Hedging Effectiveness around USDA Crop Reports

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Abstract: It is well documented that "unanticipated" information contained in USDA crop reports induces large price reactions in corn and soybean markets. Thus, a natural question that arises from this literature is: To what extent are futures hedges able to remove or reduce increased price risk around report release dates? This paper addresses this question by simulating daily futures returns, daily cash returns and daily hedged returns around report release dates for two storable commodities (corn and soybeans) in two market settings (North Central Illinois and Memphis Tennessee). Various risk measures, including "Value at Risk," are used to determine hedging effectiveness, and "Analysis of Variance" is used to uncover the underlying factors that contribute to hedging effectiveness.

Futures markets have two primary functions in agricultural commodity markets: (1) a price discovery role and (2) a price risk management role. In order to perform the price discovery role futures markets require fundamental supply and demand information. One of the most important sources of information futures traders and market agents use to appraise the balance of supply and demand of agricultural commodities are USDA reports. Recent research has shown that corn and soybean futures prices continue to react to the release of new information contained in USDA crop reports (Good and Irwin). In addition, Milonas found that the release of crop reports resulted in significant cash price responses for these same markets. Given that both futures and cash prices react significantly to the release of USDA report information, there is potential price risk associated with storing commodities when reports are released. Futures hedging effectiveness to reduce this price risk is determined by co-movements (correlations) in cash and futures prices. If movements in cash and futures prices are highly correlated and basis (defined as the difference between cash and futures price) is stable, hedging will be effective. However, if reports illicit different price responses (in terms of magnitude and speed of adjustment) in futures and cash markets, then basis will become more volatile and hedging effectiveness will be compromised. In particular cash price reactions and hence hedging effectiveness may differ substantially across regions. For example, hedging performance around report release dates may be significantly worse for mid-south (deficit) grain markets, which typically experience wider and more volatile basis levels than their mid-west (surplus) counterparts.

Hedging effectiveness around USDA reports has important implications for producers, grain elevators, and other agribusiness firms who store, buy or sell grain around USDA crop report announcements. This paper will shed light on issues such as: What marketing strategy should be employed in the presence of USDA report induced event risk? And what potential losses might a firm storing, buying or selling grain around report announcements incur? These questions are of paramount importance for agribusiness firms who regularly trade and store cash grain around report announcement dates. For example, elevators store grain throughout the crop year and are susceptible to large losses when "news" leads to big price swings and hence negatively impacts their cash positions. If the standard storage hedge does not reduce efficiently the risk of returns around the event dates, a grain holder or trader will choose an alternative strategy, or simply stay in the cash only position. Similarly feed-mills and poultry firms are often forced to purchase grain to feed and supply livestock irrespective of market conditions, and are hence vulnerable to large price moves resulting from the release of USDA reports "news".

In sum, the main objective of this paper is to examine futures hedging effectiveness around USDA crop reports. Hedging effectiveness is analyzed with respect to two storable commodities (corn and soybeans) in two market settings (North Central Illinois and Memphis Tennessee) for an eleven day event window surrounding report release dates. Specifically, Value at Risk (VAR) is used to quantify and compare price risk for hedged versus un-hedged cash positions. VAR levels derived from simulated short-futures hedging returns, cash returns and speculative short-futures returns, are then examined using Analysis of Variance (ANOVA) to uncover underlying factors that contribute to hedging effectiveness.

Data

The release dates of the USDA *Crop Production* reports were gathered from the National Agricultural Statistics Service (NASS)[1]. The monthly *Crop Production* reports are the most important and most widely anticipated releases of government-based estimates of forthcoming harvest production. These reports are issued around the 10th of each month and they estimate by state: the acreage, yields and production of various crops. For corn and soybeans, production reports are released in August, September, October, November and the final estimates are published in January. This paper examines daily cash and closing futures price (return) movements around reports released in August, September, October and November for the period from August 1992 through November 2006, yielding 60 historical events and 660 event window observations in total. Daily closing Chicago Board of Trade (CBOT) futures prices for nearby contracts (i.e. contracts that were nearest to maturity as of report release dates[2]) were obtained from Bridge Commodity Research Bureau. Nearby contracts are most actively traded by grain merchandisers for hedging purposes. Cash price data utilized in this study are corn and soybean prices from two local markets (spot markets). Spot (average elevator bid prices) prices were obtained from the USDA Agricultural Marketing Service (AMS) for Memphis, Tennessee, and North Central Illinois. Cash prices in surplus areas with excess supplies (e.g. North Central Illinois) are typically at the lower level than those in deficit areas which grow less bushels of grain and have a higher concentration of users (e.g. Memphis).

Modeling Approach

Value at Risk (VAR) is an easy-to-understand tool for evaluating and managing market risks. VAR uses standard statistical techniques to determine the worst expected loss over a given time interval, under normal market conditions, at a given confidence level (Jorion). Value at risk provides users with a summary measure of potential market risk. It is a risk management concept by which traders at the market can be informed, via single number, of the short term risk of potential losses. VAR has lately become one of the financial industry's standards for measuring exposure to financial price risk. Today, few financial companies fail to set VAR as part of their daily reporting routine and a growing number of large agribusiness firms (e.g. Tyson Foods) employ VAR as a risk measure of the portfolio of their commodity inputs and outputs.

There are several accepted methods to compute VAR. In this study we used Monte Carlo simulation approach. To this end historical cash (North Central Illinois and Memphis) and futures returns were first calculated for the eleven day event window surrounding report release dates. More specifically, prices were taken: 6 days before announcement, starting from the day t=-6 to day t=-1, and 6 days after announcement, from day t=0 to day t=5. It was determined that using 6 days prior to the release of the report and 6 days after the release should allow enough time for market traders to form positions and for prices to accurately adjust to the new information contained in the report. Using more trading days could potentially lead to the problem of other information influencing the trading decisions and decreasing the ability to measure the response of the market to the event in question. Day t=0 represents the first trading day after the new information in the report was released, and day t=-1 the last trading day before the report was released.

Daily cash return for commodity i in market j during period t (CR_{ijt}) was calculated as the percentage change between price in period t and price in period t-1.

(1) $$CR_{ijt} = \ln(CP_{ijt} / CP_{ijt-1}) \times 100$$

where: CP_{ijt} - is the cash price for commodity i in market j, and t represents the day – in event time – around the report's release that can take value from t=-5 to t=5.

Similarly, daily short-futures return for commodity i during period t (FR_{it}) was calculated as the percentage change between price in period t and price in period t-1.

(2) $FR_{it} = \ln(FP_{it} / FP_{it-1}) \times -100$

where: FP_{it} is the futures price for commodity i , and t represents the day – in event time – around the report's release that can take value from t=-5 to t=5. "Short-futures" position implies that a trader has initially sold futures contracts and will earn a positive return if prices fall the following day. This is why the term $\ln(FP_t / FP_{t-1})$ is multiplied by (-100).

Diagnostic tests indicate the returns for each cash price series CR_{ijt} (separately identified by commodity, location and event time) and futures returns FR_{it} are stochastic and not serially correlated, but that historical distributions of Memphis corn and soybean cash returns for certain days within the event window and in particular for day t=0 (the first trading day after the new information in the report was released) are leptokurtic (distribution is peaked with fat tails). In other words both small and large price changes are more likely – than under the assumption of normally distributed returns – following report release. To a lesser extent small departures from normality were also observed for North Central Illinois cash returns and futures returns for certain days across the event window. To accommodate this finding and to account for the higher than "normal" possibility of extreme price changes, simulated cash and futures returns CR^s_{ijt} and FR^s_{it} are generated by drawing 1000 iterations from a Multivariate Empirical distribution (MVE), where the shape of this distribution is defined by the historical return data. For comparison purposes simulated cash and futures returns are also generated by drawing 1000 iterations from a Multivariate Normal distribution (MVN) with the first two moments estimated from the historical returns series. Simulations using both the MVE and MVN maintain and impose historical correlation structure between CR_{ijt} and FR_{it}. Simulated daily short-futures hedged returns HR^{s}_{ijt} are then simply the arithmetic sum of CR_{ijt} and FR_{it}.

(3) $$HR_{ijt} = CR_{ijt} + FR_{it}$$

Where it is assumed hedgers match the size of cash positions (in terms of quantity of bushels) with equal sized futures positions[3].

All simulated returns were then ranked from the most negative (lowest) to the most positive (highest) value. In this study we were interested in the risk of return measure at the 95% and 99% confidence levels. This practically means that for the 95 % confidence level VAR is the 50th worst outcome out of 1,000 simulated outcomes. The VAR at the 99% confidence is the 10th worst realized return out of 1,000 simulated returns. These represent the possible losses that will be exceeded only 5% of the time and 1% of the time, respectively. Thus, these VAR measures provides us with a risk assessment of cash (un-hedged storage positions) against short-futures hedged positions for two commodities, two market locations, and across each day in the event window.

Finally Analysis of Variance models were used to quantify the relative influence of commodity type, market location, event day, and marketing/storage strategy on risk levels (VAR measures). Specifically, four separate Analysis of Variance models were estimated for VAR measures generated from MVN and MVE distributions at the 5% and 1% confidence levels. These VAR measures were regressed upon indicator (dummy) variables representing commodity type, market location, event day, and marketing/storage strategy.

(4) $$VAR_{kl} = \tilde{\alpha} + \sum_{m=-5}^{8} \tilde{B}_m D_m + u_{kl}$$

Where: k denotes assumed probability distribution, MVN or MVE, l denotes confidence level, 1% or 5%.

D_m represents 14 indicator variables D_{-5} through D_8.

D_{-5} through D_4 represent event window days t=-5 to t=4, where

$$D_{-5} = \begin{cases} 1 \ if \ t \ is \ -5 \\ 0 \ otherwise \end{cases}, D_{-4} = \begin{cases} 1 \ if \ t \ is \ -4 \\ 0 \ otherwise \end{cases}, D_{-3} = \begin{cases} 1 \ if \ t \ is \ -3 \\ 0 \ otherwise \end{cases}, D_{-2} = \begin{cases} 1 \ if \ t \ is \ -2 \\ 0 \ otherwise \end{cases}$$

$$D_{-1} = \begin{cases} 1 \ if \ t \ is \ -1 \\ 0 \ otherwise \end{cases}, D_0 = \begin{cases} 1 \ if \ t \ is \ 0 \\ 0 \ otherwise \end{cases}, D_1 = \begin{cases} 1 \ if \ t \ is \ 1 \\ 0 \ otherwise \end{cases}, D_2 = \begin{cases} 1 \ if \ t \ is \ 2 \\ 0 \ otherwise \end{cases}$$

$$D_3 = \begin{cases} 1 \ if \ t \ is \ 3 \\ 0 \ otherwise \end{cases}, D_4 = \begin{cases} 1 \ if \ t \ is \ 4 \\ 0 \ otherwise \end{cases}$$

D_5 and D_6 represent indicator variables for marketing strategy, where

$$D_5 = \begin{cases} 1 \ if \ cash \\ 0 \ otherwise \end{cases}, D_6 = \begin{cases} 1 \ if \ speculative \ short \ futures \\ 0 \ otherwise \end{cases}$$

D_7 and D_8 represent indicator variables for location and commodity type respectively, where

$$D_7 = \begin{cases} 1 \ if \ Memphis \\ 0 \ if \ NC \ Illinois \end{cases}, D_6 = \begin{cases} 1 \ if \ soybeans \\ 0 \ if \ corn \end{cases}$$

$\tilde{\alpha}$ is the intercept parameter that captures the base case where estimated VAR measures are observed for short-futures hedged corn positions in North Central Illinois on day $t=5$.

Results

Empirical results with respect to the four Analysis of Variance models are presented in tables 1 – 4. Tables 1 and 2 report parameter estimates for MVN 5% and MVE 5% models respectively, while tables 3 and 4 report parameter estimates for MNV 1% and MVE 1% models respectively.

First, we consider the question of whether hedging performance differs across the event window. Our results for each of the Analysis of Variance models clearly indicate that corn short-futures hedges for North Central Illinois result in larger potential losses immediately following report release dates. In this case, tables 1 and 2 show that 5% VAR losses (irrespective of assumed distribution) are significantly greater on day *t=0* than on other event window days. For example, $\tilde{B}_0$ is around -2% and significantly different from $\tilde{\alpha}$ at the 1% level. Thus 5%VAR short-hedged corn losses in North Central Illinois average around 3% for day *t=0* (the first trading day following report release), while for other event window days 5%VAR short-hedged corn losses in North Central Illinois average around 1%. Losses associated with day *t-1* may be considered a possible exception to this finding. In this case we find some evidence (table 1) that losses of around 1.5% for day *t=-1* are also significantly greater than losses on other pre or post-report days. Similar results are also observed in tables 3 and 4 for 1% VAR short-hedged corn losses in North Central Illinois. However, in general, potential hedging losses, as expected, are larger. For example, losses average around 1.5% for event window days other than days *t=0* and *t=-1*, while average losses of around 4% or more are observed for days *t=0* and *t=-1*. In sum, our hedging event window results are consistent with the notion that cash and futures markets may experience a temporary disconnect with the influx of "news" that induces large price movements.

Next, we turn attention to the issue of whether short-futures hedging corn in North Central Illinois reduces return risk in comparison to a simple cash corn storage marketing position. Results presented in tables 1 – 4 consistently show that a cash marketing strategy would on average, across the event window, result in significantly larger losses than those associated with short-hedges. In all four models $\tilde{B}_5$ is significantly more negative than $\tilde{\alpha}$ at the 1% level. In other words, cash storage positions would have generated on average potential losses 1% greater

(VAR 5% models) and potential losses 1.5% greater (VAR 1% models) than their short-hedge counterparts. Thus on average hedging is still preferred to a cash storage marketing strategy for holding periods encompassing the whole event window. Note further analysis would be required (taking into account possible interaction effects between marketing strategy and event window days) to determine if hedging effectively reduces risk on the event day itself (day $t=0$) or day $t=-1$. In a similar vein, speculative short-futures positions – like cash positions – would result in significantly larger potential losses compared with short-hedged positions.

Interestingly, in line with our *a-priori* expectations, results presented in tables 1 – 4 consistently indicate that – on average across the event window – hedging in Memphis market performs poorly compared to hedging in North Central Illinois market. In all four models $\tilde{B}_7$ is significantly more negative than $\tilde{\propto}$ at the 5% level. In other words, hedging corn in Memphis would have generated on average potential losses around 0.5% greater than hedging corn in North Central Illinois. Note further analysis would be required (taking into account possible interaction effects between marketing location, marketing strategy and event window days) to determine if hedging in Memphis market reduces risk on the event day itself (day $t=0$) or day $t=-1$ compared to a simple cash strategy.

On a final note, we find no statistical evidence to suggest that average event window potential losses associated with soybeans hedged in North Central Illinois differ from average event window hedged corn losses for that market. For example, in all four models $\tilde{B}_8$ is not significantly different from $\tilde{\propto}$ at conventional significance levels. However, as with the marketing strategy and location cases interaction effects would have to be examined to broaden our conclusions.

Endnotes

(1) http://usda.mannlib.cornell.edu/reports/nassr/field/pcp-bb/

(2) Given that grain elevators roll over nearby futures contracts during expiration months, the nearby corn price series used in this study comprise September contracts for August *Crop Production* reports, and December contracts for September, October and November reports. Similarly with respect to soybean prices series we use September contracts for August *Crop Production* reports, November contracts for September and October reports, and January contracts for November reports.

(3) This is not an unrealistic assumption as it is common industry practice for grain merchandisers and elevators to form naïve hedged positions where equal but opposite futures positions are held against cash positions.

References

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Table 1. Analysis of Variance (MVN VAR 5% Level)

Parameters	Estimate	Std. Error	T-Value	P-Value
A	-0.990	0.202	-4.890	<.0001
B_{-5}	-0.369	0.245	-1.500	0.135
B_{-4}	0.003	0.245	0.010	0.992
B_{-3}	-0.244	0.245	-1.000	0.322
B_{-2}	-0.006	0.245	-0.020	0.981
B_{-1}	-0.681	0.245	-2.780	0.006
B_0	-1.987	0.245	-8.100	<.0001
B_1	-0.029	0.245	-0.120	0.905
B_2	-0.094	0.245	-0.380	0.701
B_3	0.080	0.245	0.330	0.745
B_4	-0.001	0.245	-0.010	0.996
B_5	-1.246	0.128	-9.730	<.0001
B_6	-0.805	0.128	-6.290	<.0001
B_7	-0.366	0.105	-3.500	0.001
B_8	0.150	0.105	1.440	0.154
R-Square	0.664			

Table 2. Analysis of Variance (MVE VAR 5% Level)

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Parameters	Estimate	Std. Error	T-Value	P-Value
A	-0.988	0.151	-6.560	<.0001
B_{-5}	-0.494	0.182	-2.710	0.008
B_{-4}	0.002	0.182	0.010	0.990
B_{-3}	-0.088	0.182	-0.480	0.630
B_{-2}	0.015	0.182	0.080	0.935
B_{-1}	-0.228	0.182	-1.250	0.215
B_0	-2.119	0.182	-11.610	<.0001
B_1	0.079	0.182	0.430	0.665
B_2	-0.051	0.182	-0.280	0.779
B_3	0.107	0.182	0.590	0.559
B_4	0.052	0.182	0.280	0.777
B_5	-1.094	0.095	-11.480	<.0001
B_6	-0.857	0.095	-8.990	<.0001
B_7	-0.229	0.078	-2.950	0.004
B_8	0.111	0.078	1.430	0.155
R-Square	0.776			

Table 3. Analysis of Variance (MVN VAR 1% Level)

Parameters	Estimate	Std. Error	T-Value	P-Value
A	-1.406	0.279	-5.040	<.0001
B_{-5}	-0.528	0.338	-1.560	0.121
B_{-4}	-0.017	0.338	-0.050	0.959
B_{-3}	-0.381	0.338	-1.130	0.262
B_{-2}	-0.023	0.338	-0.070	0.946
B_{-1}	-0.933	0.338	-2.760	0.007
B_0	-2.803	0.338	-8.300	<.0001
B_1	-0.085	0.338	-0.250	0.803
B_2	-0.131	0.338	-0.390	0.698
B_3	0.100	0.338	0.300	0.767
B_4	-0.048	0.338	-0.140	0.887
B_5	-1.675	0.176	-9.500	<.0001
B_6	-1.123	0.176	-6.360	<.0001
B_7	-0.487	0.144	-3.380	0.001
B_8	0.186	0.144	1.290	0.198
R-Square	0.663			

Table 4. Analysis of Variance (MVE VAR 1% Level)

Parameters	Estimate	Std. Error	T-Value	P-Value
A	-1.520	0.681	-2.230	0.027
B_{-5}	-0.802	0.824	-0.970	0.333
B_{-4}	0.289	0.824	0.350	0.726
B_{-3}	-0.920	0.824	-1.110	0.268
B_{-2}	0.112	0.824	0.140	0.892
B_{-1}	-2.685	0.824	-3.260	0.002
B_0	-2.305	0.824	-2.800	0.006
B_1	-0.377	0.824	-0.460	0.649
B_2	-0.279	0.824	-0.340	0.736
B_3	0.339	0.824	0.410	0.682
B_4	-0.460	0.824	-0.560	0.578
B_5	-1.773	0.431	-4.120	<.0001
B_6	-1.056	0.431	-2.450	0.016
B_7	-0.756	0.352	-2.150	0.034
B_8	0.141	0.352	0.400	0.688
R-Square	0.306			