Commodity Risks: Describing the Unobservable

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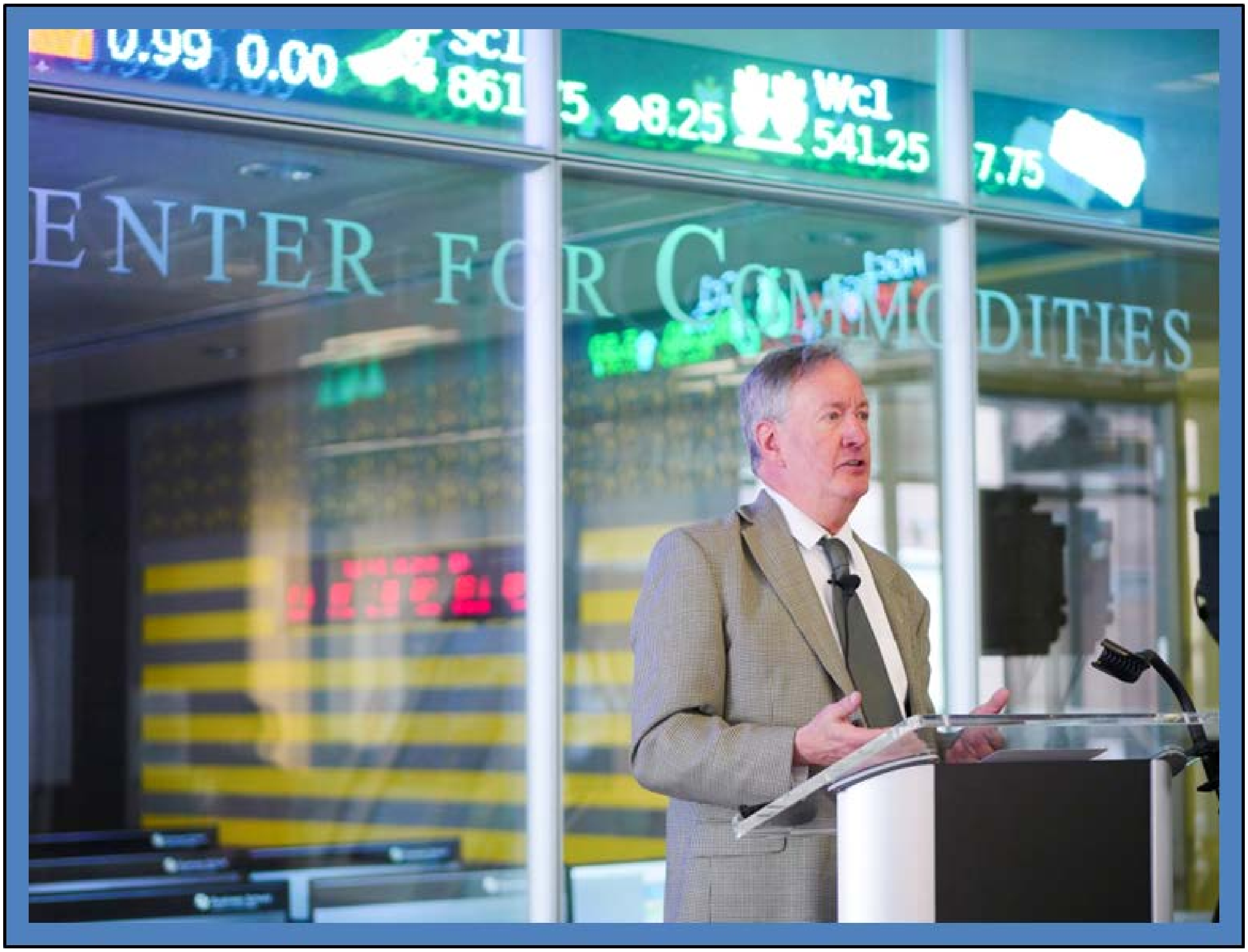


Dr. Bluford Putnam, Ph.D., Chief Economist, CME Group, and member of the J.P. Morgan Center for Commodities' (JPMCC's) Research Council, presented on "Expected Risk-Return Probability Distributions: Important Differences between Commodity and Financial Markets" at the JPMCC's 2nd International Commodities Symposium, which was held at the University of Colorado Denver Business School in August 2018.

We have observed in studying commodity markets that 100-year floods occur quite often, even multiple times a decade, so we know simple risk models can be inadequate and misleading. The challenge is that expected risk-return probability distributions cannot be directly observed. Some analysts lean heavily on examining the implied volatilities from options prices. Unfortunately, the implied volatilities all too often underestimate what is happening in the extremes of the distribution where the high impact risks are located.

Our view is that we should explore much more robust measures of risk. We need to appreciate that volatility is not the same as risk, and that the standard deviation is a very poor risk metric on which to rely so heavily. Our approach is to go beyond futures and options prices and include information from volumes and intra-day activity in our methodology to allow for multiple scenarios which avoid the bias toward the bell-shaped distributions that appear highly flawed relative to historical experience.

In this research, we first briefly make our case for why volatility is not the same as risk. We then tackle the question of why the implied volatilities derived from options prices can also be a dangerous and misleading risk metric. Then, we intuitively describe our approach and apply it to an example from the corn market to give readers a flavor of our research approach.

Volatility is Not Risk

Many analysts like volatility because the historical standard deviation is easy to calculate and fits nicely into basic risk systems and mean-variance portfolio models. The problem is that a trader, a commodity producer, or a commodity consuming commercial corporation may have asymmetrical risk preferences, preferring to avoid substantive losses rather than to make large gains. That is, if avoiding large losses is the primary risk, then a symmetrical standard-deviation based metric that only looks at the average noise level and not the extremes is certainly not appropriate. Your head is in the oven and your feet are in the freezer – on average one feels fine – and the standard deviation tells you that the risks are manageable when they may be quite dangerous for your long-term survival.

Moreover, volatility does not appropriately capture the nature of many risks when there are large uncertainties (Putnam *et al.*, 2019). We want to appreciate the behavioral patterns related to reacting to uncertainty. The science of fear often sees patterns of behavior that bear a strong resemblance to chaos theory (Gleick, 1987), and these observations may help explain the conundrum of why it is possible for elevated levels of uncertainty to co-exist with relatively low levels of market volatility.

Pretend you find yourself walking down a deserted road late at night, and you are more than a little concerned about your safety. You hear footsteps behind you. You keep on walking. The footsteps are getting closer. Your fear level is rising, and yet you keep on walking. As the footsteps get ever-nearer, perhaps you hear a sound or some catalyst, your fear reaches a point where you face a decision to turn and confront the challenge (if there is one) or run away. Once you choose, there will be no going back.

These are among the types of decisions analyzed by chaos theory. Rising fears, or uncertainties, do not trigger a change in behavior. A reaction to the rising fears takes a catalyst; fear or uncertainty alone is not a cause of volatility, yet is a source of perceived risk. In our example, the footsteps get so close as to force a decision about what action to take. And, once the decision is made, you are committed to the new path. By way of another illustration, the same thing happens on a ski slope. You are at the mountain top and resting on your skis peering down the steep expert slope. You could take the bunny slope down or you could push off on a wild ride. Once the decision is made to tackle the steep slope, there will be no turning back.

What we observe is that the uncertainties are well appreciated, from technology, demographics, social change, as well as from the current policy issues such as taxes, trade, and monetary policy. The catalyst only arrives when something actually happens that changes the consensus view from worrying about uncertainties to taking actions to manage the risks associated with the potential market-moving events.

The Dangers of Relying Primarily on Implied Volatility as a Risk Metric

Another challenge is that implied volatilities are typically calculated from straightforward options pricing models that embed the heroic assumption that prices move up or down with continuous trading – that is, price breaks or price gaps are assumed never to occur. If market participants fear the possibility of price breaks or gaps, options prices will reflect this risk and the result is a higher calculated implied volatility. But it will not be easily apparent that the implied volatility is reflecting price gap risk instead of an upward shift in the volatility regime. And, price gap risk is not the same risk as volatility regime shift risk. Depending on one's financial exposures, one of these risks could be much more important than the other. For those managing options portfolios, for example, the risk of an abrupt price break can do considerable damage to delta hedging strategies while a volatility regime shift represents a different risk, commonly known as "vega" risk. What one needs to create is a comprehensive view of the whole risk probability distribution providing a robust perception of risks, allowing for decidedly different risk scenarios, and not being biased toward bell-shaped curves.

Our conclusion is that starting from a standard deviation approach, such as implied volatility, may inadvertently make it very hard to estimate when extreme and highly dangerous risk distributions are present. The math behind this observation is quite old and goes back to the Russian mathematician, Pafnuty Lvovich Chebyshev (1821 – 1894). What most people take away from Chebyshev's Inequality Theorem is that if you know only the standard deviation you have a very good idea of the typical ranges in which values will fall most of the time. What we take away from the Inequality Theorem is that if you only know the standard deviation, you know absolutely nothing about the extremes of the distribution where the most dangerous risks reside. In short, one should look well beyond options prices and implied volatility to achieve a robust description of the unobservable risk-return probability distribution.

Attempting to Estimate Unobservable Expected Probability Distributions

From a practical perspective, our methodology starts with a Bayesian prior (i.e., our initial view of the world before examining any data) of an abnormal, bimodal risk probability distribution. We know if we start from the point of considering two highly divergent scenarios, and then let the observed data take us back to a bell-shaped curve or leave us with bimodality, that we have not ruled out or overly biased our analysis to always provide the bell-shaped curves, which are known to underestimate the extreme risks inherent in the tails of the distribution.

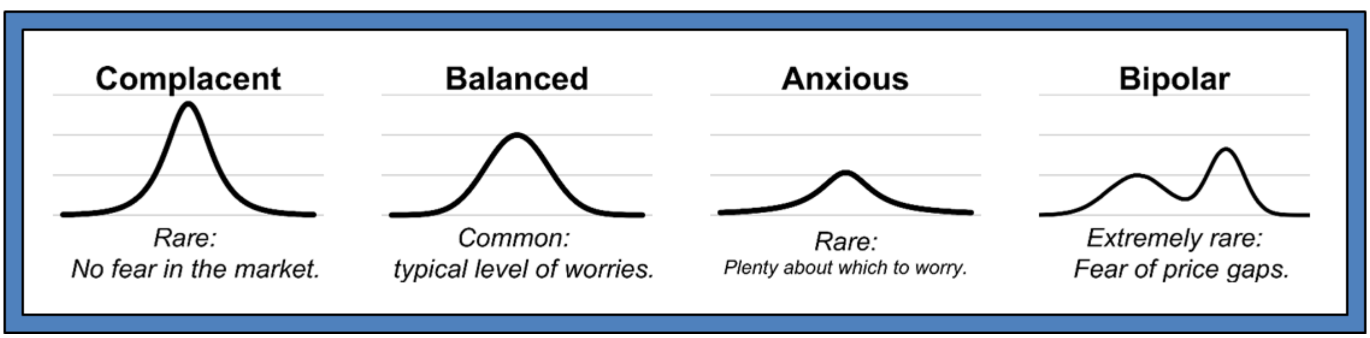
Our research is still at the early stages and is being conducted in partnership with 1Qbit, a quantum consulting and software development company, focused on solving difficult artificial intelligence and machine learning problems. So far, we have found a few metrics that are especially enlightening relative to the shape of the probability distribution. Our three primary metrics are: (1) the evolving pattern of put option trading volume relative to call option volume, (2) intra-day market activity, especially high/low spreads, and (3) implied volatility from options prices relative to historical volatility.

Studying put/call volume patterns helps us understand if one side of the market is more at the center of the current debate than the other side. For example, immediately after former Federal Reserve (Fed) Chair Ben Bernanke threw his famous "Taper Tantrum" in May 2013, he set off a debate about when the Fed would withdraw quantitative easing (QE) and raise interest rates. Put volume on Treasury note and bond prices soared relative to call volume indicating that a two-scenario situation had developed. While there is a buyer and a seller for every trade, one side thought prices would fall (yields rise) and volatility might rise very soon (buyer of puts) while the other side thought the process of exiting QE would take a long time (seller of puts).

Intra-day market dynamics help us appreciate risk in a different way. The observed high price to low price intra-day trading spread is informative in helping us assess the degree to which fat-tails might be present. Mathematically, work by Mark B. Garmen and others back in the 1970s and 1980s has shown that if one assumes a normal distribution then there is a straightforward way to estimate the standard deviation of daily returns from the intra-day high-to-low spread. Put another way, if the relationship between intra-day dynamics and the day-to-day standard deviation diverge in a significant manner, then this is strong evidence that the risk probability distribution is not normally distributed.

To ascertain the risk of price breaks we track the evolving pattern of implied volatility relative to historical volatility. While it is usual for implied volatility to exceed recent historical standard deviations, a shift in the pattern toward a much higher implied volatility may indicate that expectations for the potential of a sharp price break are building in the market. And, if a price break occurs, scenarios resolve one way or the other, so we often see a quick decline in the implied volatility representing a shift back to a single-mode bell-shaped distribution.

Figure 1
Four States of Market Participants' Perceptions of Risks



To gather all our risk information and create a probability distribution, we use a probability mixture technique that is distribution independent – that is, it is not constrained to take on a given specified shape. Most of the time, bell-shaped curves are appropriate descriptions of the probability distributions – balanced risk distributions. Our method does, however, occasionally generate some especially tall distributions (i.e., relatively lower volatility), which we classify as “complacent” and worthy of special study to see if the market may be underestimating risks. We also see on occasion some very flat distributions, not unlike the Wall Street maxim about the equity markets “climbing a wall of worry,” which we call “anxious” risk distributions. And, finally, on rare occasions our metrics support the idea of a two-scenario, event-risk bimodal distribution. That is, we classify expected risk distributions into four types: “Complacent” which are very tall and thin, “Balanced” risks with a typical bell-shape, “Anxious” reflecting a relatively flat bell-shape with very fat tails and possibly skewed one way or the other, and finally our bimodal (aka, “Bipolar”) or event risk distribution which are trying to anticipate what happens if one of two very divergent scenarios is the outcome. Figure 1 on the previous page illustrates these four types of risk distributions.

Illustration with a Case Study from the Corn Futures and Options Markets

To illustrate our probability risk distributions, we take a case covering a very interesting evolution of risk perceptions in the corn market in late 2012 and into the first half of 2013. The summer of 2012 had seen large swaths of the US corn belt experience severe drought, as illustrated in Figure 2 on the next page. Late in 2012, after the harvest, market participants’ thoughts turned to the 2013 crop, about which there was much disagreement. How much acreage would be planted after the drought year? Would 2013 see another drought or its disappearance? While not of the political version of event risk, corn market participants were worried about the drought continuing and a two-scenario market developed for a while in February 2013 as one side of the market took the view that the 2013 crop would be much better than 2012’s drought-constrained crop and other market participants worried about another poor crop. Our probability risk distribution was already in an “anxious” state late in 2012, shifted to “event risk” in February 2013, went back to “anxious” for most of the spring of 2013, before returning to the most common state, “balanced risks” in the summer of 2013. Figures 3 and 4 illustrate the corn market’s shifting risk perceptions while Figure 5 provides the drought’s impact on corn prices. Please see the following two pages.

Figure 2:
Drought Monitor for August 2012

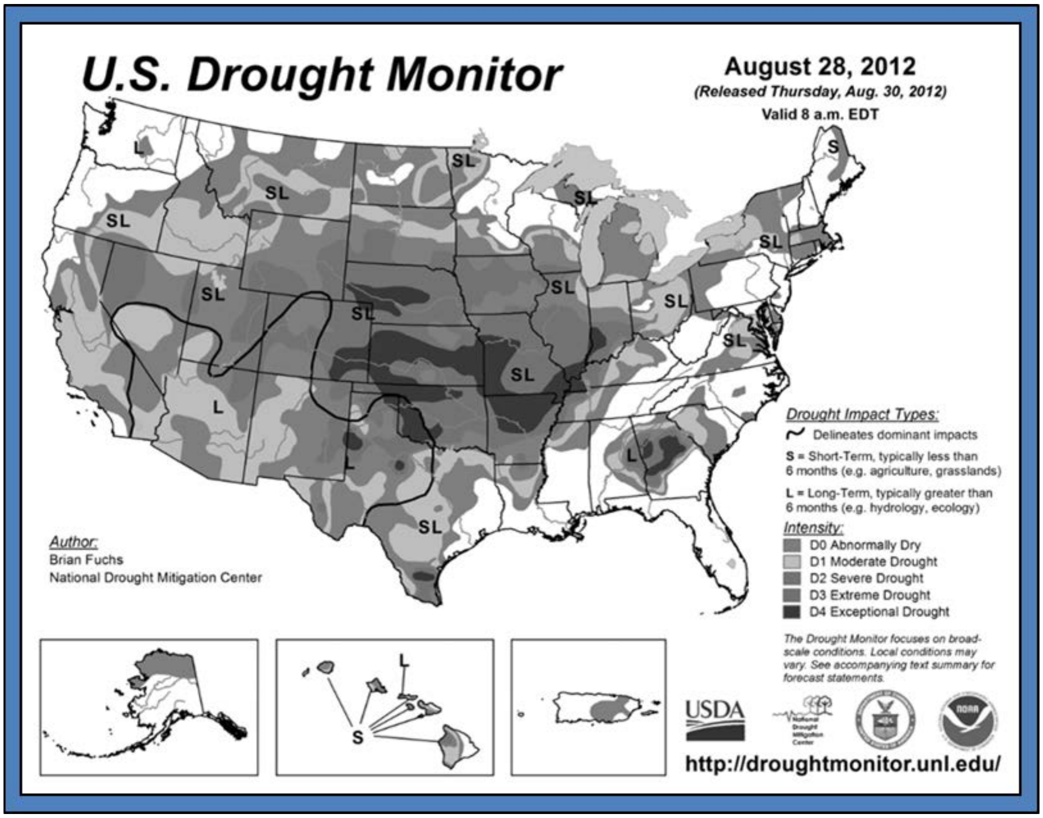


Figure 3:
Corn Market Risk Perceptions: February 15, 2013

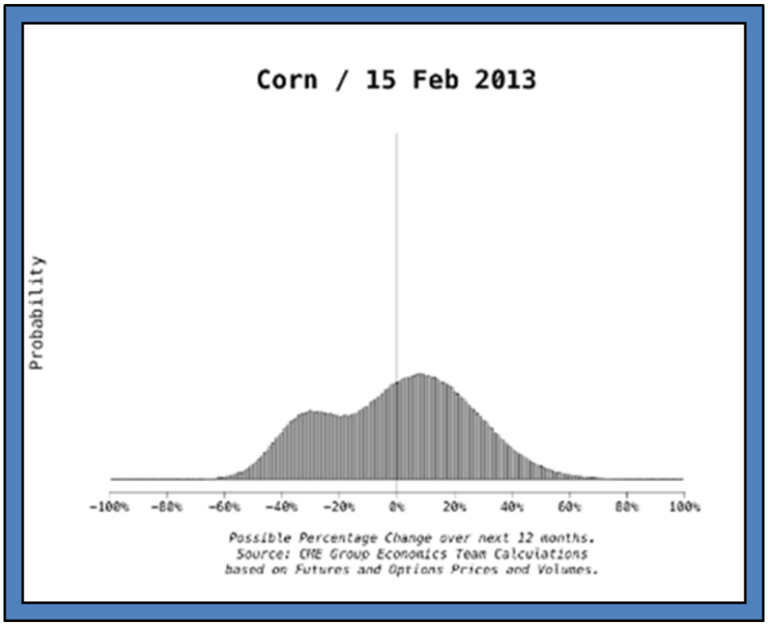


Figure 4:
Corn Market Risk Perceptions: September 16, 2013

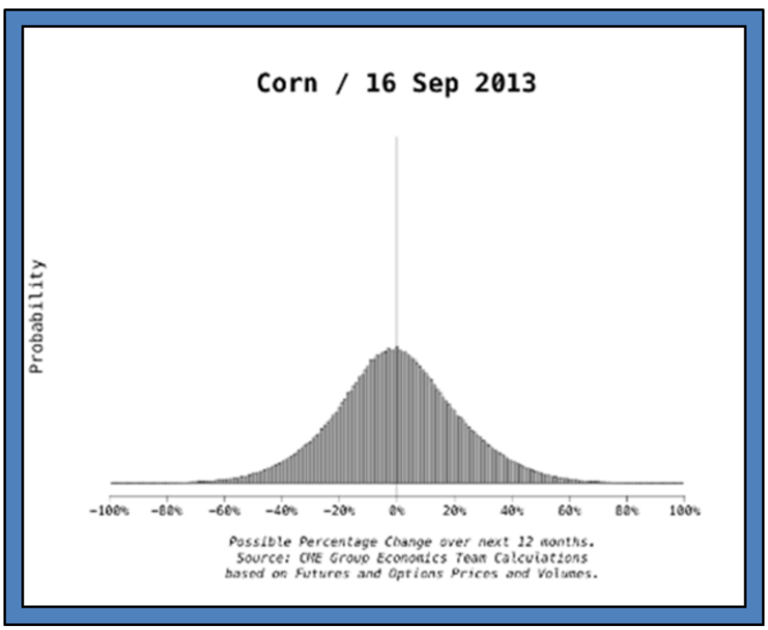


Figure 5:
Corn Futures Prices

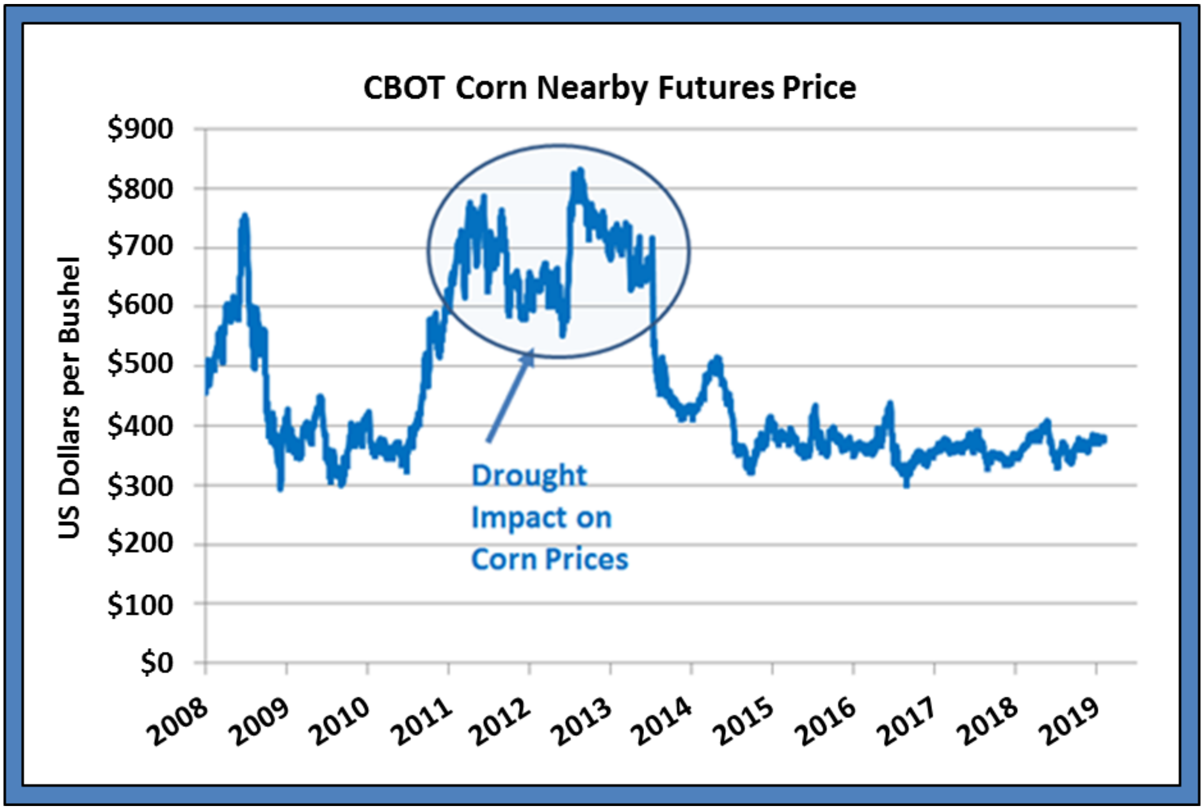


Chart created by CME Group Economics Team.

Data Source: Bloomberg Professional (LC1).

While this case study from the corn markets was presented purely as an illustration, our research methods allow for the rarest of market states – bimodal probability distributions – to occur in all of the product classes we have studied so far, which includes the commodity markets discussed here as well as our research in financial markets such as U.S. Treasury Note futures, equity index futures, and the Euro (versus USD). We believe it is important to monitor our risk states, especially when they shift from one category to the next. We do not expect the most common state – "balanced risks" occurring as much as two-thirds to three-quarters of the time, depending on the product, to provide any critical information that one would not acquire looking only at implied volatilities from options markets. We do think, however, that when the probability risk distribution shifts into a less typical state – "complacent", "anxious", or especially "event risk" – that risk managers should go on high alert. We also warn that while our naming conventions describe the risk distributions, they may not describe what happens. "Complacent" states may well be followed by volatility when some new and unexpected risk factor takes priority. "Anxious" states may or may not overstate fears, as equity analysts talk about when they say "a market is climbing a wall of worry". "Bipolar risk" states do not last long, as they tend to be resolved back to a one-scenario, single-mode distribution when the event occurs, and the outcome becomes known or when market participants become more confident that a one-scenario outlook with appropriate skepticism is more appropriate than a two-scenario approach.

An important next step in our research process will be to make our probability risk metrics available publicly. Through a partnership with 1Qbit (https://1qbit.com/), a software company specializing in solving some of the most difficult and intractable problems, curated daily data sets will be forthcoming on CME DataMine (https://www.cmegroup.com/market-data/datamine-historical-data.html). The data sets will cover eight exchange-traded futures and options products, including CME E-Mini S&P500®, CBOT U.S. Treasury 10-Year Note, CME Euro FX, NYMEX WTI crude oil, NYMEX Henry Hub natural gas, COMEX gold, CBOT soybeans, and CBOT corn. Data will go back to January 2012.

Endnotes

All examples in this report are hypothetical interpretations of situations and are used for explanation purposes only. The views in this report reflect solely those of the author and not necessarily those of CME Group or its affiliated institutions. This report and the information herein should not be considered investment advice or the results of actual market experience.

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Author Biography

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Dr. Bluford Putnam is Managing Director and Chief Economist of CME Group. As Chief Economist, Dr. Putnam is responsible for leading the economic analysis on global financial markets by identifying emerging trends, evaluating economic factors and forecasting their impact on CME Group and the company's business strategy. He also serves as CME Group's spokesperson on global economic conditions and manages external research initiatives.

Prior to joining CME Group, Dr. Putnam gained experience in the financial services industry with concentrations in central banking, investment research and portfolio management. He also has served as President of CDC Investment Management Corporation and was Managing Director and Chief Investment Officer for Equities and Asset Allocation at the Bankers Trust Company in New York. His background also includes economist positions with Kleinwort Benson, Ltd., Morgan Stanley & Company, Chase Manhattan Bank and the Federal Reserve Bank of New York. Dr. Putnam holds a bachelor's degree from Florida Presbyterian College (later renamed Eckerd College) and a Ph.D. in Economics from Tulane University.

Dr. Putnam has authored five books on international finance, as well as many articles that have been published in academic journals, including the *American Economic Review*, *Journal of Finance*, and *Review of Financial Economics* among others. His newest book, Economics Gone Astray, is now available from World Scientific (WS) Professional.

Dr. Putnam is also a member of the J.P. Morgan Center for Commodities' Research Council as well as its Advisory Council.