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Trading activity and price reversals in futures markets

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Abstract

We use the standard contrarian portfolio approach to examine short-horizon return predictability in 24 US futures markets. We find strong evidence of weekly return reversals, similar to the findings from equity market studies. When interacting between past returns and lagged changes in trading activity (volume and/or open interest), we find that the profits to contrarian portfolio strategies are, on average, positively associated with lagged changes in trading volume, but negatively related to lagged changes in open interest. We also show that futures return predictability is more pronounced if interacting between past returns and lagged changes in both volume and open interest. Our results suggest that futures market overreaction exists, and both past prices and trading activity contain useful information about future market movements. These findings have implications for futures market efficiency and are useful for futures market participants, particularly commodity pool operators.

JEL classification: G13; G14
Keywords: Futures markets; Price reversals; Overreaction; Trading volume; Open interest

1. Introduction

A large body of finance literature shows that past prices contain useful information about future market movements in equity markets. For example, Lehmann (1990) and Lo and MacKinlay (1990) find that a short-term contrarian portfolio

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strategy of buying past losers and selling past winners generates significant profits. Lehmann also shows that the contrarian profits remain significant after corrections for plausible transaction costs. The evidence on short-horizon return predictability is consistent with the overreaction hypothesis, namely, traders over-adjust their posterior beliefs to news by more than what is warranted by fundamentals (Lehmann, 1990), although market microstructure biases like lead–lag and bid–ask spread effects may explain away some of the contrarian profits (Lo and MacKinlay, 1990; Conrad et al., 1997).

Both academics and practitioners have also been interested in the role played by trading volume in predicting future market movements. Blume et al. (1994) present a model in which traders can profit from using volume information in addition to historical price information to forecast future price changes. Recent empirical finance research has shown that the relation between trading volume and expected stock returns is in general negative, although the interpretation of the negative relation has been controversial. The traditional liquidity premium hypothesis suggests that trading volume is a measure of liquidity, and high (low) volume assets should command lower (higher) returns, on average (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan et al., 1998). [1] Hence, a negative relation between volume and expected returns is consistent with the notion of liquidity premiums. Several behavioral finance studies contend that individuals are overconfident about their ability to evaluate securities, in the sense that they overestimate precision of private information signals, resulting in overreaction to private information and causing asset prices to temporarily swing away from the fundamental value (DeBondt and Thaler, 1985; Odean, 1998; Gervais and Odean, 2001). Overconfidence and overreaction themselves imply a large volume of trading and are thus positively related to the magnitude of price reversals. [2] Therefore, the investor irrationality-induced market inefficiency gives rise to a negative relation between volume and expected returns (DeBondt and Thaler, 1985; De Long et al., 1990; Odean, 1998; Statman and Thorley, 1999). [3]

Although past prices and trading activity are closely watched by futures market participants, the informational role of past prices and trading activity in broader futures markets has not been well studied. Evidence of predictable futures returns has

[1] In the literature, liquidity is often synonymous with bid–ask spread. However, bid–ask spread as a measure of liquidity has some limitations. For example, many large trades occur outside the spread, but many small trades often occur within the spread (Lee, 1993). Brennan and Subrahmanyam (1996) and Glosten and Harris (1988) show that trading volume is a major determinant of market liquidity.

[2] It should be noted that most behavioral models of asset pricing focus on intermediate and long horizons. However, as DeBondt and Thaler (1985) acknowledge, in a given economic setting, the universe of conceivable irrational behavioral patterns is unrestricted.

[3] Lee and Swaninathan (2000) make an attempt to distinguish between the two hypotheses for the volume–return relation by using share turnover as a measure of trading volume and find that both the level of and change in volume are negatively related to subsequent returns. Because this measure of volume is not highly correlated with conventional liquidity proxies, Lee and Swaminathan interpret their results as an indication that the level of and change in volume measure fluctuating investor sentiment rather than liquidity.

profound implications for market efficiency as well as practical trading strategies, because arbitrage strategies are more readily available than in equity markets due to the low cost and high liquidity of futures trading. This paper adds to the literature by providing evidence on short-horizon (1–8 weeks) return predictability for a sample of 24 actively traded US futures contracts over the July 1983–June 2000 interval. The primary focus of this study is on the following two issues: first, following a standard contrarian portfolio approach similar to that of Lehmann (1990), we examine whether consistent contrarian profits in futures markets exists; and second, we investigate futures return predictability by interacting between past returns and lagged changes in trading activity (volume and/or open interest).

An important feature of futures markets is that open interest provides an additional measure of trading activity. Open interest represents total long or short positions of all traders in a market and has been shown to covary with price changes. Bessembinder and Seguin (1993) document a positive (negative) relation between price volatility and volume (open interest) and show that the effect of volume on volatility depends on whether volume generates changes in open interest (p. 38). These authors argue that open interest represents uninformed trading by hedgers or hedging activity and is thus an important determinant of market depth. [4] Other things being equal, a market becomes deeper as open interest increases, leading to smaller price volatility. However, there has been little evidence on the relation between open interest and inter-temporal return predictability.

We find strong evidence of futures return reversals over the 1-week horizon. A contrarian strategy of buying past losers and selling past winners gives rise to an average return of 0.31% per week (16.12% per annum). This return is both statistically and economically significant given the high leverage of futures trading and high liquidity of futures markets and is robust to a one-way transaction cost (commissions and one-half the bid–ask spread) of up to 0.16%.

We also find a significant relation between lagged changes in trading activity (volume and open interest) and contrarian profits, but the relation differs for the two measures of trading activity: The relation between changes in volume and contrarian profits is positive, whereas there is a negative relation between changes in open interest and contrarian profits. As a result, when implemented in high-volume (low-open interest) contracts, a contrarian strategy is more profitable than that in low-volume (high-open interest) contracts. For example, the average return from a contrarian strategy implemented in high-volume contracts is 0.41% per week ($t = 3.07$), whereas it is only 0.04% per week ($t = 0.28$) for a contrarian strategy implemented in low-volume contracts. [5] For low-open interest contracts, a contrarian strategy generates an average return of 0.33% per week ($t = 2.56$), whereas the mean return for a contrarian strategy implemented in high-open interest contracts is only 0.10% per week ($t = 0.72$). A contrarain strategy is most profitable if it is implemented in

[4] Kyle (1985) defines market depth as the order flow required to move price by one unit.

[5] A high- (low-) volume contract is defined as the one whose volume change is above (below) the median of all volume changes of these futures markets. A similar definition applies to the high- (low-) open interest contract. For a discussion, see Section 2.3.

high-volume together with low-open interest contracts. Under this circumstance, the mean return for the 1-week contrarian strategy is as high as 0.57% per week ($t = 3.86$) or 29.64% per annum.

Further examination of return predictability for a formation/holding horizon spanning from 2 to 8 weeks shows no evidence of contrarian profits. This result holds true even if a contrarian strategy is conditional on lagged changes in trading activity (volume and open interest).

The evidence of significant contrarian profits over the 1-week horizon is in line with the findings in equity markets (Lehmann, 1990; Lo and MacKinlay, 1990; Mei and Gao, 1995). Market condition and investors' perception of risk should remain relatively unchanged over a short interval; issues like lead–lag, bid–ask spread, and nonsynchronous trading effects are trivial in futures markets (see also Table 1), and therefore the result of consistent contrarian profits points toward the market overreaction. The finding of futures market inefficiency is surprising given that futures markets are very close to a textbook model of competition and arbitrage conditions are most satisfied. [6] Nevertheless, our result tends to be in line with the previous futures market literature, for example, Ma et al. (1989), Ma et al. (1990), and Park et al. (1997). These authors find evidence of overreaction in several futures markets.

The result on the volume–return relation is also similar to that in equity markets. However, it is unlikely for the liquidity premium hypothesis to explain the informational role of volume in our highly liquid futures markets. Therefore, changes in trading volume are likely to capture overconfidence and overreaction and is thus positively associated with the magnitude of return reversals (DeBondt and Thaler, 1985; Odean, 1998; Statman and Thorley, 1999; Lee and Swaminathan, 2000; Gervais and Odean, 2001). Although there is no straightforward explanation for the relation between open interest and expected returns in the literature, our result tends to support Bessembinder and Seguin's (1993) argument that open interest represents uninformed trading by hedgers and is a proxy for market depth. Therefore, changes in volume conditional on an increase in open interest are, on average, associated with weaker price reversals than those conditional on a decrease in open interest. This is because an increase in market depth counterbalances the effect of overreaction on prices. In other words, speculators tend to move prices to a less extent in a deeper market than in a market with reduced depth. Therefore, the findings of the relation between trading activity (volume and open interest) and contrarian profits provides further support for the overreaction hypothesis.

The remainder of this paper is organized as follows. Section 2 describes the data and the contrarian portfolio strategy used throughout the paper. The empirical evidence is presented in Section 3. Section 4 contains brief conclusions of the paper.

[6] For example, there is no restriction on short selling, each contract is identical to every other in a specific market, traders are largely professionals with up-to-minute information on prices, futures trading has a sufficiently low transaction cost, the supply of contracts can grow and shrink quickly, and so on.

Table 1
Summary statistics for futures returns, trading volume, and open interest

	Mean	St. Dev.	*t*-value	Autocorrelations			
				ρ_1	ρ_2	ρ_3	ρ_4
Panel A: Summary statistics for weekly futures returns							
Financials							
Eurodollar	0.005	0.210	0.62	0.002	−0.034	−0.007	−0.098*
T-notes	0.039	0.979	1.17	−0.031*	0.041*	0.022	0.030
T-bills	0.004	0.203	0.61	−0.040*	−0.048*	−0.027	0.038
S&P 500	0.269	2.145	3.76	−0.032*	−0.007	−0.014	−0.042
NYSE	0.236	2.087	3.39	−0.027*	0.001	−0.017	−0.040*
Currencies							
British pound	0.010	1.560	0.18	−0.020	0.000	−0.033	0.012
Deutsche mark	0.036	1.576	0.68	−0.035*	0.051*	−0.033	0.017
Japanese yen	0.107	1.609	1.95	−0.002	0.011	0.007	0.002*
Swiss franc	0.044	1.708	0.76	−0.002	0.065*	0.007	0.020
Agriculturals							
Corn	0.005	3.170	0.05	−0.001	0.039	−0.019	0.024
Cotton	0.037	4.089	0.31	−0.002	0.015	−0.023*	0.069*
Feeder cattle	0.052	1.876	0.82	−0.011	−0.036*	0.015	0.019
Live cattle	0.036	2.194	0.44	−0.069*	−0.003	0.019	−0.003
Soybeans	0.020	2.939	0.20	−0.038*	0.027	−0.022	−0.023
Soybean oil	0.036	3.338	0.32	−0.065*	0.075*	−0.035	0.039
World sugar	0.131	5.527	0.70	0.002	0.070*	−0.034	0.058
Wheat	0.027	3.292	0.24	−0.026*	−0.033*	−0.025	−0.012
Commodities							
Cocoa	−0.027	3.915	−0.20	−0.059*	−0.023	−0.008	0.017
Coffee	0.106	5.471	0.56	−0.031*	−0.027	−0.075*	−0.014
Crude oil	0.120	4.886	0.73	−0.073*	0.067*	−0.045*	−0.010
Gold	−0.024	1.885	−0.37	−0.092*	−0.041*	0.074*	0.093*
Heating oil	0.118	4.920	0.72	0.007	−0.012	−0.060	0.032
Platinum	0.076	3.056	0.73	−0.097*	−0.010	0.010	0.058*
Silver	−0.040	3.385	−0.35	−0.032*	−0.035*	−0.059*	0.084*
Market	0.009	0.949	0.42	−0.059*	0.001	−0.068*	0.027

Table 1 (*continued*)

	Volume				Open interest				Change in trading activity											
									Volume						Open interest					
	Mean	St. Dev.	Max	Min	Mean	St. Dev.	Max	Min	Mean	St. Dev.	Autocorrelations				Mean	St. Dev.	Autocorrelations			
											ρ_1	ρ_2	ρ_1	ρ_1			ρ_1	ρ_2	ρ_1	ρ_1
Panel B: Summary statistics for trading activity																				
Financials																				
Eurodollar	229.66	181.29	901.05	2.99	1,417.36	1,124.37	13,274.76	29.59	0.001	0.014	−0.03	−0.15	−0.06	0.07	0.002	0.012	−0.48	−0.00	−0.00	−0.01
T-notes	56.83	51.52	336.06	1.58	206.70	176.56	694.36	9.03	0.002	0.015	−0.19	−0.02	−0.03	−0.05	0.003	0.002	0.42	0.09	−0.07	−0.10
T-bills	5.30	4.62	30.80	0.01	28.48	16.56	61.34	0.12	−0.003	0.017	−0.39	−0.03	−0.01	−0.05	−0.002	0.003	0.07	−0.18	−0.12	−0.08
S&P 500	67.87	31.87	271.23	9.74	300.02	117.19	576.81	44.03	0.000	0.011	−0.02	−0.19	−0.12	−0.04	0.001	0.002	−0.13	−0.04	−0.04	−0.06
NYSE	5.91	3.57	17.53	0.12	6.96	10.97	19.89	1.13	−0.002	0.008	−0.15	−0.23	−0.04	0.00	−0.002	0.005	0.15	−0.21	−0.13	−0.08
Currencies																				
British pound	11.28	4.81	35.34	1.66	35.64	13.05	76.78	12.65	−0.000	0.014	−0.28	−0.15	−0.11	0.03	0.000	0.005	0.16	−0.23	−0.11	−0.02
Deutsche mark	28.98	14.74	80.83	0.01	67.25	34.49	175.53	0.64	−0.000	0.011	−0.27	−0.13	−0.11	0.01	−0.000	0.005	0.21	−0.22	−0.10	−0.07
Japanese yen	21.63	10.02	83.97	1.51	62.66	27.14	154.49	13.23	0.000	0.014	−0.24	−0.22	0-.06	0.05	0.000	0.004	0.16	−0.23	−0.12	−0.10
Swiss franc	16.77	8.68	46.38	4.50	39.73	14.02	103.26	16.96	−0.000	0.010	−0.28	−0.12	−0.12	−0.02	0.000	0.004	−0.33	−0.13	−0.00	0.02
Agriculturals																				
Corn	51.79	21.73	154.79	6.95	237.31	122.36	940.46	43.69	0.001	0.010	−0.34	0.01	−0.10	−0.08	0.002	0.006	−0.28	−0.23	0.23	−0.01
Cotton	6.95	4.14	78.21	0.03	6.96	10.97	289.36	0.27	0.001	0.015	−0.33	−0.17	0.12	−0.04	0.001	0.004	0.21	0.06	0.08	0.04
Feeder cattle	1.99	0.96	30.78	0.00	12.71	5.49	140.07	0.04	−0.000	0.011	−0.30	−0.12	−0.02	0.06	0.001	0.003	0.07	0.10	−0.09	−0.07
Live cattle	14.52	5.07	30.55	0.01	71.12	28.10	135.12	0.02	−0.000	0.009	−0.34	−0.11	−0.00	−0.00	0.001	0.002	−0.13	−0.12	0.10	−0.07
Soybeans	41.08	17.43	14.17	1.83	118.07	43.35	213.22	12.53	−0.000	0.011	−0.35	−0.11	0.05	−0.05	0.001	0.003	0.07	0.00	0.03	0.06
Soybean oil	17.70	5.96	54.84	3.36	81.34	29.22	168.68	28.26	0.001	0.010	−0.32	−0.05	−0.09	−0.04	0.001	0.002	−0.07	−0.14	0.12	−0.10
World sugar	23.00	16.96	54.56	0.02	113.25	54.87	216.95	0.64	0.002	0.014	−0.33	−0.08	0.01	−0.08	0.002	0.003	0.34	−0.02	0.01	0.01
Wheat	19.39	6.20	150.84	2.68	78.16	74.58	553.79	17.38	−0.000	0.012	−0.24	−0.16	0.11	−0.09	0.001	0.007	0.058	−0.04	−0.13	−0.34
Commodities																				
Cocoa	6.08	3.30	18.73	0.02	55.09	28.79	115.79	3.39	0.001	0.014	−0.35	−0.11	0.04	−0.06	0.002	0.002	0.27	−0.05	−0.10	−0.73
Coffee	6.50	3.81	51.79	0.01	30.72	15.76	236.39	0.20	0.001	0.013	−0.37	−0.06	−0.04	0.01	0.002	0.002	−0.01	−0.35	−0.11	0.22
Crude oil	78.21	43.72	230.35	0.51	289.57	157.53	641.07	5.24	0.002	0.010	−0.22	−0.32	−0.16	0.27	0.002	0.002	−0.12	0.09	−0.04	0.01
Gold	30.78	13.94	108.69	2.00	140.25	41.39	232.36	12.19	0.001	0.015	−0.32	−0.10	0.03	−0.12	0.001	0.003	−0.06	−0.18	0.01	−0.06
Heating oil	25.12	12.01	59.99	3.47	100.43	51.84	445.45	15.21	0.001	0.009	−0.37	−0.09	−0.04	0.05	0.001	0.005	−0.42	0.00	0.01	0.03
Platinum	3.28	1.91	18.86	0.00	17.48	5.02	87.15	0.00	0.000	0.016	−0.36	−0.06	−0.02	0.01	−0.000	0.003	−0.02	−0.03	−0.06	−0.02
Silver	17.49	7.40	57.74	3.46	86.97	20.26	261.63	26.88	0.000	0.015	−0.28	−0.13	−0.41	−0.06	0.000	0.004	−0.34	−0.00	−0.04	−0.08

The return is measured as weekly (Wednesday–Wednesday) return, in percentage. The market denotes the equal-weighted average returns of all the futures contracts. Trading volume and open interest are the weekly average of daily (Thursday–Wednesday) volume and open interest respectively, in 1000 contracts. ρ_j is the jth-order autocorrelation coefficient of return or change in trading activity for individual contracts. The change in trading volume (open interest) is the weekly change in average daily trading volume (open interest) that is detrended using its sample mean.

* Indicates significance at the 0.05 level.

2. Data and methodology

2.1. Data

In this paper, we analyze weekly data on settlement prices, trading volume, and open interest for 24 US futures contracts over the July 1983–June 2000 interval. These data are obtained from Datastream International. Our sample consists of four currencies (British pound, Deutsch mark, Japanese yen, and Swiss franc); five financials (90-day Treasury bills, 10-year Treasury notes, Eurodollar, NYSE composite index, and S&P 500 index); eight agriculturals (corn, cotton, feeder cattle, live cattle, soybean, soybean oil, world sugar, and wheat); and seven commodities (cocoa, coffee, gold, crude oil, heating oil, platinum, and silver). See Appendix A for more information about these contracts. The markets are chosen for the cross-sectional difference in underlying assets and their relative economic importance and market liquidity.

This study focuses on return predictability at weekly intervals. A weekly return is defined as the continuous compounded return over the Wednesday–Wednesday interval, using settlement prices of the contract closest to expiration, except within the delivery month in which the price of the second-nearest contract is used. [7] The continuous price series has the following properties: first, it is rolled into the second-nearest contract at the beginning of delivery month; and second, it represents the price for the most actively traded contract. A side benefit of using weekly data is that it helps to reduce possible estimation biases arising from trades at bid or offer prices and nonsynchroneity in the data, although these biases appear to be trivial in our highly liquid futures markets. A weekly measure of trading activity for each market is defined as the average daily trading volume or open interest over the Thursday–Wednesday interval. Because the trading activity variables are summed across all outstanding maturities, the maturity effect problem in futures studies is bypassed.

Table 1 presents summary statistics for weekly futures returns and trading activity over the sample period. Panel A of Table 1 shows a positive unconditional mean return for all except the cocoa, gold, and silver futures markets, but the return is insignificant with the exception of the S&P 500 index, NYSE composite index, and Japanese yen futures (significant at the 10% level for the latter market). This suggests that a simple buy-and-hold strategy is unlikely to be profitable in most futures markets. Panel A also reports return autocorrelations of up to four lags for individual futures markets. The first-order autocorrelations (ρ_1) are negative for 21 out of 24 markets and significant at the 5% level for 16 markets. Higher-order autocorrelations show more negative than positive signs but are less significant than the first-order autocorrelations.

[7] To ensure that the choice of a particular day of the week, for example, Wednesday, does not affect our results, we also conduct experiments using Friday-to-Friday returns. The results (unreported) are generally consistent with those in this study.

Microstructure biases such as bid–ask bounce, lead–lag effect, and thin trading problems are likely to make a contrarian strategy profitable, even without any market overreaction. These biases typically result in positive cross-autocovariances in returns of individual securities and positive autocovariance in the portfolio return (Lo and MacKinlay, 1990; Conrad et al., 1997). To relieve the concern that microstructure biases induce contrarian profits, we compute return autocorrelation of the market index (up to four lags) and cross-autocorrelations in returns of individual contracts. [8] The last column of Panel A shows that the market return is associated with negative and significant first- and third-order autocorrelations. The cross-autocorrelations in returns of individual contracts (the result is available upon request) display more negative than positive signs, although they are small in magnitude. Thus, it does not appear that futures prices are subject to significant microstructure biases.

Panel B of Table 1 presents summary statistics for the level and change of trading activity (volume and open interest) for our sample. In terms of the level of trading volume and open interest, the Eurodollar futures is the most actively traded contract, with an average daily trading volume and open interest of about 230,000 and 1,420,000 contracts, respectively. The least actively traded is the feeder cattle futures, with an average daily trading volume of 1990 contracts only. It appears that changes in trading volume and open interest have negative autocorrelations of up to four lags for all the contracts, with a few exceptions; however, these autocorrelations are in general small in magnitude.

2.2. Basic contrarian portfolio strategies

To examine whether future returns are predictable based on past returns over short horizons in futures markets, we employ a contrarian portfolio approach similar to that of Lehmann (1990) and Lo and MacKinlay (1990). Our contrarian portfolio strategy is to go short futures contracts that outperformed the market in the past k weeks (past winners) and long those that underperformed the market over the same period (past losers), where $k = 1$, 2, 4, and 8. The portfolio weights are determined by the performance of a contract relative to the market return, which is defined as the equal-weighted average of returns on the 24 futures contracts. [9] We evaluate the performance of contrarian portfolios over a holding horizon of k weeks. [10] Because there is no restriction for traders to go long or short futures con-

[8] See Section 2.2 for the construction of the market index.

[9] The market return may have no economic meaning in futures market; therefore, this method is used solely to determine portfolio weights. We also conduct a robustness test by employing an alternative weighting method, which shows that our results are robust to different weighting methods.

[10] The choice of the formation and holding periods is arbitrary. Most previous studies focused on the 1-week horizon. Badrinath et al. (1995) and Chordia and Swaminathan (2000) suggest that it may take longer for some asset prices to revert after under/outperforming; therefore, we consider the formation/holding period up to 8 weeks. This appears appropriate given that futures trading usually concentrates on contracts that typically mature within two or three months.

tracts, the contrarian strategy is more readily available in futures markets than in equity markets with short-selling restrictions.

Short-horizon return reversals are particularly interesting because it is unlikely for investors' perception of risk to be significantly changed over a short interval. Moreover, issues such as bid–ask spread and nonsynchronous trading problems are trivial in futures markets. Therefore, consistent contrarian profits indicate the futures market overreaction. A primary difference between equity and futures markets is that futures trading is facilitated by a performance bond or margin and thus effectively involves zero investment. [11] Hence, Lehmann's contrarian portfolio approach is primarily deployed to determine portfolio weights.

Suppose there are N contracts at time t ($N = 24$). The weight of contract i in the contrarian portfolio, $w_{i,t}(k)$, is proportional to the difference between the return of the contract over the past k weeks and the equal-weighted average of returns on the N contracts during that period, that is,

$$w_{i,t}(k) = -1/N(R_{i,t-k} - R_{m,t-k}), \tag{1}$$

where $R_{i,t-k}$ is the return on contract i over the past k weeks, and $k = 1$, 2, 4, and 8. $R_{m,t-k} = (1/N)\sum_{i=1}^{N} R_{i,t-k}$ is the equal-weighted average of returns on the N contracts over the past k weeks [12] and $w_{i,t}(k)$ is positive (negative) when contract i underperforms (outperforms) the market, that is, the strategy involves buying losers and selling winners.

Because the portfolio weights sum to zero, that is, $\sum_{i=1}^{N} w_{i,t}(k) = 0$, the portfolio involves zero net investment. Futures trading itself does not involve any investment, and therefore the rationale for using this method is to assign larger weights to extreme losers and winners. An additional advantage of using a zero investment portfolio strategy is that it is simultaneously long and short futures contracts and thus is able to partly offset market risk (if any) arising from long or short contracts alone.

The total dollar investment (long and short) for the contrarian strategy, $I_t(k)$, is given by

$$I_t(k) = \sum_{j=1}^{N} |w_{i,t}(k)|. \tag{2}$$

The performance of the strategy is evaluated over a horizon of k weeks following the formation period. The dollar profits to a strategy of buying losers and selling winners at time t are given by

[11] The term *margin* in futures markets has a different meaning and serves a different purpose than that in equity markets. Rather than providing a down payment in equity markets, the margin required to buy or sell a futures contract is solely a deposit of good faith. In addition, margin can be deposited in marketable securities that continue to earn returns in equity or money markets. Therefore, it is generally held that futures trading requires no investment.

[12] We also follow Lehmann (1990) to use the 4-day return (Thursday–Wednesday) to compute portfolio weights and contrarian profits to mitigate potential bid–ask spread effects. The results (not reported) are identical to those reported here. This is not surprising because futures markets are generally highly liquid and exchange clearing houses usually use the averaged closing range of prices as the settlement price.

$$\pi_{\mathrm{W}t}(k) = \sum_{i=1}^{N_{\mathrm{W}}} w_{i,t}(k) R_{i,t}(k), \tag{3}$$

and

$$\pi_{\mathrm{L}t}(k) = \sum_{i=1}^{N_{\mathrm{L}}} w_{i,t}(k) R_{i,t}(k), \tag{4}$$

where $\pi_{\mathrm{W}t}(k)$ ($\pi_{\mathrm{L}t}(k)$) denotes the profit to winners (losers), and N_{W} (N_{L}) is the number of contracts in the winner (loser) portfolio.

The sum of profits from buying losers and selling winners gives the total profits to the contrarian strategy at time t as

$$\pi_t(k) = \sum_{i=1}^{N} w_{i,t}(k) R_{i,t}(k). \tag{5}$$

The time series average of weekly profits for the formation/holding period of k weeks is our final measure of expected contrarian profits. We report the average profits for each of the three portfolios: winner, loser, and combined (buying losers and selling winners) portfolios. Because a contrarian strategy involves zero net investment, the portfolio weights can be arbitrarily adjusted to achieve any level of profits. To provide a more intuitive measure of the significance of profits, following Chan et al. (2000), we construct a ‘‘return’’ measure. The weekly return to the contrarian portfolio at time t, $R_t(k)$, is obtained by dividing the total profits by total long or short investment and by the length of the holding period (k weeks), that is, $R_t(k) = \pi_t(k)/(0.5 * k * I_t(k))$. This return measure of profitability facilitates comparison across portfolios of contracts. One way to interpret the return is that it represents the difference in weekly returns between winners and losers.

2.3. Trading activity based contrarian strategies

Because overconfidence and overreaction themselves imply heavy trading, we expect that overreaction is more associated with an increase in volume than a decrease in volume (DeBondt and Thaler, 1985; Odean, 1998; Statman and Thorley, 1999; Gervais and Odean, 2001). Thus, changes in trading volume are positively related to the degree of return reversals and the magnitude of contrarian profits. To test if an increase (decrease) in volume is associated with greater (smaller) price reversals and larger (smaller) contrarian profits, we sort futures contracts on the basis of lagged changes in volume into high- and low-volume groups and apply the portfolio weight to each volume-based group separately. A contract is defined as a high- (low-) volume contract if the volume change of the contract between the period from $t-k$ to t and the period from $t-2k$ to $t-k$ is above (below) the median volume change of all contracts, where $k = 1$, 2, 4, and 8 weeks. A change in trading volume ($\Delta V_{i,t}^k$) between the period from $t-k$ to t and the period from $t-2k$ to $t-k$ is

$$\Delta V_{i,t}^k = V_{i,t-k} - V_{i,t-2k}, \tag{6}$$

where $V_{i,t-k}$ is the sum of weekly trading volume over the interval from $t-k$ to t for contract i, $V_{i,t-2k}$ is the sum of weekly trading volume over the interval from $t-2k$ to $t-k$, and weekly volume is measured by averaging daily trading volume over the week (Thursday–Wednesday).

We detrend weekly trading volume by dividing the trading volume by its sample mean to make the volume measure comparable across markets. As a sensitivity check, we also employ an alternative measure of volume, that is, percentage changes in volume, in the latter analysis. The ranking of changes in volume is updated each week and member contracts of each group are reassigned accordingly. A contrarian portfolio strategy is then applied to each of the two volume-based groups individually.

Another measure of futures trading activity is open interest. Previous studies show that open interest tends to proxy for market depth and is closely related to trading by hedgers who are concerned about fundamental information. Therefore, we would expect that changes in open interest counterbalance the effect of speculators' overreaction on prices, which is likely to result from changes in volume. We thus examine open interest based contrarian strategies. To proceed, we follow a similar method to categorizing volume-based portfolios; all the contracts are assigned to either high-open interest (top 50% of changes in open interest) or low-open interest groups (bottom 50% of changes in open interest) based on lagged changes in open interest between the period from $t-k$ to t and the period from $t-2k$ to $t-k$, where $k = 1$, 2, 4, and 8 weeks. To make changes in open interest comparable across markets, similar to the "detrending" of trading volume, open interest is scaled using its sample mean. The contrarian portfolio is rebalanced each week. A contrarian strategy is applied to each of the two open interest based groups individually.

If changes in volume and open interest have an effect on contrarian profits, we would expect that the interaction between past returns and lagged changes in both volume and open interest enhances the profitability of a contrarian strategy. To test for this conjecture, we employ a two-way-sorted methodology: Each week, all contracts are first sorted on the basis of lagged changes in trading volume and assigned to one of the two equal-sized volume-based portfolios. Within each volume-based portfolio, contracts are ranked on lagged changes in open interest and assigned to one of the two equal-sized open interest based groups. This gives rise to four volume and open interest based portfolios. A contrarian strategy of buying losers and selling winners is implemented separately to each of the four portfolios. We evaluate average contrarian profits and returns to volume and open interest based portfolios over a holding period of k weeks.

3. Empirical results

3.1. Profits to basic contrarian strategies

We implement the contrarian strategy of buying loser contracts and selling winner contracts over the past k weeks in the 24 futures markets over the July 1983–June

Table 2
Profits to basic contrarian strategies

	1-week	2-week	4-week	8-week
Winner profits	0.0090	−0.0303	−0.0394	−0.1838
	(0.82)	(−1.38)	(−0.93)	(−2.09)
Loser profits	0.0281	0.0378	0.0308	0.1691
	(3.00)	(2.59)	(1.14)	(2.85)
Average profits	0.0370	0.0076	−0.0086	−0.0146
	(2.71)	(0.28)	(−0.17)	(−0.14)
Aggregate investment	19.4593	27.4350	39.1088	55.4798
Weekly returns (%)	0.3105	0.0605	−0.0097	−0.0157
	(2.69)	(0.75)	(−0.18)	(−0.40)

This table reports the profit and return from a contrarian strategy that is long loser contracts and short winner contracts over short horizons. The sample period is from July 1983 to June 2000. The contrarian portfolios are formed based on past performance of contracts. The weight of a contract in the portfolio is based on the deviation of its return in the previous period from the return on an equal-weight market index. We use four different formation/holding periods, ranging from 1 to 8 weeks. All profit estimates and aggregate investment weights are multiplied by 1000. Aggregate investment weight is defined as $I_t(k) = \sum_{i=1}^{N} |w_{i,t}(k)|$, where $W_{i,t}$ is the weight of contract i at time t, and the weekly return $R_t(k) = \pi_t(k)/(0.5 * k * I_t(k))$. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero.

2000 interval and evaluate the profitability of the strategy over a horizon of k weeks, where $k = 1$, 2, 4, and 8. Table 2 reports mean profits and returns to these short-horizon contrarian strategies. [13] Also reported are t-statistics, which are for the null hypothesis that the "true" profits or returns are zero. The results show that, for the formation/holding period of one week, the average profits are 0.009 and 0.028 cents for past winners and losers, respectively, but significant only for past losers. The average profits to the contrarian portfolio are 0.037 cents, and the mean return for the contrarian strategy is 0.31% per week ($t = 2.69$) or 16.12% per annum. Therefore, it appears that a contrarian strategy yields both economically and statistically significant profits over the horizon of one week. Because lead–lag effect, bid–ask bounce, and nonsynchronous trading problems do not appear to be important in explaining the contrarian profits for these liquid futures markets (see Table 1), and it is unlikely for investors' perception of risk to be changed over the short interval, the finding of significant contrarian profits tends to support the overreaction hypothesis.

Table 2 also reports mean profits and returns for basic contrarian strategies over horizons of 2–8 weeks. The mean return for the formation/holding period of 2 weeks is positive but insignificant, but negative and insignificant for the periods of 4 and 8 weeks. The results indicate that the mean profit and return to past winners are positive only for the horizon of 1 week, whereas those to past losers are positive and sig-

[13] We compute the profit and return to the contrarian strategy for all k formation/holding horizons. To conserve space, we only report the results for the k/k strategy. The return patterns of other contrarian strategies are consistent with those reported here.

nificant for all except the horizon of 4 weeks (positive albeit insignificant). This suggests that past losers are more likely to revert than past winners.

Our results on the patterns of contrarain profits over short horizons are similar to those in equity markets (Hameed and Ting, 2000). Hameed and Ting document profitable contrarian profits for the formation/holding period of 1 week in the Malaysian stock market but not for any other horizon of up to 4 weeks.

3.2. Profits to trading activity based contrarian strategies

Table 3 presents the average profit and return from volume-based contrarian strategies. The mean profits for the high-volume group are positive for all except

Table 3
Profits to volume-based contrarian strategies

	1-week	2-week	4-week	8-week
High-volume				
Winner profits	0.0438	0.0422	0.0718	0.2634
	(3.45)	(2.12)	(1.97)	(3.41)
Loser profits	0.0086	−0.0007	−0.0255	−0.3498
	(0.56)	(−0.02)	(−0.42)	(−2.52)
Average profits	0.0524	0.0415	0.0464	−0.0864
	(2.75)	(1.02)	(0.67)	(−0.54)
Aggregate investment	21.9188	30.2405	41.8625	59.0200
Weekly returns (%)	0.4105	0.1226	0.0156	−0.0149
	(3.07)	(1.27)	(0.25)	(−0.31)
Low-volume				
Winner profits	0.0086	0.0374	0.0001	0.1173
	(0.78)	(2.05)	(0.01)	(1.62)
Loser profits	0.0057	−0.0417	−0.0100	−0.0514
	(0.44)	(−2.10)	(−0.22)	(−0.71)
Average profits	0.0143	−0.0044	−0.0099	0.0659
	(0.89)	(−0.16)	(−0.17)	(0.64)
Aggregate investment	16.2434	23.8010	34.9121	49.9688
Weekly returns (%)	0.0366	−0.0184	−0.0287	−0.0082
	(0.28)	(−0.22)	(−0.49)	(−0.21)
t-statistic	2.02	1.12	0.52	0.13
	(0.04)	(0.26)	(0.60)	(0.91)

This table reports the profit and return for volume-based contrarian portfolio strategies. The sample period is from July 1983 to June 2000. Each week, contracts are first sorted into two equal-sized volume groups based on changes in trading volume between the period from $t-2k$ to $t-k$ and the period from $t-k$ to t (volume is scaled by its sample mean). The contrarian strategy is applied to each volume group. The weight of each contract is based on the deviation of its return from the market return in the past. We use four different formation/holding periods, ranging from 1 to 8 weeks. All profit estimates and aggregate investment weights are multiplied by 1000. Aggregate investment weight is defined as $I_t(k) = \sum_{i=1}^{N} |w_{i,t}(k)|$, where $W_{i,t}$ is the weight of contract i at time t, and $R_t(k) = \pi_t(k)/(0.5 * k * I_t(k))$. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero. The t-statistics in the last row are for the hypothesis that the mean returns for the two volume panels are equal, and the figure below the t-value is the p-value.

the horizon of 8 weeks but significant only for the horizon of 1 week. However, note that the low-volume group is, on average, associated with substantially smaller contrarian profits than the high-volume group. The mean profits for the low-volume group are positive for the periods of 1 and 8 weeks and negative for other horizons, but none is statistically significant. The mean return for high-volume group is 0.41% per week for the horizon of 1 week, which is about 30% larger than that from the basic contrarian strategy (0.31%), suggesting that the interaction between past returns and lagged changes in volume indeed enhances the profitability of contrarian portfolio strategy. The *t*-test results in the last row show that the mean returns for the high- and low-volume groups are significantly different only for the 1-week horizon.

The positive relation between changes in trading volume and contrarian profits suggests that high-volume contracts are more likely to experience return reversals than low-volume contracts, broadly consistent with the findings of equity market studies (Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Hameed and Ting, 2000; Lee and Swaninathan, 2000). Different from equity markets, the liquidity premium hypothesis is unlikely to account for this result in the highly liquid futures markets. Moreover, the use of changes in volume further relieves our concern that our results are driven by liquidity effects. Therefore, the positive relation between volume and contrarian profits suggests that it takes volume to detect overreaction, consistent with the implications of behavioral finance theories (DeBondt and Thaler, 1985; Odean, 1998; Gervais and Odean, 2001).

The evidence in Table 3 also indicates that profits for high-volume group primarily stem from selling past winners. The average profits to past winners are positive and significant for all formation/holding horizons, whereas the profits to past losers are positive only for the 1-week horizon (negative and significant for the horizon of 8 weeks). This suggests that contracts that outperformed the market are more likely to experience price reversals if they are actively traded. Note that the previous results from basic contrarian strategies indicate that past losers are more likely to revert than past winners (Table 2), consistent with the evidence from equity market studies (Lehmann, 1990; Hameed and Ting, 2000). However, Table 3 shows that the contrarian profits primarily stem from selling past winners if a contrarian strategy is conditional on trading volume. [14]

Table 4 reports the results for open interest based contrarian portfolio strategies over horizons of 1, 2, 4, and 8 weeks. We begin our analysis by examining in detail the performance of a contrarian strategy over the 1-week horizon. The most striking

[14] We are not aware of any explanation for the difference in magnitude of winner and loser profits if a contrarian strategy is conditional on trading volume in futures markets. There are few explanations for this phenomenon in the contrarian literature. Statman and Thorley (1999) and Gervais and Odean (2001) show that equity investors become more overconfident and trade excessively after market gains, and, consequently, high-volume winners are more likely to revert. We provide little further insight and leave more satisfactory explanations for this result to future research.

Table 4
Profits to open interest based contrarian strategies

	1-week	2-week	4-week	8-week
High-open interest				
Winner profits	0.0305	0.0375	0.1095	0.2089
	(2.76)	(1.98)	(3.07)	(3.57)
Loser profits	−0.0064	−0.0111	−0.0181	−0.5099
	(−0.39)	(−0.41)	(−0.34)	(−3.95)
Average profits	0.0241	0.0264	0.0914	−0.3011
	(1.28)	(0.77)	(1.44)	(−2.12)
Aggregate investment	19.1184	27.2865	39.0015	55.2411
Weekly returns (%)	0.0971	0.0294	0.0262	−0.0889
	(0.72)	(0.32)	(0.42)	(−1.34)
Low-open interest				
Winner profits	0.0221	0.0329	−0.0432	0.1393
	(1.78)	(1.79)	(−1.33)	(1.58)
Loser profits	0.0220	−0.0458	−0.0370	0.1216
	(1.80)	(−1.61)	(−0.67)	(1.32)
Average profits	0.0441	−0.0129	−0.0802	0.2609
	(2.58)	(−0.38)	(−1.23)	(2.06)
Aggregate investment	17.4070	26.8449	38.1005	54.5479
Weekly returns (%)	0.3301	0.0093	−0.0247	0.0623
	(2.56)	(0.10)	(−0.39)	(1.45)
t-statistic	1.96	0.16	0.58	1.92
	(0.05)	(0.87)	(0.56)	(0.07)

This table reports the profit and return to open interest based contrarian strategies. The sample period is from July 1983 to June 2000. Every week, contracts are first sorted into two equal-sized open interest portfolios based on changes in open interest between the period from $t-2k$ to $t-k$ and the period from $t-k$ to t. The contrarian strategy is applied to each open interest based portfolio. The weight of each contract is based on the deviation of its return from the market return in the past. We use four different formation/holding periods, ranging from 1 to 8 weeks. All profit estimates and aggregate investment weights are multiplied by 1000. Aggregate investment weight is defined as $I_t(k) = \sum_{i=1}^{N} |w_{i,t}(k)|$, where $W_{i,t}$ is the weight of contract i at time t, and $R_t(k) = \pi_t(k)/(0.5 * k * I_t(k))$. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero. The t-statistics in the last row are for the hypothesis that the mean returns for the two open interest panels are equal, and the figure below the t-value is the p-value.

return pattern for the contrarian strategy is that the average return for low-open interest group is substantially larger than that for high-open interest group. The mean return for low-open interest group is 0.33% per week ($t = 2.56$), whereas the return for high-open interest group is only 0.10% per week ($t = 0.72$). The mean profit and return for high-open interest group are positive for the formation/holding periods of 2 and 4 weeks and negative for the period of 8 weeks, but none of them is statistically significant. The weekly return for low-open interest group is positive for the periods of 2 and 8 weeks and negative for the period of 4 weeks, which is again insignificant. The t-test results in the last row indicate that the mean returns for the high- and low-open interest groups are significantly different for the horizons of 1 and 8 weeks (the mean returns are significantly different only at the 10% level for the 8-week horizon, and the mean returns to the open interest based strategies are individually insignificant).

Note that the mean return to low-open interest portfolio is marginally larger than that to a simple contrarian strategy (0.31%), suggesting that changes in open interest help to enhance the profitability of contrarian strategy, although the improvement is smaller in magnitude than that for changes in trading volume. The negative relation between changes in open interest and contrarian profits tends to be consistent with the argument that open interest is directly related to trading by hedgers and thus is a proxy for market depth (Bessembinder and Seguin, 1993). An increase in open interest implies a deeper market, and consequently, the effect of volume shocks on prices is smaller compared to the case where open interest decreases, so are the contrarian profits.

We have documented a positive relation between changes in volume and contrarian profits and a negative relation between changes in open interest and contrarian profits. It is of interest to examine whether the performance of contrarian strategy is improved by conditioning on lagged changes in both volume and open interest. Table 5 presents the profits and returns from the four volume- and open interest based contrarian strategies for horizons of 1, 2, 4, and 8 weeks. Consistent with the previous results, the average profits and returns are not statistically significant except for the high-volume and low-open interest portfolio over the 1-week horizon. The t-test results in the last row show a significant difference in mean returns between high-volume together with low-open interest and low-volume together with high-open interest groups over the short horizon. The average return to high-volume and low-open interest portfolio is as high as 0.57% per week ($t = 3.86$) or 29.64% per annum over the 1-week horizon. This return is substantially larger in magnitude than that from the basic contrarian strategy (0.31%) or the contrarian strategy implemented in high-volume contracts (0.41%) or low-open interest contracts (0.33%) in Tables 2–4. Therefore, the performance of a contrarian strategy is substantially improved by interacting between past returns and lagged changes in both trading volume and open interest.

To summarize, we detect strong evidence of contrarian profits over the 1-week horizon in futures markets. A basic contrarian strategy records an average return of 0.31% per week. When a contrarian strategy is implemented in high-volume (low-open interest) contracts, the mean return for the contrarian strategy increases to 0.41% per week (0.33% per week). A more interesting result emerges when a contrarian strategy is implemented in high-volume together with low-open interest contracts. The mean weekly return increases to 0.57% per week, which is more than 80% larger than that from the basic contrarian strategy.

Our results suggest that futures prices are reliably predictable over the 1-week horizon, similar in nature to those in equity markets. In line with the findings in equity market studies, trading volume contains valuable information about future market movements. In addition, we provide novel evidence on the informational role of open interest in predicting future price changes.

Table 5
Profits to volume and open interest based contrarian strategies

	1-week	2-week	4-week	8-week
High-volume, high-open interest				
Winner profits	0.0350	0.0261	0.0133	0.2311
	(2.48)	(1.01)	(0.28)	(1.95)
Loser profits	−0.0053	0.0479	0.0502	−0.2260
	(−0.23)	(1.34)	(0.81)	(−1.65)
Average profits	0.0297	0.0740	0.0635	0.0051
	(1.12)	(1.68)	(0.80)	(0.03)
Aggregate investment	20.9466	28.5520	40.3318	56.5213
Weekly returns (%)	0.0808	0.1044	0.0005	0.0179
	(0.55)	(1.05)	(0.01)	(0.35)
High-volume, low-open interest				
Winner profits	0.0499	0.0640	0.1243	0.1603
	(2.98)	(2.51)	(2.97)	(2.16)
Loser profits	0.0263	−0.0534	−0.0723	−0.3245
	(1.71)	(−1.09)	(−0.88)	(−1.73)
Average profits	0.0762	0.0107	0.0519	−0.1642
	(3.30)	(0.19)	(0.59)	(−0.79)
Aggregate investment	21.3190	29.7854	40.4585	56.1063
Weekly returns (%)	0.5650	0.0118	0.0320	−0.0144
	(3.86)	(0.11)	(0.49)	(−0.26)
Low-volume, high-open interest				
Winner profits	0.0160	0.0078	−0.0177	0.1912
	(1.28)	(0.33)	(−0.41)	(1.71)
Loser profits	−0.0024	−0.0519	0.0246	0.0037
	(−0.17)	(−2.02)	(0.46)	(0.04)
Average profits	0.0136	−0.0441	0.0069	0.1948
	(0.76)	(−1.24)	(0.09)	(1.26)
Aggregate investment	14.8700	22.9321	34.2688	49.6559
Weekly returns (%)	0.0386	−0.1555	0.0093	0.0294
	(0.29)	(−1.64)	(0.14)	(0.66)
Low-volume, low-open interest				
Winner profits	−0.0022	0.0550	0.0246	0.0105
	(−0.15)	(2.54)	(0.67)	(0.14)
Loser profits	0.0147	−0.0263	−0.0480	−0.0993
	(0.87)	(−1.07)	(−0.82)	(−1.13)
Average profits	0.0126	0.0287	−0.0234	−0.0889
	(0.57)	(0.90)	(−0.34)	(−0.81)
Aggregate investment	16.6294	23.1449	33.4076	46.7599
Weekly returns (%)	0.0348	0.1062	−0.0274	−0.0582
	(0.24)	(1.19)	(−0.42)	(−1.38)
t-statistic	2.67	1.19	0.44	0.62
	(0.01)	(0.23)	(0.66)	(0.54)

This table reports the profits and return for volume and open interest based contrarian strategies. The sample period is from July 1983 to June 2000. Every week, contracts are first sorted into two equal-sized volume portfolios based on changes in volume between the period from $t-2k$ to $t-k$ and the period from $t-k$ to t. Within each volume group, contracts are sorted on the basis of changes in open interest into two equal-sized groups. This procedure gives rise to four volume and open interest based portfolios.

Table 5 (*continued*)
The contrarian strategy is applied to each of the four portfolios. The weight of each contract is based on the deviation of its past return from the market return. We use four different formation/holding periods, ranging from 1 to 8 weeks. All profit estimates and aggregate investment weights are multiplied by 1000. Aggregate investment weight is defined as $I_t(k) = \sum_{i=1}^{N} |w_{i,t}(k)|$, where $W_{i,t}$ is the weight of contract i at time t, and $R_t(k) = \pi_t(k)/(0.5 * k * I_t(k))$. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero. The t-statistics in the last row are for the hypothesis that the mean returns for the high volume together with low open interest and low volume together with high open interest groups are equal, and the figure below the t-value is the p-value.

3.3. Transaction costs and contrarian profits

In Table 2, we assume that all of the contrarian profits are due to market overreaction. We proceed to analyze whether our contrarian strategies remain profitable after corrections for plausible transaction costs. Following Lehmann (1990), we compute transaction costs per contract per week as

$$\text{tc} = c \times |w_{i,t} - w_{i,t-1}|,$$

where tc denotes transaction costs, $w_{i,t}$ is the portfolio weight for contract i in week t, and c is the one-way transaction cost per dollar transaction.

A futures trader typically incurs one-way transaction costs of commissions and one-half the bid–ask spread (the latter is sometimes interpreted as the market impact cost). Transaction costs vary across futures contracts. A round-trip commission is about $20 per contract for institutional investors in the S&P 500 index futures market (Lee and Nayar, 1993). [15] Lee and Nayar estimate a bid–ask spread of $25 for the S&P 500 index futures, which is equal to the minimum tick. Thus, one-way transaction costs for the S&P 500 index futures are about 0.01% of notional value. [16] Locke and Venkatesh (1997) estimate that transaction costs of futures contracts range from 0.0004% to 0.033%, which are much less than those often cited for equities. To be conservative, we select the level of one-way transaction costs ranging from 0.01% to 0.20% in our analysis.

The results of contrarian profits after corrections for transaction costs are reported in Table 6. The results indicate that the 1-week contrarian strategy remains profitable after accounting for a one-way transaction cost of up to 0.10%. The one-way transaction cost required to eliminate all contrarian profits is about 0.16%, similar to that in Conrad et al. (1997), and much larger than actual transaction costs incurred by professional futures traders. Thus, our conclusion on the profitability of contrarian strategies over the 1-week horizon remains unaltered.

[15] Large traders are often charged a round trip commission of about $10 in trading S&P 500 index futures. Some brokerages offer a one-way commission of as low as $3 in other futures markets.

[16] The one-way transaction costs are computed as $\frac{\$10+\$12.5}{400\times500} = 0.01\%$, where $10 and $12.5 are the one-way commissions and one-half the bid–ask spread, respectively, 400 is the assumed S&P 500 index level in 1990, and 500 denotes the trading unit, meaning that one contract is for delivery of $500 times the index.

Table 6
Profits to basic contrarian strategies after transaction costs

	Transaction costs			
	0.01%	0.05%	0.10%	0.20%
Winner profits	0.0088	0.0076	0.0061	0.0030
	(0.80)	(0.69)	(0.55)	(0.27)
Loser profits	0.0274	0.0262	0.0247	0.0217
	(2.93)	(2.80)	(2.64)	(2.31)
Average profits	0.0362	0.0338	0.0308	0.0247
	(2.65)	(2.47)	(2.25)	(1.80)
Weekly returns (%)	0.3012	0.2749	0.2420	0.1763
	(2.61)	(2.38)	(2.10)	(1.53)

This table reports the profitability of contrarian strategy applied to weekly returns after transaction costs are deducted. The contrarian portfolios are constructed using weights based on the previous week's contract performance. The average profit after deducting transaction costs is defined as $\pi_t(k) = \sum_{i=1}^{N} w_{i,t}(k)R_{i,t}(k) - c^*|w_{i,t}(k) - w_{i,t-1}(k)|$, where c denotes the one-way transaction cost (commissions and one-half bid–ask spread) per dollar transaction, and $W_{i,t}$ is the weight of contract i at time t. The transaction cost is chosen to be 0.01%, 0.05%, 0.1%, and 0.2%. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero.

3.4. Robustness tests

We have used the equal-weight market index as a benchmark to construct contrarian portfolios. A criticism may arise because, unlike in equity markets, there is no economic meaning for a market index in futures markets. More importantly, Lo and MacKinlay (1990) show that the use of deviations from a market index as weights implies that a large portion of measured contrarian profits is due to the positive autocovariance in the index rather than negative autocovariances in individual assets. We have shown that the return on the equal-weighted market index has a negative and significant first-order autocorrelation (Table 1), and this autocorrelation is likely to have weakened the contrarian profits as reported previously. To understand how the autocovariance in the market return affects contrarian profits, we employ an alternative portfolio weighting method. Following Conrad et al. (1994), we determine the portfolio weight of contract i at time t as

$$W_{pi,t} = R_{i,t-k} \Big/ \sum_{i=1}^{N_p} R_{i,t-k}, \quad p = \mathrm{W}, \mathrm{L}, \tag{7}$$

where N_p is the number of contracts for winners (W) or losers (L). A contract is categorized as a winner if $R_{i,t-k}$ is greater than zero and as a loser if $R_{i,t-k}$ is less than zero, where $k = 1$, 2, 4, and 8 weeks. This portfolio weighting method is economically meaningful, and any measured profits to this strategy must arise from autocovariances in returns of individual futures contracts.

Although not reported, the results show that, broadly consistent with the findings in Table 2, the mean profits and returns for the basic contrarian strategies are positive and significant for the period of 1 week, whereas those for the horizons of 2, 4, and 8 weeks are insignificant. The average return from the contrarian strategy for the horizon of 1 week is 0.61% per week ($t = 2.32$), which is substantially larger than that reported in Table 2 (0.31% per week). Therefore, the negative first-order autocovariance in the market return is likely to have reduced the contrarian profits in Table 2. We also repeat the analysis by interacting between past returns and changes in volume and open interest, and the pattern of returns for contrarian strategies (not reported) is consistent with the previous results except that the mean profits and returns are larger in magnitude than those in Table 5.

We also conduct a robustness test by using percentage changes in trading activity rather than value changes in trading activity. Value changes in trading activity may result in problems in the construction of trading activity based portfolios. For example, using value changes in volume to rank contracts often includes a few most (least) actively traded contracts in high- (low-) volume portfolios, whereas this is unlikely to occur if percentage changes in volume is used. A percentage change in trading volume (VR_{it}) between the period from $t-k$ to t and the period from $t-2k$ and $t-k$ is defined as

$$\mathrm{VR}_{it}^{k} = (V_{i,t-k} - V_{i,t-2k})/V_{i,t-2k}, \tag{8}$$

where $V_{i,t-k}$ is the sum of weekly trading volume over the interval from $t-k$ to t for contract i, $V_{i,t-2k}$ is the sum of weekly trading volume over the interval from $t-2k$ to $t-k$ and $k = 1$, 2, 4, and 8 weeks. Percentage changes in open interest are defined in the same manner as those in Eq. (8).

To conserve space, the results (available upon request) are not reported. The pattern of contrarian profits by interacting between past returns and percentage changes in trading volume and open interest is in general consistent with the previous result. For example, similar to the result in Table 5, a contrarian strategy is significantly profitable only if it is implemented in high-volume together with low-open interest contracts, which gives an average return of 0.50% per week ($t = 3.45$) or 26% per annum. Therefore, the result of a positive (negative) relation between changes in trading volume (open interest) and contrarian profits is robust to an alternative measure of trading activity.

4. Conclusions

We employ the standard contrarian portfolio approach in equity market research to examine short-horizon return predictability in broader US futures markets. We find strong evidence of price reversals over the 1-week horizon, similar to that from equity market studies. The 1-week contrarain strategy remains profitable after corrections for plausible transaction costs. We also find that return predictability is substantially improved by interacting between past returns and lagged changes in volume and/or open interest. However, volume and open interest tend to have the opposite effect on contrarian profits. There is a positive relation between lagged changes in volume and contrarian profits, whereas the relation between lagged changes in open interest and contrarian profits is negative. Furthermore, a contrarian strategy implemented in a portfolio of contracts that experienced an increase in volume together with a decrease in open interest generates the most pronounced profits over the short horizon.

It is reasonable to assume that investors' perception of risk is not significantly changed over a short interval. Bid–ask bounce, lead–lag effect, and nonsynchronous trading problems do not appear to play a role in explaining the contrarian profits in our highly liquid futures markets. Therefore, our result of consistent contrarian profits points toward the direction of market inefficiency, that is, the market overreaction. This result is particularly interesting because futures trading is very close to the textbook model of perfect competition, and a majority of market participants are professional players. [17]

The result on the relation between trading volume and contrarian profits is similar to that in equity market studies (Brennan et al., 1998; Hameed and Ting, 2000) and in general consistent with the implications of behavioral finance theories (DeBondt and Thaler, 1985; Odean, 1998; Gervais and Odean, 2001). This paper provides novel evidence on the negative relation between lagged changes in open interest and contrarian profits. This result appears to be consistent with the hypothesis that open interest is a proxy for market depth: A decrease (increase) in open interest is related to reduced (increased) market depth, and, consequently, the effect of overreaction on futures prices is larger (smaller), as are the contrarian profits. Therefore, our finding on the relation between trading activity and contrarian profits provides further support for the overreaction hypothesis.

Although an overreaction phenomenon has been seen as the foundation of many existing regulatory measures such as daily price limits and "circuit breaker" systems in futures and stock markets, this paper is the first study that systematically examines overreaction in broader futures markets. This study also contributes to the literature by showing that lagged trading volume and open interest in addition to past prices correlate with future price changes in futures markets. Therefore, our findings have implications for market efficiency and futures market regulation and are also important for futures traders, commodity pool operators in particular.

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[17] Psychological evidence shows that experts are more prone to overreaction because they have a stronger tendency to be overconfident (Griffin and Tversky, 1992). Therefore, it may not be surprising that strong evidence of overreaction is found in futures markets even with a large number of professionals.

Appendix A. Futures contracts included in our sample

Contract	Futures exchange	Contract size	Inception date
Financials			
Eurodollar	Chicago Mercantile Exchange	A principle value of $1,000,000 with a 3-month maturity	1/1983
NYSE	New York Futures Exchange	US$500 × NYSE composite stock index	1/1983
S&P 500	Chicago Mercantile Exchange	US$500 × S&P 500 stock index	1/1983
T-notes (10-year)	Chicago Board of Trade	US$100,000 face value	1/1983
T-bills (90 days)	Chicago Board of Trade	US$1,000,000 face value	1/1977
Currencies			
British pound	Chicago Mercantile Exchange	$62.500	1/1976
Deutsch mark	Chicago Mercantile Exchange	DM 125,000	1/1976
Japanese yen	Chicago Mercantile Exchange	12,500,000 yen	1/1978
Swiss franc	Chicago Mercantile Exchange	SF 125,000	1/1969
Agriculturals			
Corn	Chicago Board of Trade	5000 bushels	1/1970
Cotton	New York Cotton Exchange	50,000 pounds (approximately 100 bales)	1/1973

Feeder cattle	Chicago Mercantile Exchange	44,000 pounds	1/1978
Live cattle	Chicago Mercantile Exchange	40,000 pounds	1/1971
Soya beans	Chicago Board of Trade	5000 bushels	1/1969
Soya bean oil	Chicago Board of Trade	60,000 pounds	1/1969
World sugar	New York Coffee, Sugar & Cocoa Exchange	50 long tons (112,000 pounds)	1/1975
Wheat	Chicago Board of Trade	5000 bushels	1/1981
Commodities			
Cocoa	New York Coffee, Sugar & Cocoa Exchange	10 metric tons (22,046 pounds)	1/1981
Coffee	New York Coffee, Sugar & Cocoa Exchange	37,500 pounds in approximately 250 bags	1/1974
Crude oil	New York Mercantile Exchange	1000 US barrels (42,000 gallons)	1/1984
Gold	Commodity Exchange Inc.	100 troy ounce	1/1975
Heating oil	New York Mercantile Exchange	42,000 US gallons (1000 barrels)	1/1980
Platinum	New York Mercantile Exchange	50 troy ounces	1/1973
Silver	Commodity Exchange Inc.	5000 troy ounces	1/1977

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