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I. D. E. A.

THE "CLUMPING" OF BOND VOLATILITY

We have written previously (see *I.D.E.A. Letters* dated 10/14/93, 12/28/93, 3/28/94, 4/5/94) on the flaws in using traditional methods, such as standard deviations, to measure volatility in the financial markets. The standard deviation is not robust to outliers, and a single large swing in the market can continue to show high volatility in a moving standard deviation for the entire length of the sampling period chosen to calculate the standard deviation. This causes a tendency amongst market participants to see volatility long after it has gone (i.e., to believe that volatility is trending when it is not), and calls for the development of non-traditional, preferably outlier-resilient, methods of gauging the true volatility of the market.

One non-traditional method we have developed for the identification of "true" upticks in volatility can be referred to as a "Binomial Clumping Test." The test is based on two very reasonable assumptions: first, there can be no meaning to the idea of a pickup in market volatility unless this volatility manifests itself by way of large swings in market prices. In other words, if volatility occurs it should be identifiable. Second, if we identify historically large swings from a data set of price movements, we should be able to test whether these large swings "clump together" to a degree greater than what randomness might otherwise cause. The conclusion? Large swings identify volatility, and the clumping of large swings signals trending volatility.

Our Binomial Clumping Test proceeds as follows: given a sufficiently lengthy time series of price movements for a particular instrument, a certain percentage of the data, say 10%, is identified as being "large swings." This 10% could be split into the 5% largest declines and the 5% largest increases, or the 10% largest increases, or whatever concept the user feels justifiably could be called the identification of the most volatile moves. A period of time is then chosen, such as 5 trading days (assuming it is daily data to begin with), in which the analyst investigates the frequency with which large swings follow other large swings. For example, if a 5-day examination period is chosen, then upon each occurrence of a large swing in the data set, the computer is asked to identify, in the 5-day period following the identification of a large swing, how many 5-day periods contain 1 more large swing, 2 more large swings, etc., on up to 5 more large swings (of course those periods which show zero additional large swings also must be counted). If we were to perform this type of frequency count on randomly generated data, we would find that the frequency distribution of 0-5 additional large swings would follow the classic binomial distribution. Any deviation from the frequency counts predicted from a binomial distribution is evidence of non-randomness, and can be used to identify whether volatility has a tendency to trend.

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We performed our Binomial Clumping Test on 10 years of daily settlement prices for the Treasury Bond Futures Contract traded on LIFFE. We chose the parameters suggested above, namely that the 10% largest swings defined the most volatile trading days, and that the 5-day trading period following a large swing was the most important period to examine to see if volatility trends, or clumps. Our results are presented in the accompanying table.

As can be seen in the upper half of the table, using the entire 10-year period of daily data, there is a distinctive clumping pattern in the distribution of large swings. There are far too few occurrences of 0 or 1 additional large swings in the 5-day period after the identification of a first large swing, and there are far too many occurrences of 2-5 additional large swings in the 5-day period after the first large swing. While more sophisticated tests of the goodness of fit, such as a Chi-squared test, confirm it, it is clear from simple inspection that the Bond Contract data do not show a random pattern of dispersal in large daily swings, at least over long periods of time.

Interestingly, it does not appear that these results are matched when the data is broken up into sub-periods. We broke the 10-year data set down into 4 equal-length sub-periods, and re-calculated the Binomial Clumping Test for each sub-period. It is crucial to note that in each sub-period, the identification of the 10% largest swings is based on the 10% largest swings for that sub-period alone, and is not simply that sub-period's share of the 10% largest swings for the overall data set. Calculating the test in this manner will allow us to see whether the sub-periods yield different results than the overall period. Indeed they do. Most of the sub-periods do not show patterns of large-swing dispersal that differ significantly from what the binomial distribution would predict. Only the second sub-period, which includes the bond market's reaction to the Crash of 87, shows statistically significant differences from random dispersal, while the first sub-period is modestly significant but still inconclusive. Additionally, to the extent that the actuals do differ from the predicted levels in the four sub-periods, the pattern is not consistent - while the first, second, and fourth sub-periods all show slight deviations from randomness that would be consistent with the patterns found in the overall 10-year analysis (too few 0-1 large swings, too many 2-5 large swings), the third sub-period revealed just the opposite.

TRADING RECOMMENDATION: Given the need for large samples of data, the Binomial Clumping Test is never going to be used to identify individual volatility trading opportunities. However, the results can be used to bias the decision to make a volatility trade. The generalization that can be taken from the results seen in the table is this: While the volatile days do not tend to clump if the cutoff is set too low, they do tend to clump when the cutoff is set higher. That is to say, over shorter periods of time, the definition of a large swing is lowered by the fact that the shorter the period the lower the cutoff for defining a large swing. Thus, a sub-period's large swing is not as unusual in a historical context, and traders are not disturbed enough by it to start a snowballing effect. When the cutoff for defining a large swing is higher, such as when a very long period of time is used to identify outliers, the occurrence of a large swing is a more momentous event, and does trigger a snowball effect of other unusually large swings. Thus we would recommend that a trader considering a volatility trade be aware of the 5-year or 10-year cutoff values for the 10% largest swings, and should expect a greater probability of further large swings in the following trading week. This would imply unwinding a short volatility trade to cut losses as soon as a long-term cutoff value is reached, or entering into a long volatility trade with a 3-5 day trading horizon when a long-term cutoff value has been broken.

Binomial Clumping Test Results
U.S. Treasury Bond Futures Contract, 1984-93

Full Period Results

	Actual	Expected
0 Additional Large Swings	102	133
1 Additional Large Swing	68	74
2 Additional Large Swings	27	17
3 Additional Large Swings	22	2
4 Additional Large Swings	6	0
5 Additional Large Swings	1	0
Total Large Swings	226	226
Chi-Squared Statistic	79.7647	
Prob(Non-Randomness)	100.00%	

Sub-Period Results

	Expected	First Sub-Period Actual	Second Sub-Period Actual	Third Sub-Period Actual	Fourth Sub-Period Actual	Total Sub-Periods Expected	Total Sub-Periods Actual
0 Additional Large Swings	33	30	23	36	32	132	121
1 Additional Large Swing	18	17	17	15	17	74	66
2 Additional Large Swings	4	8	10	5	6	16	29
3 Additional Large Swings	1	1	5	0	1	2	7
4 Additional Large Swings	0	0	1	0	0	0	1
5 Additional Large Swings	0	0	0	0	0	0	0
Total Large Swings	56	56	56	56	56	224	224
Chi-Squared Statistic		3.5283	27.2859	0.7727	0.8859		21.8371
Prob(Non-Randomness)		82.87%	100.00%	32.05%	35.78%		100.00%

Sub-Periods Defined as:

First:	06/22/84	to	09/15/86
Second:	09/16/86	to	12/06/88
Third:	12/07/88	to	03/04/91
Fourth:	03/05/91	to	05/28/93