AN EMPIRICAL EXAMINATION OF THE RELATION BETWEEN FUTURES SPREADS VOLATILITY, VOLUME, AND OPEN INTEREST

PAUL BERHANU GIRMA*
MBODJA MOUGOUÉ

This study investigates the relation between petroleum futures spread variability, trading volume, and open interest in an attempt to uncover the source(s) of variability in futures spreads. The study finds that contemporaneous (lagged) volume and open interest provide significant explanation for futures spreads volatility when entered separately. The study also

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*Correspondence author, School of Business, SUNY at New Paltz, 75 S. Manheim Boulevard, New Paltz, New York 12561; e-mail: girma@newpaltz.edu

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- *Paul Berhanu Girma is an Assistant Professor of Finance in the School of Business at SUNY at New Paltz in New Paltz, New York.*
- *Mbodja Mougoué is an Associate Professor of Finance in the Department of Finance at the School of Business Administration at Wayne State University in Detroit, Michigan.*

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shows that lagged volume and lagged open interest, when entered in the conditional variance equation simultaneously, have greater effect on volatility and substantially reduce the persistence of volatility. This finding seems to support the sequential information arrival hypothesis of Copeland (1976). Finally, the findings of this study also suggest a degree of market inefficiency in petroleum futures spreads. Jrl Fut Mark 22:1083–1102, 2002

INTRODUCTION

The relation between price variability and trading volume for equities as well as futures has been the subject of a large number of empirical studies. These studies generally find that there is a positive correlation between trading volume and price variability in equities and futures markets.[1] Despite the abundant literature on the price–volume relation in stock and futures markets, however, very little is known about how futures spreads are related to either trading volume or open interest in futures markets. The lack of research in this area is surprising in light of the fact that spread trading has become popular with scalpers, day traders, as well as position traders. The main appeal of spread trading is the significant leverage it provides the trader. Because spread trading involves the simultaneous purchase and sale of two or more futures contracts, the trader's risk is limited and so too are her initial and maintenance margin requirements. For example, as of April 4, 2002, the initial margin for an outright speculative position in T-bond and 10-year T-note futures contracts on the Chicago Board of Trade (CBOT) was a total of $4,590.00, whereas the initial margin for an NOB[2] spread was only $1,147.50.

The growing importance of spread trading on U.S. futures markets, measured both in terms of volume and types of spreads, is undeniable. For example, the CBOT reports that a significant proportion of all transactions in Treasury futures contracts for the first quarter of 2002 was in the form of spread trading. Furthermore, spread trading is currently available in different markets including financial, agricultural, metal, and petroleum futures markets.[3]

[1]Karpoff (1987) provides an extensive review of the literature on the relation between price variability and trading volume.

[2]A NOB (10-year T-notes-over-T-bonds) is one of the most popular financial spreads. It involves the simultaneous buying (selling) of 10-year T-note futures and selling (buying) of T-bond futures. Other well-known financial spreads are the MOB (municipal bonds-over-T-bonds), FITE (5-year T-notes-over-10-year T-notes), and TED (Eurodollar-over-T-bill).

[3]Examples of agricultural spreads are soybeans versus soybean oil, soybeans versus soybean meal, Iowa corn yield versus Illinois corn yield, etc.

This article adds to the current research on the price–volume relation by focussing on petroleum futures spreads. More specifically, it investigates the relation between petroleum futures spread variability and trading volume and/or open interest in an attempt to uncover the source(s) of variability in oil prices. This topic is timely and of utmost importance for at least two reasons: First, whereas there is some anecdotal evidence that the recent escalation in crude oil prices has generally lead to increased profit margins for oil-producing firms, the general consensus among macroeconomists and policymakers throughout most of year 2000 was that oil-induced inflation could pose a serious threat to sustained economic growth.[4] Second, a good understanding of the source(s) of volatility in the market for petroleum futures spreads could lead to superior trading and hedging strategies.

This article extends the existing research on petroleum futures in two important ways. First, it uses GARCH modeling to address the issue of how volume impacts the volatility of futures spreads' returns. Volume has been widely used in the literature as a proxy for information arrival. Therefore, the approach taken in this study should shed additional light on how new information affects the distribution of returns for petroleum futures spreads. Second, this study also examines how market depth and the heterogeneity of beliefs affect volatility in the market for petroleum futures spreads. Following Bessembinder and Seguin (1993), Harris and Raviv (1993), and Shalen (1993), open interest is used as a proxy for market depth as well as heterogeneous belief. Overall, this study finds that the contemporaneous weighted average of volume and open interest have significant explanatory power for futures spreads volatility when entered separately. This study also finds that the lagged weighted average volume and lagged open interest provide significant explanation for futures spread volatility. This last finding may suggest a degree of market inefficiency in petroleum futures spreads. The findings of this study are consistent with previous research on price variability and volume and/or open interest.

The results of this study shed additional light on the sources of uncertainty for petroleum futures spreads. These findings are of considerable interest and importance to refiners and retailers who routinely want to hedge both the input price and output revenue to lock in their profit margin. Futures traders also can and do use futures spreads or options on futures spreads, such as credit spread options, 1:0:1 heating

[4]This concern prompted the U.S. Energy Department during the summer months of 2000 to sell significant amounts of oil out of the Strategic Oil Reserve to contain oil price increases.

oil crack spread options and 1:1:0 gasoline crack spread options for speculative reasons. This is important for refiners and retailers who only want to hedge their positions selectively when they believe the crack spreads represent an attractive opportunity to lock in a higher profit margin. Furthermore, risk arbitrageurs or speculators who trade the spreads to exploit any relative mispricing can also benefit from a better understanding of the source(s) of futures spreads (FS) volatility.[5] The findings of this study have practical implications for hedgers such as airlines companies and other users of petroleum products as well. These findings also could be of interest to speculators and market regulators fearful of potentially destabilizing excessive volatility in oil prices. Overall, the findings of this article are important to practitioners and researchers alike.

LITERATURE REVIEW

The relation between price variability and trading volume for equities as well as futures has been investigated extensively. A large number of empirical studies show that there is a positive correlation between trading volume and price variability in equities and futures markets. Epps and Epps (1976), Clark (1973), Cornell (1981), and Tauchen and Pitts (1983) find a positive relation between price variability and trading volume. Karpoff (1987) provides an extensive review of the literature on the relation of price variability and trading volume. He finds that there is a positive relationship between price change per se and volume in equities markets only. In contrast, he finds a positive relationship between absolute price change and volume in both equities and futures markets.

The two major theoretical explanations of the relation between price variability and trading volume are the sequential information arrival hypothesis of Copeland (1976) and the mixed distribution hypothesis (MDH) of Clark (1973). Copeland (1976) postulated that information arrives to traders sequentially, one at a time, until all traders receive the information and a final equilibrium is established. The hypothesis of sequential information arrival implies that there is a

[5]A number of researchers have conducted empirical studies to determine if there are profitable spread trading opportunities in intercommodity spread trading. Some of these studies included: Treasury Bills and Treasury Bonds (Jones, 1981; Easterwood & Senchack, 1986); Gold (Rolfo, 1981), gold and Eurodollar turtles (Poitras, 1987), gold and T-bill spreads (Monroe & Cohn, 1986), municipal bond and treasury bond (Arak et al., 1987), index futures (Billingsley & Chance, 1988), soybean complex spread (Johnson et al., 1991), gold-silver spread (Wahab et al., 1994), spreads in agricultural futures (Barrett & Kolb, 1995), treasury futures spreads (Park & Switzer, 1996), and petroleum futures spreads (Girma & Paulson, 1998). However, none of these studies explored the relation between the spread variability and volume (open interest).

positive relation between trading volume and price variability and, given trading volume, it may be possible to forecast price variability. The mixture of distributions hypothesis (MDH) of Clark (1973), on the other hand, postulates that price variability and trading volume relations are due to a mixture of distributions. Under MDH, the relation between price variability and trading volume is due to the joint dependence of price and volume on an underlying common (mixing) variable, and this common (mixing) variable is interpreted to be the rate of information flow to the market. The model suggests that both price and volume change simultaneously in response to the common (mixing) variable.[6]

Using a state space model, McCarthy and Najand (1993) study currency futures markets and find no significant relation between price change per se and trading volume. These results are consistent with the costly short-selling hypothesis of Karpoff (1987, 1988), and are also in line with the findings in stock markets by James and Edmister (1983) and Wood, McInish, and Ord (1985). On the other hand, McCarthy and Najand (1993) find a positive bidirectional causal relation between absolute price change and trading volume. Furthermore, in all of the currencies they investigated, volume is dependent on its own lag values as well as lagged absolute percentage price change. These findings are consistent with the sequential information arrival hypothesis of Copeland (1976).

Foster (1995) studies the relation between volume and volatility for crude oil futures market using GARCH(1,1) and Generalized Methods of Moments models, and finds that contemporaneous volume and volatility are positively related and that these variables are endogenous to the system. Foster suggests that both volume and volatility are driven by an exogenous variable assumed to be the rate of information arrival. Furthermore, Foster finds that the lagged value of volume is significant in explaining price variability, and concludes that a significant level of inefficiency characterizes the crude oil futures market.

Fujihara and Mougoué (1997) investigate the relation of crude oil, heating oil, and unleaded gasoline futures price volatility and volume using a GARCH(1,1) model, and find that volume is a significant explanatory variable even though its inclusion in the conditional variance equation does not significantly reduce the documented ARCH effects. The authors conclude that factors other than volume affect the persistence of volatility in the futures price they studied. More recently, Kocagil

[6]For extensions of the sequential information hypothesis, see Jennings, Starks, and Felligan (1981), Smirlock and Starks (1988), and McCarthy and Najand (1993). See also, Epps (1975, 1977), Epps and Epps (1976), Tauchen and Pitts (1983), and Harris (1986, 1987) for extensions of the MDH.

and Shachmurove (1998) have studied 16-futures markets, including crude oil, heating oil, and unleaded gasoline futures, and found a strong bidirectional Granger causality between absolute return and volume in most of the futures markets they studied. They also found no causality from volume to return per se, but reported a significant causality from return per se to volume in a number of futures markets. By contrast, these two authors found that high volume markets such as crude oil, unleaded gasoline, and heating oil exhibit no causality in either direction.

Finally, a number of authors have investigated the relation between open interest and price variability (see, e.g., Bessembinder & Seguin, 1993; Harris & Raviv, 1993; Shalen, 1993). Bessembinder and Seguin (1993) study the relation between price volatility, volume, and open interest for eight futures markets. Using open interest as a proxy for market depth, Bessembinder and Seguin (1993) study the impact of expected and unexpected volume and open interest on price volatility and find that both expected and unexpected volumes positively impact price volatility; however, they find that the impact of unexpected volume (on volatility) is seven times greater than that of expected volume. They also find that the coefficients of the expected open interest to volatility (when volume and open interest enter the variance model simultaneously) are negative and significant. They suggest that greater market depth tends to lower the volatility associated with a given volume, implying that a trade that leads to an increase in trading volume and open interest has a smaller effect on volatility than a trade that leads to high volume without a corresponding increase in open interest.

In light of the previous evidence, the present study explores the effect of volume and open interest on futures spreads return volatility. First, it investigates the effect of volume and open interest on futures spreads return volatility taken one at a time. Then it explores the effect of volume and open interest on futures spreads return volatility when both volume and open interest are entered in the conditional variance equation simultaneously.

DATA AND SUMMARY STATISTICS

The data used in modeling and testing the crack spread, futures spread (FS) variability, and volume and/or open interest (*OI*) relations consist of daily futures prices of crude oil, heating oil, and unleaded gasoline contracts from December 1984 to December 1999. Unleaded gasoline futures contracts began trading on the New York Mercantile Exchange (NYMEX) in December 1984 (*The Crack Spread Handbook*). The 3:2:1 Crack Spread, 1:1:0 Gasoline Crack Spread, 0:1:1 Gasoline-Heating Oil Crack Spread, and the 1:0:1 Heating Oil Crack Spread relations and trading results are based on data from December 1984 through December 1999. Our data source is a DRI database.

A single time series used to analyze the relation between crack spread variability and volume is created by taking daily closing prices, volume, and open interest, for a given calendar trading month (henceforth called M), from each contract that is deliverable in $M + 2$ months. Specifically, for each calendar trading month (M) the daily closing prices are collected from a contract that is deliverable in $M + 2$ months. On the first day of the next calendar trading month ($M + 1$) it is rolled over to the next contract that is deliverable in 2 months ($M + 3$ months). For example, if the calendar trading month is February, the daily closing prices are collected from the contract that is deliverable in April, and on the first day of March it is rolled over to the contract that is deliverable in May. The choice of contracts that are deliverable $M + 2$ months (2-month) provides a high degree of liquidity and, assuming that volume has information value, the 2-month window is the period where the volume of trade is most likely to be high. In addition, working with contracts that are deliverable $M + 2$ months avoids the problem of maturity mismatch between the three contracts.[7]

Because crude oil prices are quoted in terms of dollars per barrel, while unleaded gasoline and heating oil prices are quoted in terms of dollars per gallon it is necessary to convert all three quotations into the same unit of measure. Therefore, all prices are measured in dollars per barrel, and there are 42 gallons per barrel. The computations of the various crack spreads are as follows:

$$3{:}2{:}1 \text{ Crack Spread } (CS)_t = \tfrac{2}{3}HU_t + \tfrac{1}{3}HO_t - CL_t \tag{1}$$

$$1{:}1{:}0 \text{ Gasoline Crack Spread } (GCS)_t = HU_t - CL_t \tag{1a}$$

$$1{:}0{:}1 \text{ Heating Oil Crack Spread } (HCS)_t = HO_t - CL_t \tag{1b}$$

$$0{:}1{:}1 \text{ Gasoline-Heating Oil Crack Spread } (GHCS)_t = HU_t - HO_t \tag{1c}$$

where the symbols HU_t, HO_t, and CL_t, refer to unleaded gasoline, heating oil, and crude oil contracts, respectively. The subscript t refers to the

[7]Crude oil futures stop trading three working days before the 25th day of the month prior to the delivery month while the heating oil and unleaded gasoline contracts trade to the last trading day of the month.

time position in the time series; for example, CL_t is the closing price of crude oil contract at time t. The futures spread return at time t (FSR_t) is defined as $\ln(FS_t/FS_{t-1})$ for all the spreads under study, where FS_ts are the futures spreads series at a given day t.

The volume and open interest data that are used in this analysis are weighted averages of the underlying asset's volume and open interest consistent with the way the spreads are computed. For example, the daily weighted average volume for the 3:2:1 crack spread is $(3V_{CL} + 2V_{HU} + V_{HO})/3$ where V_{CL}, V_{HU}, and V_{HO} are the volumes for crude oil, unleaded gasoline, and heating oil contracts, respectively. Similarly, the daily weighted average volume for the 1:1:0 gasoline crack spread is $(V_{CL} + V_{HU})/2$ and the volume for the other spreads is computed in the same way. The daily weighted average open interest for each spread is also computed in the same way using the same weights as the daily average volume.

Table I shows various descriptive statistics for the daily futures crack spreads' returns. The distribution of these returns generally shows significantly positive skewness, the lone exception being the case of the 0:1:1 gasoline-heating oil crack spread return that exhibits significantly negative skewness. Furthermore, all four return series show evidence of significant excess kurtosis relative to the normal distribution. The existing literature shows that excess skewness and kurtosis are evidence of possible heteroscedasticity (see, e.g., Akgiray et al., 1991; Hall et al., 1989; Harvey & Siddique, 1999).

TABLE I
Summary Statistics for Futures Spreads Returns

	3:2:1 CS	*1:1:0 GCS*	*1:0:1 HCS*	*0:1:1 GHCS*
Mean	−0.00003	0.000048	0.001718	−0.00132
t-Statistics	−0.03039	0.039823	0.804365	−0.20421
Standard deviation	0.054644	0.074138	0.13033	0.389221
Skewness	0.721636	1.494833	7.727868	−1.00986
Kurtosis	21.97436	34.78255	210.4744	32.42082
Minimum	−0.48804	−0.62487	−1.29633	−4.18965
Maximum	.746107	1.187514	3.63139	4.553877
Q (12)	480.238	554.235	272.259	256.922
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
LM (12)	324.094	304.590	232.199	197.764
	[0.0001]	[0.0001]	[0.0001]	[0.0001]

Note. The data cover the periods from December 1984 to November 1999 and include all contracts that were deliverable through December 1999. The *Q* and LM statistics are tests for heteroscedasticity of the return series. *p*-Values appear below the parameter estimates. These tests show that the futures spreads return series are characterized by statistically significant heteroscedasticity.

Therefore, this study conducts Lagrange Multiplier (LM) test using Engle's (1982) methods for arch effects and portmanteau Q-test using the Mcleod and Li (1983) methods to test for nonlinearity or GARCH effects. The test results, also reported in Table I, show that the LM and the Q-statistics are significant at better than the 1% level, implying that all four petroleum futures spreads return series are heteroscedastic. In fact, all the p-values given below the parameter estimates in Table I are well below 0.01 strongly rejecting the null hypothesis of homoscedasticity. Finally, using the Phillips (1987) and Phillips and Perron (1988) unit root testing procedures, each series is tested for nonstationarity.[8] The empirical findings of these tests, not reported here but available upon request, firmly reject the null hypothesis of a unit root in all four futures spread return series. Rejection of the unit root hypothesis implies that the series need not be differenced to achieve stationarity, a condition necessary to avoid spurious results.

METHODOLOGY

The analysis of data in the last section suggests that the futures spreads return series are not normally distributed, and are characterized by excess kurtosis. The return series also exhibited significant heteroscedasticity, suggesting that the use of the Generalized ARCH (GARCH) model of Bollerslev (1986) is appropriate. Therefore, this study uses a GARCH framework to examine the relation between crack spreads return variability, volume, and open interest. The GARCH(1,1) model has been shown to be adequate for examining the relation between return variability and volume (Bollerslev, 1986, 1987; Lamoureux & Lastrapes, 1990; Najand & Yung, 1991, etc.).

Following Gallant, Rossi, and Tauchen (1992), Bessembinder and Seguin (1993), and Hiemstra and Jones (1994), the futures spread return series are adjusted for the systematic day-of-the-week effects. This adjustment is justified because Girma and Paulson (1998) have shown that three out of the four futures spreads return series used in this study exhibit significant seasonal tendencies. The adjustment approach taken in this study is a two-stage process similar to that of Hiemstra and Jones (1994). More specifically, the raw FSR_t series are

[8]Testing for unit roots is important because ordinary regressions that use nonstationary variables will not produce estimators that display the asymptotically normal distribution results that arise with stationary regressors. Thus, pretesting the series for nonstationarity is crucial for the validation of statistical inferences and recommendations based on empirical studies of markets for spreads.

adjusted for the day-of-the-week effects using the following regression equation:

$$FSR_t = a_0 + \sum_{i=1}^{i=4} a_i D_{it} + y_t \tag{2}$$

where D_{it} are the day-of-the-week dummies in Equation (2), a_is are the parameter estimates and y_t is the error term, respectively.

The residual, y_t, from Equation (2) above is the seasonally adjusted futures spreads return series. Throughout the remainder of the article, the analysis is based on the seasonally adjusted return series, y_t. Unlike Hiemstra and Jones (1994), this study does not adjust the variance of the residuals from Equation (2) for the day-of-the week effects. Furthermore, this study does not make any adjustment to the volume and open interest series. Finally, we estimate the GARCH(1,1) model using the adjusted futures spread return series and the level of volume and open interest as appropriate.[9] Specifically we will use

$$y_t = \mu + \varepsilon_t \tag{3}$$

$$\varepsilon_t = t \cdot d(0, h_t, \nu) \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{5}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma_1 V_{t-j} \quad (j = 0, 1) \tag{6}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \phi_1 V_{t-j} + \phi_2 (OI)_{t-j} \quad (j = 0, 1) \tag{7}$$

where y_t is the adjusted futures spread return series, V or OI, and γ are the weighted average of volume or open interest for the underlying futures contracts as appropriate on a given day and their respective parameter estimate. ϕ_1 and ϕ_2, in Equation (7), are parameter estimates for volume and open interest when both volume and open interest are entered simultaneously in the conditional variance equation. Note that Equation (6) is also used to model the relation between open interest and volatility by simply substituting open interest (OI) for volume (V).

Table I shows that all four crack spreads return series are non-normally distributed. Therefore, the model given by Equations (3) to (7) is estimated under the assumption that ε_t follows a conditional Student t-distribution because Bollerslev (1987) has shown that a GARCH model

[9]The volume and open interest series are tested for unit roots using the robust procedures of Phillips (1987) and Phillips and Perron (1988). The results of these unit root tests not provided but available upon request, reject the null hypothesis of a unit root in the volume and open interest series. Consequently, this study employs volume and open interest in their levels.

TABLE II
GARCH(1,1) Estimate for Petroleum Futures Spreads[a]

	3:2:1 CS		*1:1:0 GCS*		*1:0:1 HCS*		*0:1:1 GHCS*	
Parameters	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*
μ	−0.0002	0.7202	−0.0004	0.5373	−0.0012	0.1384	0.0042	0.0089
α_0	0.0001	0.0001	0.0001	0.0001	0.0002	0.0001	0.0045	0.0001
α_1	0.0784	0.0001	0.0900	0.0001	0.1274	0.0001	0.7081	0.0001
α_2	0.8998	0.0001	0.8838	0.0001	0.8627	0.0001	0.6354	0.0001
$1/\nu^{b}$	0.1975	0.0001	0.2634	0.0001	0.2818	0.0001	0.4140	0.0001
$\alpha_1 + \alpha_2$	0.9782		0.9738		0.9901		1.3435	
$\chi_1^2(\alpha_1 + \alpha_2 = 1)$	5.1001	0.0241	5.3210	0.0230	3.9537	0.0439	0.4473	0.5021

[a]The data cover the periods from December 1984 to November 1999 and include all contracts that were deliverable through December 1999.
[b]$1/\nu$ is reciprocal of degree of freedom and it is significantly different from zero at $\alpha = 0.01$ level of significance.

with conditional normal distribution fails to adequately capture the leptokurtocity in the standardized residuals. The empirical findings are presented and discussed in the next section.

EMPIRICAL RESULTS

Table II presents the results of a simple GARCH(1,1) model [Equation (5)] parameter estimates for the four petroleum futures spreads. Examination of the estimates in Table II shows that a GARCH(1,1) model provides an adequate characterization of the 3:2:1 crack spread, 1:1:0 gasoline crack spread, and the 1:0:1 heating oil crack spreads' volatilities. However, the 0:1:1 gasoline-heating oil crack spread has extremely high persistence, and suggests that the integrated GARCH (IGARCH) (1,1) of Engle and Bollerslev (1986) might be more appropriate to model this series.[10] Indeed, the χ^2 statistic in Table II, which formally tests the null hypothesis of an IGARCH(1,1) process, is highly significant for the 3:2:1, 1:1:0, and the 1:0:1 crack spreads but not for the 0:1:1 spread. Consequently, the results of the 0:1:1 gasoline-heating oil crack spreads in Tables III–V are based on an IGARCH(1,1) framework. Table II also shows that the reciprocal of the degree of freedom $(1/\nu)$ is significantly greater than zero, supporting the earlier findings reported in Table I that the return series are not normally distributed.[11]

[10]In an integrated GARCH (IGARCH) process, the coefficients α_1 and α_2 in the conditional variance equation sum up to 1, implying that shocks to the conditional variance persist or do not decay over time.
[11]If the returns for the petroleum futures spreads are normally distributed, the reciprocal of the degree of freedom would be zero.

Relations Between Return Volatility and Volume

Table III shows the GARCH(1,1) estimates for the four petroleum futures spreads, when volume is used as explanatory variable, in the conditional variance function [Equation (6)]. Panel A of Table III shows that current volume has a significant explanatory power for petroleum futures spread volatility. The coefficient of the contemporaneous average volume in the conditional variance equation, γ, is statistically significant at the 1% level for the 3:2:1 crack spread and the 1:0:1 heating oil crack spread and at the 10% for the 1:1:0 gasoline crack spread and the 0:1:1 gasoline-heating oil crack spread. Furthermore, there is a greater reduction in volatility persistence for the 3:2:1 crack spread from 0.9782 to 0.9090 and somewhat lower reduction in volatility persistence for the 1:1:0 gasoline crack spread from 0.9738 to 0.96984. By contrast, the inclusion of contemporaneous volume in the conditional variance increases the persistence of volatility slightly for the 1:0:1 heating oil crack spread from 0.9901 to 0.9951. Note that the 0:1:1 gasoline-heating oil crack spread is modeled using IGARCH(1,1) and the persistence is equal to 1.00, and hence, there will be no increase (decrease) in the persistence of volatility.

TABLE III

GARCH(1,1) Estimate for Petroleum Futures Spreads with Volume[a]

	3:2:1 CS		*1:1:0 GCS*		*1:0:1 HCS*		*0:1:1 GHCS*[c]	
Parameters	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*
Panel A: GARCH(1,1) Estimates for Futures Spread with Current Volume								
μ	−0.0005	0.4161	−0.00004	0.5485	−0.0012	0.1490	0.0041	0.0148
α_0	0.0001	0.0617	0.0001	0.0151	0.0000	0.9998	0.0017	0.0009
α_1	0.3009	0.0001	0.1048	0.0001	0.1449	0.0001	0.3151	0.0001
α_2	0.6081	0.0001	0.8650	0.0001	0.8502	0.0001	0.6849	0.0001
γ	9.948E-9	0.0001	2.469E-9	0.0839	9.499E-9	0.0001	9.280E-8	0.0725
$1/\nu^b$	0.2814	0.0001	0.2581	0.0001	0.2937	0.0001	0.3387	0.0001
$\alpha_1 + \alpha_2$	0.9090		0.9698		0.9951		1.0000	
Panel B: GARCH(1,1) Estimates for Futures Spread with Lagged Volume								
μ	−0.0004	0.4480	−0.0005	0.4644	−0.0012	0.1478	0.0042	0.0132
α_0	0.0001	0.1041	0.0000	0.3773	0.0000	0.8448	0.0017	0.0005
α_1	0.1945	0.0001	0.1606	0.0001	0.1406	0.0001	0.3188	0.0001
α_2	0.7420	0.0001	0.8217	0.0001	0.8540	0.0001	0.6812	0.0001
γ	4.475E-9	0.0001	8.949E-9	0.0001	8.395E-9	0.0004	9.540E-8	0.0477
$1/\nu^b$	0.2477	0.0001	0.2939	0.0001	0.2900	0.0001	0.3379	0.0001
$\alpha_1 + \alpha_2$	0.9365		0.9823		0.9946		1.0000	

[a]The data cover the periods from December 1984 to November 1999 and include all contracts that were deliverable through December 1999.

[b]$1/\nu$ is reciprocal of degree of freedom and it is significantly different from zero at $\alpha = 0.01$ level of significance.

[c]IGARCH(1,1) Estimates.

Panel B of Table III shows that lagged volume has a significant explanatory power for petroleum futures spread volatility when it is used as explanatory variable. The coefficient of the lagged volume in the conditional variance equation [Equation (6)] is statistically significant at the 1% level for the 3:2:1 crack spread, 1:1:0 gasoline crack spread and 1:0:1 heating oil crack spread. But it is significant at the 5% level for the 0:1:1 gasoline-heating oil crack spread. Furthermore, the introduction of lagged volume in the conditional variance equation reduces the observed persistence, as measured by $(\alpha_1 + \alpha_2)$, from 0.9782 to 0.9365 for the 3:2:1 spread and from 0.9738 to 0.9652 for the 1:1:0 spread. As for the 1:0:1 spread, a marginal increase in persistence $(\alpha_1 + \alpha_2)$ is observed (it rises from 0.9901 in Table II to 0.9946 in Table III).

In summary, when entered separately, the volume and lagged volume variables have a significant explanatory power for the volatility of returns for all the four spreads examined. However, the persistence of volatility remains high for all the four crack spreads and volume (current or lagged) reduces the GARCH effect in spread volatility only marginally. The persistence of spread volatility suggests that volatility shocks to spreads tend to persist and affect future volatility for a long period of time.

Relations Between Volatility and Open Interest

Table IV shows the estimates of the GARCH(1,1) model for the four petroleum futures spread when open interest is used as explanatory variable in the conditional variance function [Equation (6)].

Panel A of Table IV shows that current open interest has a significant explanatory power for the petroleum futures spreads' returns volatility, except for the 0:1:1 gasoline-heating oil crack spread. The coefficient of the contemporaneous open interest in the conditional variance equation, γ, is statistically significant at the 1% level for the 3:2:1 crack spread, 1:1:0 gasoline crack spread, and 1:0:1 heating oil crack spread. But it was not significant, at any reasonable level, for the 0:1:1 gasoline-heating oil crack spread. Furthermore, although the persistence of volatility decreases for the 3:2:1 crack spread and 1:0:1 heating oil crack spread from 0.9782 to 0.9339 and from 0.9901 to 0.9557, respectively, it increases slightly for the 1:1:0 gasoline crack spread.

Panel B of Table IV shows the impact of the lagged open interest variable on the volatility of returns for the four petroleum futures spreads. The coefficient of the lagged open interest in the conditional volatility equation, γ, is statistically significant at the 1% level for three of the four petroleum futures spread volatilities, the lone exception being

TABLE IV

GARCH(1,1) Estimate for Petroleum Futures Spreads with Open Interest[a]

	3:2:1 CS		*1:1:0 GCS*		*1:0:1 HCS*		*0:1:1 GHCS*[c]	
Parameters	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*
Panel A: GARCH(1,1) Estimates for Futures Spread with Current Open Interest								
μ	−0.0005	0.4279	−0.0005	0.4532	−0.0011	0.1719	0.0042	0.0142
α_0	0.0001	0.1962	0.0000	0.3225	0.0001	0.1361	0.0024	0.0001
α_1	0.2595	0.0001	0.11323	0.0001	0.1205	0.0001	0.3150	0.0001
α_2	0.6744	0.0001	0.8486	0.0001	0.8352	0.0001	0.6850	0.0001
γ	2.988E-9	0.0001	2.077E-9	0.0042	3.292E-9	0.0035	2.302E-8	0.9037
$1/\nu^b$	0.2635	0.0001	0.2790	0.0001	0.2623	0.0001	0.3402	0.0001
$\alpha_1 + \alpha_2$	0.9339		0.9809		0.9557		1.0000	
Panel B: GARCH(1,1) Estimates for Futures Spread with Lagged Open Interest								
μ	−0.0005	0.4267	−0.0005	0.4577	−0.0012	0.1342	0.0042	0.0140
α_0	0.0001	0.1484	0.0001	0.2824	0.0000	0.9999	0.0023	0.0001
α_1	0.2832	0.0001	0.1815	0.0001	0.2392	0.0001	0.3153	0.0001
α_2	0.6370	0.0001	0.8007	0.0001	0.7924	0.0001	0.6847	0.0001
γ	3.515E-9	0.0001	4.297E-9	0.0002	8.566E-9	0.0001	6.882E-9	0.7007
$1/\nu^b$	0.2659	0.0001	0.3024	0.0001	0.3421	0.0001	0.3397	0.0001
$\alpha_1 + \alpha_2$	0.9202		0.9822		1.0317		1.0000	

[a]The data cover the periods from December 1984 to November 1999 and include all contracts that were deliverable through December 1999.
[b]$1/\nu$ is reciprocal of degree of freedom and it is significantly different from zero at $\alpha = 0.01$ level of significance.
[c]IGARCH(1,1) Estimates.

the for 0:1:1 gasoline-heating oil crack spread. These findings are qualitatively similar to those in Panel A of Table IV. In addition, the inclusion of lagged open interest as explanatory variable in the conditional variance equation leads to an increase in volatility persistence for the 1:1:0 and the 1:0:1 spreads. For these two spreads, the persistence of volatility increases respectively from 0.9738 and 0.9901 in Table II to 0.9822 and 1.0317 in Panel B of Table IV. These results seem to suggest that, when lagged open interest is an explanatory variable in the conditional variance equation, an IGARCH(1,1) model might better characterize the 1:0:1 heating oil crack spread return series. As for the 3:2:1 crack spread, a significant reduction in volatility persistence is achieved when lagged open interest is used as explanatory variable. The persistence of volatility, when the lagged open interest variable is in the conditional variance equation, drops from 0.9782 in Table II to 0.9202 in Panel B of Table IV.

In summary, when entered separately, the open interest and lagged open interest variables have a significant explanatory power for the volatility of returns for three out of the four spreads examined. Just as in the case of volume, the persistence of volatility remains high for all the four crack spreads and open interest (current or lagged) reduces the GARCH effect in spread volatility only marginally. The persistence of spread volatility suggests that volatility shocks to spreads tend to persist and affect future volatility for a long period of time.

Relations Between Volatility, Volume, and Open Interest

Table V shows the results of estimating the GARCH(1,1) model for the four petroleum futures spreads when volume and open interest are used simultaneously as explanatory variables. In particular, Table V presents the results of exploring the explanatory power of volume and open interest when they are entered simultaneously in the conditional variance equation [Equation (7)].

Panel A of Table V reveals that when current volume and open interest are entered in the conditional variance equation simultaneously, neither one is significant at any reasonable level with the exception of the

TABLE V

GARCH(1,1) Estimate for Petroleum Futures Spreads with Volume and Open Interest[a]

	3:2:1 CS		*1:1:0 GCS*		*1:0:1 HCS*		*0:1:1 GHCS*[c]	
Parameters	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*	*Estimate*	*p-Value*
Panel A: GARCH(1,1) Estimates for Futures Spread with Current Volume & Open Interest[a]								
μ	−0.0004	0.5001	−0.0005	0.5011	−0.0013	0.1269	0.0041	0.0148
α_0	0.0005	0.0001	0.0001	0.0615	0.0000	0.9999	0.0017	0.0015
α_1	0.2232	0.0001	0.1092	0.0001	0.2757	0.0001	0.3151	0.0001
α_2	0.1164	0.0001	0.8677	0.0001	0.7850	0.0001	0.6849	0.0001
ϕ_1	1.707E-8	0.0001	0	0.9992	5.476E-9	0.6304	9.280E-8	0.3784
ϕ_2	0	1.0000	1.164E-9	0.5138	8.310E-9	0.1396	0	1.0000
$1/\nu$[b]	0.0733	0.0001	0.2723	0.0001	0.3653	0.0001	0.3387	0.0001
$\alpha_1 + \alpha_2$	0.3396		0.9769		1.0607		1.0000	
Panel B: GARCH(1,1) Estimates for Futures Spread with Lagged Volume & Open Interest								
μ	−0.0006	0.3801	0.0002	0.7885	−0.0012	0.1375	0.0042	0.0132
α_0	0.0002	0.0001	0.0008	0.0001	0.0000	0.9999	0.0017	0.0012
α_1	0.2510	0.0001	0.3912	0.0001	0.2266	0.0001	0.3188	0.0001
α_2	0.3087	0.0001	0.0249	0.0212	0.7987	0.0001	0.6812	0.0001
ϕ_1	9.110E-9	0.0068	3.112E-8	0.0001	0	1.0000	9.078E-8	0.3571
ϕ_2	4.716E-9	0.0045	8.436E-9	0.0287	7.917E-9	0.0674	2.004E-9	0.9562
$1/\nu$[b]	0.1164	0.0001	0.1194	0.0001	0.3365	0.0001	0.3380	0.0001
$\alpha_1 + \alpha_2$	0.5597		0.4161		1.0253		1.0000	

[a]The data cover the periods from December 1984 to November 1999 and includes all contracts that were deliverable through December 1999.
[b]$1/\nu$ is reciprocal of degree of freedom and it is significantly different from zero at $\alpha = 0.01$ level of significance.
[c]IGARCH(1,1) Estimates.

3:2:1 crack spread. The 3:2:1 crack spread shows that, when current volume and open interest are included in the conditional volatility equation simultaneously, only current volume achieves statistical significance at the 1.0% level. In this case, the persistence of volatility, as measured by $(\alpha_1 + \alpha_2)$, also declines dramatically from 0.9782 to 0.3396. For all other crack spreads the persistence of volatility increases significantly and past volatility can explain current volatility. Current volume and open interest do not remove the GARCH effect in three out of the four spreads.

In contrast, Panel B of Table V shows that, when lagged volume and lagged open interest are included as explanatory variables in the conditional variance equation, the coefficient of lagged volume (ϕ_1) is significant at the 1% level for the 3:2:1 crack spread and the 1:1:0 gasoline crack spread. But it is not significant for the 1:0:1 spread and 0:1:1 spread. Panel B of Table V also reveals that ϕ_2, the coefficient of the lagged open interest variable in the conditional variable equation when lagged open interest and lagged volume are considered jointly, is significant in three out of four cases. More specifically, ϕ_2 is significant at the 1% level for the 3:2:1 spread, 5% level for the 1:1:0 spread, 10% for the 1:0:1 spread, and not significant for the 0:1:1 spread.

Furthermore, the results in Panel B of Table V show that the persistence of volatility, as measured by $(\alpha_1 + \alpha_2)$, decreases dramatically for the 3:2:1 and 1:1:0 spreads. For these two spreads, the persistence of volatility decreases, respectively, from 0.9782 and 0.9738 in Table II to 0.5597 and 0.4161 in Panel B of Table V. Thus, it appears that including lagged volume and lagged open interest in the conditional variance equation has greater power of reducing the persistence in volatility for petroleum futures spreads than current volume and current open interest either separately or jointly. These findings seem to support the sequential information arrival hypothesis of Copeland (1976). Finally, these findings also suggest a degree of market inefficiency in petroleum futures spreads and are consistent with previous research on price variability and volume and/or open interest (see, e.g., Foster, 1995; Fujihara & Mougoué, 1997).

CONCLUSION

This study finds that contemporaneous weighted average of volume and open interest provide significant explanation for futures spreads volatility when entered separately. The study also finds that the lagged weighted average of volume and lagged weighted open interest provide significant explanation for futures spread volatility. Furthermore, the study finds that lagged volume and lagged open interest, when entered in the conditional variance equation simultaneously, provide significant explanatory power in three out of four cases and reduce the persistence of volatility dramatically in two out of four cases. These findings seem to support the sequential information arrival hypothesis of Copeland (1976). Finally, these findings also suggest a degree of market inefficiency in petroleum futures spreads and are consistent with previous research on price variability and volume and/or open interest.

The results of this study shed additional light on the source(s) of uncertainty for petroleum futures spreads. More specifically, the empirical results show that contemporaneous and lagged volume and open interest are significantly related to the volatility of futures spreads returns. These findings are of considerable interest to refiners and retailers who routinely seek to hedge both the input price and output revenue to lock in their profit margin. Furthermore, risk arbitrageurs or speculators who trade the spreads to exploit relative mispricing can also benefit from a better understanding of the source(s) of futures spreads (FS) volatility. The findings of this study also have practical implications for speculators, hedgers such as airlines companies, and other users of petroleum products as well. For example, it is well known that successful hedging and speculative activities in futures markets depend critically on the ability to forecast price movements. The finding that current and lagged volume and open interest affect volatility implies that a short-term improvement in predicting futures price movement can be achieved using these variables. This improvement of short-term futures price predictability should lead to the construction of more accurate hedge ratios and amelioration in investment strategies and returns.

The findings of this study also have implications for market efficiency. The fact that lagged volume and open interest are significantly related to futures spreads return volatility may be interpreted as evidence of inefficiency in these futures spreads markets. As noted by several researchers (see, e.g., Fujihara & Mougoué, 1997), such inefficiency may be attributed to a form of mimetic contagion, where traders set their prices with reference to the trading patterns of other market participants. This apparent inefficiency could also be due to the fact that futures traders base their prices on previous day's trading volume and open interest as a measure of both market consensus and market depth.

Finally, the findings of this study also could be of interest to market regulators fearful of potentially destabilizing excessive volatility in oil prices. Overall, the findings of this article are important to policymakers, practitioners, and researchers alike.

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