Do Futures Markets Overreact?

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Abstract

We examine the profitability of contrarian portfolio strategies of buying past losers and selling past winners at weekly intervals in 24 major U.S. futures markets. We document significant contrarian profits over the one-week horizon. Unlike in equity markets, we show that the contrarian profits arise solely from the negative serial dependence in returns of individual futures contracts. Furthermore, the profits remain significant after corrections for plausible transaction costs in futures trading. Imperfections in market microstructure like bid-ask spread and nonsynchronous trading are trivial in our sampled futures markets. Hence, our results point towards the futures market overreaction.

JEL classification: G13; G14

Keywords: Futures markets; Return reversals; Overreaction; Transaction costs

1. Introduction

Numerous studies in the past two decades have documented significant return predictability over short horizons in equity markets. For example, Jegadeesh (1990) provides evidence of stock return reversals over monthly intervals. Lehmann (1990) and Lo and MacKinlay (1990) find that a contrarian strategy of buying past losers and selling past winners earns significant profits at weekly intervals. Despite the existence of these patterns in equity returns is well established, explanations for why these patterns exist remain controversial. Ball and Kothari (1989) argue that the predictable returns are attributable to systematic time variation of risk premiums due to changes in market conditions and investors' perception of risk. Lehmann (1990) and De Long, Shleifer, Summers, and Waldmann (1990) contend that the return predictability reflects irrationality-induced market inefficiency, that is, the stock market systematically overreacts to new information. Lo and MacKinlay (1990) and Conrad, Gultekin, Kaul (1997) also show that the predictable returns arise in part from imperfections in market microstructure like bid-ask spread, lead-lag effect, transaction cost, and non-synchronous trading.

Return predictability over a short horizon is particularly interesting because it offers a simple way to differentiate among the hypotheses of return predictability. It is not difficult to imagine that economic conditions and investors' perception of risk should remain relatively unchanged over a short horizon, e.g., a week. Thus, if market microstructure effects are properly accounted for, evidence of predictable returns at weekly intervals suggests market inefficiency. Since the recent studies of Lehmann (1990) and Lo and MacKinlay (1990), detections of market overreaction by analyzing the profitability of short-term contrarian strategies have been of academic interest. The virtue of the contrarian portfolio approach is that it provides a neat decomposition of contrarian profits. If the profits to a contrarian strategy are mainly derived from the negative serial dependence in asset returns, we could infer that the market is inefficient based on the overreaction theories of De Bondt and Thaler (1985) and De Long, Shleifer, Summers, and Waldmann (1990).

In this paper, we extend the literature by examining the profitability of contrarian portfolio strategies at weekly intervals in broad futures markets. Following the methodology developed by Lo and MacKinlay (1990), we document significant profits to the one-week contrarian strategy implemented in a sample of 24 active U.S. futures markets. A strategy of buying past losers in the previous week and selling past winners over the same period gives rise to an average return of 0.31 percent per week (t = 2.70) or 16.1 percent per annum. Further decomposing the contrarian profits to determine the sources of profits, we find that the profits derive solely from the negative serial dependence in returns of individual futures contracts. We also show that the contrarian profits remain significant after corrections of a one-way transaction cost (commissions and one half the bid-ask spread) of up to 0.16 percent, which is substantially higher than the cost that a typical trader incurs in trading futures.

The evidence of significant contrarian profits over the short horizon in futures markets is broadly consistent with the findings in equity market studies, for example, Lehmann (1990) and Lo and MacKinlay (1990). Unlike in equity markets, issues like lead-lag, bid-ask spread and non-synchronous trading effects are trivial in our sampled active futures markets, and therefore, our results point towards the direction of market inefficiency, i.e., the futures market overreaction. At first glance, our results appear striking because futures markets are very close to the textbook model of competition, arbitrage conditions are generally satisfied, and traders are largely sophisticated professionals. However, the finding of futures market overreaction may make sense. Griffin and Tversky (1992) provide convincing psychological evidence that experts are more prone to overreact than others due to greater overconfidence. If the predictable pattern in equity returns is due to overreaction, it is not unreasonable to expect a similar pattern in futures returns. Our finding of futures market overreaction is supportive of several extant futures market studies, for example, Ma, Dare, and Donaldson (1990), Gay, Kale, Kolb, and Noe (1994), Ederington and Lee (1995), Park, Chen, and Pierzak (1997), and Fung, Mok, and Lam (2000). Unlike the extant studies, in this paper we examine this issue by investigating the profitability of contrarian portfolio strategies in a cross-section of broad futures markets.

The remainder of this paper is organized as follows. In Section 2, we discuss the mechanics of futures trading and futures investment. Sections 3 and 4 describe the data and methodology used in this paper respectively. In Section 5, we present and analyze the empirical results. The final section concludes.

2. The mechanics of futures trading and futures investment

A futures contract is an agreement to buy (or sell) a specified amount of underlying assets delivered on a future date at an agreed price upon entering the contract – futures price. The futures price is different from the value of a futures contract. Futures trading is facilitated via the margin system, that is, a trader only needs to deposit a small portion (1-6%) of the contract value into his/her margin account maintained with his/her broker when he/she goes into a long or short position in the futures. The margin required to buy or sell a futures contract is solely a deposit of good faith or a performance bond, which can be paid in cash or marketable securities. Therefore, it is generally held that futures trading requires zero investment. Upon entering a futures contract, no cash changes hands between the buyer and the seller. At the end of each trading day, all contracts are marked to market using the settlement prices, gains or losses during the day are settled by the two parties to the contract via transfers from their margin accounts. The marking to market practice ensures the value of a futures contract is reset to zero at the end of each trading day.

In a competitive market, a futures price represents the consensus of market expectations about the asset's future spot price. In determining the futures price, market participants compare the current futures price with the spot price that is expected to prevail at the maturity of the futures contract using best available information up to today. Thus, futures markets are forward looking. Only unexpected deviations from the expected future spot price are taken into account when futures prices are set, and the expected movements in the spot price are not a source of return to an investor in futures.

Given that futures trading does not need any investment, the futures return is not well defined in the finance literature, although the return distribution of commodity futures is not very different from that of stocks or other assets (Gorton and Rouwenhorst, 2004). A commonly held view on the futures return is that it represents a risk premium, i.e., the difference between the current futures price and the expected future spot price. However, the determination of futures risk premiums has been an unresolved issue. Keynes's normal backwardation theory postulates that speculators who are attracted into futures markets to bear the risks shifted from hedgers should receive risk premiums, while hedgers who obtain insurance in futures markets are supposed to pay risk premiums. Several recent studies, for example, Bessembinder (1992) and Wang (2003), provide some evidence in support of the normal backwardation theory in broad futures markets.

In sum, unlike stocks or bonds, futures prices are not the discount value of future cash flows. They rather represent bets on expected future spot prices of underlying assets. Nevertheless, returns of both stocks and futures can be characterized as risk premiums. Extant studies have also showed that the return and risk characteristics of futures contracts are comparable to those of stocks and bonds (Gorton and Rouwenhorst, 2004). Therefore, this article represents an attempt to further explore the return behavior in broad futures markets.

3. Data and descriptive statistics

This study analyzes weekly data on settlement prices for a sample of 24 actively traded U.S. futures contracts over the July 1983 - June 2000 interval. The data are collected from Datastream International. Our sample consists of four currencies (British pound, Deutsch mark, Japanese yen, and Swiss franc), five financials (90-day Treasury-bill, 10-year Treasury-note, 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 the appendix for detailed information on these contracts. The sample contracts are chosen for the cross-sectional difference in underlying assets and their relatively economic significance as well as market liquidity.

Similar to the conventional futures markets studies, for example, Bessembinder (1992) and Gorton and Rouwenhorst (2004), we define the weekly futures return as the continuously compounded return over the Wednesday – Wednesday interval, using settlement prices of the contract closest to expiration, except within delivery month in which the price of second nearest contract is used.[1] The rolling of futures contracts ensures that observations of contracts with less liquidity in expiration month or further away from expiration month are excluded from our analysis. Since a futures contract has a zero value at the end of day via the marking to market, therefore, the rolling itself should not be a source of return. Furthermore, a benefit of analyzing weekly data is that it helps to reduce possible estimation biases arising from trades at bid or ask prices and nonsynchroneity in the data, though these biases do not appear to be significant in these liquid futures markets.

Table 1 provides summary statistics for weekly futures returns over the sample period. There are 886 weekly return observations for each contract. The results show that the unconditional mean returns are positive for all except the cocoa, gold, and silver markets, but insignificant with the exception of the S&P 500 and NYSE composite index futures. Thus, a simple buy-and-hold strategy is unlikely to be profitable in majority of these futures markets. The last four columns show return autocorrelations of up to 4 lags for individual futures returns. The first-order autocorrelations (ρ_1) are negative for 21 out of 24 markets, and significant at the 5% level for 15 markets. The coefficients of first-order autocorrelations range from -0.097 (platinum) to 0.007 (heating oil), and the magnitude of the autocorrelations is roughly comparable to that of individual stock returns. For example, Lo and MacKinlay (1990) report an average first-order autocorrelation of -0.034 for individual stocks, and Mei and Gao (1995) show that the average autocorrelation is -0.05 for exchange-traded real estate securities. We also report the weekly average of trading volume and

[1] To ensure that the choice of a particular weekday, i.e., Wednesday, does not affect our results, we conduct experiments using Fridays' returns. The results (unreported) are generally consistent with those reported here.

open interest for each contract over the sample period. The most active contract is the Eurodollar futures in terms of both trading volume and open interest, for which the weekly average trading volume and open interest are 229,655 contracts and 1,433,193 contracts respectively. The least active contract is the feeder cattle, which has a weekly average trading volume of about 2,000 contracts. This is equivalent to a trading volume of 400 contracts per day, representing reasonable liquidity in futures markets. The last row of Table 1 indicates that the first-order autocorrelation for the market portfolio is -0.059 (significant at the 5% level), which is however usually positive in equity markets.[2] The negative autocorrelation of market returns has implications for the source of contrarian profits (see Section 5). Higher-order autocorrelations show more negative than positive signs, but are less significant than the first-order autocorrelations.

[Table 1] here

4. Empirical methods

A specific consequence of market overreaction is that asset returns are negatively autocorrelated, or there exist return reversals. This implies that past losers (experienced lower-than-average returns) are likely to become future winners and past winners (experienced higher-than-average returns) tend to become future losers. Therefore, we could build a costless (contrarian) portfolio in which the investment needed to buy past losers is exactly offset by the revenue from selling past winners, roll the portfolio for some length of time, unload it at the end of the period, and earn positive expected profits.

[2] For example, Lo and MacKinlay (1990) report that the coefficient of first-order correlation for the weekly equal-weighted CRSP NYSE-AMEX stock index over the 1962-1987 interval is 0.296. Details on the construction and economic meaning of the index are provided in Section 3.

In this article, we construct contrarian portfolios in a similar way to Lo and MacKinlay (1990) to study short term return predictability in futures markets.[3] Specifically, starting in July 1983, on each Wednesday (after market close), we short the futures contracts that outperformed the market over the past week (past winners) and long those that underperformed the market (past losers) in the past week. The market is proxied by an equal-weighted portfolio of all the futures contracts in our sample, and the portfolio weights are determined by a contract's performance in the previous week relative to the market portfolio over the same period. We hold the zero cost contrarian portfolio for a week and compute returns to these portfolios over the subsequent week and average returns to the portfolios over the sample period. Since there is no restriction for traders to long or short futures contracts, a contrarian strategy is more readily available to traders in futures markets than in equity markets with short-sales constraints. One of the major differences between equity and futures markets is that futures trading is facilitated by a performance bond (margin), and thus virtually involves zero investment. Hence, the Lo and MacKinlay's contrarian portfolio approach is primarily deployed to determine portfolio weights.[4]

The choice of the reference and holding periods is somewhat tricky in market efficiency tests. On the one hand, we would like to choose as short a period as possible to ensure the irrelevance of time varying risk premiums. But on the other hand, we need the length to be long enough to allow the market time to correct mispricings. French and Roll (1986) suggest that stock returns tend to revert beyond a

[3] Similar to the Lo and MacKinlay's methodology, Lehmann (1990) employs a factor of proportionality that scales the dollar investment in winner and loser portfolios to be 1. Lehmann notes that his results are invariant to this factor of proportionality.

[4] The method is solely used to determine portfolio weights also because the return on the market portfolio seems no economic meaning in futures markets. We conduct a robustness test by employing an alternative weighting method in the latter part of the paper, which shows that our results are robust to different weighting methods.

week interval. Mei and Gao (1995) show that it takes approximately a week for real estate securities to realize return reversals. Thus, the horizon of one week in our study may be appropriate. We also use 2-week and 4-week as the reference/holding periods to construct contrarian portfolios and the contrarian profits (not reported) are in general insignificant. Nevertheless, the choice of one-week horizon is consistent with previous studies on stock return reversals (Lo and MacKinlay, 1990; Lehmann, 1990).

Suppose there are N contracts in week t (N = 24 in this study) over the T periods (weeks). Each week, the contrarian portfolio is constructed from these N contracts, and the weight of contract i in the portfolio, $w_{i,t-1}$, is proportional to the difference between the return on the contract in week t-1 ($f_{i,\ t-1}$) and the equal-weighted average of returns on the N contracts ($f_{m,t-1}$) during the same period, i.e.,

$$w_{i,t-1} = -\frac{1}{N}(f_{i,t-1} - f_{m,t-1}), \quad (1)$$

where $f_{m,t-1} = \frac{1}{N}\sum_{i=1}^{N} f_{i,t-1}$ is the equal-weighted average of returns on the N contracts in week t-1, and $w_{i,t-1}$ is positive (negative) when contract i underperforms (outperforms) the market in week t-1, that is, the strategy involves buying past losers and selling past winners.

The aggregate investment of the contrarian portfolio is zero. That is, $W_{t-1} = \sum_{i=1}^{N} w_{i,t-1} = -\frac{1}{N}(\sum_{i=1}^{N} f_{i,t-1} - Nf_{m,t-1}) = 0$. The total dollar investment (long and short) for the contrarian strategy, I_t, is given by $I_t = \sum_{i=1}^{N} \left| w_{i,t-1} \right|$.

We evaluate the performance of the portfolio over the subsequent week. The dollar profits to the contrarian strategy in week t are given by

$$\pi_{Wt} = \sum_{i=1}^{N_W} w_{i,t-1} f_{i,t} , \quad (2)$$

and

$$\pi_{Lt} = \sum_{i=1}^{N_L} w_{i,t-1} f_{i,t} \ , \tag{3}$$

where π_{Wt} (π_{Lt}) denotes the profits to the winners (losers), and N_W (N_L) is the number of contracts in the winner (loser) portfolio. The sum of profits from buying past losers and selling past winners gives the total contrarian profits in week t as $\pi_t = \sum_{i=1}^{N} w_{i,t-1} f_{i,t}$, and the time series average of weekly profits over the sample period (T weeks) is our final measure of expected contrarian profits, which are given by

$$E[\pi_t] = \frac{1}{T}\sum_{i=1}^{T} \pi_t \ . \tag{4}$$

We compute average profits to each of the three portfolios: winner, loser, and the zero-cost (buying losers and selling winners) portfolios. To provide an intuitive measure of the significance of profits, following Chan, Hameed, and Tong (2000), we use a "return" measure. The weekly "return" to the contrarian strategy in week t, f_t, is measured by dividing the total profits by total long or short investment, i.e., $f_t = E[\pi_t]/(0.5 * I_t)$. This return measure of profitability facilitates comparison across portfolios of contracts. A plausible interpretation for the "return" is that it represents the difference in weekly returns between past winners and past losers.

5. Empirical results

Table 2 presents the mean profits and returns of one-week contrarian strategies implemented in the 24 futures markets over the July 1983 - June 2000 interval. Also reported are t-statistics, which are for the null hypothesis that the "true" profit or return is zero, and the standard errors are corrected for heteroscedasticity and autocorrelations using the Newey and West's (1987) procedure. The results show that the average profits are 0.009 cents and 0.028 cents for (selling) past winners and (buying) past losers respectively, but significant only for past losers. The larger profits from buying losers than selling winners suggest that futures traders tend to overreact more to bad news than to good news if the overreaction hypothesis holds. This result is consistent with the findings of Gay, Kale, Kolb, and Noe (1994) and Park, Chen, and Pierzak (1997) that futures markets are more likely to overreact to negative news than to positive news. The average profit to the contrarian portfolio is 0.037 cents for the one-week interval. To better assess the economic significance of contrarian profits, we compute the weekly return by dividing total profits by the total investment long or short, i.e., $E[\pi_t]/(0.5*I_t)$. The mean return for the contrarian strategy is 0.31 percent per week (t= 2.70) or 16.1 percent per annum. Therefore, it appears that a contrarian strategy yields both economically and statistically significant profits over the one-week horizon given the high leverage and low cost of futures trading.

Concerns may arise because the return pattern from the calendar-day data (Wednesdays' price data) are likely to be affected by the number of days that exchanges are closed. As a robustness check, we also report the results from the trading-day data that define an interval of 5 trading days as a week.[5] The beginning date of our sample is 6 July 1983, and there are about 853 weekly observations for each futures contract. We then apply the contrarian strategy in the Trading-Day sample. The last column of Table 2 shows that the return patterns from the trading-day data are similar to those from calendar-day data, but the average contrarian profit (0.05 cents) and return (0.436 percent per week) are larger than those from the

[5] Because some calendar weeks contain holidays, the use of calendar week does not employ a constant period length in computing the period returns. The resulting concern is that the use of calendar-day data may affect the profitability of contrarian strategy because some calendar weeks have less than 5 trading days for the market to correct possible market overreaction.

calendar-day data. In the remainder of this paper, we focus on the analysis of the calendar-day data.

[Table 2] here

5.1. Decomposition of contrarian profits

A common empirical implication of market overreaction is that the observed returns are negatively autocorrelated at some lag. Thus, a contrarian strategy of buying past losers and selling past winners is essentially to exploit the negative serial dependence in returns. However, as Lo and MacKinlay (1990) point out, positive contrarian profits in eq. (4) do not necessarily imply negative autocorrelations in individual asset returns. To understand the source of contrarian profits and allow for the inference about market inefficiency, Lo and MacKinlay provide a neat decomposition of contrarian profits into three components as the following

$$E[\pi_t] = O + C - \sigma^2(\mu), \tag{5}$$

where

$$O = -\frac{1}{N}\sum_{i=1}^{N} Cov(f_{i,t}, f_{i,t-1}),$$

$$C = Cov(f_{m,t}, f_{m,t-1}), \text{ and}$$

$$\sigma^2(\mu) = \frac{1}{N}\sum_{i=1}^{N}(\mu_i, \mu_m)^2,$$

O denotes the (negative) average first-order return autocovariance of the N contracts in the contrarian portfolio; C denotes the first-order autocovariance of equal-weighted portfolio returns; $\sigma^2(\mu)$ is the cross-sectional variance of mean returns; and μ_i and μ_m are the unconditional mean returns of contract i and market portfolio respectively.

If asset prices follow martingales, expected profits from a contrarian strategy will be negative as long as there is some cross-sectional variance in unconditional mean returns. If a market overreacts to new information, the autocovariance in individual asset returns will be negative, contributing positively to the contrarian profits. That is, O > 0. The magnitude of contrarian profits also depends on the autocovariance in portfolio returns. Conrad and Kaul (1988) and Lo and MacKinlay (1990) show that short-horizon equity portfolio returns are positively autocorrelated. As a result, the autocovariance in portfolio returns implies positive contrarian profits even if there is no market overreaction. Therefore, the decomposition of contrarian profits allows us to understand to what extent the profits result from serial dependence in individual asset returns, and draw the inference about market efficiency.

The three components of contrarian profits, O, C, and $\sigma^2(\mu)$, in eq. (5) are estimated as

$$\hat{O} = \frac{1}{T-1}\sum_{t=2}^{T} O_t \ , \tag{6}$$

$$\hat{C} = \frac{1}{T-1}\sum_{t=2}^{T} C_t \ , \tag{7}$$

$$\sigma^2(\hat{\mu}) = \frac{1}{N}\sum_{i=1}^{N}(\hat{\mu}_i - \hat{\mu}_m)^2 , \tag{8}$$

where $O_t = -\frac{N-1}{N^2}\sum_{i=1}^{N}(f_{i,t} f_{i,t-1} - \hat{\mu}_i^{\ 2})$, $C_t = f_{m,t} f_{m,t-1} - \hat{\mu}_m^{\ 2} - \frac{1}{N^2}\sum_{i=1}^{N}(f_{i,t} f_{i,t-1} - \hat{\mu}_i^{\ 2})$, $\hat{\mu}_i$ and $\hat{\mu}_m$ are the sample mean returns for contract i and market portfolio respectively, and T is the number of weekly observations over the sample period.

Table 3 reports the results of contrarian profit decomposition. The results show that the mean (negative) autocovariance in individual futures returns (0.042 cents), $\hat{O}$, is even larger than the total contrarian profits (0.037 cents). This occurs because both the autocovariance in portfolio returns, $\hat{C}$, and the cross-sectional variance of mean returns, $\sigma^2(\hat{\mu})$, have reduced the total contrarian profits in our study. The average autocovariance in portfolio returns reduces the contrarian profits by 0.004 cents, or 10.6 percent, while the cross-sectional variance of mean returns erodes the profits by 0.001 cents, or 1.54 percent. Thus, the negative serial dependence in individual futures returns constitutes the sole source of contrarian profits in futures markets. This finding is in a sharp contrast with that of equity market studies, for example, Lo and MacKinlay (1990) and Conrad, Gultekin, and Kaul (1997). These authors show that the positive autocovariance in portfolio returns explains a large portion of total contrarian profits in equity markets. The different results between this paper and the previous studies arise because the first-order autocovariance in portfolio returns is negative in futures markets (see Table 1), which is positive in equity markets.

[Table 3 here]

5.2. *Transaction costs and contrarian profits*

Lo and MacKinlay (1990) and Conrad, Gultekin, and Kaul (1997) show that a contrarian strategy may be profitable due to spurious return reversals caused by bid-ask spread, non-synchronous trading and other measurement errors. Moreover, arbitrage profits may be statistically, but not economically, significant because of transaction costs. This problem is more pronounced when there is a need to rebalance portfolios frequently, resulting in buying at the ask price and selling at the bid price. Data on detailed bid-ask spread are generally unavailable in futures markets.[6] We attempt to make use of estimated bid-ask spread and commissions from previous

[6] The Time and Sales data are available from major U.S. futures exchanges, such as the Chicago Board of Trade and the Chicago Mercantile Exchange. These data record the time and price of a transaction if the price differs from the previously recorded price. However, they do not provide a complete record of bid-ask prices. Bid and ask quotes in the data are identified only if the bid quote exceeds or if the ask quote is below the previously recorded transaction price.

futures market studies to examine the impact of transaction costs on the contrarian profits in futures markets.[7]

Assuming that the average one-way transaction cost (commissions and one half the bid-ask spread) in futures markets is c percent. Building and unwinding the contract at the beginning and the end of a period would incur 2c percent. Following Lehmann (1990), we compute the transaction costs per contract per week as

$$tc = c\left|w_{i,t} - w_{i,t-1}\right|, \tag{9}$$

where tc denotes the transaction cost, and $w_{i,t}$ is the portfolio weight for contract i in week t. It should be noted that eq. (9) represents the upper bound of transaction cost, because it is assumed that all the positions in the portfolio are closed out at the end of the week and rebuilt at the beginning of the following week. Moreover, as Lehmann (1990) notes, the bid-ask spread may not disadvantage a contrarian strategy because it is likely for a contrarian to sell at the ask price since majority of traders follow winners and buy at the bid price since traders have a tendency to avoid losers by selling heavily. Under this circumstance, the contrarian strategy provides the market needed liquidity.

Transaction costs vary widely across futures contracts and traders. A round trip commission is about $20 per contract for institutional investors in the S&P 500 index futures market (e.g., Lee and Nayar, 1993).[8] Lee and Nayar estimate a bid-ask spread of $25 for the S&P 500 index futures, which is equal to the minimum tick.

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[7] An alternative way to look at the effect of bid-ask spread on contrarian profits is to follow Lehmann (1990) and use the four-day return (Thursday - Wednesday) to compute portfolio weights and contrarian profits to mitigate potential bid-ask spread effects. The results (not reported) are in general identical to those reported here. This is not surprising since futures markets are in general highly liquid, and exchange clearing houses usually use the average closing range of prices as the settlement price.

[8] Large traders are often charged a round trip commission of about $10 in the S&P 500 index futures market. Some brokerages offered a one-way commission of lower than $3 in futures markets.

Thus, a one-way transaction cost for the S&P 500 index futures in Lee and Nayar (1993) is about 0.01 percent of notional value.[9] Locke and Venkatesh (1997) report that transaction costs of futures contracts range from 0.0004 percent to 0.033 percent, which are much less than those often cited for equities.[10] To be conservative, we select a level of one-way transaction cost ranging from 0.01 percent to 0.20 percent in our analysis.

The results of contrarian profits after corrections for transaction costs are shown in Table 4. For a one-way transaction cost of 0.01 percent, the conclusion on the profitability of our contrarian strategy is little changed. The average profits to the contrarian strategy decrease from 0.037 cents (t = 2.71) to 0.036 cents (t = 2.65), and the weekly average return drops from 0.311 percent to 0.301 percent. We do find that the profitability of contrarian strategy decreases with the level of transaction cost. It appears that the contrarian strategy remains significant for a one-way transaction cost of up to 0.10 percent. The one-way transaction cost required to eliminate all the contrarian profits is about 0.16 percent, which is similar in magnitude to that in Conrad, Gultekin, and Kaul (1997) and Lehmann (1990). However, the actual (one-way) transaction cost that a typical futures trader incurs is far smaller than 0.16 percent. Therefore, our result of significant contrarian profits is robust to a reasonable level of transaction cost.

[Table 4] here

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

[10] Conrad, Gultekin, and Kaul (1997) estimate that the percentage of (one-way) transaction costs varies from 0.35 percent to 1.05 percent for individual investors on the NYSE and AME, and 0.85 percent to 2.65 percent on the NASDAQ. Berkowitz, Logue, and Noser (1988) estimate that institutional investors incur an average one-way transaction cost of 0.23 percent for relatively large NYSE firms.

5.3. An alternative portfolio construction method

Lo and MacKinlay (1990) show that the use of deviations from a market index as weights to construct contrarian portfolios implies that a large portion of measured contrarian profits results from the positive autocovariance in portfolio returns rather than negative autocovariances in individual stock returns. In contrast, we have showed that the equal-weighted portfolio return has a negative and significant first-order autocorrelation in futures markets (Table 1), which weakens the profitability of contrarian strategy (Table 3). To see to what extent the autocovariance in portfolio returns has reduced contrarian profits, and to check the robustness of our results, we employ an alternative approach to construct contrarian portfolios.

Following Conrad, Hameed, and Niden (1994), we determine the weight of contract i in a contrarian portfolio in week t as

$$w_{pi,t} = f_{i,t-1} / \sum_{i=1}^{N_p} f_{i,t-1} \text{ , p = W, L}$$

where N_p is the number of contracts for winners (W) or losers (L). A contract is categorized as a winner if $f_{i,t-1}$ is greater than zero and a loser if $f_{i,t-1}$ is less than zero. Since the denominator sums only positive (negative) returns for the winner (loser) contracts, all weights are positive, and the weights for both winners and losers sum to one. A combined portfolio is formed by buying losers and selling winners. Similar to the Lo and MacKinlay's contrarian strategy, these weights also ensure that larger weights are placed on extreme winners and losers. This portfolio weighting method is economically meaningful, and more importantly, the measured profits to this strategy arise solely from the autocovariance in returns of individual futures contracts.

Table 5 reports the mean profits and returns to the one-week contrarian strategy using the new portfolio weighting method. Broadly consistent with the results in Table 2, the mean profits and returns are positive and significant. However, Table 5 shows negative profits (but insignificant) to past winners, which were positive (insignificant) in Table 2. It appears that the contrarian portfolio is more sensitive to transaction costs compared to the previous portfolio construction method. Under this circumstance, the one-way transaction cost required to eliminate all the contrarian profits is about 0.038 percent, which remains below the upper bound of transaction cost estimate in futures markets in Locke and Venkatesh (1997). Since the total investment differs for the two portfolio construction methods, it would be inappropriate to directly compare the magnitude of contrarian profits in Tables 2 and 5. A comparison can be conducted via the "return" measure. The average return for the contrarian strategy is 0.61 percent per week (t = 2.32), which is about twice as large as that in Table 2 (0.31 percent per week). Therefore, the negative autocovariance in the equal-weighted portfolio returns may have significantly reduced the contrarian profits as reported in Table 2.

[Table 5] here

6. Conclusions

In this study, we employ the standard contrarian portfolio approach in equity market research to investigate short-term return predictability in 24 major U.S. futures markets. We document both statistically and economically significant profits to the one-week contrarian strategy. Unlike in equity markets, we find that the contrarian profits arise solely from the negative serial dependence in individual futures returns, and the autocovariance in portfolio returns effectively weakens the contrarian profits. We also show that the contrarian strategy remains profitable after corrections for plausible transaction costs in futures trading. These results are robust to different portfolio construction methods.

It is reasonable to assume that economic conditions and investors' perception of risk remain relatively unchanged over the short horizon, and market imperfections like bid-ask spread and non-synchronous trading are trivial in our sampled futures markets. Therefore, our results tend to suggest the market inefficiency, that is, the futures market overreaction. Investor overreaction is thus not unique to equity markets, but perhaps a universal phenomenon. These findings are particularly striking because futures trading is very close to textbook model of perfect competition, and futures market participants are commonly regarded as sophisticated "adults". Our findings also have implications for practical trading strategies in futures markets. Managed futures fund managers and commodity pool operators can enhance their performance by monitoring past performance of individual contracts.

APPENDIX

Characteristics of Futures Markets in Our Sample

Contract	Futures Exchange	Contract Size	Start Date
British pound	Chicago Mercantile Exchange	£ 62.500	1/1976
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
Corn	Chicago Board of Trade	5000 bushels	1/1970
Cotton	New York Cotton Exchange	50,000 pounds (approximately 100 bales)	1/1973
Crude oil	New York Mercantile Exchange	1000 US barrels (42,000 gallons)	1/1984
Deutsch mark	Chicago Mercantile Exchange	DM 125,000	1/1976
Eurodollar	Chicago Mercantile Exchange	A principle value of $1,000,000 with a three-month maturity	1/1983
Feeder cattle	Chicago Mercantile Exchange	44,000 pounds	1/1978
Gold	Commodity Exchange Inc	100 troy ounce	1/1975
Heating oil	New York Mercantile Exchange	42,000 US gallons (1,000 barrels)	1/1980
Japanese yen	Chicago Mercantile Exchange	12,500,000 yen	1/1978
Live cattle	Chicago Mercantile Exchange	40,000 pounds	1/1971
NYSE	New York Futures Exchange	US$500 × NYSE composite stock index	1/1983
Platinum	New York Mercantile Exchange	50 troy ounces	1/1973
S & P 500	Chicago Mercantile Exchange	US$500 × S&P 500 stock index	1/1983
Silver	Commodity Exchange Inc.	5000 troy ounces	1/1977
Soya beans	Chicago Board of Trade	5,000 bushels	1/1969
Soya bean oil	Chicago Board of Trade	60,000 pounds	1/1969
Swiss franc	Chicago Mercantile Exchange	SF 125,000	1/1969
Wheat	Chicago Board of Trade	5,000 bushels	1/1981
World sugar	New York Coffee, Sugar & Cocoa Exchange	50 long tons (112,000 pounds)	1/1975
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

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Table 1
Summary statistics for weekly futures returns

The return is measured as the difference in logarithmic weekly settlement prices (Wednesday – Wednesday), in percent. The sample period is from July 1983 to June 2000. There are 886 weekly return observations for each contract. The Market Portfolio denotes the equal-weighted portfolio of all the futures contracts in the sample. ρ_j is the jth order autocorrelation coefficient of returns for individual contracts. Volume and open interest indicate the average weekly trading volume and open interest of the contract over the sample period respectively, which are measured in number of contracts. * denotes that the parameter is significantly different from zero at the 5% level or higher.

	Mean	**St. Dev.**	**Max**	**Min**	**Volume**	**Open Interest**	**Autocorrelation**			
							ρ_1	ρ_2	ρ_3	ρ_4
Financials										
Eurodollar	0.005	0.210	1.543	-1.415	229,655	1,433,193	0.002	-0.034*	-0.007	-0.098*
T-notes	0.039	0.979	5.317	-4.938	56,826	206,690	-0.031*	0.041*	0.022	0.030
T-bills	0.004	0.203	1.956	-1.463	5,300	28,490	-0.040*	-0.048*	-0.027	0.038
S&P 500	0.269*	2.145	7.856	-16.638	67,857	299,682	-0.032*	-0.007	-0.014	-0.042*
NYSE	0.236*	2.087	8.034	-15.278	5,913	6,669	-0.027*	0.001	-0.017	-0.040*
Currencies										
British pound	0.010	1.560	8.091	-10.207	11,279	35,969	-0.020	0.000	-0.033	0.012
Deutsche mark	0.036	1.576	8.371	-7.474	28,977	67,682	-0.035*	0.051*	-0.033	0.017
Japanese yen	0.107	1.609	12.655	-6.612	21,626	63,160	-0.002	0.011	0.007	0.002
Swiss franc	0.044	1.708	8.446	-7.294	16,771	113,083	-0.002	0.065*	0.007	0.020
Agriculturals										
Corn	0.005	3.170	10.9.9	-11.111	51,790	236,396	-0.001	0.039	-0.019	0.024
Cotton	0.037	4.089	11.253	-16.023	6,954	43,695	-0.002	0.015	-0.023*	0.069*
Feeder cattle	0.052	1.876	9.077	-9.132	1,997	1,2766	-0.011	-0.036*	0.015	0.019
Live cattle	0.036	2.194	8.278	-9.133	14,523	71,077	-0.069*	-0.003	0.019	-0.003
Soybeans	0.020	2.939	13.602	-15.768	41,079	117,835	-0.038*	0.027	-0.022	-0.023
Soybean oil	0.036	3.338	14.273	-15.162	17,699	81,365	-0.065*	0.075*	-0.035	0.039
World sugar	0.131	5.527	18.650	-12.191	23,001	78,061	0.002	0.070*	-0.034	0.058
Wheat	0.027	3.292	16.954	-18.332	19,398	40,091	-0.026*	-0.033*	-0.025	-0.012
Commodities										
Cocoa	-0.027	3.915	19.132	-14.251	6,081	55,124	-0.059*	-0.023	-0.008	0.017
Coffee	0.106	5.471	19.309	-12.395	6,503	30,738	-0.031*	-0.027	-0.075*	-0.014
Crude oil	0.120	4.886	14.398	-18.021	78,212	289,357	-0.073*	0.067*	-0.045*	-0.010
Gold	-0.024	1.885	12.869	-8.136	30,781	140,067	-0.092*	-0.041*	0.074*	0.093*
Heating oil	0.118	4.920	17.496	-15.265	25,116	100,579	0.007	-0.012	-0.0608	0.032
Platinum	0.076	3.056	19.034	-13.923	3,279	17,561	-0.097*	-0.010	0.010	0.058*
Silver	-0.040	3.385	15.031	-12.044	17,492	87,155	-0.032*	-0.035*	-0.059*	0.084*
Market Portfolio	0.009	0.949	3.199	-4.407	32,838	152,354	-0.059*	0.001	-0.068*	0.027

Table 2
Profitability of contrarian strategy

This Table reports the profitability of contrarian portfolio strategy applied to the weekly returns of 24 futures contracts. The sample period is from July 1983 to June 2000. There are 886 and 853 weekly return observations for each contract for the Calendar-Day data and Trading-Day data respectively. The portfolios use weights based on the deviation of the return on ith contract in the previous week from the return on an equal-weight market index over the same period. All profit estimates and aggregate investment weights are multiplied by 1000. Aggregate investment weight is defined as $I_t = \sum_{i=1}^{N} |w_{i,t}|$, where $w_{i,t}$ is the weight of contract *i* at time *t*, and the weekly return $f_t = E[\pi_t]/(0.5 * I_t)$. The Column Calendar-Day Data denotes the returns are computed from the Wednesday-to-Wednesday settlement prices, while the Column Trading-Day Data means that the data use the interval of 5-trading-day as a week. The numbers in parentheses are t-statistics for the null hypothesis that the relevant parameter is zero, and the standard errors are corrected using the Newey-West procedure. ** denote significance at the 1% level.

	Calendar-Day Data	**Trading-Day Data**
Winner profits	0.009	0.015
	(0.83)	(1.33)
Loser profits	0.028	0.035
	(3.01)**	(3.50)**
Average profits	0.037	0.050
	(2.72)**	(3.40)**
Aggregate investment	23.442	22.662
	(19.56)**	(17.06)**
Return (%)	0.311	0.436
	(2.70)**	(3.53)**

Table 3
Decomposition of contrarian profits

The expected profits are computed as $\hat{E}[\pi_t] = \hat{O} + \hat{C} - \sigma^2(\hat{\mu})$, where $\hat{O}$ is the average first-order autocovariance of weekly returns on the N contracts in the contrarian portfolio, $\hat{C}$ is (approximately equal to) the first-order autocovariance in weekly returns on the equal-weighted portfolio of N contracts, and $\sigma^2(\hat{\mu})$ measures the cross-sectional variance in mean returns of all individual contracts. The Table also reports the percentage contributions of $\hat{O}$, $\hat{C}$, and $\sigma^2(\hat{\mu})$ to $\hat{E}[\pi_t]$. The sample period is from July 1983 to June 2000. There are 886 weekly return observations for each contract. t-statistics are for the null hypothesis that the relevant parameter is zero, and the standard errors are corrected using the Newey-West procedure. ** denotes significance at the 1% level.

	$\hat{E}[\pi_t]$	$\hat{O}$	$\hat{C}$	$\sigma^2(\hat{\mu})$
Average profits (cents)	0.037	0.042	-0.004	0.001
t-value	2.71**	2.92**	-1.45	6.35**
Percentage of total profits	100%	112.1%	-10.6%	-1.54%

Table 4
Transaction costs and contrarian profits

This Table reports the profitability of contrarian strategy applied to weekly futures returns after corrections for transaction costs. The sample period is from July 1983 to June 2000. There are 886 weekly return observations for each contract. The contrarian portfolios are constructed using weights based on the previous week's contract performance relative to a market portfolio. The average profit after deducting transaction costs is defined as $\pi_t = \sum_{i=1}^{N} w_{i,t} f_{i,t} - c\left|w_{i,t} - w_{i,t-1}\right|$, where c denotes the one-way transaction cost (commissions and one half the bid-ask spread) per dollar transaction, and $w_{i,t}$ is the weight of contract *i* in week *t.* The transaction cost is chosen to be 0.01 percent, 0.05 percent, 0.1 percent and 0.2 percent. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero, and the standard errors are corrected using the Newey-West procedure. * and ** denote significance at the 5% and 1% level respectively.

	One-Way Transaction Cost (%)			
	0.01	**0.05**	**0.10**	**0.20**
Winner profits	0.009	0.008	0.006	0.003
	(0.80)	(0.69)	(0.55)	(0.27)
Loser profits	0.027	0.026	0.025	0.022
	(2.93)**	(2.80)**	(2.64)**	(2.31)*
Average profits	0.036	0.034	0.031	0.025
	(2.65)**	(2.47)*	(2.25)*	(1.80)
Weekly returns (%)	0.301	0.275	0.242	0.176
	(2.61)**	(2.38)*	(2.10)*	(1.53)

Table 5
Profitability of contrarian strategy using an alternative portfolio weighting method

This Table reports the profitability of contrarian strategy applied to weekly futures returns using an alternative portfolio construction approach proposed by Conrad, Hameed, and Niden (1994). The sample period is from July 1983 to June 2000. There are 886 weekly return observations for each contract. The weight of a contract in the contrarian portfolio is calculated as $w_{pi,t} = f_{i,t-1} / \sum_{i=1}^{N_p} f_{i,t-1}$,p = W, L, where N_p is the number of contracts for the winners (W) or losers (L). All profit estimates and aggregate investment weights are multiplied by 1000. Transaction costs are computed as in eq. (9). The profits and return are reported for several values of c: 0.01 percent, 0.03 percent, 0.05 percent and 0.10 percent. t-statistics in the parentheses are for the null hypothesis that the relevant parameter is zero, and the standard errors are corrected using the Newey-West procedure. * and ** denote significance at the 5% and 1% level respectively.

	Profits (cents)	One-Way Transaction Cost (%)			
		0.01	**0.03**	**0.05**	**0.10**
Winners	-0.685	-0.464	-0.218	0.519	1.746
	(-0.33)	(-0.23)	(-0.11)	(0.25)	(0.85)
Losers	5.384	5.061	4.814	4.073	2.837
	(2.85)**	(2.68)**	(2.55)*	(2.16)*	(1.50)
Average profits	6.063	5.525	5.028	3.554	1.091
	(2.31)*	(2.11)*	(1.92)	(1.36)	(0.42)
Mean return	0.606	0.552	0.503	0.355	0.109
(%)	(2.32)**	(2.12)*	(1.97)*	(1.36)	(0.42)