Heterogeneity in Producer's Marketing Strategy

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Abstract: Producers can make their market timing decisions either based on fundamental or technical analysis to reach specific financial target. A generalized mixture model is used to discriminate producers into more than one segment according to their marketing strategies. The heterogeneous selling response is the same within each segment.

Key Words: marketing strategy, heterogeneity, technical analysis, fundamental analysis

JEL Classifications: C1, G0.

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Introduction

Previous studies try to figure out how producers make their selling decisions. Some studies argue that producers should sell their products mainly according to fundamental information like storage cost, transformation cost (Zulauf and Irwin); while Klumpp and Brorsen point out that Oklahoma wheat producers positively respond to fundamental analysis (FA) but do not show much relevant to advisory service recommendations (TA); further some producers follow mechanical marketing strategies that involve selling at the same time every year.

Nearly all previous studies take all producers in one group and have the same expected objective function except Pennings et. al. But they only examine the derivative usage by producers and group market participants by determinants of hedging behavior, like risk attitude, risk perception …...Further more since they study hedging behavior instead of product selling activities in the cash market, and these determinants are coming from a survey or experiments, it is possible that producers act differently when they make actual financial decisions. We also argue that psychological information is already reflected in the actual marketing behavior by following different marketing signals (FA or TA) in each transaction.

Heterogeneity in Producer Selling Activities

When analyzing behavior, especially the crop selling activities of different producers, the homogeneity in decision makers usually can be rejected. For example, some producers may have some strategy to make more transactions in order to hedge their risk, while some producers only make a few or even only one transaction. In the real world, producers may have different strategy behaviors and following different rules. The previous study assumes they are the same and try to

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find how they may react under some conditions. Since producers may have different marketing strategies to meet different financial targets, they may have different behavior functions, either decisions to make a transaction at specific time or how many percent he should sell at each transaction. In this paper, we examine both the overall market performance and individual's behavior.

Objectives

First we examine if there is heterogeneity exist with producers' transaction decision. According to Klummp and Brorsen, there are fewer transactions were made in wheat market if futures price spread are higher, and technical analysis information, which indicated by market advisories' suggestion (MAS) has little effect on it, which means producers mainly consider FA info and expecting make more return by storage. But the R-square is very small. In this paper, we want to figure it out if not all transactions following this rule.

Second, we examine what the relationship between the market information with the percentage of crops sold at each transaction by individual producer.

Third, this study discriminates grain producers into different groups according to their market timing decisions. Some producers may sell their products mainly based on fundamental information, some may mainly base on technical analysis, and others may not have preferred information type and have mixed marketing strategy.

A generalized mixture regression model is used to classify producers into segments, so that the selling decisions response to the different kind of market signals are the same within each segment. This model also estimate the influence of the either fundamental analysis (FA) or technical analysis (MAS) signals on selling transactions for each segment identified.

Data and Methods

Wheat transaction data are collected from grain elevator, Pondcreek, located in the northern of western Oklahoma, from 1995 to 2000. Transaction information includes the number of bushels sold, price per bushel, and date of transaction, and the individual who made this trade. Futures spreads are used to represent the expected return to storage and are calculated based on Kansas City futures prices. Wheat futures contracts are sold in March, May, July, September, and December. The nearby futures spread is the futures spread that is nearest to the date of the given transactions, and the distant spread is the futures spread that is second nearest to the given transaction date. For example, the nearby spread for a transaction with a date of March 6 for a given year would be the difference between the July 6th futures price and the September 6th futures price for the given crop year. The distant spread for the same transaction would be the difference between the September 6th futures price and the July 6th futures price for that year. Market advisory's recommendations (MAS) are indicated by how many percentages of crops should sell by producers.

In this study we use generalized linear mixture regression model (GLIMIX) to simultaneously classify producers in the sample into segments on the basis of the relationship between selling decision and the market signals, and estimates the influence of the trading signals on selling actions for each segment identified. The classification is based on whether producers respond to the trading signals in the similar manner.

Economic Framework and Method

Generalized Linear Mixture Regression Method

If a sample of observations arises from a specified number of underlying populations of

unknown proportions, GLIMIX method can be used to decompose those observations into different groups, each has specified density function (Wedel and Kamakura, 1998). Since we do not have priori probability of the producers selling activity regarding the usage the indicator of MAS and the futures price spread, we need classifies the producers to separate the activity into different groups such that the effects of independent variables are the same in each group. In this study, we group crop selling activity into two groups such that the influence of future prices and MAS are the similar in each group, but dissimilar across groups.

In each GLIMIX procedure, a certain statistical distribution is assumed for each group. In order to simplify our problem, we assume these distributions are normal distributions which have different expectations but same variances. The purpose of the mixture model is to decompose the producers' population into the underlying segments.

First, assume the producers' response y_n arises from a population that is a mixture of S segments in proportions $\pi_1, \pi_2, \ldots, \pi_s$, where we do not know in advance the segment from which a particular vector of observations arises. The probabilities of π_s are positive and sum to one. We assume that the distribution of y_n, given that y_n comes from segments s, $f_s(y_n|\theta_s)$, is one of the distributions in the exponential family or the multivariate exponential family, where θ_s is the vector of regression coefficients for each segment. Conditional on segment s, the y_n are independent. The distribution $f_s(y_n|\theta_s)$ is characterized by parameters θ_s. The means of the distribution in segment s (or expectations) are denoted by μ_s.

Since we want to predict the means of the observations in each segment by using the set of explanatory variables (wah, $dist$, $mass$, $nearby$), then we specify a linear model as follows:

$$y_{is} = \sum_{k=1}^{P} X_{ip} \beta_{sp}$$

(1)

Where X_{ik} are explanatory variables, β_{sk} are parameter in segment s; $i = 1,...n$. And X_p are random effect on y_n.

The linear predictor is thus the linear combination of the explanatory variables, and the set of betas that are to be estimated. The beta coefficients can be interpreted as the amount of changes in producer use of the MAS compared to the situation as captured by figure spreads.
The unconditional probability-density function of an observation, can now be expressed in the finite mixture form:

$$f(y_n|\phi) = \sum_{s=1}^{S} \pi_s f_s(y_n|\theta_s)$$

(2)

Where the parameter vector $\phi = (\pi, \theta_s)$ and $\theta_s = \beta_s$. The parameter vector ϕ is estimated via maximum likelihood using the expectation-mixture (EM) algorithm (Redner & Walker, 1984; Titterington, 1990). By maximizing the likelihood, that set of parameters is obtained that most likely has given rise to the data at hand. The estimation algorithm is an iterative algorithm that sequentially improves upon some sets of starting values of the parameters, and permits simultaneous estimation of all model parameter. The EM algorithm is based on a multinomial distribution for the memberships; the expectation of the likelihood can be formulated over the missing observations. This involves calculations the posterior membership probabilities according to Bayes's rule and the current parameter estimates of ϕ and substituting those into the likelihood. Once this is accomplished, the likelihood can be maximized. Given the new estimates of ϕ, new posteriors can be calculate in the next E (expectation)-step, followed by a new M-(maximization) step to find the new ϕ. The E- and M-steps are thus alternated until convergence occurs. Estimates

of the posterior probability, p_{ns}, that observations of day n come from segment s can be calculated for each observation vector y_n, as shown in equation (3):

$$p_{ns} = \frac{\pi_s f_s(y_n | \theta_s)}{\sum_{s=1}^{S} \pi_s f_s(y_n | \theta_s)} \tag{3}$$

We will use equation (3) to classify producers in a particular segment.

Heterogeneity in Trade or Not Decision

One producer's selling strategy reflects as the transactions he made at discrete days with different percentage of the crops he produce in a crop year. Most producers in West Oklahoma make very few transactions in a single year, usually less then 10, some of them even only make 1 or 2, and we only have four crop years' data. We assume these producers only follow a few marketing strategy, then all these producers' transaction decisions may come from several trading rule possibilities, each of them comes from a specified density distribution.

First we aggregate all the transactions made by each producer together, and then using transaction frequency in each day as dependent variable, and using futures price spread, week from harvest, and MAS as independent variables, using GLIMIX to examine if there are two trading rules exist for these producers' transaction decisions. The statistic model for transaction decision is followed:

$$F_{ts} = \beta_{s0} + \beta_{s1} nearby_t + \beta_{s2} dist_t + \beta_{s3} wah_t + \beta_{s4} mas_{t-2} + \varepsilon_t \tag{4}$$

The subscript s indicates the different transaction response group of producers, t indicates the day that one transaction made; Dependent variable F is the transaction numbers (frequency) happened in one day; independent variable , $nearby$, $dist$, wah , and mas_{t-2} indicate nearby and distant futures spread for that day, number of week after crop harvest, lagged MAS respectively.

This means the observations have mixture density distribution.Then there may be more then one possibilities marketing strategy rules exist and this problem is a mixture density one. Each producer' marketing decision may come from one of the different latent distribution and they can be distinguished by what extent he follows this rules. For example, some of them may make their transaction more concern about fundamental analysis, some may make more of their transactions by technical analysis, and the others may have mixed strategy, then producers can be declassified into three segments. In this paper, we try to figure it out under what condition those transactions were taken. In different group, the βs will be different.

Heterogeneity in Percentage Trading Strategy

Besides transaction frequency of wheat market, how many percent of crops sold in each trade by individual is also examined. The reason we use percentage instead of quantity is that every producer try to make as much as possible profit based on his own production quantity. Respect to his financial target, it is how many percent he should sell matters instead of actual quantity in each trade, especially when compare producers' behavior. In this study, we assume percentage of each producer's crop production is equally weighted by each producer when they make their marketing strategies.

We use each producer's percentage trade in each day as equation (5):

$$per_{its} = \alpha_{s0} + \alpha_{s1}wah_t + \alpha_{s2}nearby_t + \alpha_{s3}dist_t + \alpha_{s4}mas_{t-2} + \varepsilon_t \qquad (5)$$

Where per_{its} is the percentage for individuals, which producer i of group s sold in day t. We take percentage of each transaction as dependent variable to see how the effect of futures spread and MAS on producers' selling decision.

Expected Results

According to economic theory about fundamental and technical analysis, producers who

following FA will sell if the current expected returns are greater than the maximum expected future returns to storage; while for those who following TA, they may ignore FA but following MAS to hold because they expect higher profit in the future.

[Place Figure 1 Approximately Here]

Figure 1 (a) to (d) are original data of transaction frequency respect to different market information. Figure 1 (a) and (b) show that the transaction numbers in each day separate into different groups with response to nearby and distant futures spread. This means producers may follow different rules under positive futures spread conditions compare to negative futures spread conditions. Figure 1(c) shows how transaction frequency response market advisory suggestion is nearly normal distributed with mean nearly equal zero, which mean MAS may have little effect on the sell decision, which is consistent with Klummp and Brorsen's results. But this is for the whole market transaction; we still want to know if there are some producers do following MAS more try to make aggressive profit target then other producers.

[Place Figure 2 Approximately Here]

Figure 2 (a) to (d) show the percentage trade with respect to nearby futures spread, distant futures spread, MAS and WAH respectively. We can see also the responses cluster into different groups, but percentage trades are nearly averagely distributed along y-axis. Then probably there is no relationships for producer deciding how much to sell regard to market information. This study will test this hypothesis and using GLIMIX method to test is there are more than one segment exist that the percentage trading may following specific rules by producers.

Results

Statistical Results for Transaction Frequency

To illustrate the usefulness of the generalized linear mixture-modeling framework we estimated equation (4) across the whole sample. Table 1 shows the OLS and GLIMIX regression results of expected returns to storage (futures price spread) and market advisory service recommendations on transaction frequency of the wheat market. The one segment results from OLS regression resulted in a relative low R^2 of 0.012, indicating that ignoring heterogeneity results in a model that can explain only 1.2% of the variance of producers' responses to the scenarios.

<center>**[Place Table 1 Approximately Here]**</center>

Account for heterogeneity possible exists, GLIMIX model is used to discompose the data set using equation (1) through (3). To assess the separation of the segments, an entropy statistic can be used to investigate the degree of separation in the estimated posterior probabilities as defined in equation (7):

$$E_s = 1 - \frac{\sum_{n=1}^{N}\sum_{s=1}^{S} p_{ns} \ln p_{ns}}{N \ln S} \tag{7}$$

Where p_{ns} the posterior probability that crop producer is n comes from latent group s. For example, the entropy value of 0.8 indicates that the mixture components are well separated, that is, the posteriors probabilities are close to 1 or 0.

The mixture regression shows there are two segments exist. Note, that these segments are defined by the mixture model based on statistical differences in the estimated regression coefficients for each segment. That is, the segments reveal different behavior with respect to the likelihood of information of futures spread and MAS use. The results for the two-segment model are compared with OLS in Table1.

The GLIMIX results show that the coefficients of these two groups are not significantly different except nearby futures spread. Transaction has 51.19% and 48.81% possibility made

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following rules in segment 1 and 2 separately. Coefficients for nearby futures spread are negative and those of distant futures spread are positive, but the absolute value of nearby futures spread coefficient are larger then those of distant futures spread. This means that the expected short run storage return has more effect on producers to make sell or not decisions. The higher nearby futures spread, the less chance transactions happen. These results are consistent with a marketing strategy that uses fundamental analysis. The coefficients of WAH for these two segments have same negative value. This results show that producers are more likely to make more selling transactions right after harvest. Both segments show negative relationship with market advisory's recommendations, which indicates that producers do not care market advisory's advisory or even trade opposite to those recommendations, which is consistent with Klumpp and Brorsen's result.

Econometrics Results for Percentage Trading in Each Trade Made by Individual

Now we examine the percentage trade in each transaction of in wheat market. Table 2 shows the relationships between percentage of each transaction and market information.

[Place Table 2 Approximately Here]

From the above table, the results show that the percentage sell by one producer in each transaction will increase according to time and nearby futures spread, negative to distant futures spread. And the regression also finds out that the percentage selling by producers does not have relationship with MAS significantly. Consider WAH data range is from 0 to 49, while futures spread is from -1 to 1, then the combine effect of distant futures spread and WAH are higher than that of nearby futures spread. This means producers mainly consider long run profit then short run storage profit from storage. This maybe because that for those who have low storage cost in that year (such as they build storage place themselves before), will prefer storage to make more profit before next harvest time. But the R^2 is only 0.0243, which means only 2.43% of data are

explained by this model. From Figure 2, we can see that the linear relationships between percentage trade and futures spread, WAH and MAS are not clear. We can say that most producers do not have strongly rules like following FA or TA. The results show that even producers believe they can make more profit by trying to sell different percentage of crops according to market information, from statistic point of view for the whole market, how many percent a producer sell in each trade are randomly choose at different situations.

This research also compares each producer's trading strategy and we did not find significantly difference across different producers.

Conclusions

This paper studies whether wheat producers' marketing strategies are different under different conditions and from the whole point of view, if producers have different selling rules in Western Oklahoma. The results show that producers care little about how market advisory suggest them to do, which means they do not following technical analysis to sell their product.

The results associate with transaction frequency indicate that producers are reluctant to sell if the futures spread is positive and hope make more return by storage. But when futures price spread are negative, producers may more likely to sell their products regard little of the market information, no matter fundamental or technical analysis. In addition, this paper also shows that producers do not have different trading rules significantly respect to percentage trade in each transaction. Even producers seem do have trading philosophy when they decide sell or not at the current situation, seems they do not know how much they should sell and just make their decision randomly.

References

Anderson, K.B., and H.P. Mapp. "Risk Management Programs in Extension." *Journal of Agricultural and Resource Economic*s 21(1996):31-38.

Benirschka, M., and J.K. Binkley. "Optimal Storage and Marketing Timing over Space and Time." *American Journal of Agricultural Economics* 12(1990):187-196.

Fama, E.F., and K.R., French. "Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage." *The Journal of Agricultural Business* 60(1987):155-73.

Irwin, S.H., D.L. Good, J.Martines-Filho, and L.Hagedorn. "The Pricing Performance of Market Advisory Services in Corn and Soybeans Over 1995-2003." AgMAS Project Research Report 2005-01. Internet site: http://www.farmdoc.uiuc-edu/agmas, (March 2005).

Klumpp, J.M., and B.W. Brorsen. "The impact of Marketing Strategy Information on the Producers's Selling Decision." *NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management 2005 Conference*, April 18-19, 2005.

Pennings, J.M., O. Isengildina, S. Irwin, and D. Good. "The Impact of Market Advisory Service Recommendations on Producers' Marketing Decisions." *Journal of Agricultural and Resource Economics.* 29(2004):308-327.

Pennings, J.M., and P. Garcia. "Hedging Behavior in Small and Medium-sized Enterprises: the Role of Unobserved Heterogeneity." *Journal of Banking and Finance.* 28(2004):951-978.

Tomek, W. "Commodity Futures Prices as Forecasts." *Review of Agricultural Economics* 19(1997):23-44.

Working, H. "The Theory of Price of Storage." *The American Economics Review* 39(1949):1254-1262.

Zulauf, C.R., and S.H.Irwin. "Market Efficiency and Marketing to Enhance Income of Crop

Producers." *Review of Agricultural Economics* 20(1998):308-331.

Wedel, M., W.A. Kamakura. "Market Segmentation: Conceptual and Methodological

Foundations." *In: International Series in Quantitative Marketing.* Kluwer Academic

Publisher, Boston. 1998.

Appendix: Tables and Figures.

**Table 1.** OLS vs. Mixture Regression Results for Transaction Frequency of Whole Market [a]

	Regression Coefficient Estimates (Standard errors in brackets)		
	OLS model ($S = 1$)	⌐IMIX model ($S = 2$)	
		$s = 1$	$s = 2$
Distant Futures Spread	0.7878	0.7878	0.7878
	(0.2266)		
Nearby Futures Spread	-1.2302	**-1.1578**	**-1.3066**
	(0.2140)		
Lagged market advise	-0.0993[**]	-0.0993	-0.0993
	(0.0354)		
Week after Harvest	-0.0394	-0.0394	-0.0394
	(0.0029)		
Intercept	2.2410	2.2410	2.2410
	(0.0728)		
Proportion of producers in segment (π)		0.51193	0.48807
	$R^2 = 0.2142$		

[a] Two asterisks indicates significance at the 95% level.

Table 2. OLS Regression of Percentage Selling in Each Transaction [b]

|	Regression Coefficient Estimates (Standard errors in brackets)		
	Estimate	t-value	$Pr > |t|$
Distant Futures Spread	-0.09894[****]	-1.55	0.1205
	(0.06369)		
Nearby Futures Spread	0.15887	3.14	0.0017
	(0.05059)		
Week from Harvest	0.00358	7.98	<.0001
	(0.00045)		
Intercept	0.19361	20.72	<.0001
	(0.00934)		
	$R^2 = 0.0243$		

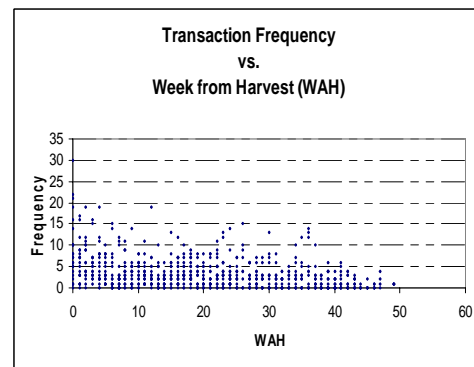[b] Four asterisks indicates significance at the 85% level.
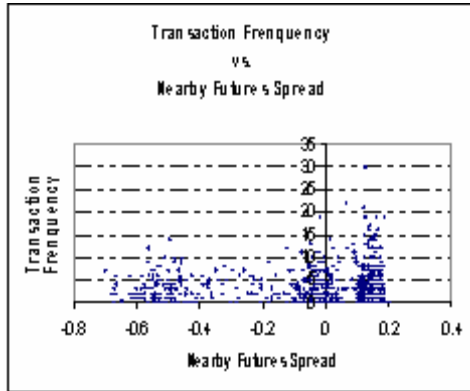
(a) Frequency vs. Nearby Futures Spread
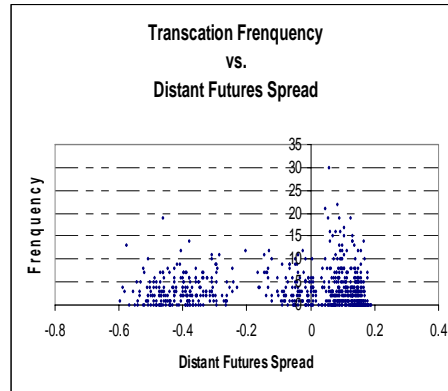
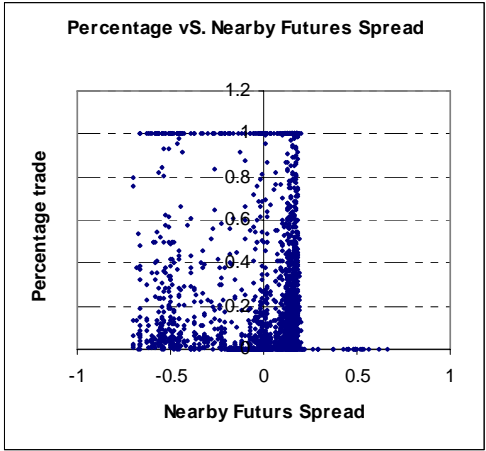(b) Frequency vs. Distant Futures Spread
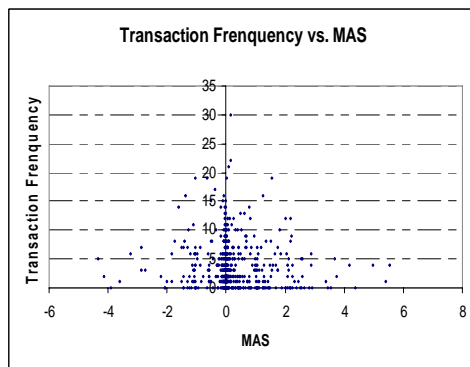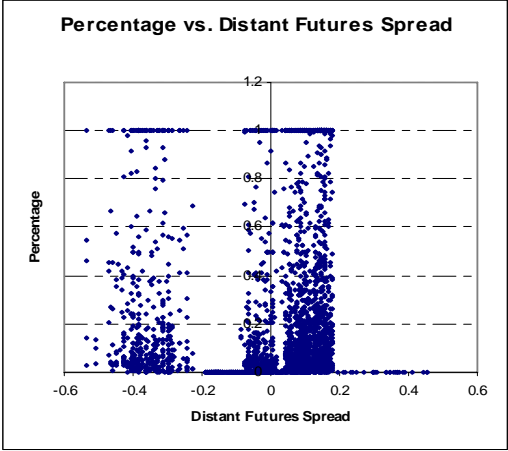

(c) Frequency vs. MAS

(d) Frequency vs. WAH

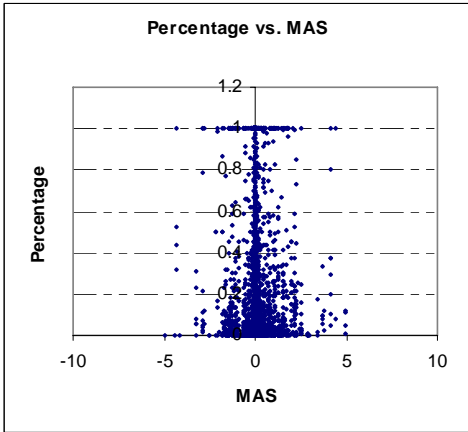**Figure 1.** Transaction Frequency vs. Futures Spread, WAH and MAS
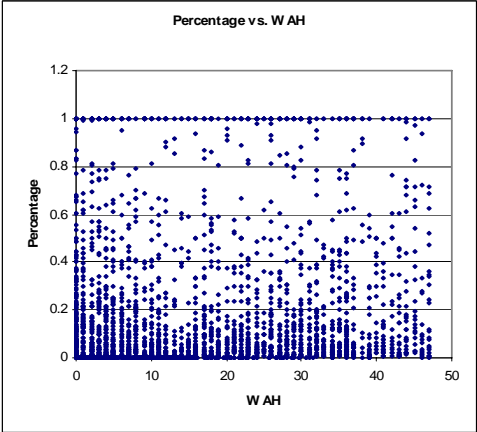
(a). Percentage vs. Nearby Futures Spread

(b). Percentage vs. Distant Futures Spread

(c). Percentage vs. MAS

(d). Percentage vs. WAH

Figure 2. Percentage of One Transaction vs. Futures Spread, WAH and MAS