New High-Probability Indicators Combining Statistics with Technical Analysis

By CYNTHIA KASE

uring the past 15 years, great progress has been made in the field of financial engineering, supported by similar advancements in personal computer technology.

Physical scientists and engineers, as well as mathematicians, have begun to penetrate the trading community. These professionals have brought with them a high level of understanding of mathematics, statistics, and physics which can, and are, being applied to the market.

Despite these advancements, most market professionals are still using technical analysis techniques that often date back to the early part of the century, or, at best, were designed using hand-held calculators. While the Stochastic indicator, moving averages, the moving average-convergence-divergence indicator (MACD), and relative strength index (RSI), all developed between 1957 and 1978, have been of value, they have been based on simplistic mathematics. This was necessary back in the days when the hand-held programmable calculator was stateof-the-art.

For many years, technical analysis was frozen in its late 1970s state because the first charting packages developed for the PC in the early 1980s were programmed with complicated, cumbersome code languages which were difficult, if not impossible, to modify. From a com-

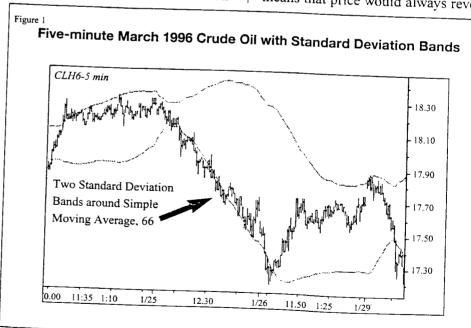
mercial standpoint, creators of charting software had no incentive to program new indicators, especially those which were complex, unless they were in high demand. This led to a classic "chicken and the egg" situation where new techniques could not be popularized because they were not found on standard charting packages, while the vendors were only willing to consider programming highly popular techniques.

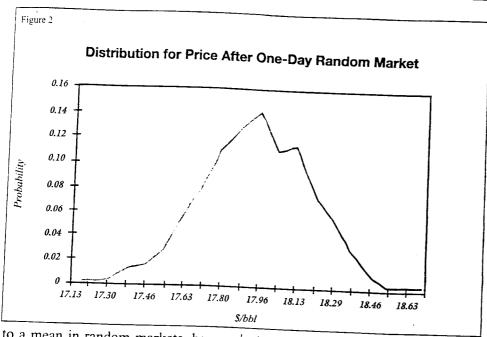
This began to change in the early 1990s with the introduction of expert language systems which allowed technical analysis software developers to devise new indicators which could then be imported directly into a charting package. In this article, we will examine three new indicators which are based on a subcategory of statistics called stochastic theory. We will look at the ran-

dom walk theory and see how a rigorous mathematical and statistical approach to the market based on this theory has led to the development of new, more accurate, and increasingly reliable indicators.

Going back to the term "sto-chastic," the well-known Stochastic indicator got its name by accident. When the developer of this indicator first presented it, he had written in the margin of his notes "a stochastic process" to remind himself to discuss the subject with a colleague. A reporter, who was covering the presentation, saw the note and named the indicator now known as the Stochastic.

In practice, stochastic theory involves the study of random motion in which all the variables are independent and more or less normally distributed. In market terms, this means that price would always revert





to a mean in random markets, hence the term "mean reverting market." It is interesting to note that first nearby contracts often do not appear to be mean reverting, but in many markets, such as energy, if one takes an average of all of the contracts traded every day, the resultant average price, called the "forward strip price," is both mean reverting and more or less normally distributed over the medium term, generally considered a four- or five-year period.

It stands to reason, then, that one way to tell whether a market is random is to determine whether it is reverting to a mean. This is the principle behind the use of standard deviation bands of price as a trading technique. In a normal bell curve, 95% of the data is held within plus and minus two standard deviations above and below the mean. When the market is in a trading range, exhibiting purely random motion, price is held within two standard deviations of the mean. In trending markets, the price continues to break above or below the two-standarddeviation mark, showing that the market is, at least in the short-term, exhibiting serial dependency or trending.

Look at a simple example of this

in Figure 1 (Five-minute March light, sweet crude oil) showing short-term crude oil price activity in a down trend. On moves against the trend, price tends to be contained within the two-standard-deviation band. On moves with the trend, the two standard deviation band is constantly broken in the direction of the trend. We can see specifically, on the morning of the 29th, a penetration of the upper band by a move which appears corrective against the trend, which then turns price behavior back in the direction of the trend.

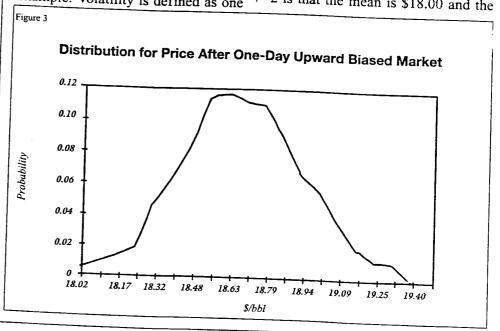
Let us take a more complex example. Volatility is defined as one

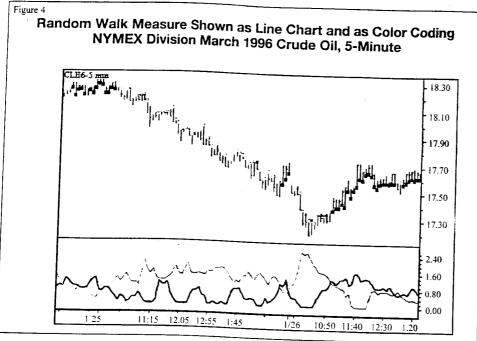
standard deviation of price change on an annualized basis. Thus, a simple volatility model assumes a bell curve or a log-normal curve with the current price as the mean and one standard deviation of price change equivalent to volatility.

In the shorter term, we can find the standard deviation for one day by dividing the annualized volatility by the square root of the number of trading days in the year (normally assumed to be 255). At 40% annualized volatility, daily volatility is roughly 2.5%. Taking this a step further, volatility of a five-minute period is roughly 0.3%.

The difference between a random and non-random market can be illustrated by evaluating the results of two Latin-Hypercube simulations. This is a model which chooses incremental price changes randomly from a data-set. While similar to the better-known Monte Carlo simulation, often used for scenario-testing, the Hypercube selects data in a more evenly distributed manner.

First, we will generate the expected price after one day, with the percentage price change over each five-minute period averaging zero, but with a standard deviation of 0.3%. The result shown in Figure 2 is that the mean is \$18.00 and the





standard deviation is 24¢. This means that prices between \$17.52 and \$18.48 would be considered within the probability for a purely random market.

The same simulation with an average rate of change of 0.2% to the upside, shown in Figure 3 shows an expectation of, after a day of trading, with a resultant mean of \$18.73, clearly outside of the random expectation two-standard deviation range.

The Random Walk Index

Studies of random motion have been recently popularized in trading applications by Mike Poulous and Alex Saitta in the form of the Random Walk Index (RWI), where:

RWI = actual price movement/ expected random walk

 $RW_{high} = \frac{high_o - low_n}{ATR \times \sqrt{n}}$

 $RW_{low} = \frac{high_n - low_o}{ATR \times \sqrt{n}}$

and ATR = average true range, and n = number of bars in the look back. This index measures the degree to which price behavior varies from a

random expectation.

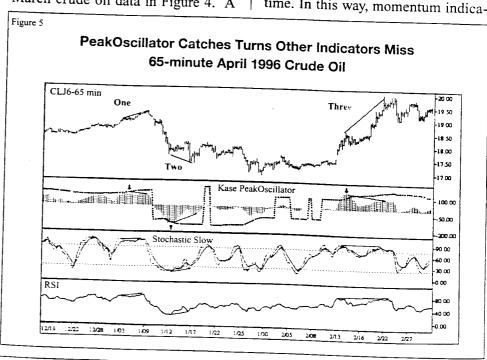
These measures of statistical deviation from purely random motion can be used in place of moving averages. The index is evaluated over a number of different look-back lengths, and the largest value chosen.

The RWI (modified somewhat from the Saitta and Poulous version to improve the math) is shown in the subgraph below the five-minute March crude oil data in Figure 4. A crossover of the RWI_{plus} shown in black over the RWI_{minus} in red is a buy signal and vice-versa. For simplicity, the bars are also color-coded. The bars with the red dot on the top are bearish with propensity to move down. Those with the blue at the bottom are bullish with the propensity to move up.

This technique is superior to the moving average crossovers in that the most significant value among many cycle lengths is chosen, an automatically self-optimizing function. The indicator is, as one would expect, subject to the drawbacks of any trending indicator system in that it tends to lag and whipsaw. Nevertheless, the technique is more highly accurate, less lagging, and causes fewer late whipsaws than a standard moving average crossover system. Whipsaws can also be eliminated to a great degree by combining the indicator with a filtering technique.

The PeakOscillator

Now, we apply stochastic theory to momentum by taking the first and second derivative of price relative to time. In this way, momentum indica-



ket velocity and market acceleration which are superior to those generally used in the market place such as the Stochastic and RSI momentum indicators or the MACD, which in a sense is an acceleration indicator.

Just as velocity is the rate of change of distance relative to time, momentum indicators generally measure the rate of change of price relative to time. Some of the earliest momentum indicators were oscillators. An oscillator is simply the difference between two moving averages.

The Kase PeakOscillator simply substitutes a statistical measure of a trend for the moving average, using longer look-back lengths than used for a trending or crossover system. This technique has a number of advantages over the traditional momentum indicators such as the Stochastic.

First, the Stochastic is normalized for local conditions (near-term price activity). Therefore, one cannot compare the value of a Stochastic in a highly volatile market with the value of a Stochastic in a quiet market. Similarly, one cannot compare a crude oil five-minute Stochastic with a natural gas 60-minute for example.

The PeakOscillator is normalized for range and thus, for volatility (range is proportional to volatility). So, we have a universal indicator that measures momentum on a level playing field, allowing us to compare momentum across markets and across time frames.

This has allowed us to determine the 90th percentile of momentum as measured by our PeakOscillator. We measured the absolute value of the oscillator over 80 years of commodity history and selected the 90th percentile. We then display the PeakOscillator along with a PeakOut line which is the higher of the 90th percentile over 80 years of commod-



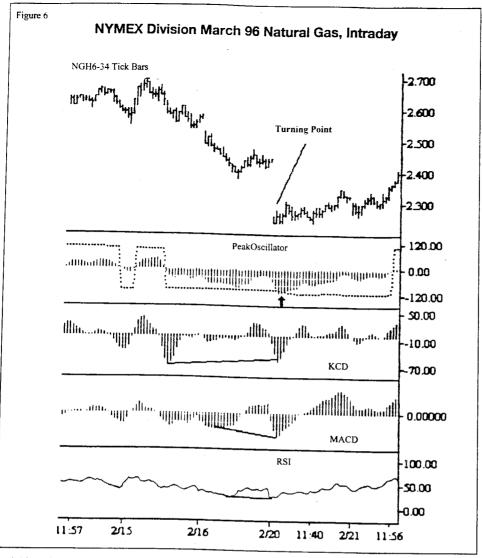
Advancements in personal computer technology supported and contributed to the progress in financial engineering.

ity history or the 98th percentile of local data. By definition, if momentum peaks through the PeakOut line and then pulls back, we have a situation where it is highly unlikely that momentum will continue in that direction.

A second advantage is simply a higher degree of reliability relative to momentum divergences. With traditional divergence, there is a difference in direction between price and momentum commonly referred to as "a higher high in price and a lower high momentum or a lower low in price and a higher low in momentum." The PeakOscillator not only generates divergence in cases where traditional indicators miss them, it also has another advantage: from time-to-time the market spikes

in such a way that a divergence signal is not possible. In order to have a divergence, we need two highs or two lows. In a spike-type formation, where there is only one high or one low, indicators such as the Stochastic or RSI fail to identify market turns. The PeakOscillator, generating a PeakOut signal, is not only warning that divergence may occur on a following high or low, but that the market could be turning on a spike-type turn.

Figure 5 (65-minute April crude oil) shows three instances in which the Kase PeakOscillator exhibited divergences following a PeakOut signal. In divergence 1, neither the RSI nor the Stochastic signaled a proper divergence — momentum sloped upward with the price —



while the PeakOscillator sloped downward, generating a reliable divergence.

In case two, all three indicators did exhibit a classic divergence signal, price sloping down and momentum sloping up. However, the PeakOscillator gave a preliminary warning that a divergence might be taking place with the PeakOut signal preceding the actual divergence. In case 3, a classic divergence is generated by the PeakOscillator following a PeakOut signal, the RSI is not divergent and the slow Stochastic is flat, exhibiting what is commonly called a class three divergence.

Thus, we can see two benefits of the PeakOscillator that we discussed earlier. That is, the advanced warning because of the PeakOut line and the higher level of reliability on divergences.

The Kase CD

As we mentioned earlier, the MACD is a second derivative or acceleration indicator. MACD is the difference between an exponential moving average oscillator and its own average:

MACD histogram = MAO_e , average (MAO_e, n)

where MAOe is an exponential moving average oscillator (usually the difference between a 12-period exponential moving average and a 26-period one) and n = the average of MAOe (usually defaulted to 9).

A new version of this indicator

that we developed, the KaseCD (KCD), simply substitutes the PeakOscillator for the moving average oscillator in the formula as follows.

KCD histogram = PeakOscillator - average (PeakOscillator, n)

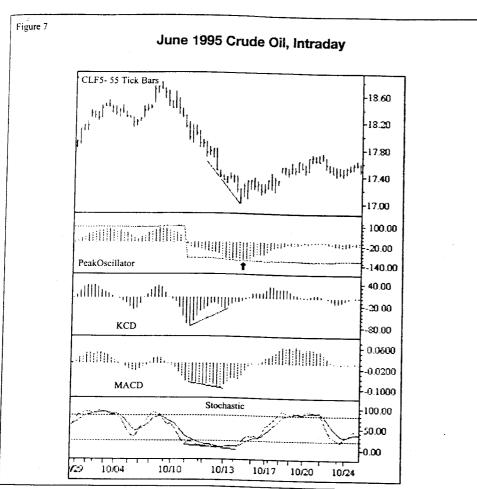
While the indicator is based on much more complex mathematics than the MACD, the display looks virtually identical. The major differences between the MACD and the KCD are that the KCD generates much more reliable divergence signals, misses false divergences that the MACD tends to trigger, and is much more stable around the zero line. The MACD, when it is close to zero, tends to generate formless. erratic histogram lines while the KCD generates more clear, rounded formations.

This provides superior results because the indices on which the indicator is based automatically search for the most significant trend length and adjusts to a cycle to provide a more in-depth evaluation of market behavior. This indicator is not only statistically sound, but also adaptive in the sense that it elects the most significant cycle length among a variety of look-back lengths for its trend parameter.

Figure 6 shows an intraday March natural gas chart. We see a market turn to the upside following what appears to be an exhaustion gap. The PeakOscillator generates a PeakOut signal confirmed by a divergence on the KCD. Neither the MACD nor RSI generate divergences, instead, they slope downward with price.

Next, Figures 7 and 8 show two instances where the PeakOut signal generated by the PeakOscillator was confirmed by the KCD. In the case of the short-term January 1995 crude oil chart, neither the MACD nor the Stochastic signaled a divergence.

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market technician who develops proprietary trading software and hedging models. She is author of the technical trading book Trading with the Odds, published by Irwin Professional Publishing. Ms. Kase began her career as a chemical engineer, traded physical oil for Chevron, and was the first commodity trader on Chemical Bank's derivatives desk. After consulting for the Saudi Oil Ministry, she launched her own firm in 1992.

The PeakOscillator and KCD described in this article were developed by Ms. Kase.

The Exchange takes no position on the effectiveness of the trading methods described in this article.

Thus, a trader using these instruments would have failed to recognize the imminence of a turn.

Finally, we see on the short-term August 1995 natural gas chart a minor level of divergence on the MACD but no divergence whatsoever on the RSI, again making it quite difficult for a trader to properly identify the market turn.

As success in world markets becomes increasingly dependent on technology, it is important for traders to keep pace in order to remain competitive. The algorithms displayed by charting systems are no exception. Toward this end, many new techniques, including those statistical methods presented in this article, have been developed.

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