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## **Hedgers' Participation in Futures Markets Under Varying Price Regimes**

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*Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's  
2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012.*

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## **Hedgers' Participation in Futures Markets Under Varying Price Regimes**

### **Abstract:**

Futures markets provide an important outlet for commercial traders to hedge their price risk; in turn, hedgers' connections to the physical market provide a foundation of market fundamentals to the futures markets. Participation by hedgers in the futures markets is important for both entities, and is subject to many factors. In this paper, we sought to study potential changes in hedgers' behavior by observing the changing relationship between their futures market positions and their physical grain stocks. This changing relationship was tested using a smooth-transitioning structural model that used data from the wheat contracts on the Chicago and Kansas City exchanges. In Chicago, we find stable levels of incremental hedging that significantly decline when futures price volatility is high and when delivery basis weakens significantly. Additionally, hedging participation has declined in recent years, coinciding with the commodity price boom. In the Kansas City contracts, in contrast, hedging behavior increased with high futures prices and, surprisingly, with increased futures price volatility. Overall, we were able to observe ostensible changes in hedgers' market participation under changing market conditions.

**Keywords:** hedging, commodity markets, volatility, smooth-transition

**JEL codes:** Q13, C32

# Hedgers' Participation in Futures Markets Under Varying Price Regimes

*Daniel J. Sanders and Timothy G. Baker*

## **I. Introduction**

Futures markets for commodities are widely acknowledged to serve two core functions: price discovery and risk management. Price discovery is accomplished by market participants evaluating all available information and bidding until an equilibrium price is achieved. In this process, traders that participate in the markets to hedge their price risk, i.e., hedgers, play an important role in tying the futures markets to the physical markets. The hedgers' knowledge of the underlying market fundamentals, coupled with the delivery process for settling contracts, ensure the derivatives of the futures markets remain connected to the physical products. This participation is critical to the health and continued functioning of the futures markets, as described by the classic papers of Working (1953, 1960). Although speculative participants are also important contributors to the functionality of futures markets, particularly for liquidity reasons, as a class of trader they alone cannot support a futures market.

Hedgers participate in futures markets to manage their price risk, the other principal role of the markets. Futures markets provide the ability to hedge by taking position in the market as a temporary substitute for an intended future transaction in the cash market. In this way, hedgers are able to push this portion of their price risk into the market, as any losses (or, alternatively, any gains) in the cash market are presumably offset by matching gains (losses) in the futures markets. Hedging with futures contracts has been at the core of the price risk management programs aimed at agricultural producers for many years by agricultural economists (for one practical example, see Hurt and Wisner, 2002), with the intent to help producers better shelter their businesses from the volatility of the larger market. Thus, we can see a symbiotic

relationship between futures markets and hedgers that is important to the everyday business functioning of both entities.

The importance of price risk management through hedging has been of continued interest to researchers for many years. Most of the research in this area has been focused on deriving and estimating the optimal hedging ratio, which is the proportion of the cash market commodity to be hedged in the futures market. The classic mean-variance ratio developed by Johnson (1960) is derived by minimizing the variance of a portfolio of cash and futures positions, and is the basis for many of reformulated measures by subsequent researchers. Numerous ratios have been developed, covering everything from classical minimum variance of prices received (Myers and Thompson, 1989) to incorporation of risk aversion through expected utility (Lence, 1995) to minimizing total profit risk (Kim, et al., 2010). A useful review of the research into optimal hedging ratios can be found in Chen, et al. (2003).

Of particular interest here is comparison of predicted optimal hedge ratios with empirical observations of producer behavior, in which producers are found to hedge notably less than what is considered theoretically optimal (Shapiro and Brorsen, 1988). Turvey and Baker (1990) focused on the role of government support programs and farm finances in a mathematical program aimed at explaining the difference; Wang, et al. (2004) incorporated government programs and insurance in their program. In both cases, market frictions such as liquidity constraints and government support were shown to have depressive effects on the hedge ratio.

In the case of this paper, our focus is on the effect of price volatility and generally high price levels on hedgers' actions. Anecdotally, there are reports that the incredible liquidity costs of meeting margin calls in volatile, high-priced markets are pushing traditional hedgers' to seek new avenues of risk protection, or even to forgo some portion of protection. If such reports were

true, then the removal of hedging trades from the market could have notable implications for the functioning of the markets. There is some theoretical support for this as well, if we consider Johnson's simple mean variance hedge ratio:

$$MV \text{ hedge ratio} = \rho \frac{\sigma_s}{\sigma_f} \quad (1)$$

Here,  $\rho$  is the correlation between the futures and spot markets,  $\sigma_s$  is the standard deviation of the spot market, and  $\sigma_f$  is the standard deviation of the futures market (Johnson, 1960). If the futures market has increased volatility, increasing  $\sigma_f$ , or if the correlation between the two markets decreases, then the hedge ratio will decline, holding other factors constant. Although this paper is not directed at hedge ratios specifically, this simple example demonstrates that if market conditions change and provide less adequate price protection, then hedgers' use of these markets should be expected to decline.

Accordingly, the use of the futures market for hedging purposes should be observable through the relationship between commercial open interest in the futures market and physical stocks of the commodity. The positive correlation between futures open interest and physical stocks has been examined in the past, notably by Irwin (1935), Working (1953, 1960), and Peck (1980), generally in support of the importance of hedgers to market performance and to counter the accusation of speculative manipulation and control.

This research seeks to take a new perspective on understanding changes in hedgers' behavior. Instead of surveying farmers about market participation or constructing expected utility or profit maximization models, we seek to test hypotheses using the observed actions of the participants in the market. Our approach tests an econometric model of hedger motivations to determine if changes in hedger behavior can be detected by changes in their participation in the futures market. The structural model for this paper is presented in the next section, while

section three details the data used in this research. The results of the models show support for the methodology presented, and conclusions and future extensions are presented in the final section.

## **II. Structural model**

The structural model developed in this paper is intended to link hedgers' risk mitigation actions to their participation in the futures markets. The specification of this model is based on two propositions, which will serve as maintained assumptions throughout the model's construction, estimation and testing:

- 1. Hedgers participate in the futures market only to hedge risk.*
- 2. Whenever possible, hedgers move price risk off their books upon receipt, either into forward contracts or into the futures market.*

Of these two points, the first is straightforward and only weakly limiting. Participants trading on organized exchanges are required to identify themselves to the U.S. Commodity Futures Trading Commission (CFTC) as either commercial traders (broadly, hedgers) or non-commercial traders (broadly, speculators). As the classification determines financially important restrictions on position limits and margin requirements, proper identification of trading activity is essential and carries penalties for traders that fail to properly identify themselves. Notably, commercial traders are presumed to pose less counterparty risk given their ties to the physical market and have lower margin requirements as a result. So, it is not economically rational that a hedger would misidentify as a speculator and pay the higher transactions cost. Essentially, Proposition 1 assumes that all observed commercial trading covers all hedging trades and only hedging trades.

The second proposition is more involved than the first. While Proposition 1 only requires that hedgers follow the reporting rules and act in their own best economic interest, Proposition 2 necessitates a more detailed description of price risk. For this assumption, hedgers only have to

bear the price risk of a commodity, while not necessarily possessing the physical commodity in and of itself. The physical commodity could be held by another party to whom the hedger is contractually tied, or even still be in the production process. We can see this distinction in the example of a corn producer that is setting a price-protecting hedge on his corn in March. The producer pushes off some of the price risk for the year's crop into the futures market, getting it off of his own books, even though the crop is still growing. Similarly, we might imagine this producer signing a forward sales contract with his local elevator for corn to be delivered and paid for in December. The elevator is now holding the price risk and by standard practice will hedge this exposure in the futures market, moving the risk off their books even though they have no grain in hand, only the contract to receive it. In either case, the price risk has been moved into the futures market. It is worth recalling at this point the earlier literature on the limited use of futures by farmers. This note is a limitation of the model framework, and it should perhaps be better described as participation by *active* hedgers.

Working from these two propositions, then we can then infer that the only reason that a hedger would change his or her futures market position is because his or her quantity of price risk has changed. From this, a testable, structural model can be constructed:

$$\Delta(\textit{open interest})_t = \beta_0 + \beta_1 \Delta(\textit{stocks})_t + \varepsilon_t \quad (2)$$

Here,  $\Delta(\textit{open interest})_t$  is the change in commercial open interest in a commodity futures market, and  $\Delta(\textit{stocks})_t$  is the change in the stocks of that commodity for which hedgers hold the price risk. Based on the propositions and the workings of the market, we can hypothesize about the signs and size of the coefficients.  $\beta_0$  is hypothesized to be zero, such that there are not systematic influences other than changes in stocks directing changes in commercial open interest.  $\beta_1$  is hypothesized to be the percentage of stocks normally hedged by active traders in

the futures market. In a market in which there is no uncertainty in production, forward contracts between supply chain members are not available, and there are no frictions or transactions costs to participating in the futures market, we would expect that  $\beta_I$  would approach one given risk adverse market participants. With the addition of forward contracts that directly connect producers to end users,  $\beta_I$  would reflect the split between forward and futures contracts. Given market frictions, competing optimization goals, portfolio diversification and correlated costs, and the previously noted relatively low levels of forward marketing by farmers,  $\beta_I$  is expected to be much smaller, while still bounded by zero and one. Additionally, we might expect that  $\beta_I$  adjusts under changing market conditions; if so, the structural model might be best described using a framework that allows for flexible parameter estimation.

### **III. Data**

The open interest data for this research comes from the weekly Commitment of Traders (COT) report issued by the CFTC. This report breaks out open interest in long, short and spread (for non-commercials only) positions, as well as total, “old,” and “other” open interest. Old open interest contains open interest in the current old crop futures only, while other open interest is for all other traded contracts.<sup>1</sup> COT reports are available for futures market positions only, as well as for futures and options positions combined, with options positions turned into equivalent synthetic futures positions through their delta values. The data used here covers the time period 1986 through 2010 (CFTC 2011), a total of 1,115 weeks.<sup>2</sup>

Preliminary testing pared the data down to provide the sharpest perspective possible, consisting of short commercial open interest, using ‘all’ contracts from the futures-only data set. The short positions reflect the majority of hedging position, and all contracts encompass both

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<sup>1</sup> For wheat, the main contract that we examine here, the first and last contract months in the crop year are July and May, respectively.

<sup>2</sup> The report was issued bi-weekly until October, 1992.

stored grain that has been hedged as well as expected future production. The exclusion of the options contracts is one weakness, as hedging activity does occur in these contract markets. However, the majority of hedging is futures based, and this data set is more extensive than the combined data set, extending an additional nine years into the past as the combined data is available only as far back as 1995.

The stocks data poses a greater challenge, as the stocks needed are those for which active hedgers hold the price risk, which could include stocks currently in storage, expected production from the current crop, or even expected production from future crops. Overall, expectations of future stocks are difficult to measure, with perhaps the best regular estimates being the estimated production numbers provided in the World Agricultural Supply and Demand Estimates (WASDE) reports issued monthly by the World Agricultural Outlook Board. These reports provide a balance sheet for commodities, including beginning supply, estimated production, trade, use and consumption, and expected ending stocks (USDA, 2011b). Quantities of actual stocks on hand are reported quarterly by the National Agricultural Statistics Service (NASS), which details total stocks as well as breaking down on- and off-farm stocks (USDA, 2011a). These reports lack the anticipated bushels, but provide an excellent estimate of available grain.

Preliminary testing of the WASDE models found relatively poor performance of the model, and for this report we focus on the NASS stocks reports. One of the additional advantages to the WASDE reports is the breakdown of wheat production and stocks by class. Although wheat is sometimes generically referred to as a single commodity, it is composed of a number of varieties, or classes, each with their own growing season, protein content, color and usage. High protein hard red spring wheat planted in spring in the Dakotas may be used for bread flour, while low protein soft red winter wheat may be planted in Ohio after corn in the fall

and be used for cake flour. Futures contracts are specified to a particular wheat class and some of smaller production classes may have no available futures contract at all. As the NASS data does not provide class-level support, the stocks reports for different classes of wheat were compiled by combining state level stocks reports based on the class which produced the majority of the wheat in that state.<sup>3</sup>

#### **IV. Model testing and estimation**

For this preliminary examination, we focus on the hard red winter wheat market, whose contract is traded on the Kansas City Board of Trade (KCBOT), and on the soft red winter wheat market, the contract for which is traded on the Chicago Board of Trade (CBOT). The hard red spring wheat contract on the Minneapolis Grain Exchange (MGE) was considered in early models, but was dropped due to its inconsistent performance, likely the result of its very thin trading.

The first step in estimating the structural model in Equation 2 was preparing the data to fit the model. The weekly COT data series was pared down to match the quarterly NASS stocks data, using the first open interest observation occurring after the official date of the stocks estimates. The stocks data were transformed from thousand bushel units into five thousand bushel units to match up with futures contracts; thus both variables in are in contract-sized units. One of the convenient features of the structural model is that it is constructed in first differences by theory. Stationarity testing using the Augmented Dickey-Fuller test found all of the first differenced data series to be stationary, eliminating any need to further manipulate the data to achieve zero-order integration.

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<sup>3</sup> Hard red winter wheat states were Kansas, Nebraska, Oklahoma, Texas, Colorado, Utah, New Mexico and Wyoming. Soft red winter wheat states were Ohio, Michigan, Illinois, Indiana, Missouri, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, North Carolina, Virginia, Maryland, Kentucky, Tennessee and Delaware.

Of particular interest in the structural model is the potential for changes in the parameter on the stocks variable,  $\beta_I$ . If hedgers' participation with the futures market was changing, then this parameter should be in flux. In particular, this paper employs the smooth-transition model, often referred to as the STAR model, which provides a model that allows the parameters to smoothly transition between values based on the underlying data regime (Lin & Teräsvirta, 1994; Teräsvirta, 1994). STAR models have been used in studying commodity markets before (see Holt and Craig, 2006 and Balagtas and Holt, 2009), but have not been employed in studying transitions in open interest. The general form of the model is:

$$y_t = [\beta_0 + \beta_1 x_t] + [\alpha_0 + \alpha_1 x_t] * G(s_t; \gamma, c) \quad (3)$$

Here,  $y_t$  is the first difference of commercial open interest,  $x_t$  is the first difference of physical stocks, and  $G(s_t; \gamma, c)$  is a smoothly transitioning function bounded by zero and one. The variable  $s_t$  is the transition variable that governs which underlying structure applies, and  $\gamma$  and  $c$  are estimated parameters that determine the speed and timing of the transition, respectively. The two general transition functions employed were the logistical (LSTAR) and exponential (ESTAR). Under the LSTAR specification, when  $s_t$  is considerably smaller than  $c$ , the function approaches zero, while when  $s_t$  is considerably larger than  $c$ , the function approaches one; the function is also able to take any value in between, as it would when a transition is underway. Under the ESTAR specification, when  $s_t$  is equal to  $c$ , the function is equal to zero, while when  $s_t$  is far from  $c$  in either direction, the function approaches one. In the regime in which  $G(.)$  is equal to zero, then the parameters are  $\beta_0$  and  $\beta_I$ , respectively. In the regime in which  $G(.)$  is equal to one, the effective parameters are  $(\alpha_0 + \beta_0)$  and  $(\alpha_I + \beta_I)$ ; in this paper, we will denote these parameter sums as  $c_0$  and  $c_I$ , respectively.

The smooth-transition framework is flexible in that it inherently envelopes the simpler threshold autoregressive model, which provides for a similar model construction but is restricted to instantaneous switching between regimes. Within the smooth-transition model, as the  $\gamma$  parameter becomes larger, the change happens so quickly as to be nearly instantaneous, effectively replicating a threshold model. More importantly, the validity of this specification can be tested, following the work of Teräsvirta (1994). Employing a third order Taylor series expansion of the transition function  $G(\cdot)$  yields the linear equivalent  $(s_t + s_t^2 + s_t^3)$ . Multiplying this approximation as applicable through the original model provides a linear function; testing the validity of the STAR approach is then accomplished through testing the multiplicative terms for joint significance using an F-test.

In this research, we tested four different transition variables. The first was time, which was essentially a test to determine if the parameters had changed in a systematic fashion over period observed. Here, time was normalized to lie between zero and one, with the time variable  $t^* = t/T$ . The second was futures prices levels, with the intent to see if the parameters, and potentially hedging behavior, changed when price levels were elevated. Similarly, the volatility of futures prices was employed to examine hedging participation as a function of volatility levels; volatility was defined as the standard deviation of the daily closing futures prices for the month prior to the observed stocks and open interest reports. Finally, for the CBOT contract, the basis value at Toledo, which is the delivery point for the CBOT wheat contract, was used to determine if basis volatility affected hedging participation. Each of the price and volatility variables was scaled by dividing through by its standard deviation to smooth the estimation process.

The Terasvirta tests for the STAR specification found statistically significant nonlinearity in the CBOT contract that fit the ESTAR function over the time variable, and the LSTAR function for futures price volatility and basis levels. The tests found nonlinearity in the KCBOT contract in the LSTAR specification for time, futures prices, and futures prices volatility. The models were estimated in SAS 9.2 using the *proc nlin* function. Significance of the parameters, including the additive parameters  $c_0$  and  $c_1$ , was determined by bootstrapping the model through 10,000 iterations. The model estimates, including the median values and 2.5% and 97.5% tails from the bootstrap, are presented in Tables 1-6.

## **V. Results**

The models estimated the CBOT contracts for hedging behavior display many of the attributes that we had initially hypothesized. Regarding the time-transitioning model (Table 1), all of the intercept terms are statistically zero, as expected. Accordingly, over time there are not systematic influences other than stocks driving commercial traders' participation in futures markets. If we examine the two key stocks parameter variables under the two regimes,  $b_1$  and  $c_1$ , both of which are statistically significant at the 5% level, we can see a sharp change in hedgers' behavior. Although the transition function is of the ESTAR family and should exhibit a V-shaped trend, the position of the centrality parameter  $c$  at 0.96, so near the end, effectively approximates an LSTAR model. The end result is that the relationship between stocks and open interest is characterized by  $c_1 = 0.34$  from the start of the series in 1986 through the beginning of 2004. Although this value is not a hedge ratio per se, it can be thought of as an approximation of the net new price risk that has been transferred into the futures market; effectively, it is a measure of incremental hedging. Recalling the work of Shapiro and Brorsen (1988) with a mean hedge ratio of 11.5%, and Wang et al. (2004) with ratios ranging between 10% and 40%, the

value of 0.34 seems quite reasonable. Beginning in 2004, however, the parameter begins a steady decline, bottoming out at  $b_I = -1.19$  at the end of 2009. It is difficult to develop a logical explanation that explains the negative sign at this point. However, we can see that as the commodity market boom that peaked in 2008 began to ramp up, the stable relationship that had existed between stocks and open interest for two decades deteriorated significantly.

The results of the volatility-transitioning CBOT model reflect some of the same movements as the time-varying model (Table 2). Again, the intercept terms are statistically insignificant in both regimes. Here, with the LSTAR specification, the low volatility regime is characterized by a  $b_I = 0.34$ , and the high volatility regime is parameterized by  $c_I = -0.96$ , both of which are significant at that 5% level. When futures prices are fairly stable, then the stocks-open interest relationship is steady at 0.34, a rational level, but as the standardized volatility gets much beyond one standard deviation, the hedging relationship falls off significantly. Here again, it is difficult to explain the negative sign, other than to note that there is significant pullback in market participation in times of significant turmoil in the markets. This reaction is predictably in line with the simple mean-variance hedge ratio, which decreases with increasing futures market volatility.

The CBOT model that transitions according to the Toledo basis value also shows some very interesting dynamics (Table 3). Following the LSTAR function, the parameters on stocks adjust from  $b_I = -1.12$  in periods of very low basis to  $c_I = 0.29$  in periods of normal to high basis. Here again, the stocks parameters are significant at the 5% level, while the intercept terms are insignificant. These estimates fit our perceptions of standard hedging practices; whenever a futures hedge is set to protect future prices, the expected price outcome is based on the expected future basis. During periods when basis is normal to strong, hedging activity can continue with

the anticipated risk management benefits. However, if basis becomes very weak and falls significantly, then the risk mitigation value of the futures hedge is diminished, and the transference of price risk into the futures market is disrupted.

When compared to the time-varying CBOT contract model, the time-based Kansas City contract model shows a very different pattern (Table 4). Notably, although the intercept in the early time period is statistically zero, it soars at the end of the sample period to more than 30,000. The stocks parameter displays a similar pattern, moving from  $b_I = 0.08$  in the early period, very low but statistically significant, to  $c_I = 1.07$  in the later observations. Given the very rapid speed of adjustment and advanced centrality of the transition ( $c = 0.99$ ), the real effect is a stable if low hedging relationship that is steady though to the middle of 2007, then rockets off with the peak of the commodity boom. Considering the late changes and unusually large parameters, it is difficult to discern if there is a real break in the hedging relationship or if the model is simply struggling to adapt to the turmoil of the boom and bust movements in the commodity markets at that time. In particular, the level of all commercial open interest in KCBOT took off in late 2010, the end of the estimation period, to more than twice the size of its 2009 levels.

The KCBOT model incorporating futures prices transitioning displays a different pattern of behavior than was initially expected (Table 5). It was hypothesized that the hedging relationship might decline with higher prices as increased transactions costs made it less attractive. If we were to accept the ideas of risk adverse hedgers and production costs tracked the market, such that market prices were consistently enough to cover costs, then there should likely be little to no connection between futures prices and hedging activities. However, contrary to both ideas, what we observe is that at low futures prices the hedging relationship is also low,

with  $b_I = 0.06$ , and when futures prices rise, the hedging relationship also rises to  $c_I = 0.39$ . This increase in the stocks-open interest relationships more closely resembles a profit-maximization action, such that more stocks' prices are tied into the futures market as prices rise.

The KCBOT volatility-transitioning model also shows some unusual characteristics (Table 6). In direct contrast to the analogous CBOT model, we see that the hedging connection is low with  $b_I = 0.07$  when volatility is low, but rises to  $c_I = 0.27$  when volatility increases, both of which are statistically significant at the 5% level. This positive correlation appears to directly contradict the ideas behind the fundamental mean-variance hedge ratio. However, if we consider the futures volatility to be a measure of the underlying market volatility, then an increase in hedging activity when prices are uncertain would be a logical response by supply chain participants to protect themselves from even greater price risk.

## **VI. Conclusions**

Price risk management is an important managerial responsibility for participants in the agricultural supply chain. These managers often use the futures markets to hedge their price risk, protecting their business from the swings of the market. In turn, their presence in the futures market provides the derivatives market with a solid connection to the physical commodities, underpinning the market. However, there are a number of influences on hedgers' willingness to use these markets, which in turn can have significant impacts on the markets themselves. This paper used a unique approach to examine hedgers' interactions in the futures markets, namely through the relationship between changing quantities of the physical stocks and commercial open interest in the related futures market. Specifically, we examined the soft red winter wheat market and its contract on the CBOT, and the hard red winter wheat market and its contract on

the KCBOT. These relationships were studied through the use of smooth-transitioning structural models.

We found that the CBOT contract demonstrated a reasonable hedging relationship of around 0.30 between changes in commercial open interest and changes in physical stocks, such that for a given increase in physical stocks, around 0.30 of that rise translated into an increase in commercial open interest. This relationship persisted among the stable periods of the market, but as we entered the commodity boom of the late 2000's and whenever futures prices became notably volatile, this relationship deteriorated significantly. Similarly, whenever basis at the delivery location, a good proxy for the general basis for the commodity, weakened significantly, the hedging relationship was disrupted. Overall, the CBOT contract showed rational behavior on the part of hedgers; with regards to the health of the market, the disruptions of the market demonstrate the possibly significant impacts that unchecked volatility and boom-and-bust cycles can have on hedgers' willingness to engage with the market.

Examination of the KCBOT contract showed some differences from that of the CBOT contract. Notably, the stable hedging participation relationships were considerably lower, stabilizing around 0.07. The linkage between hedgers' physical stocks and their participation in the market does not appear to be as strong in the hard red winter wheat market as it is in the soft red winter wheat market. One caveat to this would be if a significantly larger portion of hedgers in this market were using options contract for hedging purposes, which would not be picked up here. Moreover, the changes in participation move in contraindicated fashions, with participation increasing with both rising prices and with rising volatility. The positive linkage between volatility and participation is really best understood only if the futures market volatility is taken as generally instability in the markets, leading hedgers to make a great commitment to

protecting their incoming revenue. The positive interaction between prices and participation could indicate willingness to market with grain with greater emphasis on capturing high prices rather than protecting against price uncertainty. This result is one of the most intriguing of the paper, and bears further scrutiny.

Future research in this line of work will begin by extending the data the set farther back in time by collecting and recording the printed open interest reports from the CFTC and its predecessor, the Commodity Exchange Authority. This deeper data set will provide more the model with additional useable observations, particularly those of the volatile markets in the 1970's. Additionally, this analysis could be extended to corn, soybean, oats and rough rice markets. Of particular interest would be the differences observed in the heavily traded markets of corn and soybeans compared to the thinner and commercially dominated markets of oats and rough rice.

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## Appendix 1. Model Results

**Table 1. Chicago wheat contract using time as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	8580.45	12389.00	-49926.92	347947.93
$b_1$	-1.19	-1.80	-38.32	-0.45
$a_0$	-7160.76	-11355.00	-347160.2	54157.58
$a_1$	1.54	2.13	0.77	3.80
$c_0$	1419.69	1277.24	-2590.84	5588.77
$c_1$	0.34	0.32	0.12	0.50
$\gamma$	3.20	5.67	0.46	303.74
$c$	0.96	0.96	0.85	1.52

F-stat: 3.75      p-value: 0.0039  
R<sup>2</sup>: 0.17

**Table 2. Chicago wheat contract using futures price volatility as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	1024.40	911.89	-5186.25	5302.17
$b_1$	0.34	0.32	0.15	0.84
$a_0$	4886.80	6092.37	-10755.54	26729.04
$a_1$	-1.30	-1.42	-2.46	-0.56
$c_0$	5911.20	6990.64	-8618.04	24844
$c_1$	-0.96	-1.07	-1.92	-0.25
$\gamma$	5.59	9.22	1.65	464.02
$c$	1.35	1.35	0.88	2.41

F-stat: 3.94      p-value: 0.0053  
R<sup>2</sup>: 0.14

**Table 3. Chicago wheat contract using Toledo basis as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	1179.80	4536.72	-21352.80	38890.43
$b_1$	-1.12	-1.06	-2.06	-0.17
$a_0$	1740.80	-2096.32	-37040.26	23688.26
$a_1$	1.41	1.33	0.42	2.37
$c_0$	2920.60	2377.70	-1033.36	5947.70
$c_1$	0.29	0.27	0.11	0.43
$\gamma$	125.20	125.00	97.32	171.67
$c$	-1.93	-1.93	-1.99	-1.92

F-stat: 6.96      p-value: 0.0003  
R<sup>2</sup>: 0.19

**Table 4. Kansas City wheat contract using time as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	752.90	605.81	-1112.67	2443.54
$b_1$	0.08	0.07	0.05	0.10
$a_0$	32993.00	32885.92	18896.19	50941.71
$a_1$	0.99	0.95	0.47	1.45
$c_0$	33745.90	32618.45	19560.59	50826.43
$c_1$	1.07	1.03	0.55	1.53
$\gamma$	48.86	51.28	33.83	202.84
$c$	0.99	0.99	0.97	0.99

F-stat: 22.74      p-value: <0.0001  
R<sup>2</sup>: 0.49

**Table 5. Kansas City wheat contract using futures prices as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	864.50	1063.60	-719.27	2805.14
$b_1$	0.06	0.06	0.04	0.09
$a_0$	1771.30	-616.90	-13652.30	10383.75
$a_1$	0.32	0.35	0.18	0.51
$c_0$	2635.80	437.37	-12384.90	11435.03
$c_1$	0.39	0.41	0.25	0.57
$\gamma$	17.16	27.21	11.56	131.37
$c$	3.85	3.85	3.67	4.16

F-stat: 17.68      p-value: <0.0001

R<sup>2</sup>: 0.43

**Table 6. Kansas City wheat contract using futures price volatility as the transition variable**

Variable	Estimate	Bootstrap median	Bootstrap 2.5%	Bootstrap 97.5%
$b_0$	795.30	992.01	-712.44	2789.21
$b_1$	0.07	0.07	0.05	0.09
$a_0$	3122.90	1291.76	-8206.30	11178.10
$a_1$	0.20	0.21	0.06	0.38
$c_0$	3918.20	2309.57	-7072.45	12063.80
$c_1$	0.27	0.29	0.14	0.45
$\gamma$	77.19	77.00	19.04	470.13
$c$	1.70	1.70	1.55	1.95

F-stat: 11.82      p-value: <0.0001

R<sup>2</sup>: 0.33