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Suggested citation format:

Yang, L., and R. M. Leuthold. 1996. "An Empirical Examination of the Role of Trading Volume in Futures Markets." Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. [http://www.farmdoc.uiuc.edu/nccc134].

An Empirical Examination of the Role of Trading Volume in Futures Markets

Li Yang and Raymond M. Leuthold*

This paper investigates the trading profits and the informational role of trading volume in the frozen pork bellies futures market for reporting traders from the period 1985 through 1994. More than 95% of reporting traders make statistically zero profits on a daily basis. About half of the remaining reporting traders make positive profits and the other half percent earn negative profits consistently. Given the evidence on the examination of the relationship between trading volume and daily profits for winning traders, there is little support for the theoretical finding that traders who use information contained in trading volume do better than traders who do not. Hence, it is not clear whether trading volume provides useful information for frozen pork bellies traders to earn consistently positive returns on a daily basis.

Introduction

The relation between volume and the absolute value of price change in both equity markets and futures markets has long been a subject of research (see Karpoff (1987) for an excellent review of previous research). Numerous studies finding a positive correlation between volume and the absolute value of price change have indicated that volume may play an important role in financial markets. Blume, Easley, and O'Hara (1994) investigate theoretically the informational role of volume. Volume enters traders' learning because they use specific volume statistics in updating their beliefs. Blume, et al. show that volume provides information on information quality that can not be deduced from price statistics and that traders who use information contained in trading volume do better than traders who do not. However, the predictions of these theoretical findings have been subjected to little empirical scrutiny.

The objective of this study is to examine empirically whether trading volume provides valuable information for traders who consistently earn positive returns in the frozen pork bellies futures market during the period of 1984 to 1994.

To conduct this examination, we first investigate who are winners among reporting traders in the frozen pork bellies futures market. Hartzmark (1991) and Leuthold, Garcia and Lu (1994)

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have shown that some reporting traders earned consistent profits during the period of 1977 to 1981 and during the period of 1982 to 1990, respectively. Hence, it is expected that there are consistent winners and losers among reporting traders during the period of 1984 to 1994. Second, to examine whether trading volume is valuable for traders, daily futures profits for each winner are regressed against trading volume. The significance levels of trading volume indicate the contribution trading volume makes to winners' profits. If the levels of trading volume for the majority of winners are significant, this suggests that trading volume provides useful information for winners to make profits. Hence, our empirical results could offer support for the theoretical results by Blume, Easley and O'Hara (1994), otherwise, it is not clear whether trading volume can provide useful information for frozen pork bellies futures traders to consistently earn profits.

Data Set

The data used in this paper come from the Commodity Futures Trading Commission (CFTC) reports on the end-of-day commitments of reporting traders. They cover the period from 1/1/1985 to 12/30/1994, which gives us a sample of 2,549 traders with over 410,743 observations. In the frozen pork bellies market, all traders holding 25 contracts or more at the end of the day must report their trading activity to the CFTC, indicating long and short positions separately for each contract maturity month. The CFTC assigns a number to each reporting trader, which is used to identify individual traders. However, if a trader stops trading for more than two years, a new trader may be assigned that number later. This may create the problem that an identification number could represent two different reporting traders if there is an interruption of trading for more than two years. One way to solve this problem is to exclude these traders from our data set when such a trading gap exists. Following this rule, 501 traders have to be excluded, causing potential loss of information.

An alternative procedure examines these 501 traders' trading activities before and after the trading-gap periods. If a trader's trading behavior appears similar over these two periods, the identification number may represent one trader. If we suspect that the trader's trading behavior has changed between these two periods, we can either exclude this trader or keep the trader but exclude the one period which has less observations from our data set. It is difficult to examine all 501 traders. We selected a subsample of them who have more than three-year gaps or whose accumulated positions over the years that they are in the market ranks them among the most active 100 traders[1]. Especially for the former reason, a trader's ID number with a bigger trading gap may have a greater chance to be assigned to another trader. The total number examined in this subset is 70 out of 501. From this examination, we excluded one trader and reduce three traders' observations. It appears that few numbers have been reassigned to another trader and that this problem is less serious than originally expected.

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[1] All traders are ranked by their accumulated positions over the years they are in the market.

For statistical reasons we also have to exclude individual traders who report less than 25 separate times (observations) over the 10-year data period. So, the total number of traders analyzed is 1256.

To study how winners and losers are distributed among the traders, we group traders from different perspectives. For instance, we select the 100 largest traders as a group, and we also select the traders whose reporting periods exceed 6 years as a group, then 4 to 6 years, 2 to 4 years, and 0 to 2 years as groups.

The daily profits are used to measure traders' performance in the market. This is an approximation of actual trader's profits because the intra-day transactions and commissions are not available in the data set. Daily profits for each trader and each contract position are calculated by multiplying the end-of-day positions by the change in the settlement price between the current day and the following day for each contract. The prices are available from the Chicago Mercantile Exchange. Additional information about trader type is on the original tape, such as commodity pool operator, commodity trading advisor, managed account, and so on, but it is highly variable and unreliable for trader classification, so we do not attempt to classify traders as hedgers, spreaders or speculators.

Statistical Methodology

A. Testing for normality

Many parametric statistical tests assume an underlying normal distribution of the population. If data do not meet this assumption, we use nonparametric analysis. So, we first test if the daily profits for each trader are normally distributed. Since the profit distribution is a combination of the different position sizes and the distribution of price change, a skewed distribution of daily profits would be expected. One of two normality tests is used depending on the sample size. If the sample size is less than or equal to 2000, the Wilk-Shapiro test is used, otherwise, the Kolmogorov-Smirnov test is used.

B. Testing for mean of daily profits

A t-test is used to examine if the mean of daily trading profits is significantly different from zero, providing trader's daily profits are statistically normally distributed, otherwise, a nonparametric test is employed. Two groups of nonparametric tests are related to this study. They are the sign test and the signed rank test (Conover (1980) and Mendenhall, Wackerly, and Scheaffer (1990)). The signed rank test requires that the distribution is symmetric, but the sign test does not require this assumption. Since the specific distributions of daily profits, if they are not normally distributed, are unknown and are more likely to be skewed, we use the sign test. The sign test examines if the median rather than the mean of a sample is significantly different from zero. If the distribution of a sample is skewed, the mean may be considerably higher than the median, and, consequently, not as representative of the value that the random variable may assume. Therefore, the median is often used as a measure of central tendency.

C. Regression of the daily profit against trading volume

Blume, Easley, and O'Hara (1994) investigate theoretically the informational role of volume. They show that given a price, trading volume conveys information which can be used in a price equation to make an inference about the noisy signal value. They also demonstrate that traders who use information contained in trading volume should do better than traders who do not. Based on their theoretical findings, we conduct an empirical examination by testing if trading volume provides valuable information for traders to consistently earn profits. We regress: 1) current daily profit on current trading volume, 2) one-day-ahead profit on current trading volume, and 3) two-day-ahead profit on current trading volume for each trader who made (statistically) positive profits[2], i.e.,

$$Profit_t = \alpha_0 + \beta_0\ (trading\ volume)_t\ , \tag{1}$$

$$Profit_{t+1} = \alpha_1 + \beta_1\ (trading\ volume)_t\ , \tag{2}$$

$$Profit_{t+2} = \alpha_2 + \beta_2\ (trading\ volume)_t\ . \tag{3}$$

If there are consistent relationships between trading volume and profit across winning traders, this suggests that trading volume provides useful information for traders to consistently earn positive profits.

We use OLS to estimate the parameters in the regression model. The significance level of trading volume, β, indicates the contribution of trading volume in providing valuable information for traders to consistently earn profits. Two issues are of concern. One is the assumption of normality of the disturbance because some of traders' daily profits are not normally distributed. According to Greene (1993, p. 297), "if the regressors are well behaved, the asymptotic normality of the least squares estimator does not depend on normality of the disturbance; it is a consequence of the central limit theorem". The second issue is the problem of nonspherical disturbances: heteroskedasticity and/or autocorrelation. We use White's (1980) heteroskedastic-consistent covariance matrix estimation to correct the estimates for any unknown form of heteroskedasticity. The method to correct autocorrelation is described in Greene (1990, p. 439).

Empirical Results

[2] We can not conduct the empirical examination based on intra-day transactions because such data are not available.

A. Aggregate performance

The aggregate performance of all reporting traders in the frozen pork bellies market is assessed by their daily profits calculated as described previously. Table 1 shows that total profits from long and short positions and net profits for the entire sample and for the group of the 100 largest traders in the frozen pork bellies market for each year 1985-1994. Over this 10-year period, all reporting traders made a total of $122.5 million, generating positive profits each calendar year except for 1990[3]. The 100 largest traders made a total of $163.8 million, which is more than the total profits that all reporting traders made. Comparing the total profits for all reporting traders and the 100 largest traders, the 100 largest traders always make larger positive and less negative profits than all reporting traders do for every year except 1992. This suggests that the 100 largest traders consistently perform better than the rest of the reporting traders[4].

All reporting traders made $313.0 million from short positions and lost $190.5 million from long positions, and the 100 largest traders made $250.5 million from short positions and lost $86.7 million from long positions over the 10-year period.

B. Individual performance

Table 2 shows that for 35.1% of reporting traders their daily profits are from a normal distribution at a 5% significance level. Among these traders, for 93.7% of the traders their mean daily profits are not significantly different from zero, 2.7% of these traders have significantly positive mean daily profits, and 3.6% of these traders have negative mean daily profits.

For the traders whose daily profits are not normally distributed, there are 96.4%, 2.1%, and 1.5% of these traders that have zero, positive, and negative median daily profits at a 5% significance level, respectively. The evidence demonstrates that there is a slightly higher probability for the traders whose daily profits are not normally distributed to make positive rather than negative profits consistently.

Overall, 95.5% of reporting traders have daily profits that are not significantly different from zero, 2.3% of reporting traders make positive profits, and 2.2% of reporting traders make negative profits consistently[5]. This suggests that the majority of reporting traders make zero profits (statistically) in frozen pork bellies futures, only a few of reporting traders make statistically positive profits, and a few reporting traders earn negative profits consistently.

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[3] This means all non reporting traders lost $122.5 million (plus commissions) in the frozen pork bellies futures market for 1985-1994.

[4] Recall that these results do not include intra-day trades.

[5] The total number of traders who statistically make positive profits is 29. These traders' profits are used in the following regression testing.

C. Distribution of winners and losers

Based on the traders' accumulated positions over the period they are in the market, Table 3 reports how winners and losers are distributed. The interesting evidence is that while 12 traders among the largest 100 earn statistically positive profits, none of these largest 100 traders earn negative profits consistently. All those traders who earn negative profits consistently rank 101 and beyond in size.

Based on the length of their reporting period, we report how winners and losers are distributed in Table 4. This table shows that for the traders whose reporting periods are for more than 6 years, 55.6% are winners and none are losers, 13% of traders whose reporting periods are from 4-6 years are winners and none are losers, 4.8% are winners and none are losers in the range of the reporting period from 2-4 years, and 1.5 % are winners and 2.5 % are losers for the rest of traders. This evidence suggests that the longer a trader is in the market, the higher the probability that the trader will earn positive profits consistently[6]. The traders either make statistically positive or zero profits if their reporting periods are for more than two years. All traders who lose money consistently traded in the market less than two years. Nevertheless, 17 of 29 traders who made profits consistently traded in the market for less than 2 years.

D. Relation of daily profits and trading volume

We regress current daily profit on current trading volume, one-day-ahead profit on current trading volume, and two-day-ahead profit on current trading volume for each trader who made (statistically) positive profit consistently. There does not appear to be a consistent relationship between winners' profits and trading volume across these winning traders. Table 5 summarizes only the evidence on the relationship between trading volume and one-day-ahead profit for each consistent winner[7]. The table reports the trader's rank based on the accumulated position, total reporting trades (size), number of reporting days, and coefficients with t ratio and the R^2 statistic for the regression. There are negative relationships between trading volume and one-day-ahead daily profits for 8 of the 29 winners. One of these negative relationships is significant at the 10% level but is not significant at the 5% level. The rest of these negative relationships are not significant at the 10% level. A positive relationship is significant for only 7 of the 29 winners at the 5% level and for 5 of the 29 winners at the 10% level. Given this evidence, it is not clear that trading volume provides useful information for traders in the frozen pork bellies market who earn consistent profits.

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[6] Of course, the causation could be the other way, as long as a trader makes money consistently, the longer the trader will continue to trade. Traders who lose consistently may leave the market. However, some of the consistent losers could be hedgers with offsetting cash positions.

[7] Results from the other 2 sets of regressions, current daily profits and two-day-ahead profits on current volume, were not better than those shown.

There are three explanations. First, even though there maybe useful information contained in trading volume, these winning traders do not use it because they may have access to private information, or public information may provide enough information for them to make consistent profits. Second, valuable information contained in trading volume may be used by these traders in intra-day transactions, but we can not test for that because such data are not available. Third, trading volume does not provide consistently useful information for frozen pork bellies futures traders to make a profit. Nevertheless, these results do not appear to support the theoretical finding of Blume, Easley and O'Hara (1994).

Conclusions

This paper investigates the trading profits in the frozen pork bellies futures market for reporting traders from the period 1985 through 1994. We find more than 95% of reporting traders make statistically zero profits on a daily basis. About half of the remaining reporting traders make positive profits and the other half percent make negative profits consistently. After examining how winners and losers are distributed, we find that traders who accumulate the largest positions and who remain in the market for a longer period of time, have higher probabilities of earning consistently positive profits. None of the traders who are among the largest 100 make statistically negative profits. In general, the 100 largest traders perform better than the rest of the reporting traders. Based on the theoretical finding of Blume, Easley, and O'Hara (1994), we conduct an empirical examination of the relationship between trading volume and daily profits for the 29 winning traders, and find no consistently significant relationship between these two variables for the frozen pork bellies futures market. There is only limited evidence that trading volume provides useful information for frozen pork bellies futures traders to earn consistent profits on the daily basis.

Table 1. Aggregate Trading Results for Reporting Traders In Frozen Pork Bellies Futures

Year	Short*		Long*		Net Profit*	
	A**	B***	A	B	A	B
1985	52.40	31.80	-51.84	-26.84	0.56	4.95
1986	-19.50	-8.83	21.97	11.86	2.47	3.02
1987	-19.37	-2.76	26.21	12.70	6.84	9.94
1988	117.37	84.22	-69.01	-31.23	48.36	52.99
1989	82.04	71.02	-34.73	-8.14	47.31	62.88
1990	-15.00	-12.52	10.16	7.94	-4.84	-4.57
1991	57.91	42.96	-49.47	-28.84	8.44	14.13
1992	21.15	15.46	-13.78	-8.46	7.37	7.00
1993	-18.42	-12.56	18.59	15.92	0.17	3.37
1994	54.43	41.68	-48.62	-31.61	5.81	10.07
Total	**313.01**	**250.46**	**-190.52**	**-86.70**	**122.49**	**163.76**

* Millions of dollars. Commission are not included

** A represents the entire sample of 2549 traders.

*** B represents the 100 largest traders without exclusion.

Table 2. Mean and Distribution of Daily Profits

	Positive	Zero	Negative	Total
Normal	12*	413	16	441
Non-N.	17	786	12	815
Total	29	1199	28	1256

* The number in the table indicates the number of the traders in each category.

Table 3. Winners Distributed by their Accumulated Positions

Rank	1-100	101-500	501-1000	1001-1400**	Total
Number	(12,0)*	(4,9)	(9,13)	(4,6)	(29,28)

* The first number indicates the number of traders who make positive profit, and the second number indicates the number of traders who make negative profit, statistically.

** The traders who are ranked beyond 1400th are excluded because they have less than 25 reporting observations.

Table 4. Winners Disrtibuted by the Accumulated Positions

Year	6-10	4-6	2-4	0-2
Normal	(0,0)/0*	(0,0)/0	(0,0)/1	(12,16)/440
Non-N.	(5,0)/9	(3,0)/23	(4,0)/83	(5,12)/700
Total	(5, 0)/9	(3,0)/23	(4,0)/84	(17,28)/1140

* The first number indicates the number of traders who make positive profits, the second number indicates the number of traders who make negative profits statistically, and the third number indicates the total number of traders in that category.

Table 5. Relationship between Trading Volume and One-Day-Ahead Profit.

	Rank	Size	Days	β_1	t-ratio	R^2
1	1	1,691,639	2423	0.016	2.02*	0.003
2	4	532,798	1768	0.003	1.56**	0.002
3	5	482,240	2069	0.003	1.00	0.002
4	12	282,892	1826	0.007	2.31*	0.000
5	15	275,802	1480	0.003	1.89*	0.004
6	20	249,770	1783	0.002	2.12*	0.005
7	21	245,910	1281	0.010	2.35*	0.008
8	29	191,729	727	0.000	0.10	0.000
9	47	146,283	980	0.002	1.58**	0.008
10	63	104,630	727	0.002	1.00	0.001
11	83	82,521	770	-0.005	-1.34**	0.003
12	89	76,757	1162	0.003	2.36*	0.008
13	271	31,810	497	0.002	1.78*	0.007
14	334	21,855	248	-0.000	-0.18	0.000
15	336	21,443	396	-0.003	-1.21	0.004
16	403	14,917	262	0.002	1.40**	0.012
17	580	6,600	109	-0.005	-1.06	0.012
18	610	6,010	123	0.007	1.54**	0.019
19	684	4,761	134	0.001	0.50	0.002
20	785	3,573	37	-0.003	-0.47	0.006
21	860	3,010	63	0.000	0.09	0.000
22	1079	1,719	51	0.001	0.33	0.002
23	1084	1,709	30	0.002	0.30	0.001
24	1159	1,398	91	-0.351	-0.76	0.007
25	1168	1,368	69	0.003	1.38**	0.028
26	1211	1,200	29	-0.000	-0.21	0.001
27	1224	1,177	38	0.004	1.19	0.039
28	1339	870	32	-0.006	-0.94	0.024
29	1345	850	28	0.008	1.29**	0.042

* Significant at a 5% level.
** Significant at a 10 % level.

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Wheat Futures Price Behavior: Theoretical and Empirical Considerations

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This study analyzes the time series statistical properties of wheat futures prices to determine whether price behavior differs among intramarket contracts. We argue that the differential role of inventories, information, hedging objectives and probability of stockout across seasons provide a theoretical basis and empirical interest for finding such a difference. The behavior of May and September futures prices are indeed found to be significantly different and in ways consistent with theory. Furthermore, an endogenous contract arrival effect is found for both contracts, demonstrating the importance of developing models which incorporate market activity proxies.

Introduction

Current theoretical methods of commodity price determination emphasize the importance of storage in transmitting price shocks across periods. Nonetheless, these models do not completely explain the actual behavior of prices (Deaton and Laroque, 1992; Blank, 1989). Because storage and shocks have significantly different roles in price determination over the year, one might expect variations in price behavior among month-specific contracts. That is the focus of this study. In short, this paper conceptualizes intramarket differences implied by theoretical models of commodity price behavior, empirically tests the hypotheses raised by such analysis, and compares and contrast the findings to technical trading schemes to address these objectives. We focus on the behavior of wheat futures prices, using five years' daily data.

The paper is divided into four sections. First, we briefly review the literature on storage, commodity prices and futures price behavior. Second, comes a conceptual model of why differential price behavior is expected among intramarket contracts. Then we present methodology and empirical results of the price analysis conducted on September and May wheat futures price series. Finally, we briefly compare these results to charting methods developed by technical analysts. This paper also serves as a starting point for conceptualizing potential time series econometric issues related to modeling futures prices in a manner consistent with the underlying theory of storable commodities. However, the main purpose of this paper is to empirically analyze how commodity prices vary among seasonal contracts (referred to as intramarket contracts from this point forward in the paper).

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