yen 5-year spot mid rates. We see a distinct pattern, with higher levels of volatility at low rates - this suggests that contrary to the hypothesis, that this asset

Chart 1: Test for lognormal distribution of interest rates, JPY rate

Y-axis: % daily yield change;x-axis: yield in %

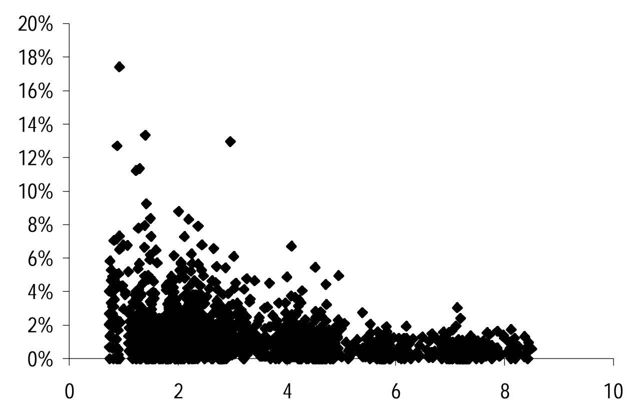


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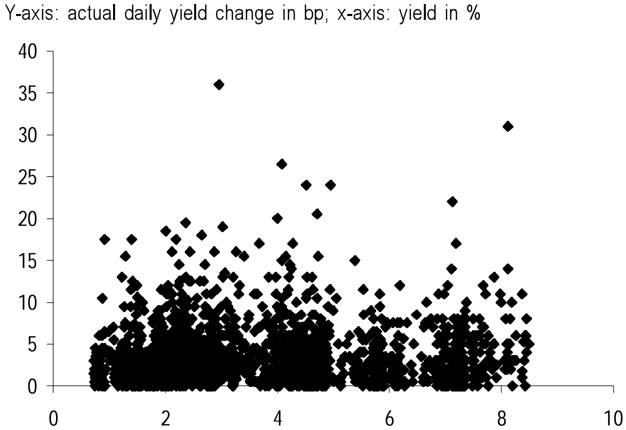
Chart 2: Normal distribution test for JPY rate

Y-axis: actual daily yield change in bp; x-axis: yield in %



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class is not lognormal. We would expect evenly distributed observations of volatility if it were (with a zero slope best fit line). In Chart 2, we assume that the same asset class has a normal distribution and plot the volatility expressed in terms of absolute changes in spread.

This time volatility is evenly distributed across the different yield levels, and we conclude that interest rates have a normal distribution function underlying their yield volatility. This conclusion is dependent on there not being a fundamental shift in the levels of volatility. This pattern holds particularly true for low rates, hence our use of Japanese yen. Similar results, if slightly less stringent, hold for the volatility distributions of €- and $-denominated interest rates.

In equities, market participants use lognormal distributions for daily returns (percent change in price). This is intuitively appropriate, as we know that market participants in interest rate markets tend to talk in terms of absolute changes ("rates have rallied by 20bp"), and in equities of percentage changes ("markets have rallied by 5%").

We think that the distribution model for credit spreads should behave like a combination of the models used for equities and interest rates. Whether we use a normal or lognormal distribution depends primarily on the level of credit spreads we consider. Using credit spreads, we show the scatter charts for credit volatility versus par spread levels (which we derived from the instantaneous rates of default) using a lognormal and a normal distribution in Charts 3 and 4, respectively. In the first chart we plot per cent volatility, while in the second one we plot actual volatility expressed in bp.

Modeling the distribution of credit spreads assuming only one of the two models used in equities and interest rates is not entirely satisfactory. The normal distribution model works well only for low spread levels. Indeed, Figure 5 shows that when credit spreads are relatively low, say up to 50 basis points, the normal distribution function has the best shape. This is to say that we can use a normal distribution function for high quality credit names, whose spreads are trading sufficiently close to Libor. As we move down the credit curve, spreads increase and tend to exhibit a lognormal distribution, as reflected in figure 4. Spreads in the 50-200bp range, behave more according to a lognormal than a normal distribution. When we look at spreads beyond 200bp, the relationship appears to break down, but we still see that a lognormal distribution is the better of the two possibilities.

This means that for names trading at tight spread levels we should look at actual volatility, known as BPV, or basis point volatility. This is similar to what happens in interest rates, where the underlying distribution model is near normal. For credit names trading at cheaper spread levels per cent volatility is preferable, as the underlying distribution is

Chart 3: Test for lognormal distribution in credit

Y-axis: actual % daily volatility; x-axis: par spreads in bp

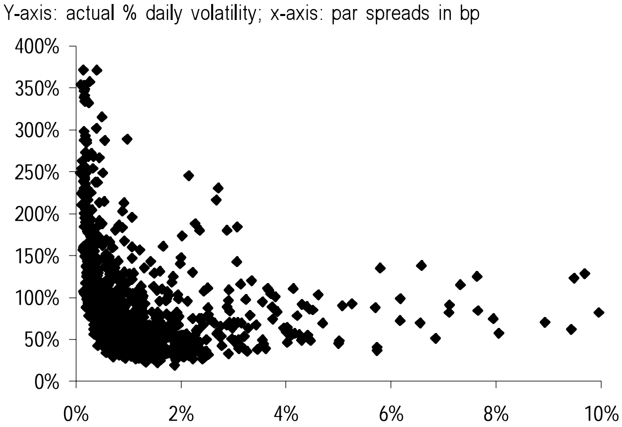

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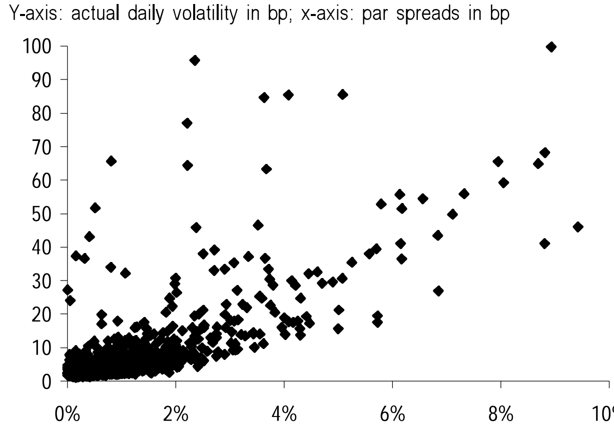
Chart 4: Test for normal distribution in credit

Y-axis: actual daily volatility in bp; x-axis: par spreads in bp



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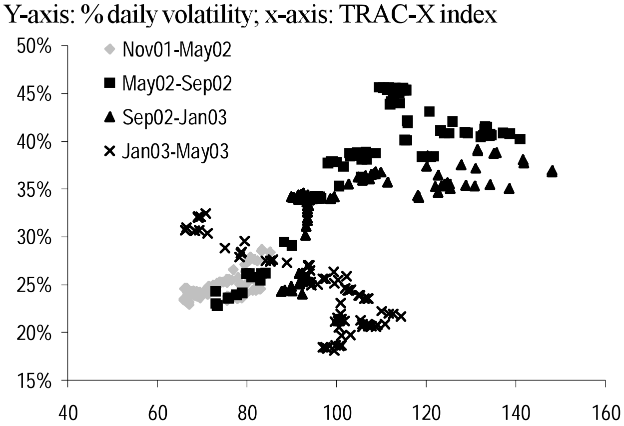
lognormal. This implies that the distribution of spreads for lower quality names behave more like equity prices than interest rates, and hence our volatility calculation will be more like an equity one.

In these analyses, however, we only look at all of the observations we have irrespective of the time frame. It is also useful to look at how these observations have changed through time. In Chart 5 we plot the three months per cent volatility for TRAC-X Europe versus TRAC-X Europe index level assuming a lognormal distribution function. This is similar to Charts 3 and 4, although we use TRAC-X rather than the whole credit market, where we have fewer observations. Also we group the observations through time - splitting them into four periods. As before flat levels indicate that the hypothesis of lognormality is true. The distribution is mostly 'lognormal' (a la equities), as volatility is constant for different index levels in each of the first three periods. However, since the beginning of the year, the rally in credit has caused the market to move much more akin to interest rates and the distribution of the index has become normal.

Therefore we think that the best way to look at volatility of credit spreads is to assume a lognormal distribution function. However, when spreads are sufficiently tight the appropriate distribution model is more likely to be normal. In particular, this means that when credit spreads rally substantially, credit volatility behaves like interest rate volatility. Alternatively, if you use a percentage volatility measure and spreads rally, then this will result in a technical increase in the reported measure, even if the market isn't actually any more volatile in an intuitive sense.

Chart 5: Distribution shape for TRAC-X index

Y-axis: % daily volatility; x-axis: TRAC-X index



Source: JPMorgan

TRAC-X Europe Volatility

Analysing the historical volatility of TRAC-X Europe presents several problems, mostly surrounding the fact that the product only started trading a matter of weeks ago. We will therefore need to look at some kind of substitute. Possible substitutes are JECI - the predecessor product to TRAC-X Europe, for which we have a 18 month history, or theoretical levels of spreads based on the underlying names in the single name CDS market. Both have limitations when considering how the volatility of TRAC-X Europe will develop.

When using JECI, which is indeed a real tradable product, we need to take into account several differences: JECI was not equally weighted, the names in JECI are different to those in TRAC-X Europe. However JECI has two major advantages in that we have history over rolls, so it reflects the mechanism in which the composition changes through time (to just use the current TRAC-X names going forward too far would mis-state the risks due to survivorship bias) and also it takes into account the fact that the product trades independently of the levels of the underlying CDS - this basis to theoretical is an important source of volatility in a tradable product.

The choice of rules and weights makes little difference to the volatility of the note. In Chart 6, we show the percent volatility of the average spread of the JECI 2 names compared with the TRAC-X average spread. Chart 7 shows the comparison of JECI 2 volatility using the actual weights and equally weighted, like TRAC-X. As can be seen in both cases the volatility hardly changes.

The difference between the theoretical spread and the level at which the market trades arises due to supply and demand. The historical level of this difference is given in Chart 3, along with the absolute level of spreads. It can be seen that this level has always been negative (because there have been net buyers of risk over this period), but that there is a pattern. When spreads widen, there seem to be more sellers of risk than buyers and hence this basis to theoretical

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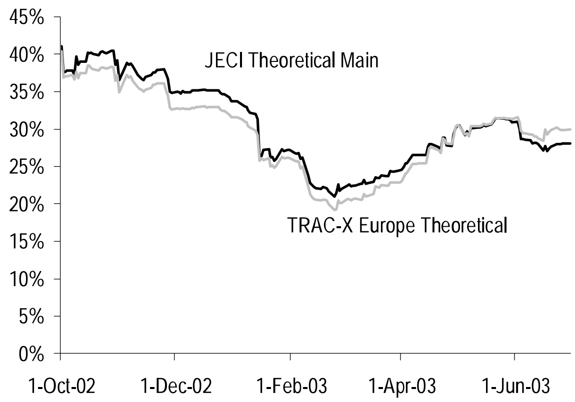
Chart 6: Percentage volatility of JECI 2 and TRAC-X Theoretical

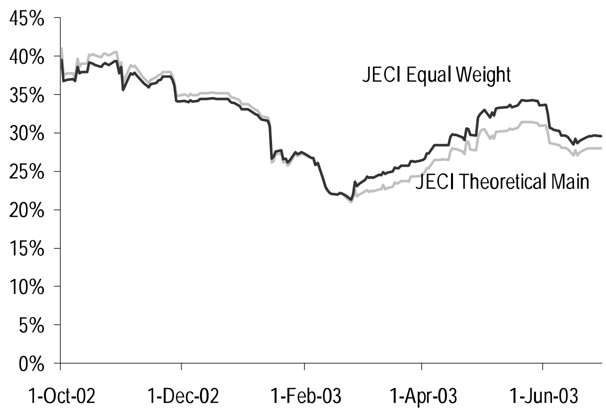
per cent



Source: JPMorgan

Chart 7: Percentage volatility of JECI 2 Equal weight against JECI 2 Theoretical

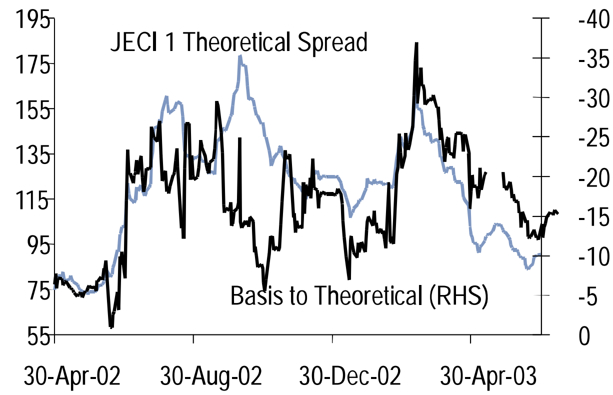
per cent



Source: JPMorgan

Chart 8: JECI 1 Theoretical spread of JECI 1 and the basis to theoretical (RHS Inverted)

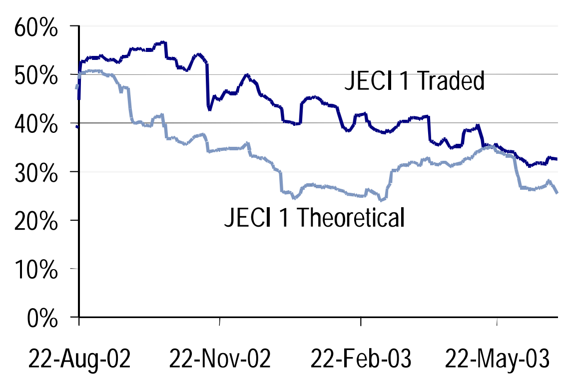
bp



Source: JPMorgan

Chart 9: Percentage volatility of JECI 1 Theoretical and JECI 1 Traded

per cent



Source: JPMorgan

increases in absolute magnitude. Intuitively this would therefore reduce the level of volatility, as it reduces the size of moves. However, as can be seen in Chart 9, the effect, when measuring the percentage volatility is to increase it - this is because the basis to theoretical always results in lower spreads. We would expect the magnetude of this difference between the traded and theoretical levels to reduce as more dealers join in to trade TRAC-X Europe, although it is unlikely to go away completely.

The first series of options to trade on TRAC-X Europe are all six month products and will not incorporate a roll. We therefore suggest using percentage volatility of the underlying names in TRAC-X Europe, but users should be aware that the historical volatility of the traded product is likely to be some 5% higher due to the way the instrument trades away from its theoretical level.

TRAC-X Europe options will initially be quoted as an upfront premium, however, market participants are likely to demand implied volatility levels. We would anticipate that users will start to look at, analyse and communicate in terms of implied volatility assuming percentage volatility. Whilst not perfect, especially for low levels of spreads, this method has the advantage of being simple, easily understood and there is a standard equation in closed form in simple text books.

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Trading Volatility

Our analysis so far has been on historical volatility. When market participants trade options they are taking a view on the future level of volatility that will be realised. They will of course use historical volatility as an input to their forecasts. Implied volatility can be considered the markets' consensus forecast of future volatility.

A good rule of thumb in other markets is that options tend to trade with an implied volatility somewhat higher than the historical levels - perhaps up to 5%. (The reasons for this are beyond the scope of this paper, but one suggestion is that the potential upside and downside from trading volatility are very different.) Moreover, market participants may well trade volatility higher than historic levels to account for the possibility of future jumps (in the case of Credit Events or blow-ups).

It is not sufficient merely to buy straddles to buy volatility - if the market goes straight up (with low volatility) such an investor will make profits. Similarly a highly volatile market which happens to return to starting levels would be a source of loss. It is more normal therefore to dynamically delta hedge - to keep market exposure to a minimum, so that all profits (or losses) come from volatility or the lack of it. Perfect delta hedging requires continuous, frictionless markets with no transaction costs. Such things do not even exist in liquid markets like equities and interest rates and even with the extra liquidity that TRAC-X has brought to credit markets, are likely some way off there. As such option traders will usually need to reduce the frequency of their hedging and take some directional risk.

The delta of an option is the first order derivative of underlying price, or the amount an option price is expected to move by for small movements in the underlying. This indicates the amount to trade to get delta neutral.

It is common to calculate delta, either using a formula (for equities using Black-Scholes) or by tweaking the input underlying level and observing the change in option price. Care should be taken with this approach in credit, as the volatility and the implicit distribution is an input. To get around the fact that the structure of volatility changes depending on the level of spreads, when calculating a delta by tweaking inputs, it will be necessary to change the volatility as well as the underlying level.

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