

Budget Cycle Value-at-Risk (VaR) for a Commodity Portfolio

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Abstract

Over the past two decades, Value-at-Risk (VaR) has become of great interest to financial managers due to federal regulations on capital reserve requirements at financial institutions. The application of this measurement has begun to spread across many different types of commodity intensive companies as well, taking this application from large bank trading operations. VaR is an appealing measure because it aggregates multiple risk factors into a single value that is easy to understand.

Traditionally, VaR is measured over a 1- to 20-day holding period due to the fact that a trading portfolio can be liquidated during this time. As a measure for a commodity intensive company that must contend with the risk of commodity price fluctuation constantly as a natural course of business, and in most cases is sensitive to budget variances on a 12-month basis, a 1- to 20-day holding period is not very useful.

Know-Risk[™], an analytical tool developed by RMI Consulting, Inc., provides forecasts of VaR for a portfolio of commodities over a much longer time horizon than traditional methodologies. The purposes of this paper are to provide validation of the tool and to discuss its applications as well as the inherent limitations of any VaR calculation.

Introduction

Over the past 20 years, Value-at-Risk (VaR) has become of great interest to financial managers due to federal regulations on capital reserve requirements at financial institutions. VaR is the maximum expected loss of a portfolio over a certain time horizon at a reasonable probability level. VaR provides a measure of loss that should only be exceeded, on average, 1 out of X number of days. For example, if the one-day holding period VaR of a portfolio is \$1,000,000 at a 99% confidence level, one would expect the loss of a portfolio to exceed \$1,000,000 on only one day over a randomly selected period of 100 days. The use of this measurement has begun to spread across many different types of commodity intensive companies as well, taking its application from large bank trading operations. VaR is appealing because the measure aggregates multiple risk factors into a single value that is easy to understand.

For practical purposes, VaR is a benchmark measure that gives commodity procurement managers a guide in decision-making. Simply stated, the higher the VaR, the greater the risk of the portfolio. Most companies when using this metric will set limits on how much risk their portfolio can contain, and eliminate or accept risk accordingly.

It must be noted that a common conclusion among many researchers who study VaR is the inherent imprecision in the calculation caused by the numerous risk factors that can affect markets. When modeling VaR, it is impossible to create a model with a parameter for every relevant market factor. In many cases, adding more parameters to a VaR model does not guarantee more-precise forecasts. However, the popularity of VaR as a benchmark and simplicity of VaR calculations make VaR models desirable by many executive decision makers.

RMI Consulting, Inc. has developed *Know-Risk™*, a web based, deal tracking and risk management program that has the ability to provide forecasts of VaR for a portfolio of commodities. It offers managers a flexible tool to analyze their portfolio's risk over a long period of time such as a budget cycle or planning period and helps to create a plan for hedging strategies.

Know-Risk™ uses relatively few assumptions and observed market prices in order to be usable, easy to understand and accurate from a statistical standpoint. The

model assumes that commodity prices are lognormally distributed and that the implied price volatility reflects all the known risk factors in the market. Users are able to customize their VaR report by choosing the time horizon, confidence level, and selected “what if” type of parameters to assess the risk due to potential changes in the composition of the portfolio.

The purposes of this paper are to provide a validation of the *Know-Risk™* VaR methodology and discuss its applications as well as the inherent limitations of any VaR calculation. The remainder of the paper is separated into three main sections. The first section describes the set up and interpretation of a *Know-Risk™* Risk Assessment Report. This description covers the parameterization of the report, portfolio characteristics, and the actual printed report. The second section presents the assumptions, parameters, and characteristics of the model. The third section discusses the methodology used for model validation as well as the results generated by the *Know-Risk™* VaR model.

Understanding the *Know-Risk™* Risk Assessment Report

In practice, the intention of the Risk Assessment Report is to help develop procurement strategies for a commodity portfolio. The user is able to choose the time horizon for the report, which most commonly would be the budget or planning horizon (See Figure 1). Therefore, many users will have the report run for the forward year, with time units in months. The other parameter that the user can choose is the confidence level. Default values are set to 75% and 95%. Once the parameters are determined, the program takes into account the open positions of the portfolio and computes the risk accordingly. For purposes of this report an open position is defined as the company’s budgeted volumes by month less the procurement volumes that have already been

Risk Assessment Report	
Report Start Date:	3/27/2007
Report End Date:	Mar 2008
Portfolio Start Date:	Mar 2007
Portfolio End Date:	Mar 2008
Location:	Chicago Electricity Chicago Gas Pittsburgh Electricity Pittsburgh Gas
NEXT >>	

Figure 1: The input screen allows users to customize the Risk Assessment Report by time horizon.

What If-Risk Assessment Report				
Pittsburgh Gas				
Date	Total	Hedged	Unhedged	What If...
7/1/2007	10000	5000	5000	<input type="text" value="5000"/>
8/1/2007	10000	5000	5000	<input type="text" value="2500"/>
9/1/2007	10000	5000	5000	<input type="text" value="2500"/>
10/1/2007	10000	5000	5000	<input type="text" value="2500"/>
11/1/2007	10000	5000	5000	<input type="text" value="1000"/>
12/1/2007	10000	5000	5000	<input type="text" value="1000"/>
1/1/2008	10000	5000	5000	<input type="text" value="0"/>
2/1/2008	10000	5000	5000	<input type="text" value="0"/>
3/1/2008	10000	5000	5000	<input type="text" value="0"/>

Figure 2: The “What If” Risk Assessment Report allows users to develop hypothetical portfolio scenarios by increasing volumes hedged.

secured. Another feature of *Know-Risk™* allows a user to input scenario volumes and re-generate the risk report showing the updated risk analysis (See Figure 2).

After the processing of the parameters and data, a report is generated displaying both a graph and a table. The horizontal axis of the graph depicts time and the unit is commonly measured in months. The vertical axis of the graph represents the dollar value (cost) of the portfolio. The graph shows a curve that represents the upper bound of the cost over the

selected time horizon (See Figure 3). The bound shows that with a certain confidence level, the cost of acquiring the portfolio of commodities will not exceed the values depicted by the lines. Because the user is able to choose the confidence level(s) for the report, more than one curve may appear on the graph.

The second feature of the report, the table, shows the dollar amounts of the bounds in the graph (See Page 5: Table 1). The left column, in this example, contains the start date and each of the forward 12 months. The next two columns show the forecasted bounds for each forward month at the given confidence level(s). For example, the table indicates that 95% of the time one would expect the actual value of the portfolio to be

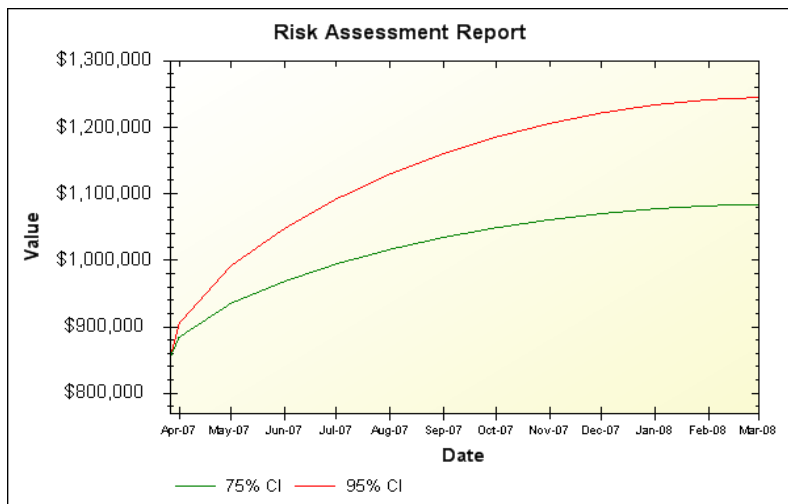


Figure 3: The graph of the Risk Assessment Report shows that with X% confidence the value (cost) of the portfolio will not exceed the value depicted by the curves.

less than \$1,092,403 when considering the portfolio positions on July 1, 2007. Monthly forecasts represent the upper bound of the portfolio for the entire time horizon given the open and closed positions for that month. The amount of risk of the portfolio diminishes over time because the expired positions are no longer subject to volatility. For example, in Table 1, the forecast for April '07 does not recalculate the standard deviation for March '07 because March positions have expired, so the standard deviation is unchanged. However, the forecast for April '07 uses the previous March '07 standard deviation as the new starting point and recalculates the standard deviations from April '07 to March '08.

Finally, after viewing the baseline report the user has the option of changing the actual hedged positions in a simple manner to see how the risk levels change through time.

Date	75% CI	95% CI
3/27/2007	\$855,488	\$855,488
4/1/2007	\$884,384	\$904,737
5/1/2007	\$935,465	\$991,798
6/1/2007	\$968,361	\$1,047,863
7/1/2007	\$994,494	\$1,092,403
8/1/2007	\$1,016,362	\$1,129,674
9/1/2007	\$1,034,401	\$1,160,418
10/1/2007	\$1,048,814	\$1,184,983
11/1/2007	\$1,060,898	\$1,205,579
12/1/2007	\$1,070,170	\$1,221,381
1/1/2008	\$1,077,369	\$1,233,651
2/1/2008	\$1,081,921	\$1,241,409
3/1/2008	\$1,083,878	\$1,244,745

Table 1: The table of the Risk Assessment Report shows the dollar amounts of the value for each month plotted in the report.

Description of Model Characteristics

Know-Risk™ constructs a forecast of VaR for a portfolio of commodities by utilizing implied volatility, forward prices, volume, days to expiration, and confidence level. There are three main methods for calculating VaR: variance-covariance method, historic simulation and Monte Carlo simulation. *Know-Risk™* is a variance-covariance (VCV) approach to VaR. A key assumption of the VCV method is that market values follow a normal distribution. When creating a VaR model there are four main steps. The description of the VCV assumptions will be given in these steps.

VaR Modeling Steps

The first step in creating a VaR model is to select the parameters of the model. *Know-Risk™* simplifies the VaR calculation by limiting the number of parameters. The parameters of this model include time horizon of the portfolio, confidence level and time unit of measurement.

The second step in creating a VaR model is selecting relevant market factors. *Know-Risk™* uses an implied price volatility obtained from the Black-76 model. The

Black-76 model uses the same calculation as the Black-Scholes model except the Black-76 model replaces the spot price of the commodity with the forward price (Black 1976). The Black-76 model assumes that changes in prices are normally distributed. Therefore, prices are assumed to be lognormal. *Know-Risk™* uses these normal theory assumptions and a VCV approach to calculate the VaR.

The third step is mapping all relevant risk factors. As previously stated, the model uses the implied volatility obtained from the Black–76 model. In order to reduce the complexity of the VaR calculation, *Know-Risk™* assumes that the implied volatility incorporates all relevant market risk factors.

The fourth step of VaR modeling is the calculation. The day a report is calculated is the report date. The program can be run on any day that relevant market information is available. *Know-Risk™* calculates an upper bound of the position for each tenure month during the time horizon. Each upper bound calculated represents the maximum value of the portfolio for the entire time horizon given what is known about the market and portfolio positions during that month. The model is programmed to make these calculations by a series of loops. The variables used to represent each time step will be described next.

Upper Bound Calculation Formula

The tenure months are the months following the report date, denoted by $t = 1, 2, \dots, n$. The variable that represents the current month in the loop while calculating the bound for tenure month t is $j = t, t + 1, t + 2, \dots, n$. For example, if the program is calculating an upper bound for February, the program does not recalculate the standard deviation for any of the expired months before February because they are no longer subject to volatility. Therefore, j represents the months from February to the end of the time horizon.

Another variable used in the calculation is

$$\bar{p} = \sum_{t=1}^n p_t / n,$$

which represents the average of the tenure month forward option prices. The standard deviation is estimated by

$$\sigma_j = p_j e^{v_j \sqrt{\tau}} - p_j,$$

where v_j is the volatility in month j . The calculation σ_j is made for all $j = t, t+1, t+2, \dots, n$. The parameter τ is the difference in tenure date and the report date divided by 360, which is used to take a proportion of the volatility that applies in month j .

To account for the expired months, the program saves the standard deviation for months in which standard deviation will not be recalculated. This is done by setting $\sigma_k^x = \sigma_j$ for $j = t$, where the superscript x denotes an expired month. Finally the average standard deviation for the tenure month t can be calculated. The average deviation is calculated by

$$\bar{\sigma}_t = \left(\sum_{j=t}^n \sigma_j + \sum_{k=1}^{t-1} \sigma_k^x \right) / n.$$

The average standard deviation takes into account the forward months that are recalculated every month and the expired months that are saved but still needed to calculate the VaR forecast.

The last step is to calculate

$$\beta_t^\alpha = \bar{p} + z_\alpha \bar{\sigma},$$

which represents the $1 - \alpha$ confidence bound for the tenure month t . In order to clarify the mathematics, an example of how the first tenure months are calculated for the report in Table 1 (Page 5) will be given.

Example Calculation

For the report in Table 1 (Page 5) the report date is 3/27/07. This report has 12 tenure months, thus $n = 12$. The first tenure month is April '07. In this calculation, $t = 1, 2, \dots, 12$, which represents the first twelve tenure months. The variable j represents the step in the calculation for month t . During the April calculation, $j = 1, 2, \dots, 12$ because $t = 1$ and $n = 12$.

The average of the tenure months' forward option prices are

$$\bar{p} = \sum_{t=1}^n p_t / n.$$

The standard deviation

$$\sigma_j = p_j e^{v_j \sqrt{\tau}} - p_j,$$

is calculated for all $j = 1, 2, \dots, 12$, and $\tau = 5/360$, the number of days between 4/1/07 and 3/27/07 divided by 360. After σ_j is calculated the program sets $\sigma_1^x = \sigma_1$ to save the standard deviation for April because it will stay constant for the rest of the tenure month calculations. The calculation for $\bar{\sigma}_t$ in April will not have the second term in the numerator. The second term would add the elements from $k = 1$ to $t - 1$, but because $t = 1$ in April the second term is not needed. Therefore, the calculation is simplified to

$$\bar{\sigma}_1 = \sum_{j=1}^n \sigma_j / n.$$

Finally, the $1 - \alpha$ confidence interval bound for tenure month April is

$$\beta_1^{1-\alpha} = \bar{p} + z_{\alpha} \bar{\sigma}_1.$$

For May, the second tenure month, $t = 2$ and $j = 2, 3, \dots, 12$. The average price of the forward option prices does not change because they are all observed on the report date. The standard deviation σ_j is now calculated for all $j = 2, 3, \dots, 12$ and $\tau = 35/360$, the number of days between 5/1/07 and 3/27/07 divided by 360. The standard deviation calculated for May is set as $\sigma_2^x = \sigma_2$ and saved to account for May during the next 10 tenure month calculations. In May, $\bar{\sigma}_2$ has both terms in the numerator, where the second term is the expired position in April. The calculation is

$$\bar{\sigma}_t = \sum_{j=2}^n \sigma_j + \sigma_1^x / n.$$

Similarly to April, the $1 - \alpha$ confidence interval for May is

$$\beta_2^{1-\alpha} = \bar{p} + z_{\alpha} \bar{\sigma}_2.$$

Model Validation

In the model development process, validation is one of the most important steps. Model validation is the process of checking to see that a model behaves as its creator intended. Typically, this process consists of two steps: (1) the manual calculations are checked for mathematical and computational correctness, and (2) the output of the model is back tested with historical data to assess the accuracy of its forecasts.

Historical Data Construction

The output of *Know-Risk™* was tested with historical data for corn, natural gas and soybean oil. The natural gas data used are from 2004 through 2006. The data used for soybean oil and corn are from January 2004 to July 2006. The reports tested were constructed with 75, 90, 95 and 99 percent confidence bounds. For simplicity, the model output tested with historical data is for a portfolio with one unit of the commodity that is an un-hedged unit.

When *Know-Risk™* calculates a report there are usually 12 bounds given for the portfolio over the year, one bound for each month. In the calculation, each time a month expires the standard deviation is saved and averaged with the new recalculated standard deviations from the current and future tenure months. When historical data were compared to the output of the model a similar approach was taken. Because the model accounts for expired positions by rolling them off and not recalculating them, the historical data used for comparison have a similar feature.

The historical data for each of the 12 months are constructed by averaging the monthly closes for expired months and the daily prices for months that have not expired. For example, a report run in January will have twelve bounds, one for each month from February to January of the next year. If the tenure month is June, the monthly settlement prices for February, March, April, May, and June are averaged with the daily settlements from the next 8 months, from July to January of the next year.

Binomial Model Validation Test Methodology

The statistical test used to validate the model is a binomial test of successes and failures. For a binomial test, all observations need to be statistically independent. *Know-Risk™* reports are calculated by using best estimates of parameters from the

price process. Therefore, different assumptions can make it difficult for observations and historical data sets to be entirely independent, especially when looking at multiple reports from the same month. Due to the need for independence, all sets of data are constructed with only one report for each month. As previously stated, the historical data are an average of daily closes and many observations use the same values for forward months and do not provide independence. Therefore, it is important that only one tenure month forecast from each report is selected.

When selecting report dates from the data there were three approaches: first day of the month, last day of the month, and a rolling date. Each data set for corn and soybean oil have approximately 30 independent observations, one tenure month from each report, where there is one report for each month from January 2004 to July 2006. Historical data for natural gas were obtained for all of 2006 and there are approximately 36 independent observations for natural gas data sets.

For the binomial test, when comparing the output of the model at the X% confidence level, it is expected that approximately X% of the actual values are below the forecasted value and approximately (100 – X)% are above the interval. When using the binomial test, if the observed value is below *Know-Risk*TM's output value (the bound) then it is considered a success and assigned a 1. If the observed value is above the bound then it is considered a failure and assigned a 0. After each output is compared to the actual, the number of successes are counted. It is expected that the number of successes divided by the number in the sample differ from X% only because of statistical error. A binomial confidence interval for $\frac{s}{n} = \hat{p}$ is used to test the accuracy of the model output. If the confidence interval for \hat{p} covers $p = X\%$ then the projected bound is deemed reasonable. In other words, if

$$\hat{p} - z_{\alpha/2} \sqrt{p(1-p)/n} < p < \hat{p} + z_{\alpha/2} \sqrt{p(1-p)/n}$$

the bound is reasonable.

Binomial Model Validation Test Results

Appendix I contains a spreadsheet that shows the results of the 108 binomial confidence intervals. A binomial confidence interval that covers p is highlighted in

green and an interval that does not cover p is highlighted in red. For corn, 32 of the 36 95% binomial confidence intervals cover p . For soybean oil, 35 of the 36 95% binomial confidence intervals cover p . For natural gas, 33 of the 36 95% binomial confidence intervals cover p . All three of the commodities together yield that 100 of the 108 forecasted bounds were accurate according to a binomial test in predicting the upper bound of the portfolio. This means 92.6% of the bounds were accurate according to a 95% binomial confidence interval.

Many authors have written on the imprecision of VaR calculations. Jorion uses the term the “inherent imprecision in VaR” because it is impossible to create a model that accounts for all risk factors and market anomalies. Marshall and Siegel suggest that variation in the actual outcome and predicted outcome should be expected. For example, in the data set used to validate *Know-Risk™* we have market anomalies such as hurricanes and historically low corn and soybean prices. Given this imprecision in VaR calculations, when comparing the output of *Know-Risk™* to historical data, 92.6% accuracy for a 95% confidence binomial test suggests there is enough accuracy to say the output is reasonable for use as a projection of the VaR of a commodity portfolio.

Conclusion

The goals of this paper are to provide an explanation and a validation of the *Know-Risk™* VaR report. When using a VaR model it is important to understand that the VaR is not the maximum loss that can be attained. The VaR is the maximum expected loss at a selected probability level. At the 95% probability level one would expect that the maximum loss of the portfolio exceeds the VaR projection on an average of 5 out of 100 randomly selected days. However, the expected magnitude of the loss on those five days is not provided by the VaR calculation.

Users of all VaR models and *Know-Risk™* should understand that the output of the model is intended to be an aid for the user in procurement hedging strategies. The purpose of *Know-Risk™* is to serve as a benchmark measure in the decision making process. The flexibility of the software allows for the user to run the report under different scenarios to help the procurement planning process.

VaR models usually estimate parameters based on the price process from market observations. *Know-Risk™* makes similar estimates. The model uses the implied price volatility to account for risk factors, forward prices and the assumption that prices are lognormally distributed. These assumptions allow for the model to be simple to understand and easy to calculate without compromising accuracy.

According to many researchers, VaR calculations are imprecise because it is impossible to account for all relevant market factors (Jorion 2001). For example, Hurricane Katrina took place at a time in the middle of the data sample used to back test the output for natural gas. Due to this imprecision, it is statistically expected that the output of the model does not accurately predict the VaR for every set of data and commodity. However, the data used to back-test *Know-Risk™* provide evidence that the program produces VaR forecasts that can help managers monitor the performance of their commodity portfolios.

References

- Atchinson, J. and Brown, J.A. C. The Lognormal Distribution (Cambridge: Cambridge University Press, 1963), 50-51.
- Berkowitz, Jeremy, and O'Brien, James. How Accurate are Value-at-Risk Models at Commercial Banks? (New York: Federal Reserve Bank, July 2001).
- Black, F. "The Pricing of Commodity Contracts," Journal of Financial Economics 3, (1976): 167-179.
- Christoffersen, Peter. "Evaluating Interval Forecasts," International Economic Review 39, no. 4 (November 1998): 841.
- Hardle, Wolfgang, Kleinow, Torsten, and Stahl, Gerhard. Applied Quantitative Finance (Berlin, Germany: Springer, 2002), 130.
- Hendricks, Darryll. Evaluation of Value-at-Risk Models Using Historical Data (New York: Federal Reserve Bank Economic Review Policy, April 1996).
- Hull, John C. Futures and Options Markets (New Jersey: Prentice-Hall, 1998), 359-375.
- Jorion, Phillipe. Value at risk: the new benchmark for managing financial risk (New York: McGraw-Hill, 2001).
- Limpert, E., Stahel, W. and Abbt, M. "Log-normal Distributions across the Sciences: Keys and Clues," BioScience, 51 (5), p. 341–352 (2001).
- Macal, Charles M. "Model Verification and Validation" (paper presented to The University of Chicago and Argonne National Laboratory at a workshop on Threat Anticipation: Social Science Methods and Models, Chicago Ill., 7-9 April 2005).
- Marshall, Chris, and Siegel, Michael. "Value at Risk: Implementing A Risk Management Standard," Journal of Derivatives 4, no. 3 (Spring 1997): 94.
- McDonald, Robert L. Derivatives Markets (Boston: Addison Wesley, 2006).
- Pilipovic, Dragana. Energy Risk (New York: McGraw-Hill, 1998).
- Ravindran, A., Phillips, Don T., and Solberg, James J. Operations Research: Principles and Practice (New York: John Wiley & Sons, 1987), 379-80.
- Wiener, Zvi. "Introduction to VaR (Value-at-Risk)" (paper presented on Risk Management and Regulation in Banking, Jerusalem, Israel, 18 May 1997)

Appendix I
 Table 1: Summary of Binomial Confidence Intervals for Natural Gas

First day of Month		n= 36		Rolling Date		n= 33		Last Day of Month		n= 36	
One Tail expected	75	90	95	One Tail expected	75	90	95	One Tail expected	75	90	95
	27	32.4	34.2	35.64	24.75	29.7	31.35	32.67	27	32.4	34.2
actual	27	34	35	36	26	32	32	32	29	32	32
%	0.75	0.944444	0.972222	1	0.787879	0.969697	0.969697	0.969697	0.805556	0.888889	0.888889
Confidence interval for p*											
St. Dev.	0.072169	0.05	0.036324	0.016583	0.075378	0.052223	0.037939	0.017321	0.072169	0.05	0.036324
95 up	0.891451	1.042444	1.043418	1.032503	0.935619	1.072055	1.044058	1.003645	0.947006	0.986889	0.960084
95 down	0.608549	0.846444	0.901027	0.967497	0.640138	0.867339	0.895336	0.935749	0.664105	0.790889	0.817694
2nd Set											
actual	29	32	33	35	26	29	29	32	26	34	35
%	0.805556	0.888889	0.916667	0.972222	0.787879	0.878788	0.878788	0.969697	0.722222	0.944444	0.972222
Confidence interval for p*											
St. Dev.	0.072169	0.05	0.036324	0.016583	0.075378	0.052223	0.037939	0.017321	0.072169	0.05	0.036324
95 up	0.947006	0.986889	0.987862	1.004725	0.935619	0.981146	0.953149	1.003645	0.863673	1.042444	1.043418
95 down	0.664105	0.790889	0.845471	0.939719	0.640138	0.77643	0.804427	0.935749	0.580771	0.846444	0.901027
3rd Set											
actual	26	33	34	35	24	30	31	32	29	32	33
%	0.722222	0.916667	0.944444	0.972222	0.727273	0.909091	0.939394	0.969697	0.805556	0.888889	0.916667
Confidence interval for p*											
St. Dev.	0.072169	0.05	0.036324	0.016583	0.075378	0.052223	0.037939	0.017321	0.072169	0.05	0.036324
95 up	0.863673	1.014667	1.01564	1.004725	0.875013	1.011449	1.013755	1.003645	0.947006	0.986889	0.987862
95 down	0.580771	0.818667	0.873249	0.939719	0.579632	0.806733	0.865033	0.935749	0.664105	0.790889	0.845471

Appendix I
Table 2: Summary of Binomial Confidence Intervals for Corn

First Day of Month		n= 31		Rollin Date		n= 32		Last Day of Month		n= 30	
One Tail	75	90	95	99	One Tail	75	90	95	99	One Tail	75
actual	24	31	31	31	actual	25	29	31	31	actual	24
%	0.774194	1	1	1	%	0.78125	0.90625	0.96875	0.96875	%	0.8
Confidence Interval for p*				Confidence Interval for p*				Confidence Interval for p*			
St. Dev.	0.077771	0.053882	0.039144	0.017871	0.076547	0.053033	0.038528	0.017589	0.054772	0.079057	0.054772
95 up	0.926625	1.105608	1.076722	1.035026	0.931281	1.010195	1.044264	1.003225	0.907354	0.954952	0.907354
95 down	0.621762	0.894392	0.923278	0.964974	0.631219	0.802305	0.893236	0.934275	0.692646	0.645048	0.692646
2nd set		n= 32		2nd set		n= 32		2nd set	n= 30		2nd set
actual	29	30	31	32	actual	26	31	31	25	actual	25
%	0.90625	0.9375	0.96875	1	%	0.8125	0.96875	0.96875	1	%	0.833333
Confidence Interval for p*				Confidence Interval for p*				Confidence Interval for p*			
St. Dev.	0.076547	0.053033	0.038528	0.017589	0.076547	0.053033	0.038528	0.017589	0.054772	0.079057	0.054772
95 up	1.056281	1.041445	1.044264	1.034475	0.962531	1.072695	1.044264	1.034475	0.95 up	0.988285	1.07402
95 down	0.756219	0.833555	0.893236	0.965525	0.662469	0.864805	0.893236	0.965525	95 down	0.678382	0.859313
3rd Set		n= 32		3rd Set		n= 32		3rd Set	n= 30		3rd Set
actual	27	30	30	32	actual	28	30	30	31	actual	28
%	0.84375	0.9375	0.9375	1	%	0.875	0.9375	0.9375	0.96875	%	0.933333
Confidence Interval for p*				Confidence Interval for p*				Confidence Interval for p*			
St. Dev.	0.076547	0.053033	0.038528	0.017589	0.076547	0.053033	0.038528	0.017589	0.054772	0.079057	0.054772
95 up	0.993781	1.041445	1.013014	1.034475	1.025031	1.041445	1.013014	1.003225	95 up	1.088285	1.07402
95 down	0.693719	0.833555	0.861986	0.965525	0.724969	0.833555	0.861986	0.934275	95 down	0.778382	0.859313
											0.922009
											0.964395

Appendix I
 Table 3: Summary of Binomial Confidence Intervals for Soybean Oil

First Day of Month		n= 30		Rolling Date		n= 31		Last Day of Month		n= 32	
One Tail	75	95	99	One Tail	75	95	99	One Tail	75	95	99
expected	22.5	28.5	29.7	expected	23.25	29.45	30.69	expected	24	28.8	30.4
actual	23	28	28	actual	22	27	31	actual	20	28	29
%	0.76667	0.933333	0.933333	%	0.709677	0.870968	1	%	0.625	0.875	0.90625
Confidence interval for p*				Confidence interval for p*				Confidence interval for p*			
St. Dev.	0.079057	0.054772	0.039791	St. Dev.	0.077771	0.053882	0.017871	St. Dev.	0.076547	0.053033	0.038528
95 up	0.921618	1.007354	1.011324	95 up	0.862109	0.976576	1.035026	95 up	0.775031	0.978945	0.981764
95 down	0.611715	0.792646	0.855343	95 down	0.557246	0.76536	0.964974	95 down	0.474969	0.771055	0.830736
2nd set				2nd set				2nd set			
actual	24	27	28	actual	25	28	31	actual	22	28	29
%	0.8	0.9	0.933333	%	0.806452	0.903226	1	%	0.709677	0.903226	0.935484
Confidence interval for p*				Confidence interval for p*				Confidence interval for p*			
St. Dev.	0.079057	0.054772	0.039791	St. Dev.	0.077771	0.053882	0.017871	St. Dev.	0.077771	0.053882	0.039144
95 up	0.954952	1.007354	1.011324	95 up	0.958884	1.008834	1.035026	95 up	0.862109	1.008834	1.012206
95 down	0.645048	0.792646	0.855343	95 down	0.65402	0.797618	0.964974	95 down	0.557246	0.797618	0.858761
3rd Set				3rd Set				3rd Set			
actual	23	27	28	actual	26	29	31	actual	25	29	31
%	0.76667	0.9	0.933333	%	0.83871	0.903226	1	%	0.806452	0.935484	0.935484
Confidence interval for p*				Confidence interval for p*				Confidence interval for p*			
St. Dev.	0.079057	0.054772	0.039791	St. Dev.	0.077771	0.053882	0.017871	St. Dev.	0.077771	0.053882	0.039144
95 up	0.921618	1.007354	1.011324	95 up	0.991142	1.008834	1.035026	95 up	0.958884	1.041092	1.012206
95 down	0.611715	0.792646	0.855343	95 down	0.686278	0.797618	0.964974	95 down	0.65402	0.829676	0.858761