USING ACTUAL PRODUCER TRANSACTIONS

TO DETERMINE PRODUCER

MARKET TIMING

By

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Bachelor of Science

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Springfield, Missouri

2003

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
July, 2005

Using Actual Producer Transactions

to Determine Producer

Market Timing

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ACKNOWLEDGEMENTS

I would like to express my appreciation to my major advisor, Dr. Wade Brorsen for his supervision and constructive guidance during my time at OSU. Without his research and ideas this thesis would not have been possible. My sincere appreciation also extends to my other committee members Dr. Kim Anderson and Dr. Chanjin Chung, whose assistance and guidance were quite valuable. To Dr. Scott Irwin, I would like to say thank you for the insightful remarks and helpful suggestions that aided me in the writing of my first two essays. Additionally, I wish to express my thanks to the rest of the faculty and staff in the Department of Agricultural Economics for making the graduate experience as painless as possible. Also, special thanks to Rita Carreira for selflessly devoting herself to teaching me econometrics and for being an exceptionally supportive officemate and friend.

I must also give a very special acknowledgement to my husband, David, for his unfaltering optimism and understanding throughout the whole process, his endless love, and the much needed distractions. Thanks also to my parents and the rest of my family for their love and support.

Finally, I would like to once again thank everyone mentioned above and all the others that made a contribution to this work.

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Introduction

Agricultural economists have supplied the agricultural industry with many studies regarding the price forecasting and marketing strategies of producers. Nearly all of these studies take a normative approach to the topic and attempt to derive an "optimal" marketing strategy for producers to follow. However, recent studies indicate that producers seldom follow the price forecasting and marketing strategy recommendations suggested by agricultural economists (Brorsen and Irwin; Musser, Patrick, and Eckman; McNew and Musser). Producers tend to avoid the complex pricing models that researchers provide and prefer more simplistic forecasting methods (Anderson and Mapp). This lack of use by producers suggests that the price forecasting and marketing strategy information being supplied to producers is not reflective of their actual marketing decisions.

In order to provide producers with more relevant marketing information, we must ask what sources of marketing strategy information actually influence the producers' marketing decisions? The majority of research on the market information used by producers focuses on results from producer surveys (Patrick and Ullerich; Batte, Schnitkey, and Jones; Ortmann et al.). These surveys indicate that producers consider private consultants, such as market advisory services[1], a highly important source of marketing information. For example, Patrick and Ullerich's study of 17 marketing information sources reported that market advisory services were outranked only by past farm records. In a study by Schroeder et al. a sample of Kansas farmers rank market advisory services as the number one source of information for developing price expectations.

While these surveys reveal the information sources producers say they use, there is limited empirical research on whether producers actually follow market advisory service recommendations in their marketing decisions. Survey responses by Pennings, Irwin, and Good and Isengildina et al. suggest few producers closely follow the specific pricing recommendations of market advisory services. Instead, producers generally use market advisory services for background information, comparing it with other information sources in order to make a decision (Pennings, Irwin, and Good; Isengildina et al.). One reason that producers do not closely follow these recommendations may be the low pricing performance shown by market advisory services. The average revenue achieved by following market advisory service recommendations for corn and soybeans is only slightly above the benchmark average (Irwin, Martines-Filho, and Good), while the average revenue achieved for wheat is well below the benchmark average (Martines-Filho, Good, and Irwin).

[1] For a subscription fee advisory services help farmers with their marketing decisions by providing marketing information, analysis and recommendations. See Isengildina et al. for a complete review of the market advisory service industry.

Zulauf and Irwin suggested using the local cash price basis (futures-cash) as a marketing signal and found that storing when the basis is larger than storage costs can be a favorable marketing strategy, given that a short futures hedge is placed at harvest. Additional research on the accuracy of price forecasting models reveals that forecasts based on econometric models generally do no better than forecasts based on futures markets (Tomek) and may even be outperformed by futures markets for certain commodities (Kastens and Schroeder).

Matwichuk found a positive relationship between the market sentiment of market advisory services and past commodity returns, suggesting that market advisory services are trend followers. Trend followers make marketing decisions based on technical rather than fundamental information (Sanders et al.). The question now is, "Do producers prefer marketing strategies based on mainly technical information, such as market advisory service recommendations, or do they prefer more fundamental strategies, such as changes in expected returns to storage?" Thus, the objective of this research is to determine how wheat producers' selling decisions correspond with market advisory service recommendations and changes in expected returns. In order to satisfy this objective, a Tobit regression model will be used to evaluate the effect of market advisory service recommendations and futures price spreads on the number of wheat sales that occur on a given day for a sample of Oklahoma wheat producers.

The majority of past research on producer marketing information consists of producer surveys that report which information sources producers say they use. However, it is possible that producers do not act in the way that they say they act. Studies on behavioral finance find that people are prone to psychological biases when making marketing decisions (Brorsen and Anderson, 2001; Kahneman and Riepe). Examples of psychological biases include overconfidence in one's ability to predict the market and the tendency to remember successes and forget failures, known as hindsight bias. Individuals typically are not aware that they have these biases. Thus, research based on producer surveys may not accurately reflect the marketing strategy needs of producers. This study goes beyond producer surveys by using actual producer transactions to obtain a more precise estimate of the relative importance in producer decisions of market advisory service recommendations and fundamental information as represented by futures market spreads.

Theory

There is no shortage of literature regarding the price of storage and the optimal marketing strategy that crop producers should follow (e.g. Working; Williams and Wright; Fackler and Livingston; Zulauf and Irwin). The theory of the price of storage explains inter-temporal price relationships between spot and futures with regards to the cost of carrying a particular commodity. It takes into account the interest foregone in storing a commodity (opportunity cost of storage), the physical cost of storage (including a risk premium), and the convenience yield for holding stocks (Working; Fama and French; Yoon and Brorsen). Thus, the price of storage, or the basis, is defined as:

(1) $$F_{t,T} - S_t = S_t R_{t,T} + W_{t,T} - C_{t,T}$$

where $F_{t,T}$ is the futures price at time t for delivery of a commodity at time T, S_t is the spot price at time t, $R_{t,T}$ is the interest foregone during storage (opportunity cost), $W_{t,T}$ is the marginal physical cost of storage (e.g. storage rent, handling costs, insurance, transport, etc.), and $C_{t,T}$ is the marginal convenience yield. The price of storage, $F_{t,T} - S_t$, can also be interpreted as the return from purchasing the commodity at t and selling it for delivery at T; this is the return to storage from time period t to T ($t < T$).

The convenience yield, as defined by Working, refers to the implicit benefits that accrue to the owner of a physical stock but not to the owner of a contract for future delivery. For example, a convenience yield may exist from holding stores of some commodities, such as wheat, because they are inputs in the production of other commodities, such as flour. Stockholders may also earn a convenience yield by being able to respond efficiently to unexpected changes in supply and demand. The theory of storage predicts an inverse relationship between convenience yields and inventories (Fama and French); therefore, the benefits for producers are greater when inventories are small. When millers, exporters, foreign countries, etc. have a high convenience yield returns to storage will be low and there will be less incentive for producers to continue to store their crop (Yoon and Brorsen).

A basic farmer marketing strategy is to continue to store as long as the expected marginal returns from storage are greater than the expected marginal costs of storage. Fackler and Livingston argue that this basic strategy is too simplistic for crop producers because it assumes that stocks can easily be replenished during the marketing year. Due to the fact that a sale out of storage is an irreversible action for a crop producer, they propose a marketing strategy that still involves storing at low prices and selling at high prices but with a cutoff price function marking the boundary between low and high prices. Thus, producers would sell if the current expected returns to storage exceed the maximum expected future returns to storage,

(2) $$E_t[(F_{t,} - S_t) - S_t R_t + W_t] > \max E_t[(F_{t+1,T} - S_{t+1,T}) - S_{t+1,T} R_{t+1,T} + W_{t+1,T}]$$

where $E_t[(F_t - S_t) - S_t R_t + W_t]$ is the expected net returns from selling at the present time *t* and $\max E_t[(F_{t+1,T} - S_{t+1,T}) - S_{t+1,T} R_{t+1,T} + W_{t+1,T}]$ are the maximum future returns to storage expected at any future date. Returns to storage are not the only factor in the producer's marketing strategy. Government programs and producers' individual cash flows and taxes could also play a role. For example, if a producer's storage cost is low government loan programs may encourage continued storage by allowing the producer to retain the real option value implicit in a loan program (Yoon and Brorsen). Producers may time their selling decisions with their need for cash inflows to make loan payments or cover production expenses. They might also hold off selling until after the first of the year in order to reduce their income tax.

Zulauf and Irwin found that the most successful strategies were those that used the futures market as a source of information. The marketing strategy they suggest is to base storage decisions on whether the current futures-cash basis (expected return to storage) exceeds the expected cost of storing and use hedging to increase the chances of acquiring the expected return. In the current study few producers likely use hedging in their marketing decisions. Considering that hedging only increased the statistical power of Zulauf and Irwin's tests, rather than increased the expected returns, their arguments still apply even though producers were not using futures.

An important element of equation (2) is that producers must form expectations about the returns to storage. Agricultural economists typically assume that producers form rational expectations. This assumption implies that producers use all available market information to make rational decisions. Producers may use fundamental information, such as changes in futures prices, or technical information, such as price trends, to make their marketing decisions. Research indicates that technical analysis, in the form of trend following, yielded small profits in the 1970s and 1980s (Covel; Lukac and Brorsen) but not in the 1990s (Park and Irwin). Market advisory services and sentiment indices have been found to follow price trends in the manner of positive feedback traders, meaning that they recommend holding when prices increase (Matwichuk, Sanders et al.). Producers, on the other hand, are typically thought to be negative feedback traders, selling after prices increase (Brorsen and Anderson, 2002; Sanders et al.). Aside from fundamental and technical strategies, producers could base their marketing decisions on non-information, known as noise trading (Black), or they could use mechanical marketing strategies that involve selling at the same time every year regardless of the market (i.e. selling at harvest). The point is that in order to better understand producers' marketing strategies we must first understand how producers form price expectations.

Data

Data are from three grain elevators located in the northern, southern, and central areas of western Oklahoma. The data span nine crop years, from the harvest of 1992 through the harvest of 2000, and contain individual producer transactions of wheat sales at each elevator. Information about each sale includes the number of bushels sold, price per bushel, and date of transaction. Sales decrease as the number of weeks after harvest increase. We attempt to measure this deviation around annual seasonal patterns of sales by including the number of weeks after harvest that the sale occurred. Harvest is a four-week period that differs for each elevator depending on location. Beginning harvest dates for the southern, central, and northern elevators are May 25, June 1, and June 12 respectively.

Table 1 contains the descriptive statistics for each elevator. The southern elevator has the highest price, lowest average number of weeks, and the highest percentage of harvest sales. According to Benirschka and Binkley, locations closer to the market typically have lower returns to storage than locations further away from the market. Therefore, southern producers are more likely to sell at or close to harvest which results in a lower average number of weeks after harvest compared to the central and northern elevators. The higher average price at the southern elevator is likely due to the fact that the southern elevator is closer to the market, and thus transportation costs are lower. Therefore, the average price is higher at the southern elevator. Another reason for the higher average price could be that harvest is slightly earlier at the southern elevator providing the potential to sell wheat before prices reach harvest lows.

Table I-1 Descriptive Statistics for Each Elevator

Descriptive Statistics	South	Central	North
Average price ($/bu.)	3.41	3.32	3.39
Average week after harvest	5	16	18
Percent harvest sales	58%	19%	14%
Number of observations	14434	7089	6389

In addition to the elevator data, wheat market advisory service recommendations were obtained from the Agricultural Market Advisory Service (AgMAS) Project at the

University of Illinois. The data contain daily selling recommendations from 34 market advisory services. Each recommendation consists of the percentage of stored crop to be sold on a given day in a given year, spanning the crop years of 1995-1999. Market advisory services offer “blanket” recommendations to farmers, meaning that the selling recommendation for a given day is typically not reflective of individual producer location. Producers in Oklahoma receive the same recommendation as producers in Illinois. For the purpose of this study we will use the average daily sales recommendations for the 34 advisory services. Since the market advisory service sales recommendations are represented as a cumulative percentage, the difference between the previous day and the following day was calculated, giving us daily recommended sales. This is the value that is used to represent market advisory service recommendations. The elevator data does not contain information on producers’ pre-harvest marketing strategies, though the number of forward contracts should be relatively small. Therefore, the study does not consider pre-harvest sales recommendations which may account for as much as 50% of the market advisory service recommendations.

Futures spreads are used to represent the expected returns to storage and are calculated based on Kansas City futures prices. Wheat futures contracts are sold in March, May, July, September, and December. Oklahoma producers do not typically store their wheat for long periods of time, therefore, only the nearby and distant futures price spreads are used. The nearby 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 July 5 for a given year would be the difference between the December 5th

futures price and the September 5th futures price for the given crop year. The distant spread for the same transaction would be the difference between the January 5th futures price and the December 5th futures price for the given crop year. Due to the fact that futures contracts are bought and sold only during certain months, a cutoff date to distinguish between the selling and delivery timeframe for those months had to be established. The cutoff date was set at the 20th of the month prior to each contract month (March, May, July, September, and December). Since all the spreads do not cover the same number of months, they were divided by the number of days in each price spread. For example, the May-July spread contains two months and the December-March spread consists of three months, so the price spreads were divided by the number of days in each spread, 61 and 90, respectively (ignoring leap years).

Before using the data certain modifications had to be performed. First, the 1998 crop year is not included in the data at the northern elevator due to missing producer transaction information. Secondly, the last two weeks in May for every year were deleted from the dataset for the southern elevator and the first two weeks in June for every year were deleted from the dataset for the northern elevator. This is due to the fact that the market advisory service data always assumed that the crop year began on June 1 and ended on May 31 of the following year. While the harvest date at the central elevator coincides with this assumption, the southern elevator's harvest is earlier in the season and the northern elevator's harvest is later in the season. Therefore, in order for the market advisory service recommendations to correctly correspond with the elevator transactions the aforementioned dates were deleted for the southern and northern elevators.

Procedure

The following regression model is estimated for each elevator to determine how producers' selling decisions correspond with market advisory service recommendations and expected returns to storage:

$$(3)\quad ws_{ikt} = \beta_0 + \sum_{y=1}^{8} \beta_{1y} cy_{yt} + \beta_2 near_{ikt} + \beta_3 dist_{ikt} + \beta_4 mas_{i,k-1,t} + \beta_5 wah_{ikt} + \beta_6 wah_{ikt}^2 + \varepsilon_{ikt}$$

where ws_{ikt} is the number of wheat sales that occurred at the i^{th} elevator on the k^{th} day in year t, cy_t is a yearly dummy variable to adjust for differences in price across years, $near_{ikt}$ is the nearby futures spread, $dist_{ikt}$ is the distant futures spread, $mas_{i,k-1,t}$ is the lagged average percent of the crop that market advisory services recommended selling on that date[2], wah_{ikt} is the number of weeks after harvest that the transaction occurred, wah_{ikt}^2 is the non-linear term for number of weeks after harvest, and ε_{ikt} is the error term such that $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$. The error term is expected to be heteroskedastic with the following variance equation:

$$(4)\quad \sigma_{ikt}^2 = \exp(\alpha_0 + \alpha_1 wah_{ikt} + \alpha_2 wah_{ikt}^2).$$

Due to the fact that the dependent variable can take on a value of zero when no transactions occur, a Tobit regression will be used to estimate the truncated model. Therefore, it allows the dependent variable to reflect when no sales take place. The Tobit regression procedure assumes normality which is not the case in our model. A square root transformation on the dependent variable was done to induce normality. The square

[2] A non-lagged market advisory service variable was considered, but was not found to be significant. Examination of the cross-correlation between the residuals of the dependent variable and the market advisory service variable led to the conclusion that the variable should be lagged by one day. This seems reasonable since it could take a day for farmers to receive the information.

root transformation is the standard transformation used with count data. The model is estimated using maximum likelihood.

As previously discussed, producers will sell if the current expected returns to storage are greater than the maximum expected future returns to storage. As the expected future returns to storage increase, producers are expected to continue storing and fewer wheat sales will take place. Thus, β_2 and β_3 are expected to be negative. Since producer surveys indicate that a large number of producers report using market advisory service recommendations, the number of wheat sales is expected to increase with the market advisory services' daily selling recommendations, so β_4 is expected to be positive. As mentioned before, Oklahoma wheat producers typically sell the majority of their crop at or close to harvest. Therefore, as weeks after harvest increase we expect to observe fewer transactions and coefficients β_5 and β_6 are expected to be negative and positive, respectively.

Results

Tables I-2, I-3, and I-4 show the results of the Tobit regression of expected returns to storage (futures price spreads) and market advisory service recommendations on number of wheat sales at the northern, central and southern elevators. As expected the variables representing the nearby and distant futures price spreads were negatively related with the number of wheat sales at all three locations. Thus, when spreads are high, producers are less likely to sell and more inclined to continue to store their wheat.

Table I-2. Regression of Market Information on Wheat Sales for Northern Elevator

	Estimate	t-value	Pr > |t|
Intercept	.4646	3.59	.0003
1996 crop year	.7137	6.27	<.0001
1997 crop year	2.9020	20.02	<.0001
1999 crop year	2.7635	17.83	<.0001
Nearby Futures Spread (*near*)	-2.4808**[a]	-8.69	<.0001
Distant Futures Spread (*dist*)	-2.8721**	-9.25	<.0001
Market Advisory Service Recommendation (*mas*)	-.0579*	-1.87	.0615
Weeks after harvest (*wah*)	-.0965**	-7.66	<.0001
Weeks after harvest squared (wah^2)	.0015**	5.45	<.0001

[a] One asterisk indicates significance at the 90% level and two asterisks indicates significance at the 95% level.

Table I-3. Regression of Market Information on Wheat Sales for Central Elevator

	Estimate	t-value	Pr > |t|
Intercept	1.8567	14.41	<.0001
1996 crop year	-.2420	-2.29	.0218
1997 crop year	.4529	2.59	.0095
1998 crop year	.7074	3.86	.001
1999 crop year	.3062	1.61	.1080
Nearby Futures Spread (*near*)	-.8778**[a]	-3.38	.0007
Distant Futures Spread (*dist*)	-.8909**	-2.80	.0050
Market Advisory Service Recommendation (*mas*)	.0203	.87	.3838
Weeks after harvest (*wah*)	-.0624**	-5.95	<.0001
Weeks after harvest squared (wah^2)	.0008**	3.54	.0004

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

Table I-4. Regression of Market Information on Wheat Sales for Southern Elevator

	Estimate	t-value	Pr > |t|
Intercept	2.9586	9.76	<.0001
1996 crop year	.0399	.16	.8727
1997 crop year	1.4263	3.61	.0003
1998 crop year	.5075	1.20	.2299
1999 crop year	.5795	1.33	.1840
Nearby Futures Spread (*near*)	-1.7803**[a]	-2.99	.0028
Distant Futures Spread (*dist*)	-.3412	-.46	.6461
Market Advisory Service Recommendation (*mas*)	-.1372**	-2.40	.0165
Weeks after harvest (*wah*)	-.2910**	-11.71	<.0001
Weeks after harvest squared (wah^2)	.0046**	9.21	<.0001

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

The nearby spreads were found to be significant at the 95% confidence level for all three elevators, while the distant futures spread was only significant at the northern and central elevators. Since the southern elevator is one of the first to harvest wheat, most southern producers sell immediately before prices reach harvest lows. Also, the returns to storage tend to increase as location moves further away from the market (Benirschka and Binkley). Therefore, more long-term storage is expected to occur at the central and northern elevators and could explain why the distant futures spread increases in significance as elevator location moves northward. These results indicate that producers are using expected returns to storage as part of their selling decision. This is consistent with a marketing strategy that uses fundamental analysis, such as using futures spreads to calculate expected returns to storage, and suggests that producers may, at least partly, base price expectations and storage decisions on fundamental information.

The regression further indicated that the market advisory service recommendation variable did not have the expected positive sign across all elevators. The sign was only positive at the central elevator. However, it was not statistically significant, signifying that market advisory service recommendations have no affect on producers' selling decisions at the central elevator. Market advisory service recommendations exhibited an inverse relationship at the southern and northern elevators where it was significant at the 95% and 90% confidence intervals, respectively. These results suggest that producers are not following the recommendations of market advisory services. Instead, they are doing the opposite of what the advisory services recommend. Market advisory services have been found to be positive feedback traders, holding when prices rise and selling when prices fall (Matwichuk; Sanders et al.), while producers have been found to be negative feedback traders, holding when prices fall and selling when prices rise (Brorsen and Anderson, 2002). Thus, producers are likely unknowingly making marketing decisions in opposite directions of market advisory service recommendations. This negative relationship indicates that most producers do not directly implement strategies based on technical information into their marketing decisions.

Table I-5 shows the elasticity of the nearby and distant spread variables as well as the market advisory service recommendation variable at each elevator.

Table I-5. The Elasticity of Selected Variables at Each Elevator

	South	**Central**	**North**
Nearby Futures Spread (*near*)	-.0546	-.0456	-.2974
Distant Futures Spread (*dist*)	-.0339	-.0723	-.1891
Market Advisory Service Recommendation (*mas*)	-.0034	.0055	- .0228

Due to the nature of the Tobit regression model the elasticity of the variables is not equal to the beta coefficients and must be calculated separately[3]. As can be seen from table I-5, the elasticities do exhibit the same signs as the coefficients in the regression model. Thus, the relationship between the dependent variable and the variables in table I-5 are the same as discussed previously. However, we can see that the effect of a change in the future spread variables is fairly small at the southern and central elevator, while the northern elevator shows a greater change in the number of wheat sales with regards to changes in the nearby and distant spreads. As the nearby and distant spreads increase the number of wheat sales at the northern elevator will decrease by 30% and 19%, respectively. A change in the market advisory service recommendations has little effect on the number of wheat sales at all three elevators, indicating once again that Oklahoma wheat producers do not seem to be following the recommendations of market advisory services.

The variables measuring number of weeks after harvest are statistically significant at the 95% confidence level and exhibit the expected signs across all three elevators indicating that as the number of weeks after harvest increase fewer wheat sales take place. This is consistent with the theory that Oklahoma wheat producers typically sell the majority of their crop at or close to harvest (Cunningham, Brorsen, and Anderson).

Conclusion

This paper determined whether Oklahoma wheat producers' market timing decisions were correlated with fundamental (expected returns) or technical (market advisory service recommendations) information. The results indicate that producers are

[3] The elasticities were calculated at the four-week harvest mean. For a thorough decomposition of the Tobit model with regards to elasticity see McDonald and Moffit.

responding to fundamental information in the form of futures spreads that provide expected returns to storage. Producers' decisions were negatively related to market advisory service recommendations. Apparently, producers typically make selling decisions that are opposite of those of trend followers. Producers normally sell when prices rise, while trend followers hold when prices rise in the hope that they will rise even further. Since market advisory services have been found to be trend followers, their recommendations do not match the marketing decisions made by producers. Therefore, despite survey results showing that producers say they view market advisory service recommendations as very important to their marketing decisions, Oklahoma wheat producers do not closely follow the recommendations. It is more likely that producers only use market advisory service recommendations as background information, comparing it with other information sources in order to make marketing decisions.

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Essay II

Determining Returns to Storage:

USDA Data versus Micro Level Data

Introduction

Agricultural economists typically use aggregate data from the United States Department of Agriculture (USDA) instead of micro level data when conducting research on returns to storage (Hagedorn and Irwin; Brorsen and Irwin). This is mainly attributed to the fact that micro level data can be difficult to obtain and can be costly in both time and money. However, concerns about using USDA data in research regarding returns to storage do exist. One concern is the potential for information loss during the aggregation process that may ultimately result in underestimating the returns to storage. Another concern about using USDA data relates to the method used to collect the data. The USDA relies mainly on surveys of elevators for information regarding prices received, bushels produced and sold, and sale dates. Elevator managers typically give the surveys to their bookkeepers, who are responsible for filling out the surveys. It is possible that the bookkeepers do not supply accurate information on the surveys. For example, they may report an average or rounded price instead of an exact price or they may give a rough estimate of the number of bushels sold or produced. Thus, using USDA data as opposed to actual elevator data could result in inaccurate research conclusions, such as underestimating the returns to storage. A need for research that compares USDA calculated returns with returns based on micro level data exists.

The prices received by producers decline as distance to the market increases due to the increase in transportation costs. Because the price at the closer location is higher than that at the further location, the opportunity cost of storing is also higher at the closer location. Thus, storage costs at two elevators that are identical expect for location will differ (Benirschka and Binkely). Given that the opportunity cost of storing does decline as the distance to the market increases, Benirschka and Binkley found that locations farther from the market have a slight advantage in commodity storage. In other words, locations farther from the market enjoy slightly higher returns to storage due to decreased opportunity costs than locations closer to the market. Wright and Williams found that commodities stored in two locations must be treated as two different commodities due to the marginal costs of transforming one commodity into the other. In this case the transformation cost would be the cost of transporting the commodity at the further elevator to the closer elevator. Thus, aggregating the two elevators without accounting for the lower opportunity cost of storing at the further location may cause the returns to storage to be underestimated.

Farmer marketing strategies are an important part of the farm management process and have been researched extensively throughout the years (i.e. Musser, Patrick, and Eckman; Zulauf and Irwin; Schroeder et al.). Researchers typically agree with the efficient market hypothesis that suggests that little profit can be made from trying to beat the market. Instead, farmers will receive an average price over the crop year. However, a recent view on farmer marketing decisions is that farmers actually do worse than average. The research on producer performance is limited to a few studies with different results. Hagedorn and Irwin found that farmers do tend to under perform the market; while a study by Brorsen and Anderson found that farmers perform above the market average. An important difference in these two studies is the data used by the researchers. Hagedorn and Irwin used USDA data and Brorsen and Anderson used micro level elevator data. Further, the lower farmer returns found by Hagedorn and Irwin are due primarily to farmers storing too long. If USDA data is indeed limited by the aforementioned concerns, then the study by Hagedorn and Irwin may have underestimated the returns farmers received and underestimated their marketing abilities.

So the question remains, “How much does using USDA data underestimate returns to storage”? The objective of this study is to determine how much lower returns to storage based on USDA data are compared to returns based on micro level data. This will be accomplished by comparing Oklahoma Department of Agriculture data with rare micro level data obtained from three Oklahoma elevators. The accuracy of the aggregation method will be tested along with comparing the returns to storage computed for each dataset. The Oklahoma wheat market provides a strong test of aggregate data because of the significant price differences within the state. Seasonality of wheat sales will also be addressed in order to determine if producers are making inefficient marketing decisions by continuing to store after prices have peaked.

Theory

In a geographically dispersed market commodity prices decrease as distance to the market increases because of the increase in transportation costs. As mentioned in the introduction, the opportunity cost of storing also decreases as distance increases, which results in producers further from the market receiving higher returns to storage. Due to this observation, Benirschka and Binkley suggest that commodities stored at two different locations be treated as two different commodities. Aggregation of the commodities may result in a loss of information, creating a biased dataset that underestimates the returns to storage.

In order to further understand how the aggregation of data could create biasness, imagine a geographically dispersed market consisting of two time periods where location A is closer to the market than location B. As can be seen from table II-1, the price at the closer location A is higher than that at the further location B for both time periods. This is due to the lower cost of transportation at the closer location. Assuming an interest cost of 5% and storage cost of $0.10 at both locations, the nominal and net returns to storage at location A are $0.20 and -$0.04 respectively. The nominal and net returns to storage at location B are $0.30 and $0.05, respectively. Location B exhibits higher returns to storage than location A. This is consistent with the belief that returns to storage increase as distance from the market increases. Now imagine that the data are aggregated and all of location A sold in period one and all of location B sold in period two. The aggregate price will be $3.20 in period one and $3.30 in period two and the nominal and net returns to storage are $0.10 and - $0.16, respectively. Thus, aggregating the data resulted in lower returns to storage than the disaggregated data and reported negative net returns even though the net returns at location B are positive. The example demonstrates how using aggregate data may lead researchers to underestimate the returns to storage.

Table II-1. Example of Aggregation Bias in Geographically Dispersed Market

	Period One Price	Period Two Price	Interest @ 5%	Storage Costs	Net Price for Period Two	Net Returns to Storage
Location A	3.20	3.50	0.16	0.10	3.24	-0.04
Location B	3.00	3.30	0.15	0.10	3.05	0.05
Aggregate	3.20	3.30	0.16	0.10	3.04	-0.16

Data and Procedures

The micro level data for this study come from three elevators located in the southern, central, and northern regions of western Oklahoma. The data span nine crop years, from the spring of 1992 through the spring of 2001[4], and contain transactions of individual producer wheat sales at each elevator. Each transaction includes the number of bushels sold, the nominal price received per bushel, and the date of the sale. Harvest is a three-week period with beginning and ending dates that vary by elevator as well as by year. The harvest start date was determined by reviewing the daily transactions that occurred around the end of May or beginning of June. The date when the number of bushels sold increased noticeably and stayed relatively high for an extended period of time was used as the beginning harvest date. The southern elevator[5] has an earlier harvest that typically begins around the end of May. Harvest at the central and northern elevators is slightly later, beginning around the first of June and the middle of June, respectively.

[4] Due to missing transactions at the northern elevator, the 1998 crop year was deleted from all datasets.
[5] Errors in the southern elevator data were found and removed; thus, the data quality for this elevator is not as good as the other two elevators.

The returns to storage will be calculated with elevator data and with USDA aggregate data obtained from the Oklahoma Department of Agriculture. The aggregate data span from the harvest of 1992 through the harvest of 2000 and contain statewide monthly average wheat production statistics. These statistics include the price received, total number of bushels produced, and the percent of wheat sold each month. Average number of bushels sold each month was calculated by multiplying the number of bushels produced by the percent sold each month. Since the USDA data contain only monthly averages, harvest is assumed to be the month of June.

Table II-2 contains descriptive statistics for each elevator, as well as the USDA data. Average price received is the average nominal price producers received over the

Table -II-2. Descriptive Statistics for Elevator Data and United States Department of Agriculture Data

Descriptive Statistics	South	Central	North	USDA
Average price received ($/bu.)	3.41	3.32	3.38	3.30
Harvest price ($/bu.)	3.38	3.25	3.36	3.28
Percent harvest sales	53.21%	17.31%	13.05%	24%
Average bushels sold at harvest	961	1728	1770	18,825
Number of observations	14470	7089	6389	108
Average beginning harvest date [a]	May 25	June 3	June 11	June 1

[a] Harvest is 3 weeks long and beginning and ending dates vary by year.

eight crop years. Harvest price is the average price received during the three week harvest period. These average prices are weighted within each year by the number of bushels sold. Percent of harvest sales is the percent of sales that occurred during the three week harvest, compared to sales for the whole year. As can be seen from table II-2, producers at the southern elevator sell slightly more than half of their wheat at harvest.

This is likely due to the earlier harvest date at the southern elevator. Producers may be trying to sell before the Kansas and Nebraska harvests begin and prices hit harvest lows. It is also interesting to note that harvest prices at the southern elevator are slightly higher than those at the other elevators, likely due to an earlier harvest. The lowest prices are observed at the central elevator. This is due to there being no competing elevator located close to the central elevator to force prices higher. Both the southern and northern elevators must offer higher prices in order to compete with the other elevators located in their areas.

Storage and interest costs were calculated for all elevators, as well as the USDA and USDA-like datasets. The storage cost, set by the elevators, averages $0.00085 per day and $0.0255 per month. Interest cost is calculated using the prime rate of the given year plus 2%. The prime rate is based on the prime rate charged by banks in June of the given year and is quoted from the Kansas City Federal Reserve Bank. Daily interest costs at each elevator are calculated by multiplying the interest rate by the elevator's average harvest price[6] and dividing the product by 365 days. The monthly interest cost for the USDA dataset is determined using the same method, except the product is divided by 12 months. The cost of carry (storage cost plus interest cost) is then figured per day for the elevators and per month for the USDA datasets. Storage and interest charges begin accumulating immediately after the three-week harvest period ends at each elevator. Thus, the southern producers start accumulating storage and interest costs on June 15, the central producers start on June 25, and the northern producers start on July 1.

[6] The average harvest price differs at each elevator due to the varying harvest dates.

The selling prices net of interest and storage at each elevator are

(1) $$netprice_{tdk} = P_{dk} - days_k\left(\frac{hp_{tk}(z_t + .02)}{365} + S_{dk}\right)$$

where *t* is the year, *d* is the day, *k* is the elevator, $netprice_{tdk}$ is the net price, P_{dk} is the nominal price received on day *d* at elevator *k*, $days_k$ is the number of days after harvest at elevator *k*, hp_{tk} is the average harvest price at elevator *k*, z_t is the prime interest rate for year *t*, and S_{dk} is the storage cost per day. The net prices for the USDA dataset are calculated using the following equation:

(2) $$netprice_{ti} = P_i - mon\left(\frac{hp_t(z_t + .02)}{12} + S_i\right)$$

where *t* is year, *i* is month, $netprice_{ti}$ is the net price, P_i is the monthly price received, *mon* is the number of months after harvest, hp_t is the harvest price, z_t is the prime interest rate, and S_i is the monthly storage cost.

In order to compare returns to storage calculated with micro level data with returns calculated with aggregate data, the elevators' daily prices must be converted to monthly prices. This was done using a weighted average to calculate monthly prices across years for each elevator, where price was weighted within each year by the number of bushels sold. Average harvest prices were then computed for each elevator, as well as the USDA data, based on the aforementioned harvest dates. Monthly nominal returns to storage from harvest for each elevator and the USDA data are calculated using the following equation:

(3) $$rtrns_i = price_i - hrvst$$

where $rtrns_i$ is the returns to storage from harvest for month *i*, $price_i$ is the nominal weighted-average price received per bushel for month *i*, and *hrvst* is the weighted-average harvest price for each dataset. For example, the returns to storage from harvest for the month of August at the northern elevator would equal the average August price minus the average harvest price ($3.35). As previously discussed, the harvest price differs for each elevator, as well as for the USDA data.

The monthly net returns to storage from harvest for each elevator and the USDA dataset are determined such that

$$netrtrns_i = netprice_i - nethrvst \tag{4}$$

where $netrtrns_i$ is the net returns to storage from harvest for month *i*, $netprice_i$ is the net price for month *i*, and *nethrvst* is the average harvest net price.

The micro level data were aggregated using the same aggregation method as the USDA. The individual producer data were aggregated by month and year and weighted monthly averages were computed using the same method as that mentioned above. Then, the bushel weighted monthly averages were aggregated by year in order to get an aggregate dataset similar to the USDA data set. Monthly nominal returns to storage from harvest were calculated for the USDA-like data set using equation (3) and assuming the harvest price to be equal to the average June price. Monthly net returns to storage from harvest were calculated using equations (2) and (4).

The monthly returns to storage from harvest at each elevator were compared to the returns to storage from harvest calculated using the USDA data. If the returns computed using the USDA data are notably less than the returns computed using the elevator data, then using aggregated data to determine returns to storage may result in smaller returns than are actually the case. It is also likely that using aggregate USDA data in storage research may result in an important loss of information.

Due to the fact that Oklahoma wheat producers typically sell the majority of their crop close to or at harvest, seasonality of wheat sales is also an important factor. The frequency of sales in each month was calculated for each elevator, as well as for the USDA data using the following equation:

$$freq_i = \frac{sales_i}{\sum_i sales_i} \tag{5}$$

where $freq_i$ is equal to the percentage of total wheat sales that occurred in month i and $sales_i$ is equal to the total number of sales that occurred in month i. Comparing the seasonality of wheat sales with returns to storage will allow us to observe whether producers continue to store their crop after price has reached its peak.

Results

Figure II-1 graphs the monthly nominal returns to storage from harvest for each elevator, as well as the USDA dataset and the USDA-like dataset. Figure II-2 graphs the monthly net returns to storage from harvest for each dataset. Both graphs show that the returns calculated using the USDA data are not much different than the returns calculated using the micro level data. However, figure II-2 does show a slightly greater difference than figure II-1 between returns based on USDA data and returns based on elevator data. This difference is due to storage costs and the varying harvest dates at each elevator. Due to the fact that harvest ends at different times for each elevator (typically around June 15 in the south, June 25 at the central location, and July 1 in the north) producers at each

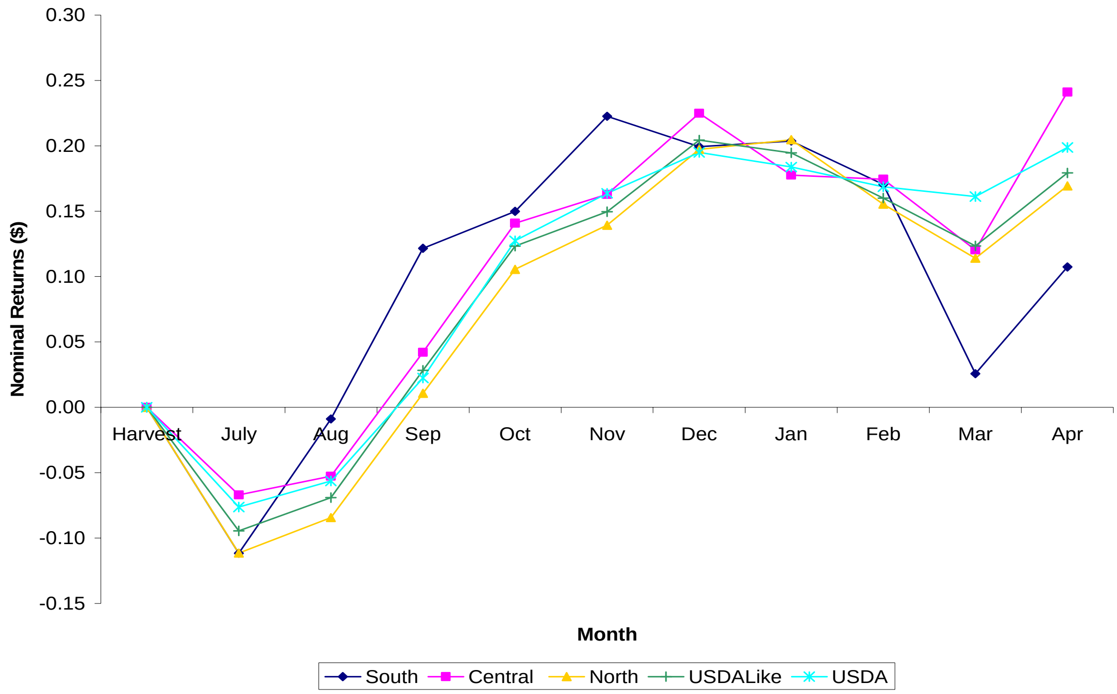

Figure II-1. Nominal returns to storage from harvest

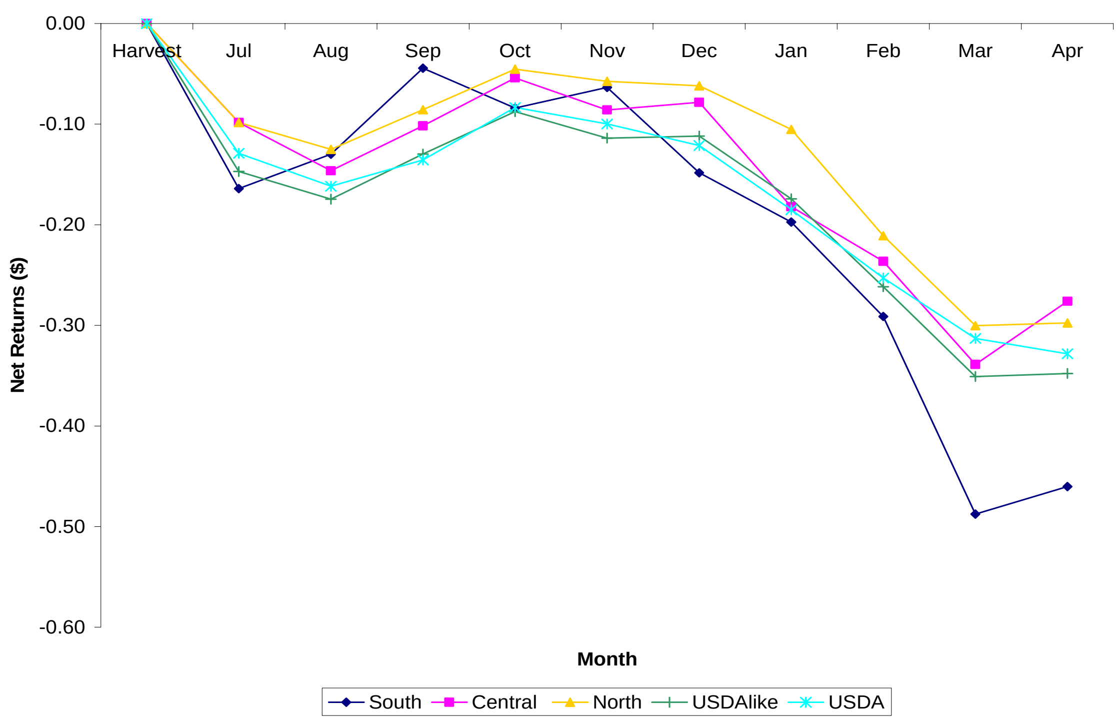

Figure II-2. Net returns to storage from harvest

location start accumulating storage charges at different times. For example, on July 5 the southern producers would have accumulated 20 days of storage charges, the central producers would have 10 days of storage charges, and the northern producers would only have five days of charges. Despite the difference between figures II-1 and II-2, they both indicate that the USDA data only slightly underestimate the net returns to storage. The USDA-like data closely resembles the actual USDA data, showing that the method used to aggregate the elevator data was consistent with the USDA method. The similarity of the USDA-like dataset with that of the USDA dataset also indicates that the data collection process used by the USDA produces data that is consistent with actual elevator data.

As can be seen from figure II-2, negative net returns to storage are common. One explanation for the negative returns is the presence of processor convenience yields[7]. Since processors receive a convenience yield from holding stores of commodities (i.e. wheat) used in the production of other commodities (i.e. flour), they will look to purchase contracts for future delivery. If the price for the deferred delivery is below the harvest price, then negative returns to storage may arise. Wright and Williams propose data aggregation as an explanation for negative returns to storage. However, the results of the current study do not support this hypothesis. Figure II-2 shows that negative returns to storage exist even when micro level data is used to calculate returns.

Returns to storage are low close to harvest and start increasing around September, reaching their peak during November and December. The negative returns during July and August are likely due to the beginning of the Kansas and Nebraska harvests. One

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[7] Convenience yields are the implicit benefits that accrue to the owners of physical stocks (processors) but not to the owners of contracts for future delivery (producers) (Yoon and Brorsen).

possible explanation for prices falling off in late December/early January is the occurrence of two world harvests. It is possible that due to the beginning of harvest in the southern-hemisphere the export demand for U.S. wheat decreases. The domestic demand for U.S. wheat remains the same, but the available supply increases, driving down price. While two world harvests is a plausible explanation, we were unable to find any seasonality in export shipment data.

Figure II-3 graphs the frequency of wheat sales by month at each elevator and for the USDA dataset.

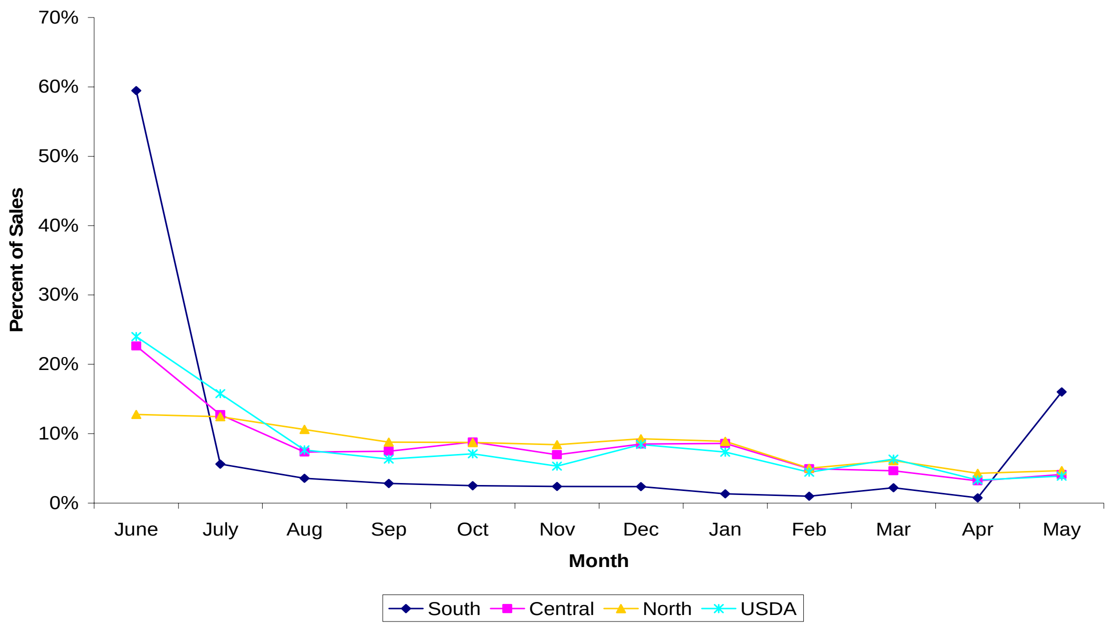

Figure II-3. Frequency of wheat sales by month

As expected, the southern producers do most of their marketing at or very close to harvest. The central and northern elevators also exhibit a high percentage of producer wheat sales during the harvest months of June and July. This is fairly consistent with OSU extension recommendations that advise producers to use mechanical marketing strategies, such as selling at harvest in the south and selling in lots of one-third on June 20, October 15, and December 15 (Anderson and Brorsen). The results show net prices are highest at harvest (figure II-2), indicating that producers should sell at harvest, regardless of location. However, net returns for October and December are close to harvest returns at the central and northern elevators, showing some support for the one-third marketing strategy[8]. Prices peak around late November and early January (figures II-1 and II-2), so storing past these months would be uneconomical for producers. The results in figure II-3 show that the majority of wheat sales occur before prices start declining in early February. However, some wheat sales do take place during the more uneconomical time period of February to May[9]. Producers may be exhibiting a psychological biasness known as the disposition effect (holding losing investments too long and selling winning investments too soon) which causes them to continue to store even though net returns are negative (Locke and Mann).

Conclusions

This study is based on the belief that the aggregation of data can cause returns to storage to be underestimated by USDA data. The objective was to determine how much USDA data underestimates the returns to storage compared to returns based on micro level data. The results indicate that the use of USDA data only slightly underestimates net returns to storage and that the USDA data accurately reflects actual elevator transactions. Therefore, USDA data appear to be accurate and almost as reliable as micro level data.

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[8] This study uses fairly high interest rates. Since many farmers have little or no debt, their opportunity cost is lower. Thus, storage might provide a greater return than a bank checking or savings account.
[9] Due to its earlier harvest, the southern elevator does show increased sales in May.

The seasonality of wheat sales was also addressed in the research. Oklahoma wheat producers tend to sell close to harvest, likely due to an earlier harvest date which results in slightly higher harvest prices. Prices peak around the end of November or beginning of January, which makes it uneconomical to continue to store past this point. However, some wheat sales do occur after prices have reached their peak. This indicates that some producers do store their grain longer than is economical.

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Essay III

The Preference for Round Number Prices

Introduction

Recent empirical research indicates that not all prices are viewed as equal. Studies show that round prices (prices ending in zero or five) appear to be more popular than non-round prices in many financial markets, such as initial public offering markets, stock markets, and foreign exchange markets (Kandel, Sarig, and Wohl; Harris; Fischer). Technical analysts take this price clustering one step further by assessing its relationship to market trends. Results of technical analysis suggest that trends tend to increase after certain prices levels (specifically round prices) are crossed (Osler; Aggarwal and Lucey). While there have been studies regarding price clustering at round numbers and its relationship to market trends in financial markets, there has been little done to address the possibility of round prices being preferred in non-financial markets. Since psychological biases, such as price preference, may result in increased risks and unexpected outcomes (Kahneman and Riepe), it is important to research whether this particular bias exists in markets outside of the financial industry.

The first objective of this paper is to determine if a preference for round prices exist within the Oklahoma wheat market. Descriptive statistics will be used to test whether round prices have a greater relative frequency than that of non-round prices. If a preference for round prices exists it may suggest that producers are making marketing decisions based on psychological biases and further education on the consequences of these biased decisions may be required. It is also possible that the preference for round prices is not coming from producers, but from the grain elevators. Elevator managers could be using management practices that may influence price.

The second objective relates to the technical analysis theory that market trends increase or decrease when round price thresholds are crossed. Specifically, the objective is to determine whether whole dollar prices are viewed as round price thresholds. This will be accomplished using a regression model that examines the change in number of market transactions (wheat sales) when price moves above or below a whole dollar amount.

Theory

If a preference for round prices in the Oklahoma wheat market does exists, it likely results from either management practices at the elevator level or psychological biasness on the part of the producer. Management practices that could influence prices include such things as negotiated prices, adjusting margins to account for market uncertainties, and producer use of sell orders. Producer psychological biasness simply indicates that producers may have an irrational inclination towards round prices.

An overview of how elevators determine producer price is needed in order to better understand the possible causes of round price dominance in the Oklahoma wheat market. Elevator managers typically determine producer price by subtracting their margin to the market price that the elevator receives. According to elevator managers, the margins they use to calculate producer price are usually based on historical margins and competitor prices and seldom change from year to year, though elevator managers may adjust the margin if significant changes in transportation costs occur. Elevator managers do not round the price they receive from the market. If rounding already exists in the market prices that elevators receive and elevator managers use round margins then producer price may be affected. However, elevator managers state that they do not usually set the margin at a round number.

Financial market research often attributes lower negotiation costs as one factor of price clustering at round numbers (Harris; Neiderhoffer). If a producer met with an elevator manager in order to negotiate a better price, it is possible that there would be a tendency to round to the nearest five or ten cent increment. Interviews with elevator managers indicate that prices are very seldom negotiated; however, if price is negotiated rounding to the nearest five or ten cent increment typically occurs. Since, negotiated prices are very rare it is unlikely that this would result in a prevalence of round prices. As for elevator managers adjusting margins to account for market uncertainties, managers report that margins are only adjusted for changes in transportation and even then the adjustment is slight. Therefore, it is also unlikely that this would cause round prices to be more dominant.

The most likely cause of any round number pricing in the wheat market is producers' use of sell orders that are placed at round prices. According to elevator managers, sell orders are a common wheat marketing tool (Smith). Sell orders are placed by the producer and give the elevator manager permission to sell a given amount of the stored crop when price reaches a certain level (Osler). The agreed upon sell price is known as the target price. Evidence from sell orders in the currency and stock markets indicate that target prices are commonly set at round prices (Harris; Osler; Fischer). Elevator managers agree that target prices on sell orders are almost always set at round prices (Smith).

The preference for setting target prices at round numbers is often attributed to the memory-economizing tendencies of individuals (Kahn, Pennachi, and Sopranzetti). Individuals tend to be better able to remember round numbers which results in a preference for round prices. Even elevator managers say that producers seem to be more "round number minded". This preference for round prices is an example of a psychological bias. Research in behavioral finance indicates that people may unknowingly incorporate certain psychological biases (errors in intuitive judgment) into their decision-making process (Kahneman and Riepe; Odean). Evidence of psychological biases have been found in both the financial and agricultural markets and include such things as overconfidence in the ability to predict the future, maintaining losing market positions, and remembering successes and forgetting failures (Brorsen and Anderson; Kahneman and Riepe; Odean). If producers do have a psychological inclination towards round numbers, it could very well cause round prices to occur more frequently.

Data

Data are from three grain elevators located in the northern, southern, and central areas of western Oklahoma. The data span nine crop years, from the harvest of 1992 through the harvest of 2000, and contain individual producer transactions of wheat sales at each elevator. Each transaction includes the number of bushels sold, price per bushel, date of transaction, and the number of weeks after harvest that the transaction took place. Harvest is a four week period that is defined differently for each elevator depending on location. Beginning harvest dates for the southern, central, and northern elevators are May 25, June 1, and June 12 respectively.

Table III-1 contains the descriptive statistics for each elevator. Average price is the nominal average price that producers received over the nine years of data. The average week after harvest is the average week that producers chose to market their wheat for all years. Percent round number prices is the percent of individual daily prices that are round numbers (prices that end in zero).

Table III-1. Descriptive Statistics for Each Elevator

Descriptive Statistics	South	Central	North
Average price ($/bu.)	3.41	3.32	3.38
Average week	5	16	18
Percent round number prices	15.39%	12.37%	11.65%
Number of observations	14434	7089	6389

The southern elevator has the highest price and lowest average number of weeks. According to Benirschka and Binkley, locations closer to the market (the Gulf) typically have higher negative returns to storage than locations further away from the market. Therefore, southern producers are more likely to sell at or close to harvest which results in a lower average number of weeks after harvest compared to the central and northern elevators. The higher average price at the southern elevator is likely due to the fact that the southern elevator is closer to the market (the Gulf), thus transportation costs are lower. Therefore, the average price is higher at the southern elevator. Another reason for the higher average price could be that harvest is slightly earlier at the southern elevator resulting in a slightly higher demand for wheat and a higher price per bushel.

Procedures

The procedures include descriptive statistics and regression analysis. The descriptive statistics are used to determine if round prices are more prevalent than non-round prices in the Oklahoma wheat market. The regression model assesses whether producers use whole dollar prices as threshold levels by estimating how the number of daily transactions changes when prices move above or below whole dollar prices.

Descriptive Statistics

In order to study the prevalence of round prices, descriptive statistics are computed and tested using methods like that of Kandel, Sarig, and Wohl and Osler. First, T_{jd} is computed, where T_{jd} is equal to the total number of transactions for each elevator j that occurred at each last digit d (d = 0,1,…,9). Then the relative frequency of transactions occurring at each last digit is determined using the following equation:

$$R_{jd} = \frac{T_{jd}}{\sum_{d} T_{jd}} \quad (1)$$

where R_{jd} is equal to the percentage of the total number of transactions at elevator j at prices that end with the last digit d. The null hypothesis is that round prices are not more prevalent than non-round prices. A chi-squared test for equal proportions is performed to determine whether a significant difference exists between the frequencies occurring at each last digit.

Regression Model

For the purpose of running the regression model the individual data were aggregated by day for each elevator, so that each observation contains the daily number of transactions, daily price per bushel, date, and number of weeks after harvest. The following regression is used to determine the effect of prices moving above or below whole dollar prices on the number of daily transactions:

(2) $$tr_{it} = \beta_0 + \sum_{k=1}^{8} \beta_{1k} cy_{kt} + \beta_2 wah_{it} + \beta_3 wah_{it}^2 + \beta_4 abv_{it} + \beta_5 abv_{i-1,t} + \beta_6 blw_{it} + \beta_7 blw_{i-1,t} + \varepsilon_{it}$$

where i is the day, t is the year, tr_{it} is the number of transactions that occurred on the i^{th} day in year t, cy_t is a dummy variable for each crop year, wah_{it} is the yearly bushel-weighted mean weeks after harvest when wheat was sold, abv_{it} is a dummy variable for the movement of price above a whole dollar value, $abv_{i-1,t}$ is the lagged movement of price above a whole dollar value, blw_{it} is a dummy variable for the movement of price below a whole dollar value, $blw_{i-1,t}$ is the lagged movement of price below a whole dollar value, and ε_{it} is the error term. The plots of error terms versus wah_{it} for the OLS model exhibited heteroskedasticity with variance increasing for low values of wah_{it}, thus the regression is estimated using maximum likelihood. The error, ε_{it}, is defined to be heteroskedastic as

(3) $$\varepsilon_{it} \sim N(0, \sigma_{it}^2)$$

and the variance of ε_{it} (σ_{it}^2) is defined as

(4) $$\sigma_{it}^2 = \exp(\alpha_0 + \alpha_1 wah_{it} + \alpha_2 wah_{it}^2).$$

It is expected that transactions will increase when price moves above a whole dollar value, therefore, β_4 and β_5 are expected to be positive. Conversely, transactions are expected to decrease when price moves below a whole dollar value, thus β_6 and β_7 are expected to be negative. Oklahoma producers typically sell the majority of their crop at or close to harvest. Therefore, as weeks after harvest increase fewer transactions are expected and β_2 is expected to be negative.

Results

<u>Descriptive Statistics</u>

Figures III-1, III-2, and III-3 show the histograms for the relative frequency of transactions at the northern, central, and southern elevators for each possible last digit in price.

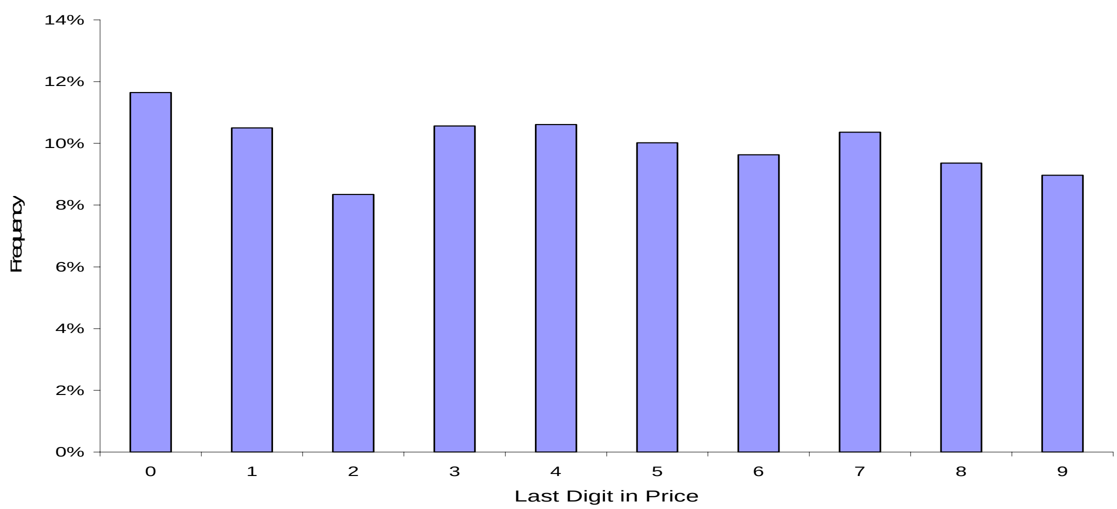

Figure III-1. Histogram of last digit in price for northern elevator

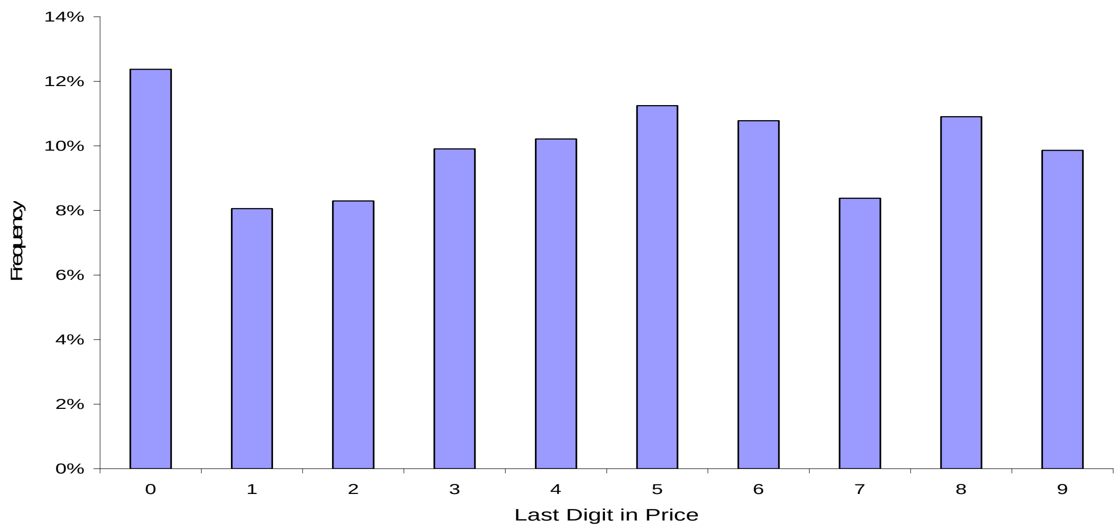

Figure III-2. Histogram of last digit in price for central elevator

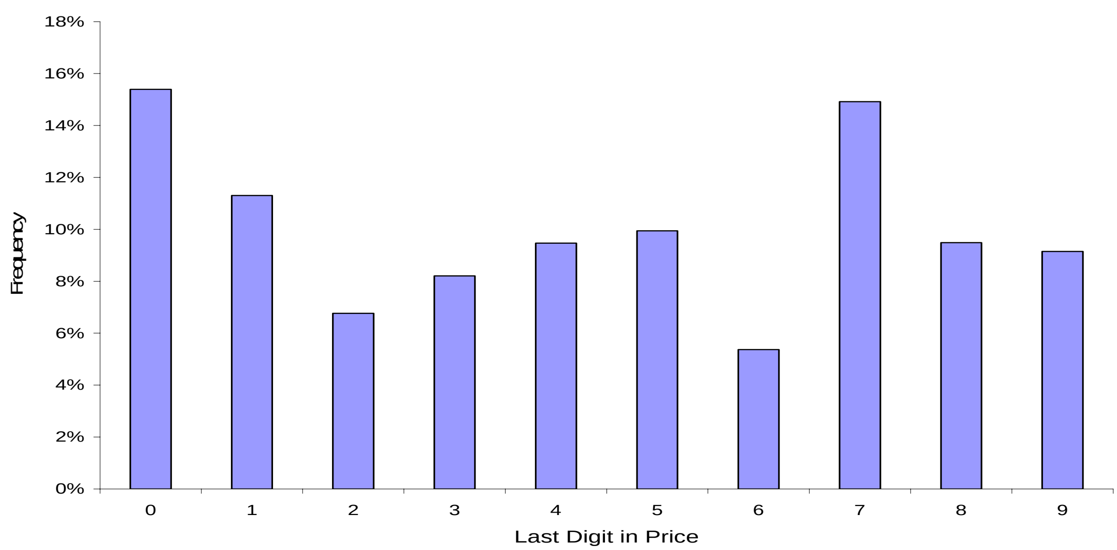

Figure III-3. Histogram of last digit in price for southern elevator

As expected more transactions take place at prices with a last digit of zero. For the chi-squared equal proportion test, the null hypothesis that the frequency of transactions is equally distributed across all last digits was rejected at all locations. The frequency of occurrence across last digits is more evenly distributed in the northern and central elevators than at the southern elevator. The southern elevator has the highest percentage of transactions occurring at zero with almost 16% and has a high percentage of transactions occurring with a last digit of seven.

As expected, the results indicate that there is a preference for round prices in the Oklahoma wheat market. However, the preference found in this study is fairly small compared to that found in studies of financial markets. It is possible that producer biasness leads to the placing of a disproportional amount of sell orders at round prices which, then leads to a prevalence of round prices in the wheat market.

Regression Model

The results of the regression of number of transactions with respect to price movement above or below a whole dollar amount are shown in table III-2. The results of the regression analysis show that the coefficients for the movement of price above a whole dollar amount and for the lagged movement of price above a whole dollar amount exhibit the expected positive sign and are significant. This indicates that as price moves beyond a whole dollar amount, the number of transactions increase. This could be interpreted as producers using whole dollar prices as threshold levels and selling when price moves across that threshold. For example, if price increases from $2.88 to $3.02 it would cross the $3.00 threshold and producers would increase their wheat sales (i.e. more transactions would occur). The coefficients for the movement of price below a whole dollar amount and for the lagged movement of price below a whole dollar amount are not significantly different from zero at the 95% confidence level, which suggests that price movement below a whole dollar amount does not significantly affect producers' decisions to sell their wheat. These results coincide with the results of technical analysis that show market trends (wheat sales) increasing after specific price levels (whole dollar prices) are crossed.

Table III-2. Regression of Whole Dollar Prices on Number of Transactions

	Estimate	t-value	Pr > |t|
Intercept	5.5121	10.08	<.0001
1993 crop year	.1097	.38	.7023
1994 crop year	-.1450	-.63	.5254
1995 crop year	.3894	1.64	.1011
1996 crop year	.3935	1.64	.1017
1997 crop year	.7004	2.27	.0235
1998 crop year	.6370	1.82	.0692
1999 crop year	.4552	1.90	.0570
2000 crop year	.3915	1.67	.0947
Weeks after harvest (*wah*)	-.1507*	-4.38	<.0001
Weeks after harvest squared (*wah2*)	.001727*	2.99	.0028
Movement above whole price (*abv*)	.8041*	2.04	.0416
Lagged movement above whole price (abv_{i-1})	1.3278*	3.00	.0027
Movement below whole price (*blw*)	-.4029	-1.75	.0806
Lagged movement below whole price (blw_{i-1})	.3601	1.16	.2441

* Indicates significance at 95% confidence level

Conclusion

This study determined whether round prices are more common in the Oklahoma wheat market. The results show that round prices are slightly more common than non-round prices at all three elevator locations. This is likely due to producers using sell orders with a majority of the target prices set at round numbers. This inclination towards round numbers could be the result of producer psychological biases. If producers allow psychological biases to influence their marketing decisions then they may experience lower returns and unexpected outcomes. Therefore, additional steps may be required in order to educate producers about the psychological mistakes that they are prone to make.

Regression analysis was used to determine the effect of movements around specific price thresholds on wheat sales. The test showed that wheat sales increased slightly when price moved above a whole dollar amount, while the effect of price movement below a whole dollar amount was not statistically significant. These results indicate that producers may be using whole number prices as threshold levels, waiting to sell after price moves above these thresholds.

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