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Is "Good Enough" Good Enough when Hedging Agricultural Commodities?

Abstract

This paper explores the returns to grain producers and processors of expending efforts to determine hedge ratios. We use cash and futures prices from Barchart.com and multi-location cash prices from the Daily Grain Review to determine if location-specific hedge ratios are superior to hedge ratios estimated for a central location then used for hedging at the specific location. We find that the price-risk management capabilities of single location hedge ratios computed the Barchart data perform well in hedging grains at other locations. This suggests that producers and processors should not invest heavily in determining precise hedge ratios that apply to a particular location. In other words, "good enough" hedge ratios are in fact good enough.

Keywords: hedging, cross-hedging, localized basis, price-risk management.

Is "Good Enough" Good Enough when Hedging Agricultural Commodities?

Any agent who deals in commodity markets must decide on the amount of resources to devote to managing commodity price risk. These price-risk management decisions might result in: a) accepting currently prevailing price risk, b) employing a one-to-one direct hedging strategy, c) determining and utilizing a risk-minimizing hedge ratio, d) hiring a consult to find the risk-minimizing hedging strategy, or e) hiring a staff of econometricians and analysts to devise sophisticated dynamic hedging strategies. According to economic principles the marginal cost of the resources employed in devising a price-risk management strategy should equal the marginal benefit of the price-risk reduction received. While the marginal cost and marginal benefit of the resources devoted to price-risk management are firm and situation specific and therefore difficult to assess, the marginal price-risk reduction of incrementally more-costly hedging strategies can be estimated. That is the focus of this paper.

More pointedly, we investigate the price-risk management returns of bringing increasingly more detailed data into the hedging decision. For example, suppose a commodity producer or processor decides to reduce price risk. One hedging strategy is to adopt a one-unit futures position to offset each unit of cash position. This strategy incurs no costs for data acquisition and data analysis. In a cross-hedging context, the producer/processor might adapt a "rule of thumb" hedge ratio that also incurs no data acquisition/analysis costs.

At greater data acquisition and analysis cost, our agent could acquire futures and cash price data from a publicly-available source and estimate risk-minimizing hedge ratios for the commodity of interest or scour the literature and websites to find hedge ratio recommendations. More costly still, our agent might realize that the hedge ratios found in the previous investigation do not apply to the local market where the effective price is determined. If the agent deems that the localization of hedging is important, then location-specific cash prices are required for hedge ratio estimation. The costs incurred in obtaining these hedge ratios would include collecting and analyzing local cash price data and the effort would likely require an understanding of basic statistics or econometrics.

This study evaluates these efforts in terms of in terms of price-risk reduction attributable to acquiring and analyzing localized spot price data in formulating a hedging strategy. Alternatively stated, we seek to determine if nonlocal hedging strategies are "good enough" even though cash prices are determined at least partially in the local market. In doing this, we distinguish between "good enough" (GE) hedge ratios and optimal hedge ratios. A "good enough" hedge ratio is defined as one that is easily computed and executed but is not necessarily unitary. While this work does not diminish the importance of optimal hedge ratios, the marginal contribution to risk management in moving from a GE hedge ratio to an optimal one may not warrant the additional analytical effort.

We proceed by first reviewing the hedging concepts and the literature on hedging. We then move to data considerations where we describe a source for local cash prices and a source for nonlocal (central market) cash prices. These considerations are the core of this study because the issue of "good enough" revolves around data acquisition and analysis costs. Third, we will focus on the results of the data as we compare generic hedge ratios to location-specific hedge ratios. Finally, we will summarize and draw implications from our analysis.

Conceptual Approach

Our conceptual representation of the hedger's decision follows Johnson (1960) and Stein (1961). Hedging models assume an agent has a given position of X_s units in the spot market for a commodity. The position can either be long ($X_s > 0$) when the agent has or will have commodity to sell, or short ($X_s < 0$) when the agent anticipates the futures purchase of the commodity. The gain or loss on the position associated with the passage of time is $X_s\ \Delta S$ where S represents the commodity's spot price and ΔS represents the price change over the time that the position is held.[1] The price risk of the unhedged position is due to the unforeseeable movements in S (S_t). S_t is represented as a random variable to express this unpredictable behavior. Using variance as the measure of risk gives $X_s^2\ V(\Delta S)$ as the price risk of the unhedged position.

The agent can choose to hedge by creating a portfolio consisting of the spot position and an X_f unit futures position. The gain or loss on the portfolio is $\pi = X_s\ \Delta S + X_f\ \Delta S$. Following Johnson and Stein, the futures position is selected to minimize the variance of the return to the portfolio, where $V(\pi) = X_s^2\ V(\Delta S) + X_f^2\ V(\Delta F) + 2\ Cov\ (\Delta F, \Delta S)$. The risk-minimizing hedge ratio is $b = X_f / X_s = -\ V(\Delta F)^{-1}\ Cov(\Delta F, \Delta S)$, where $V(\Delta F)$ and $Cov(\Delta F, \Delta S)$ respectively represent variance of ΔF and the covariance between ΔF and ΔS. Ederington (1979) demonstrates that the parameter estimates in the regression $\Delta S = \alpha + \beta\ \Delta F + \varepsilon$ provide empirical hedge ratio(s). Ederington further demonstrates that the regression R^2 measures hedge effectiveness, defined as the proportionate reduction in price risk attributed to hedging.

Anderson and Danthine (1980, 1981) generalized the Johnson, Stein and Ederington approach by modeling positions in multiple futures contracts and assuming a mean-variance utility maximization objective. In the multivariable case, X_f is a vector representing the set of futures market positions. Anderson and Danthine demonstrate that the empirical risk minimizing hedge ratios are still $b = X_f / X_s = - V(\Delta F)^{-1} Cov(\Delta F, \Delta S)$ where $V(\Delta F)$ now represents the variance-covariance matrix of price changes for the set of futures contracts under consideration as hedge vehicles, and $Cov(\Delta F, \Delta S)$ represents the covariance matrix between the set of hedge vehicles and the spot price. In this case, b is a vector conformable with ΔF. The Anderson and Danthine approach is useful for modelling cross-hedging and process hedging.

Variations of this model in the academic literature include alternative error specifications such as serially correlated residuals, ARCH and GARCH error behaviors, and error correction specifications (Lien and Shrestha, 2008; Wang, Y., C. Wu., and L Yang, 2015). Other lines of investigation have examined the constancy of hedge ratios over time and have led to the estimation of time-varying hedge ratios (Moschini and Myers, 2002; Prokopczuk, 2011; Tejeda and Goodwin, 2014). A third line of research has examined issues related to applying this model to hedging various commodities. These last studies have led to consideration of such issues as the selection of the hedge horizon, the implementation of the model in a commodity-processing context (Tzang and Leuthold,1990; Fackler and McNew, 1993; Dahlgran 2005), and selection of futures contracts for cross hedging (Dahlgran, 2000; Rahman, Turner, and Costa, 2001; and Franken and Parcell, 2003; Movafaghi 2014).

Good enough hedge ratios derive from the traditional portfolio-hedging model. Let $S = P + d$ so that S the local spot price is composed of P, a base price applicable to a central location, and d the differential between the central market price and the local price. d may be fixed, completely random, cyclical, time dependent or some combination of these behaviors. Appling the definitions from the traditional model, $\Delta S = \Delta P + \Delta d$, $\pi = X_s (\Delta P + \Delta d) + X_f \Delta S$, and $b = X_f / X_s = - V(\Delta F)^{-1} Cov(\Delta F, \Delta P + \Delta d) = - V(\Delta F)^{-1} Cov(\Delta F, \Delta P) - V(\Delta F)^{-1} Cov(\Delta F, \Delta d) = b_1 + b_2$. Hence, our optimal hedge ratio (b) consists of b_1, a hedge ratio for the central market price, plus b_2, a localizing adjustment to the base hedge ratio. b_1 is the “good enough” hedge ratio. It is valued because it is broadly based and is applicable for all of the agents who face a localized price that is based on the central market price.

We will compare GE hedge ratios to optimal hedge ratios for corn, soybeans, soybean oil, soybean meal, wheat, and oats. These commodities are chosen because of their importance and because the USDA / Agricultural Marketing Service publishes prices at selected locations for these commodities (S_t) while a commodity reporting services publishes central market prices for these exchange-traded commodities (P_t). Both price series are published with sufficient frequency to determine the central market hedge ratio and the localizing adjustment to the hedge ratio. This relationship will allow us to answer the question posed in the title of this paper. .

Data

Our data come from two sources. One dataset was compiled from a Barchart.com subscription. This subscription provided a database of daily futures and spot prices spanning the January 1, 1990 through Dec 31, 2014 time period. Observations consist of daily open, high, low, and settlement prices and trading volume and open interest for all tradable futures maturities of 193 different commodities. The database also includes cash prices for some commodities although the daily open, high, low and settlement prices are identical for the cash quotes and cash-market volume and open interest are not reported. The price quotes in this database are those published in the financial press, for example The Wall Street Journal and the futures price quotes are also available from sources such as the Chicago Mercantile Exchange. These data will be referred to as Barchart data and the cash price quotes are observations of central market prices.

Our other data source was the USDA Daily Grain Review (DGR) published by the Agricultural Marketing Service. This report contains daily high and low cash prices for corn, hard red winter wheat, soft red winter wheat, hard red spring wheat, oats, soybeans, soybean oil, and soybean meal at various locations around the United States. These data span the January 1, 2007 through Dec 31, 2014 time period.

Table 1 shows the commodities whose prices are drawn from the Barchart data and locations reported in the Daily Grain Review. This table indicates two possible cash-futures price pairings for estimating hedge ratios. Matching Barchart cash and futures prices provides generic hedge ratios that apply the Barchart central market location, while matching Barchart futures prices with location-specific DGR cash prices provides location-specific hedge ratios. The central issue of this paper is whether the generic-location hedge ratios estimated from the Barchart data are "good enough" for hedging in specific locations.

We make several assumptions that influence the data drawn from the two datasets. First, holidays and market closures result in occasional missing values. If a day's cash or futures price is not available due to a holiday or other market disruption, then the previously available price replaces the missing price. Other than for Monday holidays (Labor Day, Memorial Day), this procedure resulted in the occasional use of one day lagged prices even though this rule potentially dictates longer time lags.

Second, hedge horizons of one, two, four and thirteen weeks were selected. These horizons represent hedging applications in grain merchandising and processing. Hedge horizons of longer duration, for example nine months to one year, that would be used by a grain grower are not analyzed because the DGR data spans eight years and does not provide enough observations to reliably analyze long-term hedging outcomes.

Third, Wednesday was selected as the transaction day within each hedge cycle. This choice minimizes the effect that weekends might have on the price formation process and also avoids data that is missing because of the Thanksgiving holiday.

Finally, the nearby maturity at the time of hedge termination was used as the futures contract for each hedge provided that the nearby maturity at hedge termination is more than a week from its last trading day. If the last trading day of the nearby maturity at hedge termination was less than a week away, then the next maturity is used.[2]

These procedures resulted in complete series of matched pairs of ΔS_t and $\Delta F_{M,t}$. and ΔP_t and $\Delta F_{M,t}$. The ΔS_t can represent any of the eight commodities listed in table 1 at a central market location and come from the Barchart dataset. The ΔP_t come from the DGR dataset where locations are specified. The $\Delta F_{M,t}$ are drawn from the Barchart data set can represent any of the eight commodities listed in table 1.

Analytical Procedures

Our data analysis proceeds as follows. We first perform some preliminary analyses such as checking for unit roots, and checking for redundancy of the Barchart cash price series in the DGR data sets. We then determine a general hedge ratio regression that applies across all commodities. Next we estimate central market hedge ratios, and finally we test if these hedge ratios apply at other locations.

As the dependent variables in hedge ratio estimation, the cash prices were examined for unit roots using the Dickey-Fuller test (Dickey and Fuller, 1979, 1981; Fuller 1976). This is done to insure that spurious correlation between co-integrated series does not bias our results. While the hypothesis that weekly cash prices display a unit root was not consistently rejected, this hypothesis was rejected for the first differences in each of the cash price data series listed in table 1. As the regression models are formulated in first differences, the rejection of the unit root hypothesis for these series is equivalent to ruling out cointegration and its resulting biases.

In comparing the two data sources, we posit that the Barchart cash-price series for a commodity might correspond to one of the DGR series for the same commodity. This possibility was tested by fitting the model

(1) $\Delta S_t = \alpha + \beta \, \Delta P_t + \varepsilon_t$

to each Daily Grain Review series where S_t is the DGR spot price at time t, P_t is the Barchart spot price at time t, and Δ indicates a one-week time interval. Table 2 summarizes estimation results for each commodity and DGR location.

A unitary R^2 is a necessary for the series to be identical but a unitary R^2 could also indicate that the series vary in a proportional or even an inverse relationship. The R^2s reported in table 2 are generally in the 0.7 to 0.9 range indicating that the two series are highly correlated but no DGR series appears be perfectly correlated with its Barchart counterpart. Oats in Minneapolis ($R^2 = 0.372$) and wheat in S. Peoria on the Illinois River ($R^2 = 0.044$) are two notable exceptions to the generally observed high R^2.

A second condition for the two series to be identical is $\alpha = 0$ and $\beta = 1$ in (1). Table 2 shows the F statistics and corresponding probabilities of a larger F for H_0: $\alpha = 0$, $\beta = 1$ in (3). We fail to reject this hypothesis for soybeans, soybean oil, and soybean meal in Central Illinois (R^2 respectively of 0.918, 0.972, and 0.725), soybeans in Cincinnati, Kansas City and Omaha (R^2 of 0.854, 0.715, 0.845), and Minneapolis wheat in Minneapolis (R^2 of 0.934). These results seem to indicate that while the Barchart series are similar to some corresponding DGR series, DGR data do not perfectly match any Barchart series. Thus, we use each Barchart series to represent the central market cash price in the hedge ratio estimation regression. The Barchart data offer the added advantage of consistency with and similarity to the futures price data.

Next, we formulate a preliminary hedge-ratio model, seeking one model that fits all of the commodities well. Our preliminary candidate is

(2) $\Delta P_t = \alpha + \mu_m M_t + \beta_m M_t \times \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho\, \varepsilon_{t-1} + \upsilon_t$

where M_t is a dummy variable representing the maturity month of the nearby futures contract at time t, μ_m is the mean effect of nearby maturity M on the change in the commodity's spot price, β_m is the hedge ratio applicable to nearby futures contract M, and ε_t is the potentially serially correlated error. This model incorporates spot price change seasonality as contract maturity M is the nearby futures contract only during a specific part of the year.

From general specification (2), we select a more parsimonious model based on the statistical significance of various effects. We test the following hypotheses against the full model using the Barchart data:

H_1: $\rho = 0$.

H_2: $\beta_m = \beta$ for all M.

H_3: $\mu_m = 0$ for all M.

The results of estimating various forms of (2) and the results of testing H_1 through H_3 are summarized in Table 3. This table is arranged by hedge horizons (i.e., the magnitude of Δ) and then by commodity within the Δs. The results in table 2 indicate that in general (all commodities and all hedge horizons) H_1 and H_3 must be rejected, while the H_2 cannot be rejected. Thus, we select

(3) $\Delta P_t = \alpha + \mu_m M_t + \beta \, \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho \, \varepsilon_{t-1} + \upsilon_t$

as our base model. This model incorporates seasonality, serial correlation, and a hedge ratio that is invariant to the maturity month of the nearby contract.

The hedge ratios and effectiveness resulting from fitting (3) are shown in table 4. The hedge ratios accompanied with an * indicate situations when a one-to-one hedging strategy is statistically sub optimal.[3] This occurs with remarkable frequency over the shorter hedge horizons because the greater number of observations on the shorter hedge horizons results in lower standard of errors, and hence greater likelihood that a departure of β from unity will be detected.

We next seek to determine whether central market hedge ratios are good enough to use for hedging strategies at specific locations. We do this by estimating

(4) $\Delta S_t = \alpha + \mu_m M_t + (\hat{\beta}^* - \beta_{LOC}) \, \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho \, \varepsilon_{t-1} + \upsilon_t$.

where $\hat{\beta}^*$ represents the optimal hedge ratio estimated from the Barchart data and β_{LOC} represents a locational adjustment to the generic hedge ratio. Of primary interest in estimating this model is whether $\hat{\beta}_{LOC}$ is significantly different from zero as this indicates that hedging effectiveness is significantly improved by using a location specific hedge ratios.

Table 5 summarizes the results of estimating (4). This table is arranged by hedge horizon and location. The three statistics reported for each horizon/location combination are: (1) hedge effectiveness using the generic hedge ratio, (2) the locational adjustment to the generic hedge ratio with an indication of the statistical significance of this adjustment, and (3) the effectiveness increment associated with using the location-specific hedge ratio. Table 5 reveals that the use of the generic hedge ratio for each commodity generally results in high levels of hedge effectiveness and that the magnitude of the hedge ratio adjustment for each location is small in absolute terms. Table 5 also reveals that effectiveness gains from using location-specific are more likely to be significant in the wheat markets than in the corn or soybean markets.

Implications and Conclusions

Our objective in this paper was to determine if utilizing generic hedge ratios to hedging at specific locations would obtain price-risk protection that was "good enough". The notion of "good enough" incorporates the notion that more refined hedge ratios will require additional resources from the firm and for these additional resources, the firm might get additional risk protection. So the firm's decision is whether the incremental price-risk protection merited the additional allocation of resources. Underlying this decision process, is the uncertainty at the outset as to how much price-risk protection additional analysis would secure, uncertainty regarding existing hedge ratios which are only estimates of the true parameter, and similar uncertainty associated with even more refined estimates.

In light of these many uncertainties, hedgers typically adopt a one-to-one hedging rule. Our results indicate that this rule is suboptimal and is in fact not practical for cross-hedging applications as there is no obvious futures contract to use as a hedge vehicle.

The findings of this study help producers/processors, or at least those who deal in the markets for the commodities that we examined, as we find that hedge ratios estimated from prices at a central market are nearly the same as the risk minimizing ratios that would be estimated from price data for a more local market. Furthermore, even when the difference between local market hedge ratios and central market hedge ratios was statistically significant, the hedge ratio adjustment was small. We thus conclude that the "good enough" hedge ratios do appear to be good enough to use when hedging at a specific location. In addition to providing attractive levels of risk protection, the cost of developing "good enough" hedging strategies can be spread over the broader audience of agents to whom the resulting hedge ratios apply.

Table 1. Comparison of Barchart and Daily Grain Review price series.

Commodity (ID)	Barchart Cash Price	Barchart Futures Prices	Daily Grain Review (DGR) Cash Price Location[a]
Corn (C)	Cash corn	CBT corn	Central IL
			Chicago
			Processor Corn - Chicago
			Cincinnati-Ohio R
			Gulf
			Kansas City
			Memphis-Miss R
			Mt Vernon-Ohio R
			N. Peoria-Ill R
			Omaha
			S. Peoria-Ill R
			So IA-Miss R
			St. Louis-Miss R
			Toledo
			Toledo (not on river)
Oats (O)	Cash oats	CBT oats	Minneapolis
Soybeans (S)	Cash soybeans	CBT soybeans	Atlantic
			Central IL
			Chicago
			Cincinnati-Ohio R
			Gulf
			Kansas City
			Memphis-Miss R
			Mt Vernon-Ohio R
			N. Peoria-Ill R
			Omaha
			S. Peoria-Ill R
			So IA-Miss R
			St. Louis-Miss R
			Toledo
			Toledo (not on river)
Soybean Oil (BO)	Cash soybean oil	CBT soybean oil	Central IL
Soybean Meal (SM)	Cash soybn meal	CBT soybean meal	48 SB Meal - -Central IL
Wheat (KW)[b]	Cash wheat (KC)	Kansas City wheat	HRW - Gulf
			Ord HRW - Kansas City
			Ord HRW - PNW
			11.5 HRW - Portland
Wheat (MW)[c]	Cash wheat (MW)	MGE wheat	Minneapolis wheat
			14 DNS/NS - Minneapolis
			14 DNS/NS – Portland

Table 1 (Continued).

Commodity (ID)	Barchart Cash Price	Barchart Futures Prices	Daily Grain Review (DGR) Cash Price Location[a]
Wheat (W)[d]			
	Cash wheat (W)	CBT wheat	Atlantic
			Chicago
			Cincinnati-Ohio R
			Gulf
			Memphis-Miss R
			Mt Vernon-Ohio R
			S. Peoria-Ill R
			St. Louis-Miss R
			Toledo
			Toledo (not on river)

a/ The DGR also provides price quotes for crude corn oil and soft white wheat. Futures contracts on these commodities are not available preventing the analysis of direct hedging strategies. These two commodities are dropped from further consideration.

b/ Hard red winter wheat - the deliverable variety for the Kansas City Board of Trade wheat futures contract.

c/ Dark northern spring wheat - the deliverable variety for the Minneapolis Grain Exchange wheat futures contract.

d/ Soft red winter wheat - - the deliverable variety for the Chicago Board of Trade wheat futures contract.

Table 2. Tests for redundancy in Daily Grain Review data series.

ID	Location	R^2	Obs	F Stat[a]	Prob > F
C	Central IL	0.853	417	16.562	0.0000 ***
C	Chicago	0.881	417	4.546	0.0111 *
C	Chicago Processor Corn	0.931	417	5.592	0.0040 **
C	Cincinnati-Ohio R	0.834	417	12.071	0.0000 ***
C	Gulf	0.831	417	8.725	0.0002 ***
C	Kansas City	0.861	417	9.168	0.0001 ***
C	Memphis-Miss R	0.790	417	5.268	0.0055 **
C	Mt Vernon-Ohio R	0.838	417	4.210	0.0155 *
C	N. Peoria-Ill R	0.825	417	8.720	0.0002 ***
C	Omaha	0.887	416	7.584	0.0006 ***
C	S. Peoria-Ill R	0.844	417	7.019	0.0010 **
C	So IA-Miss R	0.869	417	11.626	0.0000 ***
C	St. Louis-Miss R	0.792	417	4.510	0.0115 *
C	Toledo	0.881	417	7.593	0.0006 ***
C	Toledo(not on river)	0.886	417	7.676	0.0005 ***
O	Minneapolis	0.343	361	127.432	0.0000 ***
S	Atlantic	0.854	417	10.421	0.0000 ***
S	Central IL	0.918	417	0.538	0.5845
S	Chicago	0.881	417	5.725	0.0035 **
S	Cincinnati-Ohio R	0.854	417	1.721	0.1802
S	Gulf	0.856	417	7.468	0.0007 ***
S	Kansas City	0.715	417	2.462	0.0865
S	Memphis-Miss R	0.838	417	7.774	0.0005 ***
S	Mt Vernon-Ohio R	0.884	417	5.477	0.0045 **
S	N. Peoria-Ill R	0.878	417	3.635	0.0272 *
S	Omaha	0.845	416	2.161	0.1165
S	S. Peoria-Ill R	0.730	417	3.779	0.0236 *
S	So IA-Miss R	0.860	417	6.341	0.0019 **
S	St. Louis-Miss R	0.828	417	4.357	0.0134 *
S	Toledo	0.894	417	9.146	0.0001 ***
S	Toledo(not on river)	0.890	417	7.407	0.0007 ***
BO	Central IL	0.972	417	1.138	0.3214
SM	Central IL	0.725	417	0.358	0.6996

Table 2. (Continued)

ID	Location	R^2	Obs	F Stat[a]	Prob > F
KW	Gulf	0.799	417	44.980	0.0000 ***
KW	Kansas City	0.814	417	46.815	0.0000 ***
KW	PNW	0.305	417	156.596	0.0000 ***
KW	Portland	0.777	417	57.987	0.0000 ***
MW	Minneapolis	0.934	417	1.803	0.1662
MW	Portland	0.314	417	38.645	0.0000 ***
W	Atlantic	0.573	417	45.763	0.0000 ***
W	Chicago	0.780	417	23.463	0.0000 ***
W	Cincinnati-Ohio R	0.773	417	41.363	0.0000 ***
W	Gulf	0.821	417	13.599	0.0000 ***
W	Memphis-Miss R	0.805	417	19.716	0.0000 ***
W	Mt Vernon-Ohio R	0.833	417	24.188	0.0000 ***
W	S. Peoria-Ill R	0.044	393	833.651	0.0000 ***
W	St. Louis-Miss R	0.929	417	4.457	0.0122 *
W	Toledo	0.794	417	36.278	0.0000 ***
W	Toledo(not on river)	0.794	417	37.083	0.0000 ***

a/ F-statistic for H_0: $\alpha = 0$ and $\beta = 1$ in $\Delta S_t = \alpha + \beta\ \Delta P_t + \varepsilon_t$

Table 3. Tests to establish a base model.

Δ	id	Model 0[a] sse (dfe)	Model 1[b] sse (dfe)	Model 2[c] sse (dfe)	Model3[d] sse (dfe)	H_1: $\rho = 0$ F-stat	H_2: $\beta_m = \beta$ F-stat	H_3: $\mu_m = 0$ F-statt
7 days	BO	29.81 (400)	30.39 (401)	31.10 (407)	32.15 (407)	7.8387 **	2.4881 *	31.4360 ***
	C	39201.33 (406)	40565.72 (407)	40009.44 (410)	39430.63 (410)	14.1307 ***	2.0924	2.3749
	KW	94306.26 (406)	105534.10 (407)	94653.52 (410)	95029.33 (410)	48.3372 ***	0.3737	3.1129 *
	MW	394519.86 (406)	398729.73 (407)	397857.02 (410)	404292.19 (410)	4.3324 *	0.8586	10.0567 ***
	O	103808.84 (406)	126066.74 (407)	104263.58 (410)	104776.24 (410)	87.0514 ***	0.4446	3.7835 **
	S	107417.31 (402)	107756.40 (403)	108991.12 (408)	113229.69 (408)	1.2690	0.9816	21.7523 ***
	SM	47792.66 (400)	48345.63 (401)	48556.37 (407)	49831.42 (407)	4.6281 *	0.9131	17.0633 ***
	W	111778.58 (406)	116425.15 (407)	115228.67 (410)	115816.69 (410)	16.8772 ***	3.1328 *	14.6671 ***
14 days	BO	24.78 (191)	25.36 (192)	26.31 (198)	28.44 (198)	4.4600 *	1.6793	28.2037 ***
	C	52875.82 (197)	54081.21 (198)	53613.48 (201)	54423.29 (201)	4.4909 *	0.6871	5.7654 ***
	KW	59394.03 (197)	64370.46 (198)	61057.98 (201)	60213.49 (201)	16.5060 ***	1.3798	2.7180 *
	MW	404440.49 (197)	410918.78 (198)	409227.29 (201)	425606.37 (201)	3.1555	0.5829	10.3097 ***
	O	22781.33 (197)	25835.89 (198)	22879.13 (201)	23680.12 (201)	26.4141 ***	0.2114	7.7722 ***
	S	115534.99 (193)	115916.08 (194)	118571.71 (199)	127087.25 (199)	0.6366	0.8455	19.2979 ***
	SM	46428.05 (191)	46741.30 (192)	49332.83 (198)	48450.16 (198)	1.2887	1.7071	8.3188 ***
	W	81277.80 (197)	83105.59 (198)	82991.15 (201)	88782.18 (201)	4.4302 *	1.0382	18.1890 ***
28 days	BO	23.58 (87)	23.65 (88)	25.07 (94)	28.27 (94)	0.2533	0.7824	17.2783 ***
	C	24096.53 (93)	24667.33 (94)	26150.91 (97)	25426.82 (97)	2.2030	1.9822	5.1342 ***
	KW	40274.24 (93)	42893.44 (94)	44324.27 (97)	42105.65 (97)	6.0482 *	2.3381	4.2290 **
	MW	362642.29 (93)	375283.23 (94)	373995.17 (97)	421097.08 (97)	3.2418	0.7279	14.9908 ***
	O	15982.06 (93)	15985.04 (94)	17081.59 (97)	16812.33 (97)	0.0173	1.5995	4.8313 **
	S	72211.77 (89)	73073.11 (90)	74732.61 (95)	85586.07 (95)	1.0616	0.5178	16.4836 ***
	SM	65423.85 (87)	77237.19 (88)	69134.61 (94)	75705.61 (94)	15.7093 ***	0.7049	13.6726 ***
	W	52866.93 (93)	52872.29 (94)	54963.51 (97)	64071.44 (97)	0.0094	0.9220	19.7102 ***
91 days	BO	19.51 (17)	19.52 (18)	29.91 (23)	33.16 (23)	0.0036	1.5100	11.8938 ***
	C	23367.90 (21)	24032.01 (22)	24144.71 (25)	31344.38 (25)	0.5968	0.1745	7.1682 ***
	KW	13502.26 (21)	13880.43 (22)	14983.86 (25)	18054.58 (25)	0.5882	0.5761	7.0802 ***
	MW	150813.36 (21)	155743.29 (22)	189544.15 (25)	205401.71 (25)	0.6865	1.3483	7.6012 ***
	O	7532.21 (21)	8297.35 (22)	9608.56 (25)	12964.64 (25)	2.1332	1.4472	15.1458 ***
	S	127657.53 (19)	128023.70 (20)	130400.09 (24)	240343.86 (24)	0.0545	0.0816	16.7718 ***
	SM	18465.75 (17)	18518.95 (18)	19617.87 (23)	31740.75 (23)	0.0490	0.1768	12.2213 ***
	W	48700.80 (21)	48860.34 (22)	67865.86 (25)	85005.83 (25)	0.0688	2.0660	15.6549 ***

Table 3 footnotes

a/ Model 0 is $\Delta P_t = \alpha + \mu_m M_t + \beta_m M_t \times \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho\, \varepsilon_{t-1} + \upsilon_t$

b/ Model 1 is $\Delta P_t = \alpha + \mu_m M_t + \beta_m M_t \times \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \upsilon_t$

c/ Model 2 is $\Delta P_t = \alpha + \mu_m M_t + \beta\, \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho\, \varepsilon_{t-1} + \upsilon_t$

d/ Model 3 is $\Delta P_t = \alpha + \beta_m M_t \times \Delta F_{mt} + \varepsilon_t$ where $\varepsilon_t = \rho\, \varepsilon_{t-1} + \upsilon_t$

Table 4. Hedge ratios and hedging effectiveness estimated from Barchart data.

Horizon:	7 days		14 days		28 days		91 days	
ID	HR[a] (std err)	Eff	HR[a] (std err)	Eff	HR[a] (std err)	Eff	HR[a] (std err)	Eff
BO	1.0148 (0.00846)	0.973	1.0194 (0.01079)	0.978	0.9959 (0.01584)	0.977	0.9829 (0.03888)	0.965
C	0.9600 * (0.02003)	0.849	0.9522 (0.03175)	0.817	0.9056 ** (0.03149)	0.895	0.8831 (0.06549)	0.879
KW	0.9959 (0.01999)	0.858	0.9994 (0.02514)	0.887	1.0172 (0.02964)	0.924	1.0466 (0.04053)	0.964
MW	0.9954 (0.03570)	0.655	1.0152 (0.05251)	0.650	0.9331 (0.07360)	0.624	0.9893 (0.14699)	0.644
O	0.9517 (0.04803)	0.489	0.9664 (0.03312)	0.809	0.9266 (0.04377)	0.822	0.9351 (0.07714)	0.855
S	0.9756 (0.01815)	0.876	0.9984 (0.02689)	0.874	1.0101 (0.03129)	0.916	0.9159 (0.08892)	0.816
SM	1.0940 ** (0.03571)	0.698	1.1500 ** (0.05395)	0.696	1.0282 (0.08845)	0.590	0.9849 (0.12108)	0.742
W	0.9514 * (0.02217)	0.818	0.9038 ** (0.02901)	0.828	0.9244 * (0.03380)	0.885	1.0043 (0.09243)	0.825

a/ *, ** and *** indicate probabilities 0.05, 0.01 and 0.001 of a greater t-value in testing H_0: $\beta = 1$.

Table 5. Location specific hedge ratios, by horizon.

Hedge horizon		7 days			14 days			28 days			91 days		
ID	Location	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}
C	Central IL	0.908	0.002	0.000	0.914	0.018	0.004	0.895	0.028	0.008	0.802	0.043	0.008
C	Chicago	0.861	0.017	0.002	0.864	0.030	0.005	0.900	0.043	0.020	0.913	0.027	0.003
C	Chicago Processor	0.860	-0.004	0.000	0.818	0.003	0.000	0.897	0.010	0.001	0.879	0.011	0.000
C	Cincinnati-Ohio R	0.835	-0.020	0.002	0.854	-0.004	0.000	0.864	0.016	0.002	0.825	0.019	0.002
C	Gulf	0.862	0.011	0.001	0.865	0.015	0.001	0.899	0.078 *	0.057	0.843	0.033	0.007
C	Kansas City	0.891	0.017	0.003	0.888	0.027	0.006	0.878	0.035	0.009	0.858	0.032	0.003
C	Memphis-Miss R	0.855	0.040	0.009	0.859	0.053	0.017	0.865	0.076 *	0.042	0.830	0.021	0.003
C	Mt Vernon-Ohio R	0.825	0.010	0.000	0.834	0.025	0.003	0.872	0.050	0.020	0.851	0.030	0.006
C	N. Peoria-Ill R	0.836	-0.003	0.000	0.843	0.001	0.000	0.870	0.040	0.012	0.826	0.030	0.005
C	Omaha	0.865	0.006	0.000	0.840	0.011	0.001	0.890	0.008	0.001	0.840	-0.006	0.000
C	S. Peoria-Ill R	0.844	0.003	0.000	0.856	0.012	0.001	0.882	0.051	0.022	0.824	0.024	0.003
C	So IA-Miss R	0.851	-0.016	0.002	0.834	0.002	0.000	0.870	0.023	0.005	0.845	-0.017	0.003
C	St. Louis-Miss R	0.808	0.009	0.000	0.839	0.022	0.003	0.870	0.063	0.027	0.858	0.028	0.005
C	Toledo	0.878	0.012	0.001	0.882	0.041	0.013	0.899	0.041	0.020	0.845	-0.034	0.009
C	Toledo(not on river)	0.876	0.009	0.001	0.881	0.034	0.009	0.903	0.044	0.024	0.846	-0.029	0.006
KW	Gulf	0.946	-0.024 *	0.010	0.949	-0.015	0.004	0.957	-0.021	0.010	0.933	-0.070	0.081
KW	Kansas City	0.957	-0.029 **	0.021	0.961	-0.029 *	0.025	0.972	-0.046 **	0.075	0.972	-0.097 ***	0.362
KW	PNW	0.160	-0.430 ***	0.281	0.586	-0.222 ***	0.124	0.538	-0.296 ***	0.239	0.754	-0.164	0.138
KW	Portland	0.917	-0.063 ***	0.050	0.931	-0.028	0.011	0.934	-0.026	0.010	0.941	-0.079	0.116
MW	Minneapolis	0.633	-0.007	0.000	0.626	-0.014	0.000	0.601	-0.008	0.000	0.580	-0.045	0.004
MW	Portland	0.362	-0.177 ***	0.028	0.456	-0.044	0.000	0.563	0.230 *	0.056	0.701	-0.119	0.046
W	Atlantic	0.643	-0.139 ***	0.054	0.589	-0.149 ***	0.060	0.637	-0.136 *	0.051	0.666	-0.039	0.000
W	Chicago	0.941	0.046 ***	0.035	0.930	0.107 ***	0.152	0.935	0.087 ***	0.108	0.956	0.029	0.019
W	Cincinnati-Ohio R	0.837	-0.055 **	0.019	0.807	-0.023	0.003	0.818	-0.008	0.000	0.871	0.082	0.038
W	Gulf	0.897	0.042 *	0.015	0.871	0.011	0.001	0.928	0.027	0.011	0.929	-0.046	0.030
W	Memphis-Miss R	0.882	0.017	0.002	0.855	0.014	0.001	0.895	0.044	0.018	0.882	-0.025	0.004
W	Mt Vernon-Ohio R	0.905	0.013	0.002	0.891	0.051 *	0.023	0.911	0.056	0.035	0.887	-0.003	0.000
W	St. Louis-Miss R	0.815	-0.003	0.000	0.836	0.008	0.000	0.871	-0.018	0.003	0.828	0.007	0.000
W	Toledo	0.955	0.014	0.005	0.944	0.086 ***	0.126	0.945	0.070 **	0.092	0.914	0.053	0.027

Table 5. (Continued).

Hedge horizon		7 days			14 days			28 days			91 days		
ID	Location	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}	eff_G	β_{LOC}	eff_{LOC}
W	Toledo(not on river)	0.955	0.012	0.003	0.945	0.083 ***	0.121	0.946	0.065 **	0.083	0.911	0.051	0.024
O	Minneapolis	0.542	-0.060	0.005	0.590	-0.068	0.008	0.632	-0.068	0.011	0.607	-0.103	0.029
S	Atlantic	0.892	-0.003	0.000	0.901	-0.011	0.001	0.930	-0.003	0.000	0.840	0.052	0.015
S	Central IL	0.828	0.022	0.002	0.865	-0.003	0.000	0.916	-0.001	0.000	0.820	0.049	0.012
S	Chicago	0.903	0.018	0.003	0.922	0.015	0.003	0.933	-0.020	0.006	0.858	0.075	0.037
S	Cincinnati-Ohio R	0.847	0.020	0.002	0.871	0.018	0.002	0.861	-0.025	0.004	0.814	0.023	0.003
S	Gulf	0.904	0.021	0.004	0.918	-0.015	0.003	0.904	-0.028	0.008	0.849	0.016	0.000
S	Kansas City	0.696	-0.021	0.001	0.735	-0.036	0.004	0.847	-0.047	0.014	0.829	0.026	0.004
S	Memphis-Miss R	0.884	0.009	0.001	0.902	0.004	0.000	0.903	0.001	0.000	0.841	0.060	0.021
S	Mt Vernon-Ohio R	0.892	0.010	0.001	0.920	0.006	0.000	0.920	-0.012	0.002	0.826	0.038	0.008
S	N. Peoria-Ill R	0.866	0.008	0.000	0.871	-0.030	0.006	0.906	-0.032	0.010	0.830	0.020	0.002
S	Omaha	0.796	-0.011	0.000	0.793	-0.046	0.009	0.854	-0.074	0.039	0.854	0.017	0.002
S	S. Peoria-Ill R	0.756	-0.001	0.000	0.777	-0.031	0.004	0.909	-0.016	0.003	0.806	0.034	0.005
S	So IA-Miss R	0.878	0.009	0.001	0.891	-0.025	0.006	0.917	-0.038	0.017	0.822	0.015	0.001
S	St. Louis-Miss R	0.883	0.032	0.008	0.899	-0.003	0.000	0.902	-0.027	0.007	0.824	0.034	0.006
S	Toledo	0.878	-0.010	0.001	0.891	-0.010	0.001	0.890	-0.038	0.012	0.888	0.079	0.056
S	Toledo(not on river)	0.870	-0.008	0.000	0.888	-0.006	0.000	0.889	-0.035	0.010	0.887	0.074	0.049
BO	Central IL	0.955	-0.007	0.001	0.970	-0.007	0.001	0.972	-0.011	0.005	0.964	-0.001	0.000
SM	Central IL	0.488	-0.016	0.000	0.470	-0.098	0.008	0.591	0.000	0.000	0.742	0.000	0.000

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Footnotes

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[1] This time horizon is more succinctly referred to as the hedge horizon. The length of the horizon is implicit in Δ.

[2] This rule insures that the maturity in the term $\Delta F_{M,t}$ is constant so that $\Delta F_{M,t}$ is the change in the price of a contract with a given maturity and not the change in the price of the nearby contract as this may involve a different maturity at two different points in time.

[3] Tests of $\beta = 1$ are more interesting in this context than are test of $\beta = 0$ as the former is a test of the one-to-one hedging strategy while the latter tests no hedging effectiveness.