Return-Volume Dynamics in Futures Markets

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INTRODUCTION

Closing price and volume of trading are two statistics that are routinely released in the media to report on the status of financial markets and are closely monitored by investors. This in turn implies that market participants believe that intrinsic knowledge of price changes and trading volume will enhance their understanding of the market dynamics and thus their financial success.

In the financial literature it is widely acknowledged that trading in asset markets is mainly induced by the arrival of new information and subsequent revisions of expectations by investors.[1] The trading volume, therefore, can be thought to reflect information about changes and *agreement* in investors' expectations (Harris and Raviv, 1993). Its relationship with price changes, however, is interpreted differently depending on whether returns are signed or unsigned, and if the relationship is simultaneous. Thus, a thorough empirical examination of *contemporaneous* and *intertemporal* relationships between volume and (signed and unsigned) returns reveals valuable information on different aspects of the dynamics and informational efficiency in futures markets.

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[1]It is shown that liquidity, portfolio rebalancing, speculation, and tax motives also may contribute to trading activity (Campbell, Grossman, and Wang, 1993; Campbell and Kyle, 1993).

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The volume-*absolute* return relationship is understood to reveal particulars about information dissemination and processing procedures in the market (Clark, 1973; Copeland, 1976; Epps 1975, 1977; Epps and Epps, 1976; Jennings, Starks and Fellingham, 1981; Tauchen and Pitts, 1983; Karpoff, 1987, 1988; Smirlock and Starks, 1988; McCarthy and Najand, 1993; Najand and Yung, 1991). Two competing hypotheses explain the information arrival process in financial markets: the mixture of distributions hypothesis and the sequential information arrival hypothesis. According to the mixture of distributions hypothesis, information dissemination is contemporaneous (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris, 1986, 1987). The sequential information arrival hypothesis, however, allows for intermediate informational equilibria in the market (Copeland, 1976; Jennings, et al., 1981). Moreover, it is argued that information asymmetry and investor heterogeneity also may affect the relationship between volume and returns; accordingly, trading volume is always positively correlated with absolute price changes and the correlation *increases* with information asymmetry (Wang, 1993, 1994). Karpoff (1987) claims that the mixture of distributions hypothesis is consistent with the empirical distribution of price changes and the difference in the correlation between volume-absolute returns over different frequencies. However, the evidence presented by Smirlock and Starks (1988) on stock markets and McCarthy and Najand (1993) on currency futures markets supports the sequential information arrival hypothesis. Nevertheless, the existing literature on information flow is based primarily on equity and bond markets, with the only exceptions of Karpoff (1988) and McCarthy and Najand (1993). Therefore, this article broadens the understanding of futures markets dynamics.

A volume-*signed* return relationship at the contemporaneous level, on the other hand, reveals information about symmetry of trading volume in up and down markets. Karpoff (1988) and Suominen (1996) suggest that in equity markets the observed positive correlation between volume and returns can be explained by the presence of differential costs in acquiring short and long positions. Accordingly, one should not observe any asymmetry in futures markets since the costs of taking short and long positions in such markets are symmetric. This can be verified by calculating the contemporaneous correlation coefficients between the two variables (Karpoff, 1988).

In turn, an analysis of the intertemporal causality relationship between volume and rate of return, e.g., checking for a causality which runs from *past* values of volume to the actual rate of return, sheds light on the informational efficiency of the market. Clearly, such a finding is not consistent with Fama's well-known definition of weak-form market efficiency and can be interpreted as evidence of informational inefficiency in the market. The implication is that efficiency, and thus abnormal profit opportunities, are in question, which justifies investors' interest in the price and volume statistics. Recently, McCarthy and Najand (1993) checked and verified the efficiency of currency futures markets. However, they excluded agricultural, metal, energy, interest rate, and index contracts from their analysis.

This study, by examining the contemporaneous and intertemporal (causality) relationships between trading volume and (signed and unsigned) returns in the case of 16 major U.S. futures markets, aims to enhance the understanding of the dynamics in futures markets by providing empirical answers for a number of questions related to information flow, trading, and efficiency in futures markets, namely:

1. Is the dissemination and processing of information in futures markets consistent with the sequential or simultaneous information arrival hypotheses? Is newly arrived information completely reflected in the contemporaneous price level, or does it also affect subsequent trading periods?
2. Is the volume-return (per se) relationship symmetric as Karpoff (1988) and Suominen (1996) predict, or does the volume behave differently depending on the direction of price moves?
3. Are futures markets efficient in processing new information or do past values of trading enhance the forecastability of prices?
4. How does the presence of information asymmetry affect market efficiency in futures markets?

The results reveal that, while the contemporaneous evidence on the volume-absolute return relationship is consistent with both the mixture of distributions hypothesis and the sequential information arrival hypothesis, as well as Wang's (1994) heterogeneous investors model, the intertemporal analysis results reject the mixture of distributions hypothesis and provides support for the sequential information arrival hypothesis. This finding is consistent with Smirlock and Starks (1988), and McCarthy and Najand (1993). Furthermore, in line with the absence of a short-selling constraint argument (Karpoff, 1988; Suominen, 1996), no significant contemporaneous relationship between trading volume and price changes is found, thus confirming symmetry of trading in futures markets.

Granger causality tests and variance decompositions reveal that, in general, past observations of trading volume do not increase the ability to forecast returns in futures markets. This outcome is in line with Fama's definition of weak-form market efficiency. Moreover, consistent with the conclusions of Campbell et al. (1993), the results illustrate that informational efficiency is more likely to be observed in markets with higher liquidity and market participation. Finally, following Wang (1994), it is found that the symmetry in information and market efficiency are positively correlated.

RETURN-VOLUME RELATIONSHIP

This section is divided into three parts. The first segment addresses the relationship between volume and absolute returns, which has implications on the information flow in futures markets. The second discusses the volume-return per se relationship, which is related to trading symmetry and informational efficiency in the markets. The last subsection briefly outlines and discusses the hypotheses tested in this study.

Volume-Absolute Return Relationship

As documented extensively by Karpoff's (1987) survey on the subject, and later confirmed by Karpoff (1988), there is overwhelming empirical evidence that absolute rates of return and trading volume are *positively* correlated. According to one view, this observation may be due to a joint dependence on a common event or variable and is referred to as the mixture of distributions hypothesis (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris, 1986, 1987). Accordingly, starting from an initial equilibrium position, a change in demand will induce a move in the price level. While the process of adjustment is underway, transactions are executed in response to the change in demand condition until equilibrium is reestablished at a new price. In this scenario, the volume of trade will rise with a change in demand (and hence, prices) *irrespective* of the direction of change. However, Clark (1973) does not imply anything about causality in either direction. Epps and Epps (1976) argue that price changes "are mixtures of distributions with volume as the mixing variable." Harris (1986, 1987) suggests that the common directing variable is the daily rate of information flow. Thus, both the price and trading volume change simultaneously when new, unexpected information arrives in the market. In other words, the mixture of distributions hypothesis suggests that there is a contemporaneous impact.

An alternative hypothesis, the sequential information arrival model, introduced by Copeland (1976), asserts that information is disseminated to a single trader at a time. The information causes a one-time upward shift in each "optimist's" demand curve by a fixed amount, δ, and a downward shift of δ in each "pessimist's" demand curve. As a result of the short sales prohibition in the model, volume generated by a pessimist is generally less than that generated by an optimist and the model simulation supports a positive correlation between the volume of trade and absolute price changes. Jennings et al. (1981) incorporate margin requirements into the model and also find that the relationship is affected by the number of investors and the mix between optimists and pessimists.

Finally, according to Wang (1994), in a framework in which investors are heterogeneous in their information and private investment opportunities and as the asymmetry in information increases, the uninformed investors demand a higher discount in price when they buy the contract from the informed investors to cover the risk of trading against private information. Therefore, trading volume is always *positively* correlated with absolute price changes. As it is shown in Wang (1994), different levels of heterogeneity among investors give rise to different return-volume dynamics. In particular, trading volume is always positively correlated with absolute price changes and the correlation *increases* with information asymmetry.

The outlined hypotheses on the information arrival process can be pictured as two extremes. On one hand, all investors receive the information simultaneously, process it, and perform their trades, where the complete information equilibrium is obtained in a single trading round with no intermediate equilibria. On the other hand, investors receive the information one at a time and trading occurs after each reception. In this case, there are a number of intermediate equilibria before the final complete information equilibrium. In other words, in the sequential information arrival model there are intermediate equilibria, whereas in the simultaneous information arrival model the adjustment is contemporaneous. Accordingly, with simultaneous information arrival, there is no information in past observations of absolute returns that can be used in forecasting future volume that is not already contained in past lags of volume.

In the sequential information arrival model, however, past values of absolute returns provide information that may *improve* volume *forecasts*, vis-à-vis forecasts based on lagged values of volume alone. Similar implications hold for the relationship between past values of volume and future returns. Therefore, despite the fact that both theories imply a positive contemporaneous relationship between absolute returns and volume, the dynamic response predicted is different. Granger causality tests can be employed to examine the empirical validity of the sequential information arrival model versus the simultaneous information arrival model, i.e., mixture of distributions hypothesis. Accordingly, the sequential arrival of information implies a positive causal relationship in both directions (Smirlock and Starks, 1988; Hiemstra and Jones, 1994). However, the mixture of distributions model of Epps and Epps (1976) suggests only a positive contemporaneous causal relationship running from trading volume to absolute stock returns. Clark's (1973) model, however, which treats trading volume as a proxy for the speed of information flow, implies no causal relationship between absolute returns and volume.

Volume-Return Per Se Relationship

The majority of empirical evidence on volume-return (per se) relationship is based on bond and stock market studies (Granger and Morgenstern, 1963; Morgan, 1976; Epps, 1975, 1977; Westerfield, 1977; Rogalski, 1978; Jennings et al., 1981; Harris, 1986), with two exceptions: Karpoff (1988) and McCarthy and Najand (1993). As the survey by Karpoff (1987) points out, the majority of studies conducted on stock markets note a *positive* contemporaneous correlation between volume and return per se.

From a theoretical point of view, the price-volume relationship has been the basis for the modeling of prices in the mixture of distributions hypothesis framework (Epps and Epps, 1976; Clark, 1973; Tauchen and Pitts, 1983; Harris, 1986, 1987, 1989; Eitan and Harris, 1986), as well as the outcome of the sequential information arrival models (Copeland, 1976; Jennings et al., 1981). Epps's (1975) testable hypothesis is that bulls consider assets to be riskier than bears do, and thus, a bull's demand function is steeper than that of a bear. This implies that the ratio of volume to a positive price change would be greater than that of the ratio of volume to a negative price change: correspondingly, the overall correlation ought to be positive. Copeland (1976) and Jennings et al. (1981) show that the volume that results when a previously uninformed trader reacts pessimistically to new information is less than when the trader responds optimistically. Therefore, the authors also conclude that volume expands with increases in prices, whereas it falls with declining prices.

The absence of documentation of a positive correlation between volume and returns in futures markets (Karpoff, 1988; McCarthy and Najand, 1993), in contrast to stock markets where the costs of taking long and short positions are symmetric, indicates that the differential cost of short sales is crucial in determining the volume-return relationship. This view is supported by Suominen (1996), who illustrates that the introduction of a short sales constraint leads to a *positive* correlation between returns and trading volume.

Several studies illustrate that *past* values of trading volume and realized returns can *forecast* future returns in stock markets (Morse, 1980; Gallant, Rossi, and Tauchen, 1992; LeBaron, 1992; Campbell et al., 1993). In addition, Campbell et al. (1993) demonstrate that the first-order daily return autocorrelation tends to decline with trading volume. This finding implies that in markets with a high volume of trading, the return series should not exhibit any significant autocorrelation. Thus, it will follow a random walk process, the hallmark of market efficiency. The causality and ability to forecast can be tested with the help of an intertemporal causality test, e.g., the Granger causality test, between volume and returns to shed some light on the relationship between informational efficiency and liquidity in the market. According to the findings of Campbell et al. (1993), one should expect to find no statistical causation in the case of heavily traded commodities. Such a relationship is more likely in a "thin" market.

Tested Hypotheses

In this study, the volume-return (per se and absolute value) relationship is investigated first in a contemporaneous framework. According to asymmetric information models (e.g., Wang, 1994), as well as the mixture of distributions and sequential information arrival theories, one would expect to find a significant, *positive* contemporaneous correlation between absolute returns and volume of trade. On the other hand, the contemporaneous correlation between the signed returns and volume is expected to be either positive, as in the case of stock market studies, or indistinguishable from zero. The latter outcome is consistent with Karpoff (1988), who claims that absence of asymmetry of costs for taking long and short positions in futures markets leads to symmetry of trading in up and down markets.

As argued by Gallant et al. (1992), an examination of the joint dynamics of prices and volume provides a more complete and comprehensive view of markets in general. Therefore, a vector autoregression (VAR) framework is applied to capture the intertemporal dynamics in the behavior of trading volume and return series. Campbell (1991) and Campbell and Ammer (1993) illustrate an alternative method of identifying determinants of variation in a given variable: variance decomposition in a VAR context. Thus, the joint dynamics of contract prices and volume are subjected to a variance decomposition analysis to complement the VAR causality tests.

As discussed in the previous subsection, a bidirectional causality relationship between volume and absolute returns is implied by the sequential information arrival hypothesis (Smirlock and Starks, 1988; Hiemstra and Jones, 1994). The mixture of distributions hypothesis, however, predicts no significant intertemporal causality in either direction (Clark, 1973; Epps and Epps, 1976).

The intertemporal causality test between volume and return per se can be viewed as a standard informational market efficiency test (Majnoni and Massa, 1996), where an indication of causality from past values of volume to returns violates assumptions of the weak-form efficiency hypothesis. In light of Campbell et al. (1993), one would expect that commodity markets with *high* volumes of trading and liquidity should be more *efficient* than markets with low trading. Thus, in futures markets with a high daily volume of trading, such as S&P 500, Treasury bond, crude oil, heating oil markets, etc., one is more likely to observe informational efficiency, and vice versa.

Finally, in the framework of Wang (1994), which shows that a rise in the asymmetry of information leads to an increase in the correlation between contemporaneous volume and absolute returns, the correlation coefficients (which are unitless measures) can be used to rank the markets in terms of informational asymmetry. Consequently, by inspecting how the top and bottom five markets fare in efficiency tests, one can deduce the nature of the information asymmetry-market efficiency relationship in the context of futures markets.

DATA

The study includes real (agricultural, metal, and energy) and financial (index and interest rate) futures contracts: Daily data for 16 U.S. futures markets are obtained from Knight-Ridder—CRB InfoTech Commodity Database for the period between 2 January 1980 and 31 October 1995. In particular, the following commodities are included in the sample: copper, corn, crude oil, gasoline, gold, heating oil, live cattle, orange juice, palladium, platinum, silver, soybeans, sugar (world), wheat, S&P 500 index and Treasury bond. Three of the futures contracts commenced trading later than January 1980. They are crude oil, which began to trade on 30 March 1983; gasoline, which started on 3 December 1984; and S&P 500 index contracts, which commenced trading on 21 April 1982. Table I presents the exchanges where the futures contracts are traded.

TABLE I

List of Included Futures Contracts and Places Traded

Commodity	*Market Traded*
Copper	Commodity Exchange—New York (COMEX)
Corn	Chicago Board of Trade (CBT)
Crude oil	New York Mercantile Exchange (NYMEX)
Gasoline	New York Mercantile Exchange (NYMEX)
Gold	Commodity Exchange—New York (COMEX)
Heating oil	New York Mercantile Exchange (NYMEX)
Live cattle	Chicago Mercantile Exchange (CME)
Orange juice	New York Cotton Exchange (NYCE)
Palladium	New York Mercantile Exchange (NYMEX)
Platinum	New York Mercantile Exchange (NYMEX)
Silver	Commodity Exchange—New York (COMEX)
Soybeans	Mid-America Commodity Exchange—Chicago (MIDAM)
S&P 500	Chicago Mercantile Exchange (CME)
Sugar	Coffee, Sugar, and Cocoa Exchange—New York (CSCE)
Treasury bond	Chicago Board of Trade (CBT)
Wheat	Kansas City Board of Trade (KBT)

It is known that in futures markets the bulk of positions are rolled over so that the volume of trade increases until the month of delivery and then shifts to the next nearby contract. Therefore, trades on the first two nearby contracts account for a major portion of the trading volume in futures markets (McCarthy and Najand, 1993); thus, in the analysis, only near-month contracts are employed.

The rate of return series is calculated by taking the natural log of the ratio of two consecutive prices, i.e., $ROR_t = \ln(P_t/P_{t-1})$, where P_t is the price at time, t, and P_{t-1} is the price in the previous period. Both Phillips-Perron and augmented Dickey-Fuller (ADF) tests are applied to ROR, its absolute value (AROR), and trading volume (VOL) series, for all contracts in the sample to check for the presence of a unit root.[2] The test results presented in Table II show that *none* of the series contains a unit root.[3]

METHODOLOGY

To check the symmetry of the volume-return (per se) relationship as predicted by Karpoff (1988) and to confirm the positive correlation between

[2]The lag structures in Phillips-Perron tests are determined by the method suggested in Newey and West (1992). The sensitivity of ADF tests with respect to the number of lags is checked by estimating the ADF tests with three alternative lag structures, i.e., 1, 5, and 10 lags.

[3]The *only* exception is the ADF(10) test result for the (gasoline) volume of trade variable. Nevertheless, since the existence of a unit root is strongly rejected by the Phillips-Perron test, as well as the ADF tests for 1 and 5 lags for the same variable, the (gasoline) volume is not treated as difference stationary in the rest of the paper.

TABLE II

Unit Root Tests

Commodity		Phillips-Perron	ADF(1)	ADF(5)	ADF(10)
Copper	ROR	−62.631[c]	−44.949[c]	−26.496[c]	−18.402[c]
	AROR	−57.302[c]	−34.671[c]	−16.134[c]	−10.171[c]
	Volume	−38.265[c]	−25.549[c]	−14.668[c]	−10.718[c]
Corn	ROR	−60.524[c]	−44.633[c]	−25.756[c]	−19.310[c]
	AROR	−58.176[c]	−35.209[c]	−16.348[c]	−10.745[c]
	Volume	−31.142[c]	−19.959[c]	−11.547[c]	−8.251[c]
Crude oil	ROR	−57.191[c]	−42.244[c]	−25.442[c]	−17.318[c]
	AROR	−43.947[c]	−25.993[c]	−13.502[c]	−8.157[c]
	Volume	−10.874[c]	−10.169[c]	−6.776[c]	−4.385[c]
Gasoline	ROR	−50.265[c]	−35.514[c]	−22.880[c]	−15.358[c]
	AROR	−45.250[c]	−26.913[c]	−13.915[c]	−9.566[c]
	Volume	−10.252[c]	−8.862[c]	−4.151[c]	−2.800
Gold	ROR	−65.245[c]	−43.306[c]	−27.730[c]	−21.159[c]
	AROR	−56.309[c]	−33.304[c]	−16.251[c]	−12.109[c]
	Volume	−39.994[c]	−25.465[c]	−14.992[c]	−10.951[c]
Heating oil	ROR	−63.706[c]	−43.711[c]	−29.579[c]	−19.376[c]
	AROR	−56.372[c]	−31.064[c]	−16.006[c]	−10.048[c]
	Volume	−17.846[c]	−14.295[c]	−7.225[c]	−4.967[c]
Live cattle	ROR	−61.301[c]	−44.388[c]	−26.446[c]	−20.351[c]
	AROR	−60.689[c]	−41.315[c]	−21.511[c]	−13.911[c]
	Volume	−38.725[c]	−26.942[c]	−13.694[c]	−10.364[c]
Orange juice	ROR	−63.143[c]	−45.316[c]	−24.598[c]	−18.572[c]
	AROR	−55.725[c]	−34.892[c]	−19.900[c]	−13.700[c]
	Volume	−32.044[c]	−22.352[c]	−12.062[c]	−8.260[c]
Palladium	ROR	−63.440[c]	−42.679[c]	−25.854[c]	−18.775[c]
	AROR	−52.513[c]	−33.129[c]	−18.768[c]	−14.105[c]
	Volume	−34.103[c]	−20.581[c]	−11.653[c]	−9.479[c]
Platinum	ROR	−63.541[c]	−42.393[c]	−27.683[c]	−20.079[c]
	AROR	−57.101[c]	−35.333[c]	−17.316[c]	−11.282[c]
	Volume	−32.784[c]	−21.169[c]	−11.087[c]	−8.047[c]
Silver	ROR	−62.451[c]	−43.805[c]	−25.672[c]	−19.915[c]
	AROR	−52.779[c]	−33.583[c]	−16.638[c]	−12.053[c]
	Volume	−26.693[c]	−17.679[c]	−9.853[c]	−6.955[c]
Soybeans	ROR	−63.095[c]	−46.045[c]	−27.202[c]	−19.092[c]
	AROR	−58.836[c]	−34.337[c]	−14.981[c]	−9.553[c]
	Volume	−31.413[c]	−18.861[c]	−10.164[c]	−7.443[c]
S&P 500	ROR	−60.955[c]	−46.769[c]	−24.836[c]	−18.971[c]
	AROR	−50.099[c]	−28.683[c]	−15.916[c]	−12.617[c]
	Volume	−18.965[c]	−15.539[c]	−10.823[c]	−8.517[c]
Sugar	ROR	−65.857[c]	−48.334[c]	−25.809[c]	−19.216[c]
	AROR	−56.307[c]	−39.368[c]	−19.492[c]	−13.420[c]
	Volume	−39.046[c]	−24.568[c]	−13.043[c]	−9.521[c]
Treasury bond	ROR	−62.095[c]	−43.957[c]	−25.941[c]	−18.703[c]
	AROR	−62.730[c]	−41.531[c]	−18.422[c]	−12.789[c]
	Volume	−37.653[c]	−21.329[c]	−10.688[c]	−7.691[c]
Wheat	ROR	−63.562[c]	−47.238[c]	−27.857[c]	−19.583[c]
	AROR	−57.458[c]	−39.838[c]	−21.724[c]	−14.754[c]
	Volume	−34.536[c]	−21.009[c]	−11.168[c]	−7.908[c]

[a]Significance is at the 10% level (not shown).
[b]Significance is at the 5% level (not shown).
[c]Significance is at the 1% level.

volume and absolute returns, contemporaneous correlation coefficients are estimated for all contracts. The results are reported in the following section (see Table III).

Expectational revisions play an important role in the dynamics of financial markets; however, they are unobservable. Cutler, Poterba, and Summers (1989), Fama (1990), and Stambaugh (1990) used contemporaneous regressions to deal with this problem. The contemporaneous regression approach uses a vector of explanatory variables that proxies for the unobserved component. Nevertheless, there are well-documented problems with this approach. Due to the difficulties with contemporaneous regressions, VARs are preferred by many studies which address this issue. (Campbell and Shiller, 1987, 1988a, 1988b; Kandel and Stambaugh, 1988; Fama and French, 1988a, 1988b; Richardson and Stock, 1989; Campbell, 1991; Hodrick, 1992). The VAR approach postulates that the unobserved components of returns can be written as linear combinations of innovations to observable variables, thereby adequately capturing the dynamics of the data.

To check for causality and feedback relationships among the variables, a VAR-based econometric model is implemented where the responses of return and trading volume to movements in either volume or return can be identified for each commodity. The model is presented in two sets of equations: the first set, eqs. (1a) and (1b), models the relationship between the rate of return, ROR, and volume traded, VOL. The second set, eqs. (2a) and (2b), models the relationship between the absolute value of the rate of return, AROR, and volume traded. Employing the rate of returns and volume trade data, one can statistically determine whether there are causal relationships running from rate of return (or its absolute value) to volume, volume to rate of return (or its absolute value), or in both directions for a given futures market (Smirlock and Starks, 1988; McCarthy and Najand, 1993).

$$ROR_t = \sum_{j=1}^{M} a_i ROR_{t-i} + \sum_{j=1}^{N} b_j VOL_{t-j} + \varepsilon_{1at} \tag{1a}$$

$$VOL_t = \sum_{k=1}^{Q} c_k ROR_{t-k} + \sum_{l=1}^{P} d_l VOL_{t-l} + \varepsilon_{1bt} \tag{1b}$$

$$AROR_t = \sum_{\gamma=1}^{Q} e_\gamma AROR_{t-\gamma} + \sum_{\delta=1}^{R} f_\delta VOL_{t-\delta} + \varepsilon_{2at} \tag{2a}$$

$$VOL_t = \sum_{\eta=1}^{S} g_\eta AROR_{t-\eta} + \sum_{\theta=1}^{V} h_\theta VOL_{t-\theta} + \varepsilon_{2bt} \tag{2b}$$

Two alternative tests are performed for choosing the optimal lag length in estimated models: the first is based on the Schwarz information criterion (Schwarz, 1978) and the second is Sims' VAR lag-length test (Sims, 1980). In the original Schwarz information criterion, no lags of the dependent variable are included on the right-hand side of the equation. In the modified version, both the dependent and independent variables can have 1–36 lags. Thus, in eq. (1a), both M and N are set equal to 36. The same parameters are applied to eqs. (1b), (2a), and (2b).

The Schwarz criterion uses a function of the residual sum of squares together with a penalty for large numbers of parameters. The selection of the lag length is based on minimizing the criterion function over different alternatives for the lag length. Specifically, the Schwarz information criterion minimizes the expression: $T \times \log(RSS) + K \times (\log T)$, where T is the number of observations, RSS is the sum of squared residuals, and K is the number of regressors.

In a VAR system, the hypotheses to be tested include more than one equation. The test recommended in this case is based on the likelihood ratio test as $(T - C) \times (\log | \Sigma_r - \Sigma_u|)$, where T is the number of observations, C is the correction suggested by Sims (1980, p. 17) to improve small sample properties, and Σ_r and Σ_u are the restricted and unrestricted covariance matrices, respectively. The correction, C, is equal to the number of variables in each unrestricted equation in the system. The above expression is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of restrictions. The Sims (1980) test determines the optimal lag length in a VAR context, capturing the cross impacts of lags of all variables in the model.

Subsequently, two sets of Granger causality tests are performed: one for each set of lag structures estimated in the previous section, i.e., according to the Schwarz and Sims criteria. The causality tests indicate whether movements in contract prices, or the rate of return, forecast movements in volume traded and vice versa. The tests are also conducted to verify whether the absolute value of changes in the rate of return helps predict movements in volume traded and vice versa. An inherent potential problem of causality tests is that the magnitude and significance of the results may depend on the method of selecting the lag lengths in the model. In that respect, estimation of two different sets of causality tests serves as an indirect test of the robustness of the coefficient estimates.

The Granger causality test results are complemented with a decomposition of variance analysis. It is known that in a two-step forecasting procedure, the prediction error depends not only upon the second period's innovation, but on the first period's innovation as well. In general, using the standard econometric notation, the moving average representation can be written as

$$y_t = X_t b + \sum_{s=0}^{\infty} A_s u_{t-s} \tag{3}$$

Thus, the error in the k-step ahead forecast is

$$\sum_{s=0}^{k-1} A_s u_{t-s} - \sum_{s=0}^{k-1} A_s G v_{t-s} \tag{4}$$

where GG′ is a factorization of the covariance matrix of u, and the v's are orthogonalized innovations. The decomposition of variance is the apportionment of the variance of the error among the components of v. Forecast variance decomposition analysis results capture the dynamic linkages between rate of return and volume at *various* points in time: The error variances are decomposed at 10, 20, 25, and 90 steps (trading days) ahead to capture movements at different points in the futures contract's maturity. Thus, they offer an understanding about the magnitude of causation at different points in time (Campbell and Ammer, 1993).

EMPIRICAL RESULTS

This section details the results of the study and is divided into four parts. The first segment addresses the contemporaneous correlation between volume and (signed and unsigned) returns. The second part discusses the model selection, i.e., lag-length tests. The third outlines the results of the Granger causality tests. The final subsection presents the outcome of forecast variance decompositions.

Contemporaneous Correlations

To verify the short-selling constraint hypothesis (Karpoff, 1988; Suominen, 1996) and to confirm the predictions of the mixture of distributions and sequential information arrival hypotheses, as well as Wang's (1994) heterogeneous investor model, the contemporaneous correlation between absolute returns (AROR) and volume (VOL) is computed. The corresponding correlation coefficients are estimated and reported in Table III.

As expected, almost all values under the absolute return-volume correlation column are found to be significant and *positive*.[4] On the other

[4]Gasoline and Treasury bond contracts also yield significant positive correlation coefficients if the whole sample is divided into two subsamples for estimation. In both cases, the more recent subsample yields positive correlation coefficients which are significant at that 1% level: 0.094 for gasoline and 0.358 for Treasury bonds.

TABLE III

Contemporaneous Correlation Coefficients

Commodity	*AROR—VOL*	*ROR—VOL*
Copper	0.361[c]	−0.010
Corn	0.238[c]	−0.006
Crude oil	0.235[c]	0.005
Gasoline	−0.022	−0.018
Gold	0.386[c]	−0.011
Heating oil	0.195[c]	0.000
Live cattle	0.217[c]	0.025
Orange juice	0.371[c]	−0.033[b]
Palladium	0.197[c]	−0.012
Platinum	0.232[b]	−0.022
Silver	0.125[c]	−0.010
Soybeans	0.372[c]	−0.016
S&P 500	0.056[c]	−0.020
Sugar	0.243[c]	0.000
Treasury bond	−0.153[c]	0.017
Wheat	0.237[c]	0.002

[a]Significance at the 10% level (not shown).
[b]Significance at the 5% level.
[c]Significance at the 1% level.

hand, the volume-return per se (ROR) correlations support Karpoff's (1988) hypothesis that absence of trading cost asymmetry assures symmetric trading volume in futures markets and, thus, a zero correlation between contemporaneous volume of trade and return. The only exception is orange juice, which exhibits a *negative* correlation which is significant at the 5% level.[5]

Lag-Length Tests

The optimal lag lengths for the VAR systems are tested in two alternative ways: the Schwarz criterion and the Sims test. The results of both tests are tabulated in Table IV. The first row of Table IV e.g., reveals that for copper, when volume is the dependent variable and the rate of return (absolute rate of return) is the independent variable, the optimal lag length is 5(3). Similarly, when the rate of return (absolute rate of return) and volume are the dependent and independent variables respectively, the optimal lag length for the model is 1(11).

Note that the Sims test (1980), by its structure, calculates a symmetric lag length for a given set of variables: One does not have to dis-

[5]It is documented that orange juice, unlike the other contracts in the study, exhibits certain peculiarities that are unique to the citrus industry (McPhee, 1967; Roll, 1984).

TABLE IV

Lag-Length Tests

	Schwarz Test				Sims Test	
Commodity	*VOLRR*	*VOLAR*	*RRVOL*	*ARVOL*	*ROR and Volume*	*AROR and Volume*
Copper	5	3	1	11	10	15
Corn	5	3	1	8	10	15
Crude oil	20	2	1	11	20	20
Gasoline	10	1	1	5	15	15
Gold	4	1	1	10	10	15
Heating oil	14	3	3	8	20	20
Live cattle	6	1	1	4	10	15
Orange juice	10	1	1	3	15	15
Palladium	6	4	1	5	10	10
Platinum	10	4	1	10	15	15
Silver	10	4	1	8	10	10
Soybeans	5	1	1	11	10	15
S&P 500	4	3	2	6	15	20
Sugar	8	3	2	5	15	15
Treasury bond	15	2	1	6	10	15
Wheat	5	2	1	1	10	15

Notes: VOLRR (VOLAR) indicates that the volume is the dependent variable and the rate of return (absolute rate of return) is the independent variable. RRVOL (ARVOL) indicates that the rate of return (absolute rate of return) is the dependent variable and volume is the independent variable.

tinguish between cases when a variable is dependent or independent as in the former test. Therefore, in the case of copper, e.g., the optimal lag length for a model with volume and rate of return is 10, whereas the model with volume and the absolute rate of return calls for an optimal lag length of 15.

Table IV shows that certain relationships exist between the lag lengths: The optimal lag lengths for VOLRR (VOL: dependent variable; ROR: independent variable) are always *larger* than VOLAR (VOL: dependent variable; AROR: independent variable) models. In other words, models explaining variations in volume need a much longer memory span in terms of rate of return as opposed to absolute rate of return. Changes in absolute prices account for volume of trade variations with much shorter memory. On the other hand, RRVOL (ROR: dependent variable; VOL: independent variable) models call for *fewer* number of lags (or at most equal, as in the case of wheat) than the ARVOL (AROR: dependent variable; VOL: independent variable) models. The Sims test results illustrate that econometric systems that model absolute return-volume relationships require longer lags than volume-return (per se) models.

TABLE V

Granger Causality Test Results According to Schwarz Lag Structure

Commodity	*Relationship*	*AROR and Volume*		*ROR and Volume*	
Copper	Volume → Return	No	(0.793)	No	(0.0681)
	Return → Volume	Yes	(0.000)	Yes	(0.042)
Corn	Volume → Return	Yes	(0.000)	No	(0.851)
	Return → Volume	Yes	(0.000)	Yes	(0.001)
Crude oil	Volume → Return	Yes	(0.001)	No	(0.987)
	Return → Volume	Yes	(0.000)	No	(0.734)
Gasoline	Volume → Return	No	(0.106)	No	(0.681)
	Return → Volume	No	(0.236)	No	(0.117)
Gold	Volume → Return	Yes	(0.028)	No	(0.516)
	Return → Volume	Yes	(0.004)	Yes	(0.032)
Heating oil	Volume → Return	Yes	(0.011)	No	(0.939)
	Return → Volume	Yes	(0.000)	No	(0.415)
Live cattle	Volume → Return	Yes	(0.000)	No	(0.815)
	Return → Volume	Yes	(0.002)	Yes	(0.045)
Orange juice	Volume → Return	Yes	(0.000)	Yes	(0.003)
	Return → Volume	No	(0.575)	Yes	(0.000)
Palladium	Volume → Return	No	(0.860)	No	(0.664)
	Return → Volume	Yes	(0.000)	Yes	(0.007)
Platinum	Volume → Return	No	(0.162)	No	(0.990)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Silver	Volume → Return	Yes	(0.000)	No	(0.573)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Soybeans	Volume → Return	Yes	(0.000)	No	(0.784)
	Return → Volume	Yes	(0.002)	Yes	(0.000)
S&P 500	Volume → Return	Yes	(0.000)	No	(0.585)
	Return → Volume	Yes	(0.000)	No	(0.093)
Sugar	Volume → Return	Yes	(0.011)	No	(0.084)
	Return → Volume	Yes	(0.000)	Yes	(0.002)
Treasury bond	Volume → Return	Yes	(0.000)	No	(0.674)
	Return → Volume	Yes	(0.000)	No	(0.806)
Wheat	Volume → Return	Yes	(0.029)	No	(0.836)
	Return → Volume	Yes	(0.000)	No	(0.096)

Notes: p-values for significance of causality relationships are reported in parentheses. "Yes (No)" indicates presence (absence) of causality with a p-value of equal or less than 0.05.

Granger Causality Tests

The causality tests are performed with both Schwarz and Sims lag structures and the results are reported in Tables V and VI, respectively.[6] Both tables demonstrate that there is a statistically significant *causality* flowing from *absolute* rate of return to volume, for *all* commodities, except gasoline and orange juice. The reverse causality, i.e., from volume to absolute

[6]In both tables the second column indicates the direction of causation. All entries marked "Yes" in the third and fourth columns imply that there is presence of Granger causality at the 1–5% significance level.

TABLE VI

Granger Causality Test Results According to Sims Lag Structure

Commodity	*Relationship*	*AROR and Volume*		*ROR and Volume*	
Copper	Volume → Return	No	(0.888)	No	(0.630)
	Return → Volume	Yes	(0.000)	Yes	(0.038)
Corn	Volume → Return	Yes	(0.001)	No	(0.318)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Crude oil	Volume → Return	Yes	(0.001)	No	(0.320)
	Return → Volume	Yes	(0.008)	No	(0.737)
Gasoline	Volume → Return	No	(0.174)	No	(0.883)
	Return → Volume	No	(0.140)	No	(0.240)
Gold	Volume → Return	Yes	(0.019)	No	(0.072)
	Return → Volume	Yes	(0.000)	Yes	(0.004)
Heating oil	Volume → Return	Yes	(0.050)	No	(0.547)
	Volume → Return	Yes	(0.000)	No	(0.541)
Live cattle	Volume → Return	Yes	(0.001)	No	(0.597)
	Return → Volume	Yes	(0.000)	Yes	(0.045)
Orange juice	Volume → Return	Yes	(0.000)	Yes	(0.000)
	Return → Volume	No	(0.305)	Yes	(0.000)
Palladium	Volume → Return	No	(0.479)	No	(0.693)
	Return → Volume	Yes	(0.000)	Yes	(0.002)
Platinum	Volume → Return	No	(0.283)	No	(0.668)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Silver	Volume → Return	Yes	(0.002)	No	(0.595)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Soybeans	Volume → Return	Yes	(0.000)	Yes	(0.041)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
S&P 500	Volume → Return	Yes	(0.000)	No	(0.713)
	Return → Volume	Yes	(0.000)	No	(0.270)
Sugar	Volume → Return	Yes	(0.002)	No	(0.683)
	Return → Volume	Yes	(0.000)	Yes	(0.000)
Treasury bond	Volume → Return	Yes	(0.009)	No	(0.666)
	Return → Volume	Yes	(0.044)	No	(0.816)
Wheat	Volume → Return	Yes	(0.044)	No	(0.453)
	Return → Volume	Yes	(0.000)	No	(0.057)

Notes: p-Values for significance of causality relationships are reported in parentheses. "Yes (No)" Indicates presence (absence) of causality with a p-value of equal or less than 0.05.

returns, also holds for *all* commodities, except copper, gasoline, palladium, platinum, and orange juice. Accordingly, the majority of contracts, i.e., corn, crude oil, gold, heating oil, live cattle, silver, soybeans, S&P 500, sugar, wheat, and Treasury bond futures contracts, exhibit a bidirectional causality between absolute returns and trading volume. As discussed earlier, the evidence of a significant Granger causality relationship between absolute returns and volume *contradicts* the mixture of distributions hypothesis and *supports* the sequential information arrival hypothesis (Hiemstra and Jones, 1994). Moreover, it is also *consistent* with the findings of Smirlock and Starks (1988), McCarthy and Najand (1993), and Moosa and Al-Loughani (1995).

Despite the finding of zero contemporaneous correlation between volume and return per se in all markets (Table III), Tables V and VI illustrate that there is significant *positive intertemporal causality* running from past values of returns to volume in all commodities, except crude oil, gasoline, heating oil, S&P 500 index, Treasury bond, and wheat contracts, all heavily traded futures markets. The causality from returns to volume is consistent with the conclusions of Hiemstra and Jones (1994) and Moosa and Al-Loughani (1995). The finding of no causality relationship in *either* direction for high volume markets supports the hypothesis that markets with high volumes of trade tend to be more efficient (James and Edmister, 1983; Wood, McInish, and Ord, 1985; Campbell et al., 1993). On the other hand, the presence of a causality running from past values of trading volume to actual returns is rejected by overwhelming evidence in Tables V and VI: The only statistically significant causality running in that direction, which is reported by both tables, is observed in the orange juice market.[7]

The absence of causality from volume to returns in futures markets, i.e., presence of *market efficiency*, is consistent with previous studies (e.g., McCarthy and Najand, 1993; Hiemstra and Jones, 1994; Moosa and Al-Loughani, 1995). However, note that in contrast to McCarthy and Najand (1993), who could *not* find *any* relationship between volume and rate of return, this study reports a bidirectional causal relationship for the orange juice contract, and a causation stemming from the rate of return to volume for many other contracts in the sample. Campbell et al. (1993) suggest that an increase in trading volume and participation in a market increase the level of informational efficiency. Accordingly, this study does not detect any causality relationship in actively traded futures markets, such as financial, index, and energy futures, i.e., the S&P 500, Treasury bond, crude oil, heating oil, and gasoline. It is known that another category of futures which also are traded heavily are foreign exchange contracts. In that light, it is not surprising for McCarthy and Najand (1993) not to detect any relationship since their sample focuses explicitly on foreign exchange contracts.

In summation, the conducted causality tests for the volume-absolute return relationship support the sequential information arrival hypothesis (Copeland, 1976; Jennings et al., 1981; Hiemstra and Jones, 1994). The results are consistent with the empirical findings of Smirlock and Starks

[7]Table VI also reports a similar causality in the soybean market. However, this is not confirmed by Table V.

(1988) and McCarthy and Najand (1993). The volume-return (per se) tests, on the other hand, illustrate that, in general, futures markets are informationally efficient. This finding is consistent with a number of previous studies (Neftci, 1984; Canarella, 1985; Gross, 1988; Ma, 1989; Crowder, 1993; McCarthy and Najand, 1993; Beck, 1994; Froot, 1995). Finally, the detected causality running from past values of returns to volume in some markets is in agreement with previous findings by Hiemstra and Jones (1994) and Moosa and Al-Loughani (1995).

Note that relatively high-volume markets, such as S&P 500, Treasury bond, crude oil, heating oil, and wheat futures markets, display no causal relationship in *either* direction. In contrast, relatively thin markets exhibit at least a relationship from past returns to volume. This result can be interpreted to indicate indirect support for the existence of a positive association between informational efficiency and the level of trading and participation in a market (James and Edmister, 1983; Wood et al., 1985; Carter, 1989; Campbell et al., 1993).

Finally, following Wang's (1994) finding on the positive relationship between degree of asymmetry in information and the magnitude of the volume-absolute return relationship, futures contracts are ranked according to their AROR-VOL correlations, i.e., presence of information asymmetry in respective markets. Five contracts with the highest correlations are identified (*top five*): corn, gold, orange juice, soybeans, and sugar. Similarly, the five contracts with the lowest correlations (*bottom five*) turn out to be: gasoline, heating oil, silver, S&P 500 index, and Treasury bond. Consequently, these contract's performance in market efficiency tests is examined: Four of the five bottom contracts (gasoline, heating oil, S&P 500, and Treasury bond) exhibit *no* causal relationships in *either* direction; the only exception is silver, which exhibits a causal relationship from returns to volume. On the other hand, *all* of the top five contracts display a causal relationship from past values of returns to volume; moreover, orange juice exhibits a bidirectional relationship. In addition, based on Tables III and VI, the correlation between the magnitude of volume-absolute return correlations and the p-values for the existence of causality (running from past values of volume to returns) is estimated for all contracts in the sample. Note that the existence of causality is inversely related to market efficiency, and a high p-value for market inefficiency implies that markets are *not* inefficient. Thus, a direct (inverse) relationship between information asymmetry and market efficiency implies a positive (negative) correlation. The estimation results find the correlation coefficient to be negative: -0.685.[8] This finding con-

[8]Using the corrected correlation coefficients (see footnote 4) of 0.094 and 0.358 for gasoline and Treasury bonds, respectively, one obtains a similar correlation estimate: -0.659.

firms the observations about the performance of the top and bottom five commodities during the market efficiency tests. Thus, the results reveal that there is an *inverse* relationship between the presence of information asymmetry and efficiency in the market.

Decomposition of Forecast Variance Results

The decomposition of forecast variances for all 16 futures contracts is presented in Table VII. Column A in Table VII exhibits the results of the volume-rate of return model and column B presents the results of the volume-absolute rate of return model. The results of the forecast variance decomposition tests are in agreement with the findings of the Granger causality tests in Tables V and VI.

The percentage of the variance in the rate of return attributable to volume is negligible for the 16 futures contracts. These results mirror the Granger causality results. For corn, crude oil, gold, palladium, platinum, silver, sugar, S&P 500 index, and Treasury bonds, the decomposition and Granger causality results support each other, indicating that the rate of return influences the variance in volume traded. Moreover, the variance decomposition results also hint at the existence of causality from returns to volume in the cases of gasoline and heating oil.

The variance decomposition results, however, do not confirm the causality findings in the case of copper, live cattle, and wheat. The return variance compositions in the case of orange juice and soybeans also reveal that the contribution of volume is minimal. In addition, it is noticed that the timing of decomposition is crucial in the determination of causality. For example, in the case of gold and heating oil, the variance decomposition supports the Granger causality results for only the 90 step-ahead trading day. The decomposition test indicates that there is weak evidence for bidirectional feedback between rate of return and volume only in the case of orange juice, which confirms the Granger causality test findings about bidirectional causality in the case of orange juice.

The Granger and decomposition test results are almost *identical* in analyzing the absolute rate of return- volume relationship. The only difference is gold, where the variance decomposition does not support causality in any direction. Moreover, the causality from returns to volume in the case of gasoline is determined from the variance decomposition but not the Granger causality tests.

Finally, there is evidence for bidirectional causality between volume and the absolute rate of return for corn, crude oil, live cattle, silver, soybeans, S&P 500, and Treasury bonds. As noted previously, the timing of

TABLE VII

Decomposition of Forecast Variance Results

		Dependent Variable: VOL (A)			Dependent Variable: VOL (B)			Dependent Variable: ROR			Dependent Variable: AROR		
Commodity	*Step*	*Standard Error*	*VOL*	*ROR*	*Standard Error*	*VOL*	*AROR*	*Standard Error*	*VOL*	*ROR*	*Standard Error*	*VOL*	*AROR*
Copper	10	0.461	99.046	0.954	0.461	97.848	2.152	1.681	0.146	99.854	1.121	0.209	99.791
	20	0.479	98.517	1.483	0.481	97.728	2.272	1.682	0.197	99.803	1.153	0.235	99.765
	25	0.481	98.440	1.560	0.486	97.603	2.397	1.682	0.199	99.801	1.159	0.235	99.765
	90	0.483	98.372	1.628	0.495	97.277	2.723	1.682	0.200	99.800	1.172	0.230	99.770
Corn	10	0.373	98.453	1.547	0.373	98.392	1.608	1.381	0.269	99.731	0.982	0.793	99.207
	20	0.410	96.791	3.209	0.412	97.236	2.764	1.381	0.276	99.724	1.005	1.189	98.811
	25	0.419	96.493	3.507	0.423	96.664	3.336	1.381	0.277	99.723	1.010	1.371	98.629
	90	0.437	95.967	4.033	0.454	93.768	6.232	1.381	0.280	99.720	1.021	2.528	97.472
Crude oil	10	0.388	99.914	0.086	0.386	99.427	0.573	2.351	0.342	99.658	1.690	1.480	99.520
	20	0.403	99.867	0.133	0.402	99.248	0.752	2.367	0.584	99.416	1.746	1.824	98.176
	25	0.431	99.758	0.242	0.429	99.188	0.812	2.368	0.600	99.400	1.772	1.972	98.028
	90	0.550	99.742	0.258	0.550	96.940	3.060	2.368	0.610	99.390	1.842	2.481	97.519
Gasoline	10	0.404	98.657	1.343	0.403	99.467	0.533	2.344	0.530	99.470	1.683	1.095	98.905
	20	0.458	97.967	2.033	0.456	98.804	1.196	2.355	0.659	99.341	1.721	1.211	98.789
	25	0.482	97.668	2.332	0.479	98.312	1.688	2.355	0.668	99.332	1.728	1.218	98.782
	90	0.685	96.277	3.723	0.686	93.604	6.396	2.355	0.673	99.327	1.738	1.242	98.758
Gold	10	0.478	98.330	1.670	0.470	99.038	0.962	1.290	0.341	99.659	0.899	0.795	99.205
	20	0.498	98.070	1.930	0.492	99.071	0.929	1.290	0.411	99.589	0.928	1.006	98.994
	25	0.500	98.022	1.978	0.497	99.058	0.943	1.290	0.413	99.587	0.935	1.041	98.959
	90	0.503	97.978	2.022	0.506	99.007	0.993	1.290	0.414	99.586	0.952	1.122	98.878
Heating oil	10	0.388	99.823	0.177	0.383	98.677	1.323	2.210	0.154	99.846	1.636	0.679	99.321
	20	0.417	99.053	0.947	0.410	98.439	1.561	2.228	0.429	99.571	1.683	0.968	99.032
	25	0.437	98.853	1.047	0.429	98.202	1.798	2.230	0.441	99.559	1.701	1.017	98.983
	90	0.576	97.893	2.107	0.574	91.681	8.319	2.231	0.451	99.549	1.740	1.483	98.517
Live cattle	10	0.350	99.609	0.391	0.343	99.319	0.681	1.118	0.204	99.796	0.805	0.287	99.713
	20	0.372	99.618	0.382	0.362	98.746	1.254	1.118	0.210	99.790	0.813	0.905	99.095
	25	0.377	99.625	0.375	0.367	98.588	1.412	1.118	0.211	99.789	0.814	1.133	98.867
	90	0.383	99.635	0.365	0.380	97.970	2.030	1.118	0.211	99.789	0.818	2.031	97.969
Orange juice	10	0.643	97.584	2.416	0.641	99.671	0.329	1.823	1.823	0.918	1.348	0.314	99.686
	20	0.704	96.812	3.188	0.704	99.680	0.320	1.824	1.009	98.991	1.359	1.369	98.631
	25	0.725	96.468	3.532	0.724	99.694	0.306	1.824	1.010	98.990	1.362	1.751	98.249
	90	0.824	95.437	4.563	0.822	99.753	0.247	1.824	1.018	98.982	1.380	4.316	95.684
Palladium	10	0.810	98.281	1.179	0.804	98.099	1.901	1.957	0.138	99.862	1.417	0.238	99.762

TABLE VII (Continued)

Decomposition of Forecast Variance Results

		Dependent Variable: VOL (A)			Dependent Variable: VOL (B)			Dependent Variable: ROR			Dependent Variable: AROR		
Commodity	Step	Standard Error	VOL	ROR	Standard Error	VOL	AROR	Standard Error	VOL	ROR	Standard Error	VOL	AROR
	20	0.873	97.332	2.668	0.875	95.984	4.016	1.958	0.189	99.811	1.438	0.273	99.727
	25	0.885	97.159	2.841	0.894	95.087	4.913	1.958	0.189	99.811	1.440	0.297	99.703
	90	0.904	96.925	3.075	0.933	92.726	7.274	1.958	0.190	99.810	1.444	0.400	99.600
Platinum	10	0.536	97.430	2.570	0.534	98.304	1.696	1.833	0.193	99.807	1.209	0.254	99.746
	20	0.582	95.569	4.431	0.578	98.146	1.854	1.836	0.312	99.688	1.257	0.375	99.625
	25	0.596	95.104	4.896	0.593	97.913	2.087	1.836	0.315	99.685	1.270	0.396	99.604
	90	0.650	93.624	6.376	0.663	95.055	4.945	1.836	0.318	99.682	1.316	1.079	98.921
Silver	10	0.582	97.439	2.561	0.572	98.380	1.620	2.206	0.170	99.830	1.630	0.451	99.549
	20	0.658	96.949	3.051	0.653	96.336	3.664	2.207	0.181	99.819	1.678	1.051	98.949
	25	0.681	96.791	3.209	0.681	95.229	4.771	2.207	0.184	99.816	1.690	1.406	98.594
	90	0.753	96.365	3.635	0.809	89.298	10.702	2.208	0.197	99.803	1.730	3.841	96.159
Soybeans	10	0.354	96.733	3.267	0.348	99.141	0.859	1.372	0.434	99.566	0.897	0.551	99.449
	20	0.393	95.474	4.526	0.383	99.063	0.937	1.372	0.454	99.546	0.922	1.580	98.420
	25	0.403	95.177	4.823	0.395	98.954	1.046	1.372	0.454	99.546	0.928	2.078	97.922
	90	0.426	94.565	5.436	0.434	98.148	1.852	1.372	0.454	99.546	0.952	6.168	93.832
Sugar	10	0.530	98.353	1.647	0.516	98.260	1.740	3.091	0.144	99.856	2.177	0.861	99.139
	20	0.567	97.295	2.705	0.555	96.374	3.626	3.092	0.177	99.823	2.219	0.943	99.057
	25	0.575	97.126	2.874	0.568	95.401	4.599	3.092	0.180	99.820	2.227	0.940	99.060
	90	0.587	96.876	3.124	0.620	90.212	9.788	3.092	0.185	99.815	2.243	1.069	98.931
Wheat	10	0.443	99.309	0.691	0.436	97.862	2.138	1.589	0.236	99.764	1.168	0.391	99.609
	20	0.481	99.166	0.834	0.476	96.699	3.301	1.589	0.254	99.746	1.178	0.670	99.330
	25	0.491	99.131	0.869	0.490	96.111	3.889	1.589	0.254	99.746	1.179	0.736	99.264
	90	0.511	99.061	0.939	0.532	94.147	5.853	1.589	0.256	99.744	1.181	1.053	98.947
S&P	10	0.368	99.734	0.266	0.373	96.779	3.221	1.217	0.367	99.633	0.975	0.881	99.119
	20	0.398	99.569	0.431	0.405	95.436	4.564	1.216	0.419	99.581	0.987	0.977	99.023
	25	0.411	99.579	0.421	0.421	94.686	5.314	1.219	0.421	99.579	0.990	1.064	98.936
	90	0.449	99.555	0.445	0.471	91.836	8.164	1.219	0.424	99.576	0.994	1.351	98.649
Treasury bond	10	0.439	99.869	0.131	0.402	98.995	1.005	0.827	0.267	99.733	0.515	0.718	99.282
	20	0.486	99.847	0.153	0.413	98.734	1.266	0.828	0.304	99.696	0.518	1.095	98.905
	25	0.506	99.856	0.144	0.418	98.661	1.339	0.828	0.305	99.695	0.521	1.439	98.561
	90	0.659	99.905	0.095	0.454	96.275	3.725	0.828	0.308	99.692	0.537	2.498	97.502

the decomposition is important in determining whether there is causality: In most cases, magnitudes of 10-day ahead forecast coefficients are significantly different from 90-day ahead forecast variance.

CONCLUSIONS

In the light of recent developments about trading volume, information dissemination, and market efficiency in the financial literature, this study empirically investigates these issues by analyzing volume and (signed and unsigned) return relationship in futures markets, in both a contemporaneous and intertemporal framework. In particular, this study concentrates on the following issues: (i) Is the dissemination and processing of information in futures markets consistent with the sequential or simultaneous information arrival hypotheses? (ii) Is the volume-return (per se) relationship symmetric or does the volume behave differently depending on the direction of price moves? (iii) Are futures markets efficient in processing new information or do past values of trading enhance the forecastability of prices? (iv) How does the presence of information asymmetry affect market efficiency?

Daily data (1985–1995) for 16 U.S. futures contracts, including energy, agricultural, index, and financial futures contracts, are employed in the study. The volume-return relationships are tested in a contemporaneous and intertemporal setting for two alternative model specifications, i.e., Schwarz and Sims, to account for differences in model selection. Nevertheless, a comparison of causality results reveals that the findings are almost identical in both models. Finally, the robustness of these results is verified by a variance decomposition analysis.

The findings on the contemporaneous relationship between volume and absolute returns are consistent with both the mixture of distributions hypothesis and sequential information arrival hypothesis, as well as Wang's (1994) heterogeneous investors model. Nevertheless, the intertemporal Granger causality test results provide contradictory evidence against the mixture of distributions hypothesis, which claims that there is no information in past observations of absolute returns which can be used in forecasting volume that is not already contained in past lags of volume, and vice versa (Smirlock and Starks, 1988). Consistent with Karpoff (1988), McCarthy and Najand (1993), and Hiemstra and Jones (1994), changes in the absolute returns are found to Granger-cause volume in almost all futures markets. In turn, typically, changes in volume Granger-cause absolute returns, which confirms the findings of Smirlock and Starks (1988), McCarthy and Najand (1993), and Hiemstra and

Jones (1994). Thus, evidence on the Granger causality relationship between volume and absolute returns supports the sequential information arrival hypothesis (Hiemstra and Jones, 1994), suggesting that there are a number of intermediate equilibria before the final complete informational equilibrium can be reached (Copeland, 1976; Jennings et al., 1981).

As Karpoff (1988) and Suominen (1996) argue, the existence of a short-selling constraint, in the form of either a prohibition or differential cost of taking short- and long positions, is likely to induce a positive contemporaneous correlation between volume and returns per se. Consequently, trading volume will behave differently in up- and down markets. Nevertheless, the absence of such a differential cost of trading in futures markets should therefore lead to symmetry of trading, i.e., a zero correlation between returns and volume. In line with this argument, no statistically significant contemporaneous relationship between trading volume and price changes is detected. Hence, the present study confirms symmetry of trading volume in futures markets.

Granger causality tests on the volume-returns per se relationship reveal that, in general, futures markets process new information efficiently. The results indicate that except in the case of orange juice futures, there is *no* significant causality from past values of volume to returns, thus confirming presence of *efficiency* in futures markets. Yet, both tests reveal that there is statistically significant causality in the reverse order, which is consistent with previous studies (Hiemstra and Jones, 1994; Moosa and Al-Loughani, 1995). Accordingly, a change in the past observations of rate of return Granger-causes volume of trade in copper, corn, gold, live cattle, orange juice, palladium, platinum, silver, soybeans, and sugar futures markets. Furthermore, it is noted that high-volume markets, e.g., S&P 500, Treasury bonds, crude oil, gasoline, heating oil, and wheat, exhibit *no* causality in *either* direction. This finding is consistent with the conclusions of Campbell et al. (1993), who found that there is a *positive* relationship between informational efficiency and the level of trading and participation in a given market. Finally, based on Wang's (1994) finding on the positive relationship between the degree of asymmetric information and the correlation coefficient between volume and absolute returns, it is found that there is an *inverse* relationship between presence of asymmetric information and efficiency in futures markets.

Variance decompositions, which are performed in conjunction with Granger causality tests, confirm the findings of the causality tests. Moreover, based on the decomposition of variance results, it is evident that the time horizon is important in assessing causality relationships. In many instances, the percentage of the dependent variable explained by the independent variable increases with time. For instance, for silver futures, the absolute rate of return accounts for 10% of the variance of volume traded at the 90-day ahead forecasts. However, this number decreases to 4.7% at the 25-day and 1.6% at the 10-day ahead forecast variances.

BIBLIOGRAPHY

Beck, S. E. (1994): "Cointegration and Market Efficiency in Commodities Futures Markets," *Applied Economics,* 26:249–257.

Campbell, J. Y. (1991): "A Variance Decomposition for Stock Returns," *Economic Journal,* 111(405):157–179.

Campbell, J. Y., and Ammer, J. (1993): "What Moves the Stock and Bond Markets? A Variance Decomposition For Long-Term Asset Returns," *Journal of Finance,* 48:3–37.

Campbell, J. Y., and Kyle, A. S. (1993): "Smart Money, Noise Trading and Stock Price Behavior," *Review of Economic Studies,* 60:1–34.

Campbell, J. Y., and Shiller, R. (1987): "Cointegration and Tests of Present Value Models," *Journal of Political Economy,* 95:1062–1088.

Campbell, J. Y., and Shiller, R. (1988a): "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies,* 1:195–228.

Campbell, J. Y., and Shiller, R. (1988b): "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance,* 43:661–676.

Campbell, J. Y., Grossman, S. J., and Wang, J. (1993): "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics,* 108:905–939.

Canarella, G. (1985): "Efficiency of Commodity Futures: A Vector Autoregression Analysis," *The Journal of Futures Markets,* 5:57–76.

Carter, C. A. (1989): "Arbitrage Opportunities between Thin and Liquid Futures Markets," *The Journal of Futures Markets,* 9:347–353.

Clark, P. K. (1973): "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices," *Econometrica,* 41:135–155.

Copeland, T. E. (1976): "A Model of Asset Trading under the Assumption of Sequential Information Arrival," *Journal of Finance,* 31:1149–1168.

Crowder, W. J. (1993): "A Cointegration Test for Oil Futures Market Efficiency," *The Journal of Futures Markets,* 13:933–941.

Cutler, D. M., Poterba, J. M., and Summers, L. H. (1989): "What Moves Stock Prices?" *Journal of Portfolio Management,* 15:4–12.

Eitan, G., and Harris, L. (1986): "Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures," *Journal of Finance,* 41:815–829.

Epps, T. W. (1975): "Security Price Changes and Transaction Volumes: Theory and Evidence," *American Economic Review,* 65:586–597.

Epps, T. W. (1977): "Security Price Changes and Transaction Volumes: Some Additional Evidence," *Journal of Financial and Quantitative Analysis,* 12:141–146.

Epps, T. W., and Epps, M. L. (1976): "The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distribution Hypothesis," *Econometrica,* 44:305–321.

Fama, E. F. (1990): "Stock Returns, Expected Returns, and Real Activity," *Journal of Finance,* 45:1089–1108.

Fama, E. F., and French, K. R. (1988a): "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics,* 22:3–25.

Fama, E. F., and French, K. R. (1988b): "Business Cycles and the Behavior of Metals Prices," *Journal of Finance,* 43:1075–1093.

Fama, E. F., and French K. R. (1988c): "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy,* 96:246–273.

Froot, K. A. (1995): "New Trading Practices and Short-Run Market Efficiency," *The Journal of Futures Markets,* 15:731–765.

Gallant, A. R., Rossi, P. E., and Tauchen, G. (1992): "Stock Prices and Volume," *The Review of Financial Studies,* 5:199–242.

Gross, M. (1988): "A Semi-Strong Test of the Efficiency of the Aluminum and Copper Markets at the LME," *The Journal of Futures Markets,* 8:67–77.

Granger, C. W. J., and Morgenstern, O. (1963): "Spectral Analysis of New York Stock Market Prices," *Kyklos,* 16(Fasc. 1 1963):1–27.

Harris, L. (1986): "Cross-Security Tests of Mixture of Distributions Hypothesis," *Journal of Financial and Quantitative Analysis,* 21:39–46.

Harris, L. (1987): "Transaction Data Tests of the Mixture of Distributions Hypothesis," *Journal of Financial and Quantitative Analysis,* 22:127–141.

Harris, L. (1989): "S&P Cash Stock Price Volatilities," *Journal of Finance,* 44:1155–1175.

Harris, M., and Raviv, A. (1993): "Differences of Opinion Make a Horse Race," *Review of Financial Studies,* 6:473–506.

Hiemstra, C., and Jones, J. (1994): "Testing for Linear and Non-Linear Granger Causality in the Stock Price-Volume Relation," *Journal of Finance,* 49:1639–1664.

Hodrick, R. J. (1992): "Dividend Yields and Expected Stock Returns, Alternative Procedures for Inference and Measurement," *Review of Financial Studies,* 5:357–386.

James, C., and Edmister R. O. (1983): "The Relation between Common Stock Returns Trading Activities and Market Value," *Journal of Finance,* 38:1075–1086.

Jennings, R. H., Starks, L. T., and Fellingham, J. C. (1981): "An Equilibrium Model of Asset Trading with Sequential Information Arrival," *Journal of Finance,* 36:143–161.

Kandel, S., and Stambaugh, R. F. (1988): "Modeling Expected Stock Returns for Short and Long Horizons." Working paper 42-88, Rodney L. White Center for Financial Research, Wharton School, University of Pennsylvania, Philadelphia.

Karpoff, J. M. (1987): "The Relation between Price Changes and Trading Volume: A Survey," *Journal of Financial and Quantitative Analysis,* 22:109–126.

Karpoff, J. M. (1988): "Costly Short Sales and the Correlation of Returns with Volume," *Journal of Financial Research,* 11:173–188.

LeBaron, B. (1992): "Some Relations between Volatility and Serial Correlation in Stock Market Returns," *Journal of Business,* 65:199–219.

Ma, C. W. (1989): "Forecasting Efficiency of Energy Futures Prices," *The Journal of Futures Markets,* 9:393–419.

Majnoni, G., and Massa, M. (1996): "Share Prices and Trading Volume: Indications of Stock Exchange Efficiency," *Banca D'Italia,* No. 236:1–63.

McCarthy, J., and Najand, M. (1993): "State Space Modeling of Price and Volume Dependence: Evidence from Currency Futures," *The Journal of Futures Markets,* 13:335–344.

McPhee, J. (1967): *Oranges.* New York: Farrar, Straus and Giroux.

Moosa, I., and Al-Loughani, N. E. (1995): "Testing the Price-Volume Relation in Emerging Asian Stock Markets," *Journal of Asian Economics,* 6:407–422.

Morgan, I. G. (1976): "Stock Prices and Heteroskedasticity," *Journal of Business,* 49:496–508.

Morse, D. (1980): "Asymmetric Information in Securities Market and Trading Volume," *Journal of Financial and Quantitative Analysis,* 40:1129–1146.

Najand, M., and Yung, K. (1991): "A GARCH Examination of the Relationship between Volume and Price Variability in Futures Markets," *The Journal of Futures Markets,* 11:613–621.

Neftci, S. (1984): "Can Chartists Outperform the Market? Market Efficiency Tests for 'Technical Analysis,' " *The Journal of Futures Markets,* 4:465–478.

Newey, W. K., and West, K. D. (1992): "A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix." Mimeo, University of Wisconsin-Madison.

Richardson, M., and Stock, J. H. (1989): "Drawing Inferences from Statistics Based on Multi-Year Asset Returns," *Journal of Financial Economics,* 25:323–348.

Rogalski, R. J. (1978): "The Dependence of Prices and Volume," *The Review of Economics and Statistics,* 36:268–274.

Roll, R. (1984): "Orange Juice and Weather," *The American Economic Review,* 74:861–880.

Schwarz, G. (1978): "Estimating the Dimension of a Model," *Annals of Statistics,* 6:461–464.

Sims, C. A. (1980): "Macroeconomics and Reality," *Econometrica,* 48:1–49.

Smirlock, M., and Starks, L. (1988): "An Empirical Analysis of the Stock Price-Volume Relationship," *Journal of Financial Research,* 8:31–41.

Stambaugh, R. F. (1990): "Factors in Expected Returns." Unpublished paper, Wharton School, University of Pennsylvania, Philadelphia.

Suominen, M. (1996): "Trading Volume and Information Revelation in Stock Markets." Working paper, Department of Economics, University of Pennsylvania, Philadelphia.

Tauchen, G., and Pitts, M. (1983): "The Price Variability-Volume Relationship on Speculative Markets," *Econometrica,* 59:371–396.

Wang, J. (1993): "A Model of Intertemporal Asset Prices under Asymmetric Information," *Review of Economic Studies,* 60:249–282.

Wang, J. (1994): "A Model of Competitive Stock Trading Volume," *Journal of Political Economy,* 102:127–168.

Westerfield, R. (1977): "The Distribution of Common Stock Price Changes: An Application of Transactions Time and Subordinated Stochastic Models," *Journal of Financial and Quantitative Analysis*, 12:743–765.

Wood, R. A., McInish, T. H., and Ord, J. K. (1985): "An Investigation of Transaction Data for NYSE Stocks," *Journal of Finance*, 60:723–739.

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