Managed Futures, Positive Feedback Trading, and Futures Price Volatility

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A major issue in recent years is the role that large, managed futures funds and pools play in futures markets. Many market participants argue that managed futures trading increases price volatility due to the size of managed futures trading and reliance on positive feedback trading systems. The purpose of this study is to provide new evidence on the impact of managed futures trading on futures price volatility. A unique data set on managed futures trading is analyzed for the period 1 December 1988 through 31 March 1989. The data set includes the daily trading volume of large commodity pools for 36 different futures markets. Regression results are unequivocal with respect to the impact of commodity pool trading on futures price volatility. For the 72 estimated regressions (two for each market), the coefficient on commodity pool trading volume is significantly different from zero in only four cases. These results constitute strong evidence that, at least for this sample period, commodity pool trading is not associated with increases in futures price volatility. © 1999 John Wiley & Sons, Inc. Jrl Fut Mark 19: 759–776, 1999

In recent months . . . commodity funds have been pouring money into grains, copper, cocoa and other commodity pits as never before. These

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> funds' rush to position themselves in those markets has coincided with commodity price swings that are unusually jagged and extreme. And that's raising concerns in some quarters that, at least on a short-term basis, the commodity futures markets no longer accurately reflect the economic realities of supply and demand (p. C1).
>
> —Taylor and Behrmann, *The Wall Street Journal*

A new concern has been repeatedly voiced in recent years regarding price discovery in futures markets. The concern, colorfully depicted in the above quotation, is that trading by large, managed futures funds and pools artificially increases price volatility.[1,2] Two factors appear to be driving the apprehensions regarding managed futures trading. First, investment in managed futures has skyrocketed since the early 1980s. Managed Accounts Reports, a firm that tracks the industry, estimates that investment in managed futures grew from less than \$200 million in 1980 to \$19 billion in 1994. Second, managed futures trading is purported to be guided by similar, positive feedback trading systems (Elton, Gruber, & Rentzler, 1987; Brorsen & Irwin, 1987).[3] This may cause unwarranted futures price movements as managed funds and pools attempt to simultaneously buy after a price increase or sell after a price decrease.

Recent advances in theoretical modeling lend credence to concerns about the market impacts of positive feedback trading by managed futures funds and pools. In the new models, positive feedback trading is a type of non-informational "noise" trading (Black, 1986). This type of trading may not be eliminated from the market because risk aversion on the part of rational traders prevents them from taking large arbitrage positions. Hence, noise trading persists in the market, and it destabilizes prices (for example, De Long, Shleifer, Summers, & Waldman, 1990).

Only one previous study formally investigates the impact of managed futures trading on futures price volatility. Brorsen and Irwin (1987) do not find a significant relationship between commodity pool trading and

[1]Managed futures funds and pools combine investors' moneys for the purpose of speculating in futures and options markets. Funds and pools are organized and managed by Commodity Pool Operators (CPOs). A professional trading advisor, known as a Commodity Trading Advisor (CTA) is employed by the CPO to direct the trading of a fund. Managed futures investments also are known as commodity funds, futures funds, and commodity pools. The official term used by the Commodity Futures Trading Commission (CFTC) in all regulatory matters is commodity pool. Throughout the remainder of this article, the terms managed futures, managed funds and pools, and commodity pools will be used interchangeably.

[2]As pointed out by a reviewer, populist agricultural organizations have been making a similar contention about futures speculation for decades.

[3]Positive feedback trading systems also are known as technical trading systems. These systems are based on historical price patterns, and include moving average, price channel, and momentum systems. Previous research indicates technical systems tend to generate similar futures trading signals (Lukac, Brorsen, & Irwin, 1988).

futures price volatility. However, this finding should be treated quite cautiously. First, Brorsen and Irwin estimate the relationship between price volatility and managed futures open interest, when theoretical models suggest that trading volume, not open interest, is related to price behavior (for example, Karpoff, 1987). Second, managed futures open interest is estimated with considerable error because Brorsen and Irwin derive their open interest series from aggregate data on public commodity pools. Third, pool open interest is estimated only on a quarterly basis when concerns center on daily or intra-day price behavior.

The purpose of this study is to provide new evidence on the impact of managed futures trading on futures price volatility. A unique data set on managed futures trading, collected by the Commodity Futures Trading Commission (CFTC), is analyzed for the period 1 December 1988 through 31 March 1989. The data set includes the daily trading volume of large commodity pools for 36 different futures markets. The cross-section of markets is broad, and includes currency, energy, food and fiber, grain, interest rate, livestock, metal, and stock index futures contracts.

DATA ON COMMODITY POOL TRADING VOLUME

The CFTC maintains an extensive database on the trading history of large traders in all futures markets. However, managed futures traders are not explicitly identified in the collection of large trader data. So, when concerns about managed futures trading arose in the late 1980s, the CFTC conducted a special survey to determine the magnitude of managed futures trading in United States futures markets. The special survey required all "large" Commodity Pool Operators (CPOs) registered with the CFTC to report trades for the period 1 December 1988 through 31 March 1989. A comprehensive description of the survey and data is found in a working paper published by the CFTC (1991).

It is important to note that the trading volume data from the survey represents a subset of all managed futures trading volume. Individual managed accounts are not included in the totals, as well as much of the non–United States pool and fund industry. Nevertheless, there is no obvious reason to expect the CPO data to be unrepresentative of all managed futures trading behavior.

The raw records obtained from the survey contain the total trading volume in a futures contract each day when CPOs held reportable positions. Long and short trading volume is identified separately for each day. Given that the focus of this study is on market price volatility, trading volume is aggregated across all CPOs in each market and contract each day. Unfortunately, the data available for any single contract is limited because the time period of the survey is relatively short. This precludes statistical analysis on a contract-by-contract basis. Instead, trading volume data for consecutive contracts in a market are linked to create a time series of sufficient length for statistical analysis.

The linked volume series are based on the concept of a "nearby" futures contract series, which is widely-used in futures market research. Hence, aggregate CPO trading volume is based on the volume of CPO trading in the contract nearest-to-maturity, except during the expiration period for each contract.[4] To assure that expiration effects are minimized, rollover to the next nearest-to-maturity contract is done on the business day closest to the 15th day of the calendar month previous to expiration.

Eleven markets are removed from the data set for a variety of reasons. First, several markets have no records or very few records in the final data set, and, hence, these markets are dropped. Second, mini-contracts traded at the Mid-America Exchange are excluded due to the replication of these contracts with other contracts. Third, one market traded for only a short time period and it was not possible to identify its expiration months from public sources.

A total of 36 futures markets are included in the analysis, representing a large and diversified cross-section of market types. This will minimize spurious results due to the particular circumstances of an individual market or a small set of markets. To facilitate the presentation of results, the individual markets are categorized into eight groups. The groups are: (i) currency, (ii) energy, (iii) food and fiber, (iv) grain, (v) interest rate, (vi) livestock, (vii) metal, and (viii) stock index. The group classification is based on similarity of supply/demand patterns and/or common physical characteristics.

TRADING BEHAVIOR OF COMMODITY POOLS

Theoretical models (for example, De Long, Shleifer, Summers, & Waldman, 1990) suggest that the characteristics of managed futures trading have important implications for the possible impacts of such trading on futures price volatility. In order to better understand the trading behavior

[4]The nearby volume series for commodity pools capture most of the trading volume of pools during the sample period. On average, about three quarters of total trading volume of commodity pools is included in the nearby series. This corroborates Brorsen and Irwin's survey result that public commodity pools place about 80% of their trades in contracts nearest-to-maturity (excluding the delivery period).

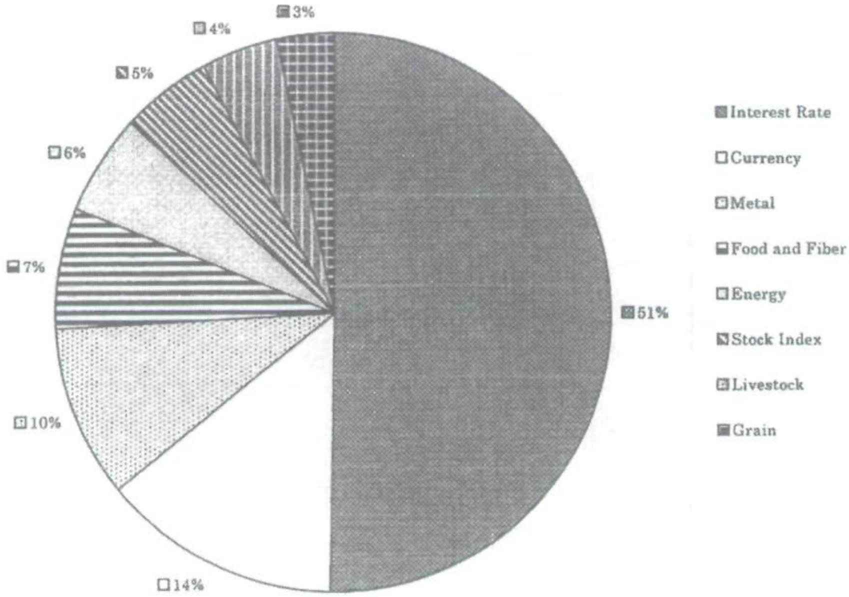

FIGURE 1
Composition of Long Commodity Pool Trading Volume, December 1, 1988–March 31, 1989.

of managed futures, several different sets of results are presented in this section.

The market composition of commodity pool trading volume over the sample period is shown in Figures 1 and 2. The results are arrived at by first summing the number of contracts traded (long or short) across all CPOs and trading days for each market. Then, for ease of presentation, the totals for each market are aggregated by market group. The Figures show the overwhelming dominance of financial futures trading in the portfolios of commodity pools. The combined total of interest rate and currency futures trading represents about two thirds of all commodity pool trading volume. Interest rate futures trading alone is 51% of all long pool trading volume and 42% of all short pool trading volume.[5] The largest non-financial group is metals, which represents 10% and 12% of long and short pool trading volume, respectively. The remaining five groups have trading volume totals of less than 8% each, long or short.

The concentration of commodity pool trading in financial futures markets is not surprising, as these are the largest and most liquid markets. It is interesting to note that commodity pool trading is not concentrated

[5]Nearly all of the interest rate trading volume is associate with two contracts, U.S. Treasury bond futures and Eurodollar futures.

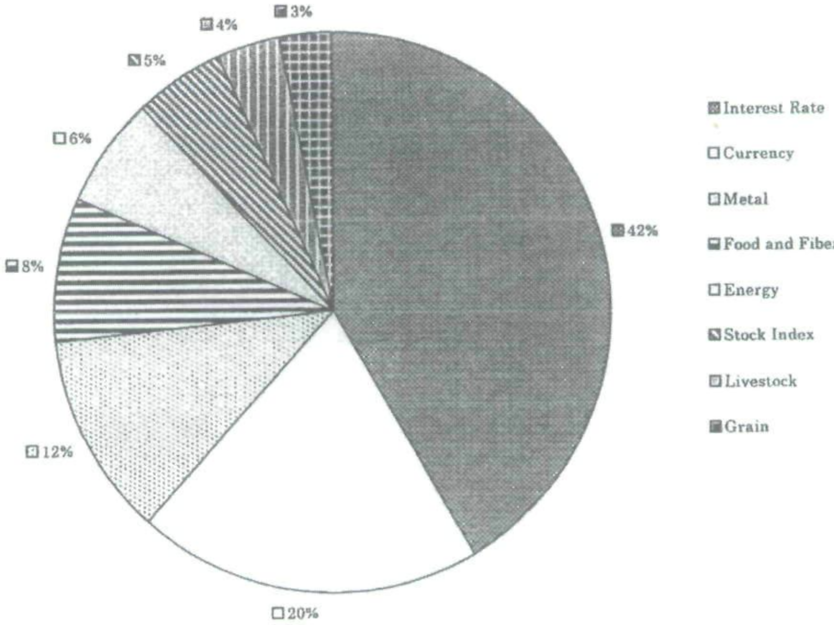

FIGURE 2
Composition of Short Commodity Pool Trading Volume, December 1, 1988–March 31, 1989.

in smaller futures markets, such as livestock futures. This corroborates the observation that CPOs and CTAs are aware of the possible market impacts of their trading and seek to minimize the impacts by limiting the size of their trading in smaller markets. This, of course, does not necessarily mean that the relative size of pool trading is small in these markets.

Results for the timing of commodity pool trading versus other market participants are presented in Table I. Timing is indicated by the correlation of the daily trading volume of commodity pools with total market trading volume. Note that market trading volume is based on the volume of the nearest-to-expiration futures contract, as defined earlier. Also, the trading volume of commodity pools is subtracted from the market total before computing the correlation.

The correlation coefficients indicate that commodity pools generally trade when other market participants trade. That is, commodity pool trading volume generally is positively correlated with market trading volume. The correlations for long, short, and gross (long plus short) pool trading volume tend to range from about 0.20 to 0.50. Most of these positive correlations are statistically significant as well. Overall, the results in Table I indicate commodity pools tend to trade when market volume is high

TABLE I

Correlation of Daily Commodity Pool Trading with Market Volume, December 1988–March 1989

		Correlation		
Group	*Futures Contract*	*Long Pool Volume and Market Volume*	*Short Pool Volume and Market Volume*	*Long plus Short Pool Volume and Market Volume*
Currency	Canadian Dollar	0.24[a]	0.25[a]	0.35[a]
	Deutsche Mark	0.36[a]	0.27[a]	0.42[a]
	Japanese Yen	0.44[a]	0.37[a]	0.57[a]
	Pound Sterling	−0.17	0.14	0.06
	Swiss Franc	0.32[a]	0.08	0.26[a]
	US Dollar	0.44[a]	0.28[a]	0.55[a]
Energy	Crude Oil	0.34[a]	0.29[a]	0.39[a]
	Heating Oil	0.05	0.28[a]	0.24[a]
	Unleaded Gasoline	0.03	−0.06	−0.04
Food & Fiber	Cocoa	0.14	0.22[a]	0.34[a]
	Coffee	0.37[a]	0.31[a]	0.53[a]
	Cotton	0.47[a]	0.35[a]	0.62[a]
	Lumber	0.06	0.45[a]	0.32[a]
	Orange Juice	0.22[a]	0.26[a]	0.28[a]
	Sugar	0.28[a]	0.47[a]	0.56[a]
Grain	Corn	0.28[a]	0.34[a]	0.44[a]
	Soybean Oil	−0.01	0.40[a]	0.32[a]
	Soybeans	0.24[a]	0.07	0.22[a]
	Wheat, CHI	0.29[a]	0.07	0.29[a]
	Wheat, KC	−0.11	NA	−0.11
Interest Rate	5-year Treasury Notes	0.10	0.09	0.15
	Eurodollars	0.24[a]	0.36[a]	0.41[a]
	Municipal Bond	0.13	0.30[a]	0.21
	US Treasury Bills	0.33[a]	0.14	0.32[a]
	US Treasury Bonds	0.62[a]	0.59[a]	0.69[a]
Livestock	Feeder Cattle	0.34[a]	0.54[a]	0.60[a]
	Live Cattle	0.36[a]	0.25[a]	0.48[a]
	Live Hogs	0.55[a]	0.01	0.52[a]
	Pork Bellies	0.30[a]	0.32[a]	0.44[a]
Metal	Copper	0.34[a]	0.31[a]	0.51[a]
	Gold	0.40[a]	0.38[a]	0.56[a]
	Palladium	0.18	−0.01	0.17
	Platinum	0.56[a]	0.18	0.52[a]
	Silver	0.38[a]	0.39[a]	0.56[a]
Stock Index	NYSE Composite	0.16	0.17	0.24[a]
	S&P 500	0.47[a]	0.52[a]	0.61[a]

[a]Statistical significance at the 5% level. NA means not applicable.

rather than low. There is no evidence that commodity pools have a tendency to trade heavily during illiquid market periods, and thereby potentially increase price volatility. Instead, the fact that commodity pools tend to trade during liquid market periods probably works towards diminishing the price impact of their trading.

As noted earlier, a key factor driving the concern about managed futures is the use of similar, positive feedback trading systems. Although there is extensive anecdotal evidence to support this belief, no direct empirical evidence has been available to date.[6] The relationship between commodity pool trading volume and past price movements is estimating using the following regression model for each futures market:

$$NCPV_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta p_{t-i} + \varepsilon_t \tag{1}$$

where $NCPV_t$ is net commodity pool trading volume (number of long contracts minus number of short contracts) on day t, Δp_{t-i} is the continuously-compounded change in the closing futures price for day $t - i$, and ε_t is a standard, normal error term.[7] The appropriate lag structure for each regression is determined via the AIC criterion (Akaike, 1969). Note that $NCPV_t$ will take on positive values when commodity pools are net buyers of contracts, negative values when pools are net sellers, and zero when no volume is recorded. Slope coefficients in eq. (1) can be thought of as the sensitivities of commodity pool "demand" to past price movements. Positive slope coefficients are evidence of positive feedback trading by commodity pools, whereas negative coefficients are evidence of negative feedback trading. The net feedback effect is given by the sum of slope coefficients for each regression.

Estimation results for the daily feedback regressions are presented in Table II. With a few exceptions, the number of price change lags included in the regressions is small. The vast majority of lags are between one and five days, indicating that feedback from price changes to commodity pool trading is of a short-term nature, typically less than a week. The adjusted R^2s indicate that the regressions explain a surprisingly large

[6]Indirect evidence of this tendency also is found in the 1991 CFTC working paper that presented the commodity pool trading data. In an appendix, it is shown that CTAs have a statistically significant tendency to be on the same side of the market at the same time. This is evidence of "herding" in CTA trading behavior. The analysis in this section seeks to determine whether this trading behavior is related to past price movements.

[7]Daily opening, closing, high, and low prices are obtained for each contract from Technical Tools, Inc. At contract rollover points, price changes are not calculated across contracts. Instead, the price change for the "new" nearby contract on the rollover date is calculated based on the price on the day of the rollover and the price and the day previous to rollover.

TABLE II

Results of Daily Feedback Regression Models for Commodity Pool Trading Volume, December 1988–March 1989

Group	Futures Contract	Regression Statistics: No. Price Change Lags	Adj. R^2	Sum of Slope Coefficients	F-test: Sum of Slope Coefficients Equals Zero
Currency	Canadian Dollar	1	0.00	10640.10	1.35
	Deutsche Mark	3	0.03	40132.37	5.23[a]
	Japanese Yen	2	0.12	51787.18	12.25[a]
	Pound Sterling	1	0.06	9064.21	5.81[a]
	Swiss Franc	1	0.01	5677.28	1.41
	US Dollar	1	0.01	−9967.11	1.89
Energy	Crude Oil	3	0.08	2534.21	0.14
	Heating Oil	1	−0.01	134.31	0.01
	Unleaded Gasoline	1	0.01	238.57	1.50
Food & Fiber	Cocoa	9	0.28	14398.30	30.17[a]
	Coffee	4	0.16	5339.30	17.63[a]
	Cotton	5	0.44	18320.25	54.66[a]
	Lumber	1	−0.01	183.97	0.11
	Orange Juice	1	0.02	120.58	2.89
	Sugar	2	0.15	14408.95	16.35[a]
Grain	Corn	3	0.15	11139.98	10.26[a]
	Soybean Oil	3	0.26	16984.67	31.53[a]
	Soybeans	1	0.01	1028.80	1.90
	Wheat, CHI	2	0.06	2323.18	7.26[a]
	Wheat, KC	2	0.03	−485.66	2.20
Interest Rate	5-year Treasury Notes	1	−0.01	−1241.16	0.07
	Eurodollars	15	0.16	−805475.30	1.34
	Municipal Bond	12	0.21	8234.02	4.27[a]
	US Treasury Bills	1	0.02	−39697.98	2.29
	US Treasury Bonds	1	0.03	66011.22	3.19
Livestock	Feeder Cattle	1	0.03	956.78	3.55[a]
	Live Cattle	4	0.40	57793.80	48.04[a]
	Live Hogs	7	0.53	47628.22	86.17[a]
	Pork Bellies	2	0.19	2417.08	20.89[a]
Metal	Copper	2	0.23	6161.84	22.19[a]
	Gold	1	0.02	16112.71	2.50
	Palladium	1	0.01	−71.66	2.16
	Platinum	5	0.29	8700.66	34.39[a]
	Silver	3	0.34	35617.95	34.39[a]
Stock Index	NYSE Composite	1	−0.01	252.92	0.04
	S&P 500	1	0.01	7945.94	2.10

[a]indicates statistical significance at the 5% level.

part of the variation in commodity pool trading volume. Fourteen of the regressions have adjusted R^2s that exceed 0.15 and three (cotton, live cattle, and live hogs) exceed 0.40. The average adjusted R^2 across all 36 regressions is 0.12. The explanatory power of past price changes is particularly notable in light of the fact that high frequency data are modeled.

The sum of slope coefficients is positive for 30 of the 36 markets. Furthermore, F-tests indicate that 18 of the 30 positive sums are statistically different from zero at the 5% level of significance. Some intriguing differences are observed across groups. Pool trading in energy, interest rate and stock index futures exhibits little or no relationship to past price changes, whereas trading in food and fiber, grain, livestock, and metals trading exhibits a substantial relationship. The currency finding is especially interesting, as it corroborates the oft-expressed view that positive feedback trading strategies are widely employed in these markets (for example, Frankel & Froot, 1990). Finally, it should be emphasized that the feedback results are based on only a four-month time series. The difference in results across groups may be a function of the particular sample period analyzed, rather than some underlying fundamental factor. Overall, the feedback regression results suggest that commodity pools use similar, positive feedback trading systems to guide trading decisions. This confirms widespread beliefs about the trading styles of managed funds and pools, and indicates a potential for "herd-like" behavior that could increase price volatility.

COMMODITY POOL TRADING AND PRICE VOLATILITY

The results in the previous section present a mixed story in terms of commodity pool trading behavior. On one hand, commodity pools trade primarily in large markets and during periods of relatively high market volume. These two characteristics tend to minimize the effect of pool trading on price volatility. On the other hand, commodity pools' use of positive feedback trading systems indicates a potential for "herd-like" behavior that could increase price volatility. These conflicting pieces of information reinforce the need for direct tests of the impact of pool trading on futures price volatility. Before presenting these results, though, it is useful to examine descriptive statistics on the size of pool trading. This will help provide further perspective for the potential price volatility impact of managed futures trading.

Descriptive statistics for the relative size of commodity pool trading are reported in Table III. Relative size is calculated by dividing commodity

TABLE III

Descriptive Statistics for Daily Trading Volume of Commodity Pools, Percentage of Market Volume, December 1988–March 1989

		Daily Trading Volume of Commodity Pools								
		Long		*Short*		*Long plus Short*		*Long minus Short*		
Group	*Futures Contract*	*Average*	*Maximum*	*Average*	*Maximum*	*Average*	*Maximum*	*Average*	*Minimum*	*Maximum*
		percentage of market trading volume								
Currency	Canadian Dollar	1.8	33.7	0.8	15.4	2.6	33.7	1.0	−15.3	33.7
	Deutsche Mark	1.2	9.4	1.7	25.2	3.0	25.2	−0.5	−25.2	9.4
	Japanese Yen	1.5	29.3	2.0	17.1	3.4	29.3	−0.5	−17.1	29.3
	Pound Sterling	0.9	23.8	1.3	10.8	2.2	23.8	−0.5	−10.7	23.8
	Swiss Franc	0.7	25.8	1.2	14.3	1.9	25.8	−0.5	−14.3	25.8
	US Dollar	2.1	28.7	4.0	47.4	6.1	48.4	−1.9	−46.4	28.7
Energy	Crude Oil	0.6	3.7	0.7	7.3	1.3	8.3	−0.1	−6.3	3.7
	Heating Oil	1.2	7.9	0.8	9.2	1.9	9.2	0.4	−9.2	7.1
	Unleaded Gasoline	0.1	2.9	0.2	5.1	0.3	5.6	0.0	−5.1	1.5
Food & Fiber	Cocoa	2.2	31.5	2.7	15.9	4.9	47.4	−0.4	−13.2	17.1
	Coffee	1.3	16.4	1.0	10.8	2.3	16.4	0.3	−10.0	16.4
	Cotton	1.7	10.6	1.1	8.0	2.7	12.9	0.6	−8.0	10.6
	Lumber	0.9	27.9	0.9	11.6	1.8	27.9	0.0	−11.6	27.9
	Orange Juice	0.2	10.1	0.3	5.6	0.5	10.1	−0.1	−5.6	10.1
	Sugar	1.3	7.7	1.9	12.1	3.2	14.0	−0.6	−10.2	6.7
Grain	Corn	0.3	4.4	0.3	2.2	0.6	4.6	0.0	−2.2	4.2
	Soybean Oil	0.9	7.4	0.9	8.7	1.7	8.7	0.0	−8.7	7.4
	Soybeans	0.1	0.8	0.1	1.5	0.1	1.5	0.0	−1.5	0.8
	Wheat, CHI	0.3	7.4	0.1	2.2	0.4	7.4	0.2	−2.2	7.4
	Wheat, KC	0.1	7.2	0.0	0.0	0.1	7.2	0.1	0.0	7.2
Interest Rate	5-year Treasury Notes	1.1	12.7	0.8	7.9	1.9	12.7	0.3	−7.9	12.7
	Eurodollars	0.6	3.9	0.5	3.4	1.1	4.8	0.1	−3.4	3.3
	Municipal Bond	0.6	19.2	0.2	7.9	0.9	19.2	0.4	−2.8	19.2
	US Treasury Bills	1.6	12.3	1.9	18.4	3.4	20.3	−0.3	−18.4	9.9
	US Treasury Bonds	1.1	6.9	1.0	4.7	2.0	10.4	0.1	−4.0	4.6

TABLE III (Continued)

Descriptive Statistics for Daily Trading Volume of Commodity Pools, Percentage of Market Volume, December 1988–March 1989

		Daily Trading Volume of Commodity Pools								
		Long		*Short*		*Long plus Short*		*Long minus Short*		
Group	*Futures Contract*	*Average*	*Maximum*	*Average*	*Maximum*	*Average*	*Maximum*	*Average*	*Minimum*	*Maximum*
Livestock	Feeder Cattle	0.4	11.3	0.1	4.3	0.4	11.3	0.3	−4.3	11.3
	Live Cattle	1.1	12.0	1.0	9.5	2.0	12.2	0.1	−9.3	11.8
	Live Hogs	2.3	12.3	2.2	19.0	4.5	19.0	0.1	−19.0	11.9
	Pork Bellies	0.6	6.5	1.0	9.1	1.6	9.1	−0.4	−9.1	6.3
Metal	Copper	1.0	7.0	1.3	6.5	2.3	8.5	−0.3	−6.5	5.7
	Gold	0.8	7.0	1.3	13.3	2.1	13.3	−0.5	−13.3	6.0
	Palladium	0.3	6.3	0.1	6.1	0.4	6.7	0.1	−5.5	6.3
	Platinum	0.8	5.5	1.4	10.4	2.2	10.4	−0.6	−10.4	4.5
	Silver	1.4	9.6	1.2	11.2	2.6	12.8	0.3	−10.8	9.6
Stock Index	NYSE Composite	0.3	8.1	0.2	8.5	0.6	8.5	0.1	−8.5	8.1
	S&P 500	1.2	5.5	0.9	5.5	2.0	6.1	0.3	−5.0	5.5

pool trading volume by total market trading volume. The statistics show that the average number of contracts traded per day is not large when compared to the average daily market trading volume. The largest percentage for long plus short trading volume is only 6.1% (U.S. dollar index). Averaging across all 36 markets, average daily trading volume (long plus short) is a minuscule 2.0%.

Although the trading volume of commodity pools is small on average, maximum percentages show that trading on some days is a large fraction of total trading in the market. There are nine markets in which the maximum one day percentage for long plus short volume exceeds 20% (cocoa, Canadian dollar, Deutsche mark, lumber, pound, Swiss franc, U.S. dollar index, and U.S. Treasury bills), and two markets in which the maximum exceeds 40% (cocoa, U.S. dollar index). It is interesting to note that commodity pool trading, in terms of relative size, is somewhat concentrated in two groups: currency, and food and fiber futures markets.

Following Kodres (1994), the direct impact of commodity pool trading volume on futures price volatility is estimated in a regression framework. Specifically, a measure of futures price volatility is regressed against information control variables and measures of the volume of commodity pool trading. For a given commodity, the first regression model is:

$$\sigma_t = \beta_0 + \sum_{j=1}^{k} \beta_j \sigma_{t-j} + \gamma_1 \%GCPV_t + \mu_t \tag{2}$$

where σ_t is the daily volatility (standard deviation) estimate on day t, $\%GCPV_t$ is the gross trading volume of commodity pools (long plus short) as a percentage of market trading volume on day t, and μ_t is a standard, normal error term. For a given commodity, the second regression model is:

$$\sigma_t = \beta_0 + \sum_{j=1}^{k} \beta_j \sigma_{t-j} + \gamma_1 \%NCPV_t + \mu_t \tag{3}$$

where $\%NCPV_t$ is the net trading volume of commodity pools (long minus short) as a percentage of market trading volume on day t, and all other variables are the same as in regression (2). Lagged volatilities are to control for other information effects. The AIC information criterion is used to determine the number of lagged volatility terms in each equation.

Following Chang, Pinegar, and Schacter (1997), Parkinson's (1980) extreme-value estimator is used to measure price volatility. For a given commodity, Parkinson's estimator is:

$$\sigma_t = 0.601 \ln(H_t/L_t) \tag{4}$$

where H_t is the high futures price for day t, L_t is the low futures price for day t, and ln is the natural logarithm. After an outlier screen is applied to the data, Wiggins (1991) reports that extreme-value estimators are more efficient than close-to-close estimators.

The results of estimating regressions (2) and (3) are shown in Tables IV and V, respectively.[8] These results are unequivocal with respect to the impact of commodity pool trading on futures price volatility. For the 72 different regressions, the coefficient on commodity pool trading is significantly different from zero in only four cases (cocoa and feeder cattle, Table IV; U.S. dollar and S&P 500, Table V). This is equal to the number of significant coefficients expected based purely on a random chance.[9] Furthermore, two of the significant coefficients (cocoa and S&P 500) are negative, indicating pool trading in these markets is associated with decreasing price volatility. Finally, it is worthwhile to note the lack of a pattern in the signs of the coefficients for the commodity pool trading variables. The signs appear to be randomly distributed, with about half positive and half negative.

These results constitute strong evidence that, at least for this sample period, commodity pool trading is not associated with increases in futures price volatility. The appropriate conclusion is that commodity pool trading, despite the use of positive feedback trading systems, did not have any significant relationship with futures price volatility across a broad spectrum of markets.

SUMMARY AND CONCLUSIONS

In recent years, a new concern has been repeatedly voiced regarding price discovery in futures markets. The concern is that trading by large, managed futures funds and pools artificially increases price volatility. Only one previous study formally investigates the impact of commodity pool trading on futures price behavior. The purpose of this research is to provide new evidence on the impact of managed futures trading on futures price volatility. A unique data set on managed futures trading is analyzed

[8]Several alternative specifications of the volatility regressions are estimated. The Newey-West heteroskedastic-autocorrelation consistent covariance estimator is used instead of OLS. Results are not substantially changed with the alternative estimator. Dummy variables for day-of-the-week and month effects also are included, with no qualitative change in the results. These results can be obtained from the corresponding author upon request.

[9]At a 5% significance level, four significant coefficients would be expected based on random chance (0.05 x 72).

TABLE IV

Regression Results for Daily Volatility Models, Long plus Short Commodity Pool Trading Volume, December 1988–March 1989

		Regression Statistics				
Group	Futures Contract	No. of Volatility Lags	Adj. R^2	F-test: Slope Coefficients Equal Zero	Coefficient on Long plus Short Pool Volume	t-statistic
Currency	Canadian Dollar	2	0.04	2.17	0.0018	0.84
	Deutsche Mark	3	0.07	2.44	−0.0086	−1.35
	Japanese Yen	1	0.01	1.60	−0.0043	−0.98
	Pound Sterling	1	0.01	1.38	−0.0095	−1.55
	Swiss Franc	3	0.02	1.46	−0.0094	−1.21
	US Dollar	1	0.00	1.10	0.0017	0.86
Energy	Crude Oil	5	0.08	2.13	0.0191	0.49
	Heating Oil	3	0.03	1.53	0.0199	0.76
	Unleaded Gasoline	5	0.15	3.43[a]	−0.0516	−0.98
Food & Fiber	Cocoa	2	0.04	2.19	−0.0264	−1.99[a]
	Coffee	2	0.32	14.13[a]	0.0037	0.12
	Cotton	1	0.01	1.35	0.0076	0.40
	Lumber	1	0.00	1.01	0.0098	1.42
	Orange Juice	1	0.16	9.04[a]	0.0239	0.65
	Sugar	1	0.01	1.32	0.0246	0.65
Grain	Corn	1	0.03	2.15	0.0889	1.75
	Soybean Oil	2	0.02	1.53	0.0197	0.87
	Soybeans	1	−0.02	0.14	0.0881	0.51
	Wheat, CHI	2	0.07	2.90[a]	−0.0189	−0.46
	Wheat, KC	1	0.00	0.89	0.0210	0.57
Interest Rate	5-year Treasury Notes	2	0.02	1.56	−0.0072	−1.63
	Eurodollars	2	0.06	2.81[a]	−0.0040	−0.71
	Municipal Bond	1	0.02	1.68	0.0084	1.32
	US Treasury Bills	2	−0.01	0.68	−0.0001	−0.09
	US Treasury Bonds	1	0.00	0.85	−0.0071	−0.49
Livestock	Feeder Cattle	3	0.10	3.34[a]	0.0395	2.88[a]
	Live Cattle	1	0.00	0.89	0.0111	1.26
	Live Hogs	2	0.00	0.97	−0.0064	−0.87
	Pork Bellies	14	0.16	2.07[a]	−0.0366	−0.95
Metal	Copper	2	0.01	1.34	0.0025	0.55
	Gold	1	0.01	1.41	0.0267	1.61
	Palladium	2	0.17	6.60[a]	0.0015	0.02
	Platinum	1	−0.01	0.44	0.0160	0.62
	Silver	1	0.00	0.92	0.0237	1.13
Stock Index	NYSE Composite	2	0.02	1.48	0.0204	1.13
	S&P 500	1	0.00	0.82	0.0240	1.28

[a]Statistical significance at the 5% level.

TABLE V

Regression Results for Daily Volatility Models, Long minus Short Commodity Pool Trading Volume, December 1988–March 1989

		Regression Statistics				
Group	*Futures Contract*	*No. of Volatility Lags*	*Adj. R^2*	*F-test: Slope Coefficients Equal Zero*	*Coefficient on Long minus Short Pool Volume*	*t-statistic*
Currency	Canadian Dollar	2	0.03	1.96	0.0008	0.37
	Deutsche Mark	3	0.05	2.16	0.0052	0.90
	Japanese Yen	1	0.01	1.23	−0.0019	−0.49
	Pound Sterling	1	−0.01	0.70	−0.0057	−1.02
	Swiss Franc	3	0.01	1.14	0.0036	0.49
	US Dollar	1	0.05	3.32[a]	0.0043	2.26[a]
Energy	Crude Oil	5	0.07	2.10	−0.0117	−0.26
	Heating Oil	3	0.02	1.39	−0.0038	−0.15
	Unleaded Gasoline	5	0.14	3.24[a]	−0.0163	−0.22
Food & Fiber	Cocoa	2	0.00	1.00	−0.0103	−0.71
	Coffee	2	0.33	14.21[a]	0.0109	0.43
	Cotton	1	0.01	1.29	−0.0029	−0.19
	Lumber	1	−0.02	0.02	−0.0012	−0.18
	Orange Juice	1	0.18	9.73[a]	0.0462	1.25
	Sugar	1	0.00	1.10	0.0030	0.09
Grain	Corn	1	−0.01	0.60	−0.0075	−0.15
	Soybean Oil	2	0.01	1.37	0.0107	0.54
	Soybeans	1	−0.02	0.14	−0.0842	−0.53
	Wheat, CHI	2	0.07	2.95[a]	−0.0236	−0.58
	Wheat, KC	1	0.00	0.89	0.0210	0.57
Interest Rate	5-year Treasury Notes	1	−0.02	0.24	0.0020	0.50
	Eurodollars	2	0.06	2.63	−0.0008	−0.16
	Municipal Bonds	1	0.00	0.99	0.0049	0.62
	US Treasury Bills	2	−0.01	0.68	−0.0001	−0.06
	US Treasury Bonds	1	−0.01	0.78	−0.0061	−0.30
Livestock	Feeder Cattle	3	0.02	1.52	0.0172	1.21
	Live Cattle	1	−0.01	0.60	−0.0078	−1.00
	Live Hogs	1	−0.01	0.56	0.0047	0.82
	Pork Bellies	14	0.18	2.20[a]	0.0512	1.48
Metal	Copper	2	0.05	2.43	−0.0064	−1.85
	Gold	1	−0.02	0.24	−0.0076	−0.51
	Palladium	2	0.17	6.68[a]	0.0285	0.44
	Platinum	1	0.01	1.23	0.0340	1.40
	Silver	1	−0.02	0.28	−0.0006	−0.03
Stock Index	NYSE Composite	2	0.00	1.04	−0.0017	−0.10
	S&P 500	2	0.07	2.91[a]	−0.0412	−2.55[a]

[a]Statistical significance at the 5% level.

for the period 1 December 1988 through 31 March 1989. The data set includes the daily trading volume of large commodity pools for 36 different futures markets.

The first part of the analysis investigates the trading behavior of commodity pools over the sample period. These results present a mixed story in terms of commodity pool trading behavior. On one hand, commodity pools trade primarily in large markets and during periods of relatively high market volume. These two characteristics tend to minimize the effect of pool trading on price volatility. On the other hand, commodity pools appear to use similar, positive feedback trading systems, indicating a potential for "herd-like" behavior that could increase price volatility.

The second part of the analysis examines the size and price impact of commodity pool trading volume. The findings indicate that daily average trading volume of commodity pools over the sample period is a small percentage of total trading volume. Averaging across all 36 markets, the figure for average daily trading volume is a minuscule 2.0%. Whereas the trading volume of commodity pools is small on average, maximum percentages show that trading on some days is a large fraction of the total trading in the market. There are nine markets where the maximum one day percentage for long plus short volume exceeds 20%.

Regression results are unequivocal with respect to the direct impact of commodity pool trading on futures price volatility. For the 72 estimated regressions (two for each market), the coefficient on commodity pool trading volume is significantly different from zero in only four cases. This is the number of significant coefficients expected based purely on a random chance. These results constitute strong evidence that, at least for this sample period, commodity pool trading is not associated with increases in futures price volatility. The appropriate conclusion is that commodity pool trading did not have any significant relationship with futures price volatility across a broad spectrum of markets. This evidence is at odds with much of the conventional wisdom regarding the market impacts of managed futures trading.

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