Price Momentum and Trading Volume In Commodity Futures Markets

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Commodities and Momentum

Abstract

In this study, we investigate whether momentum and other trend-following strategies are profitable when implemented in commodity futures markets. The study is motivated by the relatively low transactions costs in commodity futures, the supposition that commodity futures markets and equity markets are likely to be influenced by markedly different factors and the availability of commitments data in futures. We find that momentum profits in commodity futures are highly significant for short and intermediate time horizons, and that abnormal returns are at least equal in magnitude to those that have been reported in stocks. Interestingly, we show that pure trend-following strategies generally perform even better than momentum strategies.

Our results appear to be robust with respect to the particular set of commodities they are implemented with, and also with respect to the time period (although post-1981 profits, albeit still highly significant, are lower then pre-1981). Unlike in the stock market, our results show that trading volume adds little information useful for predicting future returns. However, when we examine the relation between net long positions by trader type and trading rule indicators, we find strong evidence that in most futures markets commercial traders are contrarians, while non-commercial traders use trend-following strategies in the aggregate.

Commodities and Momentum

I. Introduction and Review of the Literature

In recent years, many published studies have reported that relatively simple trading strategies based on past cross-sectional stock returns yield significant future abnormal returns. Both long horizon (3-5 year) contrarian strategies that rely on return reversals, and intermediate horizon (1-12 month) momentum strategies based on return continuations, have been shown to be surprisingly profitable.[1]

Findings regarding the momentum strategies appear to be particularly robust with respect to different methodological approaches, time periods, and countries examined. Jegadeesh and Titman (1993) were the first to report significant intermediate horizon momentum profits in the U.S. stock market. Using a different methodological approach, Conrad and Kaul (1998) nevertheless report similar findings. Conrad and Kaul, as well as Grundy and Martin (2001) show that the momentum strategies work in all subperiods they examine, being consistently profitable in the U.S. stock market since the 1920's. Similarly, Jegadeesh and Titman (2001) find that in the 1990 - 1998 period (which was not included in their original 1993 paper) momentum strategies continue to be profitable to about the same degree as earlier; that is, the best strategies earn abnormal returns of approximately one percent per month, before trading costs are considered. Rouwenhorst (1998) examines stock returns in twelve European markets between 1980 and 1995. He provides evidence that international equity markets exhibit medium-term return continuation across all sample markets. He also suggests that there exists a common factor driving the profitability of momentum strategies since the international momentum returns are correlated with those of the United States. Chan, Hameed and Tong (2000) find statistically significant evidence of momentum profits implemented with international stock market indices. In a further investigation, Chan et al. examine the role of trading volume and return continuation. They find higher momentum profit

[1] The long horizon contrarian strategies have been examined by DeBondt and Thaler (1985, 1987), and Conrad and Kaul (1998) in U.S. Markets, and by Richards (1997) in an international context. The momentum literature is reviewed in more detail below.

portfolios are associated with higher trading volume in the previous period. Therefore, they believe that volume plays an informational role when implementing a momentum strategy.

The supplemental information provided by trading volume is confirmed by Lee and Swaminathan's (2000) comprehensive investigation of return momentum and volume in the U.S. equity market. Their results show that over a longer time horizon (3- to 5-years), initial winner portfolios significantly underperform initial loser portfolios and suggest that at least a portion of the initial momentum gain is from an "overreaction." Adding the information on trading volume to a momentum strategy, they find that past trading volume predicts both the magnitude and the persistence of future price momentum. Specifically, high (low) volume winners (losers) experience faster momentum reversals. Therefore, they conclude that the information contained in past trading volume can be used to explain short and medium time horizon underreaction and long term overreaction effects.

The causes of momentum and/or contrarian profits have been the subject of considerable debate. As Korajczyk and Sadka (2004) note, the consensus in the literature is that risk factors fail to completely explain intermediate horizon momentum profits. Fama and French (1996) concede that their three-factor asset pricing model does not explain returns to momentum portfolios; Grundy and Martin (2001) confirm that the momentum strategy's average profitability cannot be explained as a reward for bearing the dynamic exposure to the three factors of the Fama and French model, nor by exposure to industry factors. Nevertheless, some studies, e.g. Conrad and Kaul (1998), have indicated momentum profits could be a by-product of certain stocks being riskier than others in some unknown way, and thus having higher expected returns. This is because momentum strategies take long (short) positions in stocks with high (low) past returns; if these past returns are high (low) because of unknown systematic risk factors, then the same stocks should continue to earn relatively high (low) returns in future periods. If this interpretation is correct, then momentum profits can be consistent with market efficiency.

Conrad and Kaul (1998) argue that the cross-sectional variation in the mean returns of individual securities plays an important role in their profitability, and could potentially account for the profitability of momentum strategies. However, more recent findings cast substantial doubt on the Conrad and Kaul hypothesis. If momentum profits were due primarily to cross-sectional differences in mean returns, then past winners (losers) should continue to be superior (inferior) performers indefinitely into the future, but Jegadeesh and Titman (2001) find that momentum portfolio (winners minus losers) returns are positive only during the first twelve months of portfolio formation; if anything, momentum portfolio returns beyond this 12-month horizon are negative.[2]

Taking a different tack, Chen and Hong (2002) and Jegadeesh and Titman (2002) decompose momentum profits, and argue that the profitaility of momentum strategies is mostly due to time series dependence in realized returns rather than cross-sectional variation in expected returns. These findings are interesting because a large number of empirical studies have examined trend-following trading strategies in stocks, currencies and commodities. These strategies are more directly designed to exploit pure time series dependence in returns than are momentum strategies, because the latter also have a cross-sectional component. Yet, as Sullivan, Timmermann and White (1999) argue, the evidence regarding the performance of pure trend-following strategies, while mixed, does not strongly support the notion that these strategies earn abnormal returns, particularly once data-snooping biases are taken into account. In contrast, most studies that have applied momentum strategies to stock returns found that these strategies are highly profitable, and the almost uniformly good performance of momentum strategies across different time periods and countries suggests that data-snooping does not fully explain these findings.

We suspect that the divergent findings regarding momentum and trend-following strategies in the literature stem from differences in *research design* rather than from any inherent superiority in the momentum decision rule per se. Most momentum studies have used monthly data across many decades and include a large cross-section of stocks, some of which are implicitly purchased and some of which are sold short, thus ensuring that much of the idiosyncratic risk associated with the positions generated by the momentum rules is eliminated. In contrast, studies that have examined trend-following trading rules

[2] As another risk-based explanation, Chordia and Shivakumar (2002) allege that momentum profits can be accounted for by exposure to macroeconomic risk factors; however, Griffin, Ji and Martin (2003) demonstrate that this linkage does not exist in an international context.

typically used daily data over a shorter time horizon, and have not aggregated the returns across securities. An interesting question is whether previously applied trend-following trading rules would also be found profitable if they were examined with the research design typical of a momentum study. We explore this issue extensively for the commodity futures dataset in our study.

The robustness and persistence of momentum profits could possibly suggest that market prices are driven by irrational agents. Jegadeesh and Titman (1993) initially suggested that individual stock momentum might be driven by investor underreaction to firm-specific information. Furthermore, Chan, Jegadeesh, and Lakonishok (1996) show that stock prices underreact to earnings news and momentum profits concentrate on the subsequent earnings announcements. Daniel, Hirshleifer, and Subrahmanyam (1998) develop a theory based on investor overconfidence and on changes in confidence resulting from biased self-attribution of investment outcomes. Their theory implies that investors overreact to private information signals and underreact to public information signals. Barberis, Shlefier, and Vishny (1998) present a model based on psychological evidence and produce a wide range of over- and under-reaction values. Hong, Lim, and Stein (2000) find that momentum strategies work better among stocks with low analyst coverage when holding firm size fixed. In addition, the effect of analyst coverage is greater for stocks that are past losers than it is for past winners.

The purpose of our study is to conduct a comprehensive examination of momentum and other trend-following strategies in commodity futures markets, using a research design that is typical of momentum studies applied to stock returns. Because, to our knowledge, ours is the first study that explicitly examines momentum strategies outside of equity markets, and because commodity futures differ from stocks in important ways, we believe our study makes a useful contribution to the literature.

Regarding the differences between stocks and commodity futures, three considerations, in particular, stand out. First, the relatively low transactions costs in futures markets, and the ease of taking short positions, imply that momentum strategies can be implemented at much lower cost than in the stock market. Numerous studies have estimated trading costs in futures markets; See, for example, Followill and Rodriguez (1991), Laux and Senchack (1992), Fleming, Ostdiek and Whaley (1996), and Locke and

Venkatesh (1997). All of these studies agree that effective bid-ask spreads in virtually all futures are less than $40 per contract; in most cases, they are considerably less. The most accurate study to date is almost certainly that of Locke and Venkatesh (1997). They obtained proprietary data from the Chicago Mercantile Exchange and directly calculated average customer transactions costs from the futures trade register, for 12 different commodities over the period 1/1/1992 – 6/30/1992. Their results are reproduced in the second column of Table 1. Based on the Locke and Venkatesh estimates of effective bid-ask spreads, and assuming additional transactions costs of $10 per contract to reflect a typical discount broker commission that a representative investor might pay when trading multiple contracts, we calculate total round-turn transactions costs as a percentage of contract value for these 12 CME commodities, many of which are all also included in our study. These estimates range from a low of 0.002% of notional contract value for Eurodollar futures to a high of 0.146% for Pork Bellies. The currency and financial futures all have total transactions costs of 0.036% of contract value or less, while the livestock and lumber futures are in the range of 0.044% to 0.146%.

< INSERT TABLE 1 HERE >

It is instructive to compare these estimates of transaction costs in futures to previously published estimates of round-turn transaction costs in stocks prior to the decimalization of stock quotes in early 2001. The latter range from 0.56% of transaction value for large institutional investors buying S&P 500 stocks [Fleming, Ostdiek and Whaley (1996)] to greater than 4% for trades in small capitalization/low price stocks [Stoll and Whaley (1983); Bhardwaj and Brooks (1992)]. Given these transactions costs, it is hardly surprising that Korajczyk and Sadka (2004) find that certain equally-weighted momentum strategies that look good on paper are difficult or impossible to profitably implement in practice. Indeed, Lesmond, Schill and Zhou (2004) go further: they show that stocks used in momentum strategies are disproportionately drawn from among stocks with high trading costs, and that it is doubtful that any such strategies are profitable in the stock market once transactions costs are fully and properly tallied.

An additional issue is that the implementation of momentum strategies requires a zero-cost trading strategy, whereby securities that are predicted to earn relatively poor returns are sold short, with proceeds from these short sales used to finance the purchase of securities expected to earn superior returns. In futures markets, taking a short position (i.e. contractually agreeing to deliver the underlying commodity at a future date) is as easy as taking a long position; there are no special restrictions on short positions, and transactions costs associated with them are identical to those on long positions. In contrast, short-sellers in stock markets generally do not receive use of (or interest on) the short sale proceeds, and the uptick rule prevents short sales whenever the latest recorded transaction price is below the previously-recorded price. Given that the majority of momentum strategy returns in the stock market are apparently generated by return continuation among poorly performing stocks, these short sale constraints have a significant impact (Lesmond, Schill and Zhou, 2004). Thus, in sum, it is clearly not an exaggeration to say that the ease of implementing momentum strategies, and transactions costs associated with doing so, are orders of magnitude less in commodity futures markets than in stock markets. Consequently, finding momentum profits in commodity futures could constitute much stronger support for behavioral models, which attribute momentum profits to cognitive biases by investors, because the existence of momentum profits could not convincingly be attributed to market frictions that prevent informed traders from arbitraging away price discrepancies induced by noise traders.

The second reason why examining momentum strategies in commodity futures markets is likely to yield useful insights is that returns on commodity futures are likely to have very different time series properties. Unlike stocks, commodity futures prices are not driven by corporate earnings announcements. Moreover, commodities may have very dissimilar exposures to macroeconomic shocks. In the 1970's, for example, when inflation was high, stocks performed poorly, but the prices of most commodities rose by more than general inflation would have warranted. On these grounds, also, we believe that finding momentum profits in commodity futures could therefore point to broader, more general manifestations of cognitive bias by investors, as opposed to earnings surprises, institutional constraints or other factors unique to the stock market, as their ultimate cause.

A final reason for examining momentum in commodity futures markets is the availability of interesting data on trader positions in futures markets that is not generally available in the stock market. In

U.S futures markets, large traders must periodically report their open positions to the Commodity Futures Trading Commission (CFTC), and the CFTC, in turn, publishes this information in the Commitments of Traders (COT) report. From this data, it is possible to discern the temporal variations in net long or net short positions of commercial, non-commercial and non-reporting traders in each futures market, and to ascertain for each class of traders whether, in the aggregate, they pursue momentum or contrarian strategies. Finding that different classes of traders pursue different strategies could shed new light upon the underlying reasons for the profitability of momentum strategies.[3]

The main results of our study are very interesting. In contrast to previously-reported findings in equity markets, we find no significant long-horizon contrarian profits in commodity futures. However, momentum profits are highly significant for short and intermediate time horizons, and the abnormal returns earned by the best strategies are at least as large as those that have been reported in stocks. When we compare the profitability of momentum strategies, which have both a time series and a cross-sectional component, to those from various trend-following trading rules that focus only on time-series dependence in returns, we find that the trend-following strategies perform at least as well, if not better, than the momentum strategies. This finding suggests that momentum profits are likely generalizable to most any trend-following trading rule, and even though there are no earnings announcements in commodities, investors appear to initially underreact to new information to about the same degree that they do in the stock market. Our results also, however, suggest that some of the trend-chasing profits are due to eventual investor overreaction: when we examine returns to momentum or DMAC portfolios out to a horizon of 24 months post-formation, we find that these momentum portfolios earn large positive profits for the first 11 post-formation months, but then often earn significant negative returns between months 12 and 24. These findings are similar to those reported by Jegadeesh and Titman for U.S. stocks in the pre-1990 period.

[3] In an interesting study using a unique data set, Grinblatt and Keloharju (2000) are able to conduct a disaggregation by trader type for the Finnish stock market. They find that foreign investors tend to be momentum investors and earn abnormal returns at the expense of domestic household investors, who tend to be contrarians.

Our results appear to be robust with respect to the particular set of commodities they are implemented with. We show that limiting the strategy to only those markets where prices can depart from full carry does not change the basic conclusions regarding the profitability of momentum or contrarian strategies. We also show that 32 out of 35 commodities make positive contributions to the 2-month formation period momentum strategy and to the 1 month / 6 month / .025 DMAC trading rule which we treat as representative of pure trend-following strategies. Finally, we show throughout the paper that our results are reasonably robust with respect to the time period examined (although post-1981 profits, albeit still highly significant, are lower then pre-1981). The robustness of our basic findings across two very different subperiods suggests that our findings are not solely attributable to data-snooping biases.

Our results incorporating past trading volume show that, unlike in the stock market, volume adds little information; that is, when we control for price momentum, there generally are no significant differences in the returns of high vs. low volume commodities. However, when we examine the temporal relations between net long positions by trader type and trading rule indicators, some very interesting findings emerge. We find strong evidence that in most futures markets commercial traders are contrarians, while both non-commercial traders and, to a lesser extent, non-reporting traders use trend-following strategies in the aggregate.

The balance of the paper is organized as follows. Section II describes our sample and methodology for constructing unit value indices. Section III contains our basic momentum and trend-following trading rule tests and results. Section IV examines the relation between momentum and trading volume, and Section V the relation between trading rule indicators and the positions of various classes of traders. Section VI concludes the paper.

II. Data and Construction of Unit Value Indices

From the Commodity Research Bureau (CRB) historical data CD, we extract daily closing prices, trading volume and open interest for thirty-five commodity futures markets. In each case, we use the nearby contract, rolling over to the next contract on the last day of the month before contract expiration.

To avoid distortions caused by contract rollovers, we ensure that percentage price changes are always calculated using data from the same contract; thus, on rollover days we extract prices for both the nearby and first-deferred contracts.[4] Once we have obtained a series of daily returns (adjusted for rollover) for each commodity, we construct a daily unit value index from the daily returns.

For the purpose of constructing series used to measure *formation period returns* for momentum and other trend-following strategies, we convert the data for each commodity to a monthly frequency by sampling the daily unit value indexes on the last trading day of each calendar month, and by summing the daily volume and open interest within each calendar month. However, series used for the measurement of *holding period returns* are constructed differently. This is primarily because some of the contracts included in our study have price limits, whereby the maximum allowable price fluctuation per day is limited by the exchange. On days when price limits are reached, trading effectively shuts down, and traders must wait until the limits are no longer binding before trading activity resumes. Clearly, the implementation of a momentum strategy requiring monthly rebalancing will be inhibited if some markets are closed due to price limits.

To ensure that the results we report are not an artifact of price limits and that our strategies are actually implementable, holding period returns are measured using a dataset from which price limit days are removed. Specifically, we identify price limit days for each commodity from return and trading volume data, and we create a second monthly unit value index for each commodity which is sampled on the *first day of each calendar month that is not a limit day.* Thus, throughout the study we use unadjusted monthly unit value indices (which are sampled on the last day of each month) in the formation period to generate trading signals, and the adjusted unit values to compute returns during the holding period, which starts the following month. This procedure ensures that there is at least a one-day lag between the generation of trading signals and the taking of positions, and that both entry and exit trades are delayed until price limits are no longer binding.

[4] This issue does not arise for trading volume or open interest, because the CRB reports total volume and open interest across all contracts currently traded; i.e. volume and open interest are not specific to one expiration month.

The commodities in our study are traded on several different exchanges, and have different start dates. We include in our study all futures markets carried on the CRB CD that have at least ten years of available data; however, we exclude stock index and interest rate futures, as we wish to focus this study on markets that have not been previously examined in a momentum context. Nine of the commodities included in our study begin on July 1, 1959. Nine begin sometime in the 1960's, ten in the 1970's, and the remaining seven commodities start in 1980 or later. The last trading day for each commodity is December 31, 2003. Table 2 lists the 35 sample commodities, along with their start dates and the commodity categories they belong to. The major categories of commodities include: currencies, energy, foodstuffs, grains, industrials, livestock and metals.

< Insert Table 2 here >

Among these categories, currencies and precious metals (Gold, Platinum and Silver) are generally considered to be "full carry" markets, in the sense that the cost of carrying the spot commodity for delivery against a futures contract consists almost exclusively of financing costs. In other markets, which are not full carry, storage, insurance and transportation costs associated with arbitrage between cash and futures markets are nontrivial. Consequently, the association between cash and futures prices in full carry markets is likely to be much closer than in non-full carry markets, and the two types of markets may exhibit different time series characteristics. For this reason, when implementing momentum strategies, we do so for both all commodities, and for a restricted sample that excludes full carry markets. This non-full carry sample excludes all of the currencies, the precious metals, and the CRB index.

The data on trader positions, as published in the Commitments of Traders (COT) Report, is downloaded from the CFTC's web site (http://www.cftc.gov/dea/history/deahist-cot-ftp.htm). The file provided by the CFTC contains long and short positions (in terms of number of contracts) by trader type, and total open interest, for each futures market. From these figures we calculate net long positions for each trader type i in month t as (Contracts Long_{it} – Contracts Short_{it}) / Open Interest_t. Because the open interest measures total open interest in the market without reference to the type of trader, the sum of the net long positions (as we define them) across the three classes of traders (commercial, non-commercial, and non-reporting) must equal zero. Like our volume data from the CRB, the COT data is aggregated across all contract months. The data is not currently available from the CFTC prior to 1986. It is available on a mid-month and end-of-month basis between January 1986 and September 1992 (although the CFTC cautions that the mid-month data may contain errors), and on a weekly basis after October 1992. To construct end-of-month COT data which matches our trading rule indicators as closely as possible, we use only the last week in each calendar month after October 1992.

III. Momentum and Trend-Following Trading Rule Tests and Results

The momentum tests are conducted as follows. At the end of each calendar month, from July 1959 to December 2003, we rank all eligible commodities independently on the basis of past holding period returns, where the return for each commodity in each month is measured as the percentage change in the unit value index relative to the reference month.[5] We form ten different formation periods *J*, where *J* ranges from 1 month to 60 months. Based on each commodity's past returns, we then group it into one of three portfolios (P1 to P3), where P1 consists of past winners (top 1/3 of commodities, based on formation period return) and P3 of past losers (bottom 1/3 of commodities). We then measure K-period holding period returns for each commodity, using a different unit value series which is sampled on the first trading day of each calendar month that is not a price limit-impacted day.

To test the significance of momentum profits in each portfolio, we use *t*-statistics that are asymptotically distributed as *N* (0,1), under the null hypothesis that the "true" profits are zero. Since in general we use overlapping data, we correct our standard errors for heteroskedasticity and autocorrelation

[5] Margins in futures markets can be posted using Treasury Bills. Consequently, the "return" as we calculate it is an excess return that would be earned by an investor who uses no leverage (i.e. posts T-bills with a market value equal to the full contract value of the futures contract) and takes a long position.

using the Newey and West (1987) adjustment. In every case, the number of lags used in the adjustment equals the number of months of overlap.[6]

To investigate the robustness of returns to momentum strategies, we examine the performance of momentum portfolios in two separate time periods, the pre-1981 (July 1959 – December 1981) and post-1981 (January 1982 – December 2003) subperiods of approximately equal length. 1981 represents a convenient break point between a period of generally rising inflation (1960-81) and generally falling inflation (1982-2003). Further, Irwin and Yoshimaru (1999) argue that investments in managed futures funds (which combine investors' moneys for the purpose of speculating in futures and options markets) have exploded since the early 1980's, growing from $200 Million in 1980 to $19 Billion in 1994, and that these funds tend to engage in positive feedback trading strategies. If more traders are pursuing such strategies, we might intuitively expect momentum profits to be lower in our second subperiod.

< insert Table 3 here >

To begin the analysis, we first implement strategies for which the length of the formation period and the future holding period is identical, i.e. $J = K$. Similar to Jegadeesh and Titman's (1993, 2001) approach, we divide our sample commodities into three portfolios based on their past returns, and P1-P3 is the difference in realized profits between winners and loser portfolios, i.e. profits accruing to a strategy of taking long positions in past winners and short positions in past losers. Table 3 summarizes average realized profits for momentum strategies implemented with all commodities in the entire sample period, as well as broken down by pre- vs. post-1981. Table 3 also reports the *t*-statistics in parentheses for testing the statistical significance of the average profits (losses).

[6] The use of unadjusted average P1-P3 returns, along with Newey and West standard errors to assess statistical significance, has been criticized in some studies on the grounds that there may be a downward bias in small samples in computing the P1-P3 returns, and because statistical inferences will be invalid if the returns are not normally distributed. Mostly, however, these issues pertain to assessing the profitability of long-horizon contrarian strategies, which are not the main focus of our study. Nevertheless, following Richards (1997), we conducted a bootstrap experiment on a sample of 18 commodities for the 1982-2003 period. Briefly, the procedure consisted of a temporally-random resampling of the monthly logarithmic returns in our dataset 1000 times, and then comparing the mean returns resulting from the momentum strategies applied to the actual data to those obtained using the randomized data. Heeding the warning of Jegadeesh and Titman (2002), we conducted each resampling without replacement, and we preserved the contemporaneous relations in the monthly data across commodities. The results

Panel A in Table 3 contains the realized profits for our entire sample period. These results show that momentum strategies with formation and holding periods of up to 9 months uniformly earn significant positive abnormal returns. If we divide the total holding period returns by the length of the holding period, then it appears that the intrinsic profitability is highest at the shortest horizons, e.g. 1-2 months. The t-statistics are also greatest at these horizons, but they do remain highly significant out through 9 months. These findings, both in terms of the magnitude of momentum profits and their significance, are similar to what have been reported in equity markets by Jegadeesh and Titman and others, although the horizon over which momentum strategies are profitable appears to be slightly shorter than when momentum strategies are implemented with individual stocks. In this respect, our findings more closely parallel Chan, Hameed, and Tong's (2000) study of momentum effects in international stock market indexes. We should also note that, in contrast to findings in equity markets, our results show virtually no evidence of long-horizon contrarian profits. We do find significant contrarian profits at the 24 month horizon for our full sample period, but at any other horizon longer than 9 months, or for subsamples of the data, there is no evidence that contrarian strategies are profitable.

Panels B and C in Table 3 report profits from two subsample periods: pre- and post 1981. Not surprisingly, in light of the fact that the first period was characterized by rising inflation and commodity prices, and the second period by the opposite effects, we see that in Panel B, the profits in general (for all portfolios and horizons) are higher than in Panel C. Generally, during the pre-1981 period, the past winner portfolios post significantly positive subsequent returns while the past losers show only small losses. Conversely, post-1981, the past winners at best break even, while the past losers show significant losses in the post-formation period. However, momentum strategies that simultaneously take long positions in past winners, and short positions in past losers (P1-P3) are significantly profitable in both periods, although the profitability appears lower, and slightly less significant, post-1981. Another

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of this exercise (not reported) revealed no evidence of substantial bias in calculating mean P1-P3 returns at any horizon, and gave no indication that the inferences based on Newey and West standard errors were misleading.

difference appears to be that, in the pre-1981 period, the significance of the momentum profits extends out to formation and holding priods of 9 months, whereas post-1981 the significance ends after 6 months.

We next examine whether momentum profits differ depending on the type of market. In order to do so, we distinguish between those futures markets that are reasonably close to full carry (i.e. precious metals, currencies), where the underlying commodities are easily and cheaply storable, and where the futures price approximately equals the spot price multiplied by one plus the periodic interest rate (precious metals) or interest rate differential (currencies), and those that are not full carry (i.e. energy, foodstuffs, grains/oilseeds, livestock/meats), where storing and delivering the underlying commodity are not necessarily cheap, where supply and/or demand are seasonal, and where the futures price can fluctuate much more freely relative to the spot price.

< Insert Table 4 here >

In Table 4, we report average realized profits for momentum strategies implemented only with non-full carry commodities (25 commodities) selected from our full sample of 35 commodities. The format of Table 4 is identical to Table 3: Panel A shows the profits from our entire sample period for formation/holding periods up to 60-months, while Panels B and C contain results, respectively, for the pre- and post-1981 periods. A comparison of the two tables indicates that the profits obtained from implementing momentum strategies exclusively with non-full carry commodities are very similar to those obtained when all 35 commodities are used. Indeed, in all three panels, there are virtually no noteworthy differences between the two sets of results. Consequently, in the rest of the paper, we report results only for strategies implemented with the full set of 35 commodities.

As motivated in the introductory section, we next examine if trend-following trading rules designed to exploit time-series dependence in returns work as well as the momentum strategies. We estimate profits accruing to various parameterizations of two simple trend-following approaches in our study. In the dual moving average crossover (DMAC) strategy, a long position is taken in a commodity if the short-term moving average unit value (STMA) exceeds the long-term moving average unit value (LTMA) by B percent, i.e. if STMA > LTMA*(1+B), and a short position is taken if STMA < LTMA*(1-

B). No position in a commodity is taken when STMA is within the band, i.e. when LTMA*(1-B) < STMA < LTMA*(1+B). Given our monthly dataset, we limit STMA to 1 month (i.e. the STMA is the latest end-of-month unit value), while for LTMA we alternately use 3, 6, 9 and 12 months. For B we use 5% per annum, which implies that B=.0125, .025, .0375 and .05, respectively, at 3, 6, 9 and 12 month horizons for LTMA. The other approach we examine is the channel strategy. In this strategy, a long position is taken in a commodity if the latest end-of-month unit value exceeds the maximum of the end-of-month unit values over the previous L months, and a short position if the latest unit value is less than the minimum of the end-of month unit values over the previous L months. Again, if the latest unit value is between the minimum and maximum observed over the previous L months, no position is taken in the commodity. We examine channel rules with lag lengths of 3, 6, 9 and 12 months.[7]

In order to compare trend-following and momentum strategies, and to provide a better indication of the profit potential of these approaches, we focus on one-month holding periods. Table 5 reports mean returns and Newey and West t-statistics associated with 4 different parameterizations each of momentum, DMAC and channel strategies, for both the entire sample and for the pre-1981 and post-1981 periods. Each month, the P1 portfolios contain commodities in which a long position is taken (i.e. in the top third in terms of formation period return in the case of momentum strategies, above the upper bound of the band in the case of DMAC strategies, or above the previous L-month maximum in the channel approach), the P2 portfolios contain those commodities on which a particular system is neutral, and the P3 portfolios those commodities in which a system indicates that a short position is warranted.

< Insert Table 5 Here >

The results in Table 5 strongly indicate that there is nothing inherently unique in the momentum strategies, because all of the trend-following strategies yield significant profits in all time periods examined. Indeed, we find that the profitability of DMAC and Channel strategies actually appears to be

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[7] Both DMAC and Channel strategies have been extensively used in previous studies. For example, Brock, Lakonishok and LeBaron (1992) and Sullivan, Timmermann and White (1999) apply DMAC strategies to the S&P 500 index, and Szakmary and Mathur (1997) use DMAC rules in currencies. Channel strategies have been applied in currency futures by Taylor (1994) and in a broad cross section of futures by Lukac and Brorsen (1990).

higher. For the entire 1959-2003 sample period in Panel A, the long-short (P1-P3) momentum strategies earn between approximately 1.0% and 1.4% per month; the P1-P3 DMAC strategies earn between 1.5% and 1.8%, and the P1-P3 channel strategies between approximately 1.7% and 2.1%. In the post-1981 period (Panel C), momentum strategies have a profitability range of about 0.6% to 1.1%; corresponding ranges for DMAC and channel rules are 1-1.4%, and 1.4-1.8% per month, respectively. Another noteworthy feature of the results is that for every single strategy examined, in every subperiod, we observe a monotonic relation between mean realized return and portfolio classification based on past returns: the P1 portfolios always outperform the P2 portfolios, and the P2 always outperform the P3.[8]

< Insert Table 6 Here >

Further insight into the amazing profitability of trend-following strategies in commodity futures can be gleaned from the results presented in Table 6. Here we disaggregate returns on a commodity-by-commodity basis for two representative trading rules, the 2-month formation period momentum strategy and the 1 month / 6 month / .025 DMAC rule. For each commodity, we report the mean return in those months when it is assigned to portfolio P1 and to portfolio P3, the difference in means between those months when it is in P1 and when it is in P3, and a t-statistic for a two-tailed test of the null hypothesis that the difference in means equals zero. The results show that for the 2-month momentum and the 1 month / 6 month / .025 DMAC strategies, 32 out of 35 commodities exhibit positive P1-P3 returns, thus indicating that the efficacy of these strategies is widespread. We note, however, that for only 6 out of 35 commodities in the case of the momentum strategy, and for only 10 of 35 in the case of the DMAC strategy, is the P1-P3 return significantly positive at the 5% level or better. These finings underscore the fact that the huge t-statistics we report in Table 5 arise largely from the pooling of results across markets:

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[8] Keeping in mind the pernicious effects of data mining, we made every possible attempt to *avoid* optimizing the parameters used in the DMAC and channel strategies. For the channel strategies, we report results for all the strategies we estimated. For the DMAC strategies, however, we were forced to try alternative parameterizations of the band width, because the initial band width chosen (20% per annum) resulted in too many commodities being assigned to the P2, as opposed to the P1 or P3 portfolios. In general, we found that higher values of B in the DMAC strategies result in higher mean returns for P1-P3 strategies, but these returns are more volatile due to insufficient diversification within the P1 and P3 portfolios.

by simultaneously engaging in trend-following trading strategies in 35 markets we eliminate much of the idiosyncratic variance and thereby enhance the statistical significance of the mean realized returns.

Our next step is to examine more closely the temporal nature of the returns accruing to trend-following strategies in commodity futures. We want to learn how far into the future these strategies generate positive returns, and if the returns eventually reverse and become negative. We do so by again using the two representative strategies in Table 6 and examining the returns to these strategies from the 1st through the 24th post-formation month.

< Insert Table 7 Here >

Table 7 lists monthly profits accruing to a 2-month formation period momentum strategy, and to a 1 month / 6 month / .025 DMAC rule, from 1 to 24 months post-formation; we report profits for the entire sample period, as well as the pre-1981 and post-1981 periods. In all sample periods examined, the implemented momentum strategy generates uniformly positive profits up to the 11th month post-formation. These positive profits tend to be statistically significant for the first four post-formation months, and again for post-formation months 9-11. Starting with the 12th month, the profitability turns predominantly negative, albeit it is insignificant for most months. The only important difference observed between the pre- and post-1981 periods is that, in the latter period, there is decidedly less evidence of profitability in the 2nd through 4th post-formation months.

The 1 month / 6 month / .025 DMAC strategy in Table 7 exhibits somewhat accentuated performance, both in its initial profitability and later reversals, compared with the 2 month momentum strategy. In virtually all periods, the DMAC strategy has higher profitability in the first 8 post-formation months, and then shows larger reversals in post-frormation months 12 through 15, and 22 through 24.

< Insert Figures 1a-c and 2a-c here >

To make the reversal effects hinted at in Table 7 easier to visualize, the cumulative profits of the momentum strategy by post-formation month are shown graphically in Figures 1a-c, and those arising from the DMAC strategy are shown in Figures 2a-c. Altogether, these figures strongly indicate that while trend-following strategies initially earn positive returns, cumulative profits eventually reverse and fall to very low levels if the positions are maintained long enough beyond portfolio formation. These findings are very similar to those reported by Jegadeesh and Titman (2001) for the pre-1990 period in the U.S. stock market. However, unlike Jegadeesh and Titman, we find that the reversal effect is evident in all subsamples of our data, and does not disappear in the last period. Our findings are thus even more consistent with the predictions of behavioral models than those reported by Jegadeesh and Titman.

Before moving on, it is worthwile to examine two remaining issues that are of obvious interest: whether the trend-following trading profits documented in this study are likely to be related to risk premia, and whether these profits would disappear if transactions costs were taken into account. To address the risk premium issue, we regressed the monthly returns resulting from the 2-month formation period momentum, and 1 month / 6 month / .025 DMAC strategies examined in Tables 6 and 7 against two different sets of factors: the monthly Fama and French (1993) excess market return, book-to-market, and size factors (these were downloaded from Prof. French's website at the University of Rochester), and, separately, three factors shown by Bessembinder and Chan (1992) to be strongly related to commodity futures returns. This latter set consists of the 3-month T-bill yield, the default premium (Moody's BAA long-term corporate bond yield minus AAA yield), and the dividend yield on the S&P 500 index; data on these series were downloaded from the St. Louis Federal Reserve's FRED II database and from Datastream. Our Fama and French factor regression results (not reported in the paper) indicated that these factors are not related to the returns on trend-following strategies in commodity futures. In the case of the Bessembinder and Chan factors, we found that while the factors were in a few cases significantly related to the trading rule returns, they did not in any way explain the *mean profitability* of these returns. We therefore conclude that commonly-used risk premium models are unlikely to explain the profitability of trend-following strategies in commodities.

Given the estimates in Table 1, it is also extremely unlikely that transactions costs eliminate the trading rule profits documented in this study. Consider the 1-month holding period strategies in Table 5, in the *post-1981* period during which the returns to these strategies have been somewhat lower. These returns still range between 0.6% and 1.8% *per month*, with most strategies producing returns between 1%

and 1.4%. Suppose transactions costs, on average, are in the upper-end of the range for the commodities listed in Table 1. A strategy that takes long postions in $10,000,000 worth of commodities (in terms of total contract value) and simultaneous short positions in a different set of commodities with the same total contract value, and does not require positions to be rolled-over during the one-month holding period, would incur 2 sets of transactions costs totalling at most .3% of the $10,000,000 contract value. Thus, even after transactions costs, the strategies simulated here, used without leverage, would earn excess returns (above the T-bill returns earned on margin deposits) in the range of 0.3% - 1.5% per month.

IV. Momentum and Trading Volume

Lee and Swaminathan (2000) study the interaction between past trading volume and past returns in the U.S. equity market. They find that firms with high past turnover ratios exhibit many glamour characteristics and earn lower future returns. This finding, along with other findings in their study, inspires us to investigate the role that past trading volume plays in commodity futures markets. We examine interrelations between return momentum and trading volume by independently sorting these commodities based on their past returns and on their trading volume over the past *J* months, and place each commodity into one of three volume portfolios (V1 to V3), where V1 consists of high volume and V3 low volume. To control for differences across markets relative to market size, for the purposes of this study we define "trading volume" as the total reported volume for a calendar month divided by total open interest. In the context of futures markets, this is analogous to Lee and Swaminathan's (2000) use of monthly volume of shares traded divided by total shares outstanding in stocks.

< insert Table 8 here >

Table 8 reports returns to portfolios formed on the basis of a two-way sort between commodity past returns and past trading volume for the period 1960-1999.[9] To create this table, we sort all sample

[9] We conducted the volume tests in an earlier draft of this study; due to their time-consuming nature, we did not redo these tests when we extended our sample to 2003. However, we do not believe that updating the sample would materially change the results. In addition to the full 1960-1999 sample results shown in Table 8, we conducted tests

commodities at the beginning of each month based on their returns over the past *J* months, and divide them into three portfolios (P1, the winner portfolio to P3, the loser portfolio). We then independently sort these same commodities into three volume portfolios (V1 to V3). V1 represents the highest volume portfolio and V3 represents the lowest volume portfolio. It is portfolios formed from the intersections of these two independent sorts that are examined in Table 8. For example, P1V1 represents mean returns to a strategy that takes long positions in commodities that rank in the top third on the basis of both past returns and past volume, i.e. high volume winners. P1V3 represents low volume winners, P3V1 high volume losers, and P3V3 low volume losers. Because sorts for past return and volume are independent, there are some periods when no commodity simultaneously satisfies both the return condition and the volume condition; at these times it is assumed that no position is taken and a zero return is assigned.

For simplicity, we make the formation period *J* and the holding period *K* identical in Table 8, and examine formation/holding periods of the same length as those reported in Table 3. Each box in Table 8 represents a different formation period J. Within each box, we report returns and associated t-statistics for each of 9 portfolios independently sorted based on past returns and past volume. The most interesting results within each box are contained in the final column. This column gives the returns to strategies that, holding return momentum constant, take long positions in high volume commodities and short positions in low volume commodities. If trading volume adds anything in a momentum framework, then the figures in this column should be significantly different from zero. Most emphatically, this is not what we find: For any J up to 48 months, there is no significant difference in performance for high past volume vs. low past volume portfolios, if we hold past price momentum constant. The only significant figure we obtain is for J=60, where we find that high volume winners significantly outperform low volume winners over the following 60 months. The isolated nature of this result, however, probably indicates that it is coincidental.

Another interesting finding in Table 8 is given in the bottom row of each box, where we test if price momentum is still present when we hold past trading volume constant. At horizons up to 6 months,

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for the 1960-1981 and 1982-1999 subperiods. There were virtually no differences in the results in any important respect across the two periods.

the answer is an unadulterated yes: regardless of volume, price momentum is large and uniformly statistically significant. Beyond J=6, the results are not clear cut. At J=24, the results indicate that a contrarian strategy would have worked for high volume commodities, but at J=60 the polar opposite momentum strategy appears to be profitable. Again, we believe these later findings are due to chance and not indicative of anything substantive. Overall, we believe the results in Table 8 show that trading volume does not contain information that is useful for predicting future returns in commodity futures markets.

V. Trend-Following Trading Rule Indicators and the Commitments of Traders

The availability of Commitments of Traders (COT) data for1986-2003 allows us to examine linkages between trend-following trading rule indicators and the net long positions of various classes of traders for an 18-year period. The goal of this exercise is to ascertain whether each class, in the aggregate, is a "momentum" trader or a "contrarian" trader. For a momentum trader, we would expect to see a positive relation between past returns and the trader's current net long position: when past returns have been high, the trader should be net long in the market to a greater degree than when past returns have been low. Conversely, for a contrarian trader, we expect a negative relation between past returns and the trader's current net long position: when past returns have been high, the trader should be net long in the market to a lesser degree than when past returns have been low. The three classes of traders whose aggregate positions, on a commodity-by-commodity basis, are broken down in the COT database are reporting commercial traders, reporting non-commercial traders, and non-reporting traders. The latter's positions are deduced from knowledge of total open interest in the market, the positions of reporting traders, and the fact that there must be a short position for every long position in futures markets. Most previous studies have categorized commercial traders as "hedgers", but a recent study by Ederington and Lee (2002) in the heating oil market found that the commercial group included some traders with no known positions in cash and/or forward markets; consequently, it may not be appropriate to treat traders who the CFTC classifies as commercial as hedgers. There appears, however, to be universal agreement in the literature that the non-commercial category consists almost exclusively of speculators, while little is known (in the aggregate) about the motivation of non-reporting traders.

We formally estimate the link between net long postions and indicators from the two trend-following strategies that are the focus of Tables 6 and 7 via the following regressions:

(1) $\text{Net Long}_{it} = B_{i0} + B_{i1}\,\text{PMOM}_t + e_t$

(2) $\text{Net Long}_{it} = B_{i0} + B_{i1}\,\text{PDMAC}_t + e_t$

where $\text{Net Long}_{it} = (\text{Contracts Long}_{it} - \text{Contracts Short}_{it}) / \text{Total Open Interest}_t$ for trader type i (alternately commercial, non-commercial and non-reporting) at end of month t, PMOM_t equals 1, 0 or -1, respectively, if the return based on a commodity's unit value index is ranked in the top, middle or bottom third across all commodities over a 2-month formation period ending at the end of month t, and PDMAC_t equals 1, 0 or -1, respectively, if the unit value index of a commodity at the end of month t is > 1.025 times the 6-month average, between .975 and 1.025 times the 6-month average, or < .975 times the 6-month average unit value index. Regressions (1) and (2) are estimated separately for each commodity and trader class.[10]

Estimates of regression (1) for each of 35 futures markets and 3 trader classes are reported in Table 9. With the exception of a few commodities which begin trading after 1986 and/or for which COT data could not be obtained through 2003, these estimates are for the January 1986 – November 2003 period.[11] For each regression Table 9 reports coefficient estimates, t-statistics, and the regression R^2. Looking first at the results across commodities for commercial traders, we note that 34 of the 35 slope (B_1) coefficients are negative; of these, 29 are significantly negative at 5% or better, and 27 at 1% or

[10] Using the COT data, Wang (2003, Table 7) examines the contemporaneous relation between *changes* in net positions by trader type and returns. We conducted Augmented Dickey-Fuller (1979) and Phillips and Perron (1988) unit root tests on the net long series, and determined that none of these series, for any commodity or trader type, contains a unit root. Consequently, we believe that differencing the net long series is unwarranted, and report results for regressions (1) and (2) in levels form. When the regressions are estimated using first differences of both the dependent and independent variables, the r-squares are lower but inferences remain unchanged.

[11] The exceptions, and the associated time periods across which regressions are estimated, are as follows: AD (8/1992-11/2003), CR (10/1986-4/2000), NG (4/1990-11/2003), PA (1/1986-7/2000), RR (8/1987-11/2003) and SE (9/1987-4/2000).

better. These results strongly indicate that in the vast majority of markets, commercial traders trade *counter* to a 2-month momentum strategy, i.e. when the momentum strategy indicates a long position should be taken, in the aggregate these traders *reduce* their net long positions, and vice-versa. Thus, we could characterize commercial traders as contrarians, in the aggregate. In contrast, the non-commercial traders clearly appear to be momentum traders in an aggregate sense: the estimated slope coefficient in each and every commodity for these traders is positive, and 32 of the 35 slopes are significant at 1%. It is more difficult to generalize about the behavior of the non-reporting traders. In 18 markets, we observe significant positive slope coefficients, indicating momentum trading. However, in 4 markets (interestingly, all related to livestock) significant negative slopes indicate that the non-reporting traders tend to be contrarians.

Estimates of regression (2) for each of 35 commodities and 3 classes of traders are reported in Table 10. The Table 10 results produce markedly similar inferences regarding the behavior of the three trader classes as those in Table 9. A significant negative relation is found for commercial traders between net long positions and contemporaneous position indicators from the 1 month / 6 month / .025 DMAC rule, in 28 of the 35 markets examined, and an insignificant negative relation in 6 of the remaining 7. For reporting non-commercial traders, we observe a positive relation in all 35 markets, and the relation is significant (at 1% or better) in 32 cases. As before, the relation between net long positions and the trading rule indicator for non-reporting traders is mixed. What is most noteworthy about the results in Table 10 is the generally high R^2 observed for both commercial and non-commercial traders. For the former group, the R^2 in Table 10 is higher than in Table 9 in 28 cases, and for the later group the R^2 is higher in 31 cases. To us, these results are an indication that the DMAC trading rule is more closely related to the contrarian tendencies of commercial traders and to the positive feedback strategies that seem to be employed by non-commercial traders, than is the momentum rule.

VI. Conclusion

In this study, we investigate whether momentum and other trend-following trading strategies are profitable when implemented in commodity futures markets. The study is motivated by the relatively low transactions costs in commodity futures, by the fact that commodity futures markets and equity markets are likely to exhibit very different time series properties and be influenced by markedly different factors, and by the availability of trader commitments data in commdodity futures markets that may shed further light on which classes of traders engage in momentum trading.

Our main finding is that both momentum and other trend-following strategies generate highly significant positive returns for short and intermediate time horizons, and that the returns earned by these strategies are at least equal in magnitude to those that have been reported in stocks. The fact that pure trend-following strategies such as dual moving average crossover and channel rules generate returns that tend to be even higher than momentum strategies in our study suggests that it is positive serial correlation in asset returns, combined with the research design of momentum studies, that leads to the conclusion that momentum strategies earn significant profits (as opposed to anything particularly magical or unique about the momentum strategy per se).[12] It would be interesting to see if pure trend-following strategies similarly outperform momentum strategies in the stock market.

Our results appear to be robust with respect to the particular set of commodities they are implemented with. We show that limiting the strategy to only those markets where prices can depart from full carry does not change the basic conclusions regarding the profitability of momentum or contrarian strategies. We also show that 32 out of 35 commodities make positive contributions to the 2-month formation period momentum strategy and to the 1 month / 6 month / .025 DMAC trading rule which we treat as representative of pure trend-following strategies. Finally, we show throughout the paper that our

[12] Further results from a bootstrap experiment already described in a previous footnote are also relevant here. When we scramble commodity returns series (without replacement) so as to remove temporal dependence in returns, but leave the distributions of the return series, and contemporaneous cross-sectional relations among them intact, we find that the momentum trading rules applied to the scrambled series do not produce significant profits at any horizon. The implication is that eliminating time-series dependence in the commodity futures' returns eliminates

results are reasonably robust with respect to the time period examined (although post-1981 profits, albeit still highly significant, are lower then pre-1981). The robustness of our basic findings across two very different subperiods suggests that our findings are not solely attributable to data-snooping biases.

The trend-following profits we document are unlikely to be explainable by known risk factors, and are too large to be subsumed by the relatively low transactions costs in futures markets. Our results incorporating past trading volume show that, unlike in the stock market, volume adds little information; that is, when we control for past return momentum, there generally are no significant differences in the realized returns of high vs. low volume commodities. However, when we examine the temporal relations between net long positions by trader type and trading rule indicators, some very interesting findings emerge. We find strong evidence that, in most futures markets, commercial traders are contrarians, and that non-commercial traders use trend-following strategies in the aggregate. While the latter finding was expected, given the prevalence of managed futures funds and commodity pools among reporting non-commercial traders during the 1986-2003 period, the stylized fact that in most markets it is the commercial traders (and not, for the most part, the non-reporting traders) that are contrarians in the aggregate is surprising. While these findings suggest that momentum profits are being driven by hedging pressure, it is not immediately obvious *why* these large, presumably knowledgeable commercial traders are employing contrarian trading strategies when these strategies are unprofitable on average. Are they rationally reducing their risk in some way by doing so? Or are commercial traders contrarians because they are succumbing to behavioral biases such as loss aversion and/or the tendency to lock-in favorable commodity prices too soon? We believe that a more detailed examination of the temporal relations between commercial traders' positions and commodity futures returns, perhaps in a Granger-causality framework, though beyond the scope of this study, is likely to produce further useful insights into the momentum phenomenon in commodity markets.

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momentum profits, and the cross-sectional component of the momentum decision rule does not contribute to its profitability.

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TABLE 1

Estimated Round-Turn Transactions Costs in Futures Markets, 1/1/1992 - 6/30/1992

Commodity	Effective Bid-Ask Spread*	Other Transaction Costs	Average Futures Price	Contract Multiplier	Contract Value**	Transactions Costs as Percent of Conract Value***
Live Hogs	7.30	10	59.1180	400	23647	0.073%
Pork Bellies	10.32	10	34.7100	400	13884	0.146%
Live Cattle	3.07	10	74.8270	400	29931	0.044%
Lumber	15.92	10	236.6500	110	26032	0.100%
Feeder Cattle	9.42	10	78.9580	500	39479	0.049%
Canadian Dollar	6.05	10	0.8402	100000	84020	0.019%
Swiss Franc	20.89	10	0.6783	125000	84788	0.036%
Deutschemark	14.28	10	0.6140	125000	76750	0.032%
Pound Sterling	18.12	10	1.7732	62500	110825	0.025%
Japanese Yen	17.47	10	0.7721	125000	96513	0.028%
Eurodollars	4.81	10	95.8100	10000	958100	0.002%
S&P 500 Index	16.58	10	411.5700	500	205785	0.013%

* Direct estimates from Locke and Venkatesh (1997, Table II, p. 240).

** Equals Average Futures Price x Contract Multiplier

*** Equals (effective Bid-Ask Spread + Other Transactions Costs) / Contract Value

Table 2

List of Sample Commodities

Symbol	Commodity	Start Date	Category	Symbol	Commodity	Start Date	Category
AD	Australian Dollar/US Dollar	01/13/1987	Currencies	**KW**	Wheat, No. 2 Hard Winter	01/05/1970	Grains
BO	Soybean Oil	07/01/1959	Grains	**LB**	Lumber	10/01/1969	Industrials
BP	British Pound/US Dollar	05/16/1972	Currencies	**LC**	Live Cattle	11/30/1964	Livestock
C-	Corn	07/01/1959	Grains	**LH***	Lean hogs	02/28/1966	Livestock
CC	Cocoa	07/01/1959	Foodstuffs	**NG**	Natural Gas	04/04/1990	Energy
CD	Canadian Dollar/US Dollar	05/16/1972	Currencies	**O-**	Oats	07/01/1959	Grains
CL	Crude Oil	03/30/1983	Energy	**PA**	Palladium	01/03/1977	Metals
CR	CRB Future Index	06/12/1986	Commodity Indices	**PB**	Pork Bellies	09/18/1961	Livestock
CT	Cotton	07/01/1959	Industrials	**PL**	Platinum	03/04/1968	Metals
DM*	Deutsche Mark/US Dollar	05/16/1972	Currencies	**RR**	Rough Rice	08/20/1986	Grains
FC	Feeder Cattle	11/30/1971	Livestock	**S-**	Soybeans	07/01/1959	Grains
GC	Gold	12/31/1974	Metals	**SB**	Sugar #11/World Raw	01/04/1961	Foodstuffs
HG	Copper High Grade	07/01/1959	Metals	**SE**	Sugar #14/Domestic Raw	07/07/1987	Foodstuffs
HO	Heating Oil	11/14/1978	Energy	**SF**	Swiss Franc/US Dollar	05/16/1972	Currencies
HU	Gasoline	12/03/1984	Energy	**SI**	Silver	06/12/1963	Metals
JO	Orange Juice	02/01/1967	Foodstuffs	**SM**	Soybean Meal	07/01/1959	Grains
JY	Japanese Yen/US Dollar	05/16/1972	Currencies	**W-**	Wheat, No. 2 Soft Red	07/01/1959	Grains
KC	Coffee	01/03/1961	Foodstuffs				

* We switch to the Euro/US Dollar market in place of the DM on March 1, 1999.

** We switch to Lean Hogs in place of Live Hogs on Nov. 1, 1996.

Table 3
Average Momentum Profits for All Sample Commodities

	Panel A: Entire Sample Period				Panel B: Pre-1981 Period				Panel C: Post-1981 Period			
J / K	**P1**	**P2**	**P3**	**P1-P3**	**P1**	**P2**	**P3**	**P1-P3**	**P1**	**P2**	**P3**	**P1-P3**
1mon	0.0059	-0.0013	-0.0041	0.0100	0.0085	-0.0020	-0.0020	0.0105	0.0033	-0.0006	-0.0063	0.0096
	(3.1252)**	(-.8704)	(-2.3021)*	(4.8214)**	(2.714)**	(-.7560)	(-.6944)	(3.2678)**	(1.5713)	(-.4324)	(-2.9989)**	(3.6249)**
2mon	0.0104	0.0004	-0.0105	0.0209	0.0169	0.0015	-0.0099	0.0268	0.0040	-0.0004	-0.0112	0.0152
	(2.9115)**	(.1834)	(-3.0617)**	(5.9411)**	(2.7077)**	(.3542)	(-1.7381)	(4.8067)**	(1.2246)	(-.1721)	(-2.9359)**	(3.6370)**
3mon	0.0139	-0.0014	-0.0128	0.0267	0.0225	0.0035	-0.0133	0.0358	0.0058	-0.0059	-0.0119	0.0177
	(2.576)*	(-.3467)	(-2.6999)**	(5.2238)**	(2.3398)*	(.5159)	(-1.7388)	(4.2617)**	(1.2244)	(-1.5914)	(-2.1280)*	(3.1117)**
6mon	0.0163	0.0044	-0.0222	0.0384	0.0316	0.0098	-0.0155	0.0471	0.0017	0.0011	-0.0262	0.0279
	(1.6553)	(.513)	(-2.2232)*	(4.2358)**	(1.8953)	(.6578)	(-.9653)	(3.2336)**	(.1693)	(.1438)	(-2.2678)*	(2.6216)**
9mon	0.0168	0.0157	-0.0327	0.0495	0.0397	0.0348	-0.0239	0.0637	-0.0032	0.0013	-0.0342	0.0310
	(1.0145)	(1.1475)	(-2.1434)*	(3.6687)**	(1.4119)	(1.4486)	(-.9961)	(3.1551)**	(-.1886)	(.1111)	(-1.9516)	(1.7793)
12mon	0.0027	0.0152	-0.0178	0.0205	0.0328	0.0529	-0.0081	0.0409	-0.0192	-0.0138	-0.0155	-0.0037
	(.1146)	(.7606)	(-.8367)	(1.1372)	(.8312)	(1.5433)	(-.2355)	(1.3672)	(-.8745)	(-.8197)	(-.6664)	(-.1832)
24mon	-0.0560	0.0263	0.0230	-0.0791	0.0179	0.1201	0.0872	-0.0694	-0.0721	-0.0292	-0.0159	-0.0562
	(-1.0893)	(.6043)	(.5281)	(-2.0528)*	(.2099)	(1.8444)	(1.2707)	(-1.3306)	(-2.3985)*	(-.7241)	(-.3160)	(-1.1023)
36mon	-0.0389	0.0089	0.0266	-0.0655	0.1038	0.1287	0.2120	-0.1082	-0.0769	-0.0250	-0.0810	0.0041
	(-.5137)	(.1444)	(.3580)	(-1.2747)	(.8224)	(1.3740)	(2.0922)*	(-1.2962)	(-2.356)*	(-.5186)	(-1.1668)	(.0641)
48mon	0.0177	-0.0104	0.0108	0.0070	0.2901	0.1288	0.3363	-0.0462	-0.0830	-0.0108	-0.1304	0.0474
	(.1654)	(-.1132)	(.0922)	(.1018)	(1.9229)	(.7963)	(2.1879)*	(-.3266)	(-1.5667)	(-.2292)	(-2.2449)*	(.6502)
60mon	0.0483	-0.0042	0.0269	0.0214	0.4504	0.2542	0.5349	-0.0846	-0.0875	-0.0217	-0.1559	0.0684
	(.3167)	(-.0343)	(.1536)	(.2422)	(2.1159)*	(1.4209)	(2.7298)**	(-.5121)	(-1.198)	(-.465)	(-3.5411)**	(.7735)

Note: The table provides means of holding period (K) returns for various portfolios. The P1 portfolios contain commodities ranked in the top third, across all 35 commodities, in terms of formation period (J) return, the P2 portfolios commodities ranked in the middle third, and the P3 portfolios commodities ranked in the bottom third. Figures in parentheses are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, indicate significance at the 5% and 1% levels.

Table 4
Average Momentum Profits for Non-Full Carry Commodities

	Panel A: Entire Sample Period				Panel B: Pre-1981 Period				Panel C: Post-1981 Period			
J / K	P1	P2	P3	P1-P3	P1	P2	P3	P1-P3	P1	P2	P3	P1-P3
1mon	0.0065	-0.0002	-0.0052	0.0117	0.0074	0.0013	-0.0035	0.0109	0.0055	-0.0018	-0.0070	0.0125
	(3.0560)**	(-.1207)	(-2.5968)*	(4.9044)**	(2.2078)*	(.4221)	(-1.1118)	(3.1657)**	(2.1481)*	(-.8687)	(-2.7802)**	(3.7909)**
2mon	0.0111	0.0013	-0.0105	0.0216	0.0188	0.0023	-0.0103	0.0291	0.0035	0.0003	-0.0108	0.0143
	(2.8604)**	(.4256)	(-2.8195)**	(5.466)**	(2.9752)**	(.4531)	(-1.7327)	(5.0453)**	(.7981)	(.1107)	(-2.4187)*	(2.7109)**
3mon	0.0143	0.0002	-0.0120	0.0263	0.0229	0.0072	-0.0134	0.0363	0.0060	-0.0066	-0.0105	0.0165
	(2.4636)*	(.0332)	(-2.2664)*	(4.5373)**	(2.3617)*	(.9569)	(-1.5781)	(4.1856)**	(.9752)	(-1.2942)	(-1.6256)	(2.1771)*
6mon	0.0183	0.0081	-0.0229	0.0412	0.0370	0.0126	-0.0149	0.0519	-0.0001	0.0053	-0.0276	0.0275
	(1.6242)	(.8243)	(-2.1024)*	(3.7896)**	(2.0995)*	(.7712)	(-.8486)	(3.1321)**	(-.0044)	(.4961)	(-2.2197)*	(2.0201)*
9mon	0.0168	0.0160	-0.0266	0.0434	0.0436	0.0384	-0.0194	0.0630	-0.0071	-0.0010	-0.0269	0.0198
	(.9097)	(.9934)	(-1.6906)	(2.7118)**	(1.4943)	(1.478)	(-.7857)	(2.8387)**	(-.3273)	(-.0594)	(-1.4744)	(.893)
12mon	0.0014	0.0133	-0.0101	0.0114	0.0361	0.0506	-0.0005	0.0366	-0.0252	-0.0138	-0.0074	-0.0177
	(.0559)	(.595)	(-.4443)	(.5461)	(.9197)	(1.4411)	(-.0137)	(1.1367)	(-.9272)	(-.5634)	(-.3017)	(-.6705)
24mon	-0.0573	0.0120	0.0338	-0.0911	0.0041	0.0956	0.1149	-0.1108	-0.0594	-0.0333	-0.0217	-0.0377
	(-1.0765)	(.2654)	(.6754)	(-2.0816)	(.047)	(1.3872)	(1.4667)	(-1.8503)	(-1.6093)	(-.7322)	(-.3732)	(-.6628)
36mon	-0.0297	-0.0073	0.0351	-0.0648	0.1033	0.1011	0.2251	-0.1219	-0.0650	-0.0235	-0.0803	0.0153
	(-.3837)	(-.1065)	(.4448)	(-1.1431)	(.7695)	(.9804)	(2.1025)*	(-1.3994)	(-1.6722)	(-.3919)	(-.9937)	(.21)
48mon	0.0452	-0.0511	0.0190	0.0262	0.3039	0.0670	0.3335	-0.0296	-0.0652	-0.0305	-0.1100	0.0448
	(.4407)	(-.5314)	(.1555)	(.3659)	(1.9861)*	(.4126)	(2.0063)*	(-.2211)	(-1.1721)	(-.4702)	(-1.3995)	(.5225)
60mon	0.0878	-0.0424	0.0214	0.0664	0.4396	0.2372	0.5008	-0.0612	-0.0563	-0.0447	-0.1417	0.0855
	(.6238)	(-.3141)	(.1218)	(.6557)	(2.0179)*	(1.314)	(2.3382)*	(-.3889)	(-.6306)	(-.8542)	(-2.2961)*	(.9114)

Note: The table provides means of holding period (K) returns for various portfolios. The P1 portfolios contain commodities ranked in the top third, Across 25 non-full-carry commodities, in terms of formation period (J) return, the P2 portfolios commodities ranked in the middle third, and the P3 portfolios commodities ranked in the bottom third.Figures in parentheses are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, indicate significance at the 5% and 1% levels.

Table 5
A Comparison of Momentum, DMAC and Channel Strategies, 1 Month Holding Periods

	Panel A: Entire Sample Period				Panel B: Pre-1981 Period				Panel C: Post-1981 Period			
	P1	P2	P3	P1-P3	P1	P2	P3	P1-P3	P1	P2	P3	P1-P3
Formation Period					Momentum Strategies							
1 mon	0.0059	-0.0013	-0.0041	0.0100	0.0085	-0.0020	-0.0020	0.0105	0.0033	-0.0006	-0.0063	0.0096
	(3.1252)**	(-.8704)	(-2.3021)*	(4.8214)**	(2.714)**	(-.756)	(-.6944)	(3.2678)**	(1.5713)	(-.4324)	(-2.9989)**	(3.6249)**
2 mon	0.0072	-0.0001	-0.0067	0.0139	0.0112	-0.0005	-0.0063	0.0175	0.0032	0.0004	-0.0070	0.0103
	(3.5696)**	(-.0467)	(-3.8322)**	(6.4925)**	(3.2523)**	(-.1988)	(-2.3326)*	(5.3574)**	(1.5429)	(.249)	(-3.216)**	(3.7392)**
3 mon	0.0076	-0.0021	-0.0055	0.0131	0.0099	-0.0009	-0.0053	0.0152	0.0052	-0.0033	-0.0058	0.0110
	(3.8064)**	(-1.4109)	(-3.171)**	(6.1512)**	(2.8489)**	(-.358)	(-1.8961)	(4.3673)**	(2.7421)**	(-2.1076)	(-2.7592)**	(4.5028)**
6 mon	0.0044	0.0010	-0.0054	0.0098	0.0083	0.0009	-0.0056	0.0139	0.0005	0.0011	-0.0051	0.0057
	(2.1441)*	(.7461)	(-2.9365)**	(4.5681)**	(2.3082)*	(.404)	(-1.8631)	(3.9378)**	(.2665)	(.7369)	(-2.465)*	(2.3623)*
STMA / LTMA / Band					Dual Moving Average Crossover Strategies							
1 mon / 3 mon / .0125	0.0077	0.0001	-0.0075	0.0152	0.0114	0.0012	-0.0088	0.0203	0.0039	-0.0010	-0.0061	0.0100
	(3.9083)**	(.0679)	(-3.9073)**	(6.9226)**	(3.4689)**	(.4672)	(-2.8244)**	(5.8898)**	(1.8539)	(-.652)	(-2.7936)**	(3.754)**
1 mon / 6 mon / .025	0.0093	0.0000	-0.0087	0.0181	0.0128	0.0015	-0.0094	0.0222	0.0059	-0.0015	-0.0080	0.0139
	(4.2883)**	(.0117)	(-4.7672)**	(7.5607)**	(3.4259)**	(.694)	(-3.1871)**	(5.7589)**	(2.6446)**	(-.9959)	(-3.7199)**	(4.9722)**
1 mon / 9 mon / .0375	0.0084	0.0008	-0.0084	0.0167	0.0114	0.0019	-0.0092	0.0206	0.0054	-0.0003	-0.0075	0.0129
	(3.8542)**	(.6004)	(-4.5792)**	(6.9668)**	(3.1148)**	(.8298)	(-3.0676)**	(5.2451)**	(2.293)*	(-.2417)	(-3.5952)**	(4.674)**
1 mon / 12 mon / .05	0.0078	-0.0002	-0.0072	0.0150	0.0110	-0.0007	-0.0063	0.0173	0.0046	0.0003	-0.0081	0.0127
	(3.5600)**	(-.1674)	(-3.4939)**	(6.1628)**	(3.0849)**	(-.3082)	(-1.8073)	(4.5183)**	(1.8237)	(.189)	(-3.6233)**	(4.2244)**
Lag Length					Channel Strategies							
3 mon	0.0090	-0.0007	-0.0075	0.0166	0.0115	0.0020	-0.0081	0.0196	0.0066	-0.0034	-0.0070	0.0135
	(4.8208)**	(-.3927)	(-4.2166)**	(7.6545)**	(3.6413)**	(.6434)	(-2.8054)**	(5.6585)**	(3.2785)**	(-2.0088)*	(-3.3231)**	(5.247)**
6 mon	0.0110	-0.0008	-0.0088	0.0198	0.0142	0.0005	-0.0089	0.0231	0.0078	-0.0022	-0.0087	0.0165
	(5.1832)**	(-.5389)	(-4.582)**	(7.8868)**	(3.9865)**	(.1971)	(-2.8475)**	(5.7133)**	(3.3995)**	(-1.4771)	(-3.8897)**	(5.564)**
9 mon	0.0107	-0.0002	-0.0094	0.0201	0.0140	0.0010	-0.0098	0.0238	0.0075	-0.0014	-0.0089	0.0164
	(4.5038)**	(-.1374)	(-4.5154)**	(6.9246)**	(3.6105)**	(.3814)	(-2.9951)**	(5.2155)**	(2.7063)**	(-.9981)	(-3.4936)**	(4.5837)**
12 mon	0.0121	0.0003	-0.0090	0.0210	0.0142	0.0020	-0.0096	0.0238	0.0100	-0.0013	-0.0083	0.0183
	(4.6994)**	(.2173)	(-4.1712)**	(6.9789)**	(3.5035)**	(.733)	(-2.8186)**	(5.1255)**	(3.1467)**	(-.9278)	(-3.1597)**	(4.7538)**

Figures in parentheses are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, denote significance at the 5% and 1% levels.

Table 6
Mean Returns by Commodity, 1 Month Holding Periods

	2-month Formation Period Momentum Strategy					1 month / 6 month / .025 Dual Moving Average Crossover				
	When FP Return is in: Top 1/3	Bottom 1/3	Diff. in Mean, Top - Bottom	t-Stat		When DMAC Indicator is: Above Upr Bd	Below Lwr Bd	Diff. in Mean, Above - Below	t-Stat	
AD	0.0031	-0.0009	0.0040	0.6219		0.0033	0.0035	-0.0003	-0.0386	
BO	0.0135	-0.0058	0.0193	2.1292	*	0.0180	-0.0088	0.0268	3.0808	**
BP	0.0027	0.0007	0.0020	0.4346		0.0028	-0.0062	0.0090	1.8107	
C-	0.0002	-0.0119	0.0121	1.8554		0.0056	-0.0106	0.0163	2.3069	*
CC	0.0012	-0.0041	0.0053	0.5930		0.0093	-0.0047	0.0140	1.5376	
CD	-0.0021	0.0001	-0.0023	-0.7486		0.0032	0.0073	-0.0041	-0.7025	
CL	0.0095	-0.0061	0.0155	1.0557		0.0172	-0.0031	0.0202	1.5095	
CR	-0.0061	0.0030	-0.0090	-1.0728		0.0022	-0.0055	0.0077	1.3387	
CT	0.0021	-0.0067	0.0088	1.3433		0.0091	-0.0094	0.0185	2.7525	**
DM	0.0058	-0.0056	0.0115	2.4950	*	0.0045	-0.0044	0.0089	1.8780	
FC	0.0044	0.0016	0.0028	0.4145		0.0075	-0.0046	0.0121	1.5910	
GC	0.0075	-0.0082	0.0157	1.7718		0.0074	-0.0113	0.0187	2.0914	*
HG	0.0032	-0.0034	0.0066	0.7092		0.0088	-0.0047	0.0135	1.5152	
HO	0.0067	0.0041	0.0026	0.2159		0.0081	-0.0044	0.0126	1.0123	
HU	0.0038	0.0130	-0.0092	-0.6517		0.0139	0.0067	0.0072	0.4630	
JO	0.0005	-0.0054	0.0059	0.5602		0.0050	-0.0056	0.0106	1.0429	
JY	0.0066	-0.0045	0.0111	1.8553		0.0049	-0.0045	0.0095	1.8412	
KC	0.0031	-0.0061	0.0092	0.7005		0.0079	-0.0057	0.0136	1.0795	
KW	0.0058	-0.0036	0.0094	1.1811		0.0122	-0.0073	0.0194	2.2718	*
LB	0.0008	-0.0095	0.0103	1.0247		0.0080	-0.0161	0.0241	2.4330	*
LC	0.0067	0.0048	0.0019	0.2775		0.0080	-0.0027	0.0106	1.4180	
LH	0.0025	0.0007	0.0018	0.2008		0.0101	-0.0005	0.0106	1.2017	
NG	0.0132	-0.0062	0.0195	0.8266		0.0285	-0.0043	0.0328	1.3918	
O-	-0.0013	-0.0105	0.0092	1.1479		-0.0053	-0.0099	0.0046	0.5774	
PA	0.0315	-0.0245	0.0560	3.9465	**	0.0325	-0.0289	0.0614	4.4517	**
PB	-0.0031	-0.0084	0.0053	0.4608		-0.0041	-0.0012	-0.0029	-0.2593	
PL	0.0022	-0.0045	0.0066	0.6739		0.0072	-0.0135	0.0207	1.8520	
RR	0.0117	-0.0161	0.0278	2.0185	*	0.0157	-0.0230	0.0387	2.5957	*
S-	0.0089	-0.0028	0.0117	1.2449		0.0045	-0.0014	0.0059	0.6200	
SB	0.0212	-0.0230	0.0442	3.4954	**	0.0216	-0.0265	0.0481	3.8091	**
SE	0.0005	-0.0033	0.0037	0.6250		0.0026	-0.0061	0.0087	0.9830	
SF	0.0065	-0.0039	0.0103	2.0251	*	0.0090	-0.0071	0.0160	3.1256	**
SI	0.0040	-0.0121	0.0162	1.3114		0.0076	-0.0085	0.0162	1.2447	
SM	0.0122	-0.0064	0.0186	1.8963		0.0101	-0.0078	0.0180	1.9002	
W-	-0.0003	-0.0034	0.0031	0.4627		0.0048	-0.0085	0.0133	1.8453	

Note: * and **, respectively, indicate significance at the 5% and 1% levels.

Table 7

Returns on Momentum and DMAC Strategies, by Post-Formation Month

Figures in bold below are mean monthly returns to Portfolio 1 minus Portfolio 3 strategies. For the two-month momentum strategies, Portfolio 1 consists of commodities ranked in the top third, and Portfolio 3 those in the bottom third, based on formation period return. For the Dual Moving Average Crossover strategies, Portfolio 1 contains those commodities for which the unit value index at the end of the last month is greater than 1.025 times the average unit value index over the last 6 months, and Portfolio 3 those commodities whose latest unit value index is less than 0.975 times the 6-month average. Figures in parentheses are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, indicate significance at the 5% and 1% levels.

Post-Formation Month	**2-Month Formation Period Momentum Strategy**			**1 month / 6 month / .025 Dual Moving Average Crossover**		
	Entire Sample	**Pre-1981**	**Post-1981**	**Entire Sample**	**Pre-1981**	**Post-1981**
1st	**0.0139**	**0.0175**	**0.0103**	**0.0181**	**0.0222**	**0.0139**
	(6.4925)**	(5.3574)**	(3.7392)**	(7.5607)**	(5.7589)**	(4.9722)**
2nd	**0.0069**	**0.0092**	**0.0046**	**0.0086**	**0.0120**	**0.0052**
	(3.2388)**	(2.5973)*	(1.9538)	(3.6365)**	(3.0388)**	(2.0104)*
3rd	**0.0061**	**0.0102**	**0.0020**	**0.0059**	**0.0093**	**0.0026**
	(2.7892)**	(2.8794)**	(.7871)	(2.5372)*	(2.4357)*	(.9608)
4th	**0.0048**	**0.0086**	**0.0010**	**0.0048**	**0.0095**	**0.0002**
	(2.2759)*	(2.5697)*	(.3884)	(2.0385)*	(2.4958)*	(.0704)
5th	**0.0039**	**0.0051**	**0.0027**	**0.0039**	**0.0062**	**0.0017**
	(1.9396)	(1.5661)	(1.1456)	(1.6543)	(1.6394)	(.5833)
6th	**0.0028**	**0.0025**	**0.0032**	**0.0059**	**0.0060**	**0.0058**
	(1.3399)	(.7383)	(1.2548)	(2.5149)*	(1.6366)	(1.9767)*
7th	**0.0029**	**0.0022**	**0.0036**	**0.0048**	**0.0047**	**0.0048**
	(1.4612)	(.7017)	(1.457)	(2.0329)*	(1.2338)	(1.7525)
8th	**0.0030**	**0.0048**	**0.0011**	**0.0071**	**0.0093**	**0.0050**
	(1.3918)	(1.4342)	(.4289)	(2.974)**	(2.3717)*	(1.799)
9th	**0.0078**	**0.0088**	**0.0068**	**0.0072**	**0.0056**	**0.0088**
	(3.738)**	(2.6887)**	(2.6233)*	(2.8704)**	(1.3677)	(2.9545)**
10th	**0.0112**	**0.0099**	**0.0124**	**0.0055**	**0.0045**	**0.0065**
	(5.3578)**	(3.0365)**	(4.7672)**	(2.3229)*	(1.1797)	(2.2698)*
11th	**0.0051**	**0.0047**	**0.0056**	**0.0000**	**-0.0013**	**0.0013**
	(2.4424)*	(1.4277)	(2.1127)*	(.0173)	(-.2985)	(.4244)
12th	**-0.0034**	**-0.0019**	**-0.0049**	**-0.0058**	**-0.0052**	**-0.0064**
	(-1.6247)	(-.5492)	(-1.9524)	(-2.2675)*	(-1.2729)	(-2.031)*
13th	**-0.0038**	**-0.0004**	**-0.0072**	**-0.0080**	**-0.0055**	**-0.0103**
	(-1.9362)	(-.1097)	(-3.1098)**	(-3.2906)**	(-1.2957)	(-4.1906)**
14th	**-0.0060**	**-0.0032**	**-0.0087**	**-0.0068**	**-0.0043**	**-0.0092**
	(-2.9139)**	(-.9173)	(-3.8254)**	(-2.9439)**	(-1.0906)	(-3.6334)**
15th	**-0.0059**	**-0.0073**	**-0.0044**	**-0.0077**	**-0.0084**	**-0.0071**
	(-2.7587)**	(-2.1372)*	(-1.748)	(-3.4706)**	(-2.4478)*	(-2.4713)*
16th	**-0.0024**	**-0.0053**	**0.0004**	**-0.0018**	**-0.0046**	**0.0009**
	(-1.2189)	(-1.631)	(.1713)	(-.8045)	(-1.3287)	(.3329)
17th	**-0.0041**	**-0.0051**	**-0.0032**	**-0.0024**	**-0.0051**	**0.0002**
	(-1.8904)	(-1.4106)	(-1.2778)	(-1.0053)	(-1.2862)	(.0897)
18th	**-0.0027**	**-0.0055**	**0.0000**	**-0.0018**	**-0.0052**	**0.0013**
	(-1.2457)	(-1.4652)	(-.009)	(-.7818)	(-1.3383)	(.4782)
19th	**-0.0014**	**-0.0010**	**-0.0018**	**-0.0006**	**-0.0048**	**0.0032**
	(-.675)	(-.2878)	(-.7339)	(-.2648)	(-1.1515)	(1.2266)
20th	**0.0004**	**-0.0016**	**0.0023**	**0.0013**	**-0.0023**	**0.0046**
	(.1783)	(-.4418)	(.7954)	(.5300)	(-.5515)	(1.7057)
21st	**0.0011**	**-0.0014**	**0.0034**	**0.0002**	**-0.0029**	**0.0031**
	(.538)	(-.3954)	(1.4506)	(.0878)	(-.6606)	(1.1013)
22nd	**-0.0024**	**-0.0038**	**-0.0012**	**-0.0069**	**-0.0081**	**-0.0059**
	(-1.1779)	(-1.0937)	(-.4972)	(-2.7299)**	(-1.8552)	(-2.1174)*
23rd	**-0.0035**	**-0.0046**	**-0.0024**	**-0.0068**	**-0.0067**	**-0.0069**
	(-1.7137)	(-1.3833)	(-1.0126)	(-2.8699)**	(-1.6575)	(-2.6328)**
24th	**-0.0065**	**-0.0037**	**-0.0092**	**-0.0109**	**-0.0110**	**-0.0108**
	(-3.2696)**	(-1.1266)	(-3.849)**	(-4.6368)**	(-2.7804)**	(-4.0329)**

Table 8

Returns on Commodity Futures Portfolios Formed Based on Past Returns and Trading Volume

Panel A: Entire Sample Period

	J = 1				*J* = 2				*J* = 3				*J* = 6			
	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3
P1	**0.008**	**0.009**	**0.007**	**0.0016**	**0.011**	**0.015**	**0.005**	**0.006**	**0.009**	**0.027**	**0.007**	**0.002**	**0.018**	**0.024**	**0.007**	**0.012**
	(2.640)***	(3.120)***	(2.079)**	(0.497)	(2.181)**	(2.720)***	(1.035)	(1.015)	(1.121)	(3.587)***	(0.820)	(0.244)	(1.331)	(1.551)	(0.425)	(0.713)
P2	**-0.001**	**0.001**	**-0.003**	**0.002**	**-0.001**	**0.002**	**0.003**	**-0.004**	**-0.010**	**0.003**	**0.002**	**-0.003**	**0.005**	**0.010**	**0.008**	**-0.003**
	(-0.318)	(0.427)	(-1.373)	(0.763)	(-0.351)	(0.705)	(0.760)	(-0.905)	(-0.189)	(0.577)	(0.349)	(-0.460)	(0.472)	(0.731)	(0.679)	(-0.256)
P3	**-0.005**	**-0.004**	**-0.007**	**0.002**	**-0.010**	**-0.008**	**-0.013**	**0.004**	**-0.011**	**-0.015**	**-0.017**	**0.006**	**-0.026**	**-0.021**	**-0.019**	**-0.007**
	(-1.611)	(-1.873)*	(-2.946)***	(0.695)	(-1.850)*	(-1.885)*	(-2.998)***	(0.672)	(-1.362)	(-2.362)***	(-2.593)***	(0.681)	(-2.066)**	(-1.793)*	(-1.315)	(-0.405)
P1-P3	**0.013**	**0.013**	**0.014**		**0.021**	**0.023**	**0.019**		**0.019**	**0.042**	**0.023**		**0.044**	**0.045**	**0.025**	
	(3.235)***	(4.101)***	(4.084)***		(3.520)***	(3.830)***	(3.433)***		(2.047)**	(5.141)***	(2.919)***		(2.715)***	(2.863)***	(1.759)*	

	J = 9				*J* = 12				*J* = 24				*J* = 36			
	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3
P1	**0.004**	**0.034**	**0.003**	**0.002**	**-0.022**	**0.042**	**-0.009**	**-0.013**	**-0.115**	**0.008**	**-0.030**	**-0.085**	**-0.044**	**-0.001**	**0.014**	**-0.058**
	(0.210)	(1.446)	(0.103)	(0.090)	(-0.775)	(1.380)	(-0.265)	(-0.471)	(-1.970)**	(0.122)	(-0.416)	(-1.181)	(-0.393)	(-0.004)	(0.136)	(-0.465)
P2	**0.009**	**0.036**	**0.025**	**-0.016**	**-0.008**	**0.034**	**0.037**	**-0.045**	**0.005**	**0.038**	**0.076**	**-0.070**	**0.014**	**0.001**	**0.012**	**0.002**
	(0.519)	(1.571)	(1.335)	(-0.792)	(-0.383)	(1.230)	(1.257)	(-1.465)	(0.112)	(0.589)	(1.470)	(-1.559)	(0.216)	(0.001)	(0.161)	(0.032)
P3	**-0.034**	**-0.022**	**-0.018**	**-0.015**	**-0.007**	**0.003**	**-0.002**	**-0.005**	**0.031**	**0.076**	**0.018**	**0.013**	**0.054**	**0.063**	**0.030**	**0.024**
	(-1.780)*	(-1.023)	(-0.875)	(-0.63)	(-0.273)	(0.090)	(-0.078)	(-0.176)	(0.677)	(1.129)	(0.325)	(0.187)	(0.806)	(0.809)	(0.334)	(0.273)
P1-P3	**0.038**	**0.056**	**0.021**		**-0.015**	**0.039**	**-0.007**		**-0.146**	**-0.068**	**-0.048**		**-0.098**	**-0.064**	**-0.017**	
	(1.614)	(2.214)**	(1.062)		(-0.549)	(1.194)	(-0.233)		(-2.370)***	(-1.026)	(-0.615)		(-0.960)	(-0.699)	(-0.182)	

	J = 48				*J* = 60			
	V1	V2	V3	V1-V3	V1	V2	V3	V1-V3
P1	**0.149**	**0.036**	**-0.020**	**0.169**	**0.194**	**0.143**	**-0.124**	**0.318**
	(0.848)	(0.323)	(-0.210)	(1.009)	(1.181)	(0.850)	(-1.525)	(2.274)**
P2	**0.017**	**0.012**	**0.037**	**-0.019**	**0.043**	**0.023**	**0.110**	**-0.067**
	(0.161)	(0.115)	(0.349)	(-0.234)	(0.279)	(0.144)	(0.886)	(-0.950)
P3	**-0.018**	**0.034**	**0.025**	**-0.044**	**-0.102**	**0.115**	**0.008**	**-0.110**
	(-0.145)	(0.292)	(0.172)	(-0.665)	(-0.558)	(0.550)	(0.032)	(-0.751)
P1-P3	**0.168**	**0.002**	**-0.045**		**0.296**	**0.028**	**-0.132**	
	(1.417)	(0.052)	(-0.340)		(2.514)***	(0.406)	(-0.547)	

Figures in parentheses are t-statistics. *, **, and ***, respectively, indicate significance at the 10%, 5%, and 1% levels.

Table 9

Relation Between Traders' Net Long Positions and 2-month Formation Period Momentum Indicators

The figures below are estimates of the following regression model: Net $Long_{it} = B_0 + B_1\ PMOM_t + e_t$, where $NetLong_{it}$ is defined as (contracts $long_{it}$ – contracts $short_{it}$) / open $interest_t$ for trader class i at the end of month t, and $PMOM_t$ equals 1, 0 or -1, respectively, if the return based on a commodity's unit value index is in the top, middle or bottom third over a 2-month formation period ending at the end of month t. The regressions are estimated separately for each commodity and each class of traders. Figures in parentheses below coefficient estimates are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, denote significance at the 5% and 1% levels.

	Commercial Traders			Non-Commercial Traders			Non-Reporting Traders		
	B_0	B_1	R^2	B_0	B_1	R^2	B_0	B_1	R^2
AD	-0.068	-0.387	0.281	0.012	0.210	0.297	0.056	0.177	0.217
	(-1.123)	(-7.948)**		(0.409)	(7.671)**		(1.683)	(6.566)**	
BO	-0.139	-0.135	0.357	0.050	0.088	0.332	0.089	0.047	0.257
	(-7.506)**	(-10.69)**		(3.956)*	(8.858)**		(11.000)**	(8.709)**	
BP	0.002	-0.269	0.215	0.004	0.165	0.221	-0.006	0.104	0.159
	(0.065)	(-8.656)**		(0.227)	(8.824)**		(-0.371)	(7.317)**	
C-	-0.000	-0.098	0.343	0.064	0.087	0.460	-0.064	0.011	0.017
	(-0.005)	(-9.837)**		(7.325)**	(10.468)**		(-7.604)**	(1.900)	
CC	-0.103	-0.063	0.109	0.033	0.062	0.185	0.070	0.000	-0.005
	(-4.714)**	(-3.931)**		(2.055)*	(5.314)**		(8.819)**	(0.065)	
CD	-0.127	-0.145	0.042	0.017	0.096	0.045	0.109	0.049	0.018
	(-3.120)**	(-2.991)**		(0.700)	(3.088)**		(4.887)**	(2.123)*	
CL	0.009	-0.049	0.233	-0.005	0.033	0.202	-0.004	0.015	0.138
	(1.045)	(-6.731)**		(-0.852)	(5.909)**		(-0.969)	(5.121)**	
CR	-0.005	0.000	-0.006	-0.173	0.008	-0.005	0.177	-0.009	-0.005
	(-2.153)*	(0.418)		(-10.27)**	(0.364)		(10.467)**	(-0.386)	
CT	-0.057	-0.150	0.348	-0.001	0.122	0.312	0.058	0.028	0.137
	(-2.669)*	(-9.455)**		(-0.050)	(8.393)**		(7.662)**	(4.270)**	
DM	-0.052	-0.216	0.258	0.004	0.130	0.282	0.048	0.086	0.159
	(-1.647)	(-8.206)**		(0.244)	(8.782)**		(2.529)*	(5.604)**	
FC	0.084	-0.024	0.017	0.066	0.084	0.234	-0.149	-0.060	0.094
	(5.685)**	(-1.712)		(5.311)**	(7.659)**		(-8.251)**	(-4.042)**	
GC	-0.034	-0.164	0.195	-0.016	0.115	0.187	0.051	0.049	0.131
	(-1.150)	(-7.350)**		(-0.779)	(7.226)**		(4.394)**	(5.452)**	
HG	-0.167	-0.128	0.215	0.077	0.105	0.258	0.090	0.024	0.048
	(-6.250)**	(-7.174)**		(4.159)**	(8.113)**		(7.814)**	(3.199)**	
HO	-0.094	-0.057	0.257	0.015	0.039	0.277	0.079	0.019	0.093
	(-10.48)**	(-7.960)**		(2.831)**	(8.000)**		(12.924)**	(4.271)**	
HU	-0.065	-0.057	0.212	0.045	0.041	0.215	0.020	0.016	0.089
	(-6.383)**	(-6.926)**		(6.229)**	(6.932)**		(4.506)**	(4.648)**	
JO	-0.125	-0.064	0.042	0.045	0.080	0.178	0.080	-0.016	0.005
	(-3.898)**	(-2.480)*		(2.595)*	(6.132)**		(4.304)**	(-1.022)	
JY	0.083	-0.255	0.291	-0.055	0.146	0.228	-0.028	0.109	0.313
	(2.377)*	(-8.213)**		(-2.300)*	(6.784)**		(-2.021)*	(8.271)**	
KC	-0.200	-0.094	0.293	0.079	0.086	0.323	0.121	0.008	0.026
	(-14.11)**	(-9.708)**		(6.996)**	(10.043)**		(23.778)**	(2.352)*	
KW	-0.016	-0.054	0.118	0.026	0.050	0.261	-0.010	0.004	-0.003
	(-1.025)	(-5.139)**		(3.402)**	(8.970)**		(-0.839)	(0.550)	
LB	-0.093	-0.078	0.137	0.033	0.056	0.106	0.061	0.021	0.018
	(-4.545)**	(-4.768)**		(2.063)*	(4.819)**		(4.016)**	(2.135)*	

Table 9(cont.)

	Commercial Traders			Non-Commercial Traders			Non-Reporting Traders		
	B_0	B_1	R^2	B_0	B_1	R^2	B_0	B_1	R^2
LC	-0.091	-0.023	0.018	0.063	0.057	0.159	0.027	-0.034	0.063
	(-5.684)**	(-2.097)*		(4.970)**	(5.351)**		(2.066)*	(-4.356)**	
LH	0.004	-0.064	0.232	0.048	0.103	0.371	-0.051	-0.040	0.174
	(0.337)	(-6.827)**		(3.679)**	(9.672)**		(-6.244)**	(-5.351)**	
NG	-0.081	-0.059	0.408	0.019	0.052	0.444	0.061	0.007	0.026
	(-9.480)**	(-9.618)**		(3.014)**	(9.972)**		(11.062)**	(2.158)*	
O-	-0.358	-0.009	-0.002	0.100	0.026	0.086	0.257	-0.016	0.007
	(-19.40)**	(-0.668)		(11.927)**	(4.009)**		(15.026)**	(-1.261)	
PA	-0.334	-0.030	0.006	0.166	0.041	0.042	0.168	-0.011	0.001
	(-9.067)**	(-1.061)		(7.055)**	(2.086)*		(9.471)**	(-0.844)	
PB	-0.027	-0.011	0.001	-0.022	0.109	0.294	0.049	-0.098	0.236
	(-1.697)	(-0.846)		(-1.259)	(8.381)**		(2.425)**	(-7.530)**	
PL	-0.346	-0.134	0.204	0.194	0.123	0.217	0.152	0.011	0.006
	(-13.38)**	(-6.610)**		(8.796)**	(6.556)**		(13.795)**	(1.373)	
RR	-0.043	-0.055	0.067	-0.001	0.037	0.103	0.045	0.018	0.008
	(-1.730)	(-3.240)**		(-0.088)	(3.787)**		(2.246)**	(1.321)	
S-	-0.134	-0.085	0.186	0.075	0.074	0.242	0.058	0.011	0.015
	(-7.014)**	(-6.647)**		(5.564)**	(8.095)**		(6.875)**	(1.867)	
SB	-0.209	-0.140	0.306	0.089	0.097	0.321	0.120	0.044	0.169
	(-8.712)**	(-9.561)**		(5.828)**	(9.588)**		(10.447)**	(5.866)**	
SE	-0.016	-0.001	-0.006	-0.004	0.001	-0.004	0.020	0.000	-0.007
	(-2.675)**	(-0.177)		(-2.098)*	(0.703)		(3.456)**	(0.012)	
SF	0.057	-0.342	0.406	-0.043	0.195	0.362	-0.014	0.147	0.368
	(1.752)	(-10.96)**		(-2.159)*	(9.658)**		(-0.894)	(10.496)**	
SI	-0.416	-0.070	0.157	0.189	0.077	0.193	0.228	-0.006	0.004
	(-25.97)**	(-6.572)**		(11.606)**	(6.933)**		(29.551)**	(-1.228)	
SM	-0.133	-0.112	0.395	0.042	0.077	0.407	0.091	0.035	0.231
	(-9.970)**	(-11.05)**		(4.839)**	(11.544)**		(14.410)**	(7.601)**	
W-	-0.129	-0.084	0.224	0.068	0.083	0.309	0.061	0.001	-0.005
	(-8.538)**	(-6.653)**		(5.704)**	(8.038)**		(5.680)**	(0.114)	

Table 10
Relation Between Traders' Net Long Positions and 1 month / 6 month / .025 DMAC Indicators

The figures below are estimates of the following regression model: Net $Long_{it} = B_0 + B_1\ PDMAC_t + e_t$, where $NetLong_{it}$ is defined as (contracts $long_{it}$ – contracts $short_{it}$) / open $interest_t$ for trader class i at the end of month t, and $PDMAC_t$ equals 1, 0 or -1, respectively, if the unit value index of a commodity at the end of month t is > 1.025 times the 6-month average, between .975 and 1.025 times the 6-month average, or < .975 times the 6-month average unit value index. The regressions are estimated separately for each commodity and each class of traders. Figures in parentheses below coefficient estimates are t-statistics based on Newey and West (1987) standard errors. * and **, respectively, denote significance at the 5% and 1% levels.

	Commercial Traders			Non-Commercial Traders			Non-Reporting Traders		
Mkt	B_0	B_1	R^2	B_0	B_1	R^2	B_0	B_1	R^2
AD	-0.086	-0.530	0.603	0.022	0.277	0.588	0.064	0.253	0.509
	(-2.342)*	(-15.57)**		(1.217)	(12.436)**		(2.850)**	(13.041)**	
BO	-0.154	-0.158	0.518	0.060	0.101	0.464	0.094	0.057	0.397
	(-10.21)**	(-12.04)**		(5.424)**	(10.467)**		(13.592)**	(8.707)**	
BP	0.023	-0.413	0.402	-0.006	0.231	0.341	-0.017	0.182	0.392
	(0.945)	(-15.40)**		(-0.387)	(12.929)**		(-1.401)	(13.259)**	
C-	-0.014	-0.116	0.503	0.074	0.097	0.597	-0.061	0.019	0.063
	(-1.190)	(-12.06)**		(9.728)**	(12.561)**		(-7.305)**	(2.762)**	
CC	-0.110	-0.067	0.111	0.041	0.069	0.200	0.069	-0.001	-0.004
	(-4.836)**	(-3.371)**		(2.371)*	(4.604)**		(9.035)**	(-0.210)	
CD	-0.112	-0.488	0.302	0.008	0.303	0.287	0.103	0.184	0.179
	(-3.554)**	(-18.44)**		(0.416)	(21.224)**		(5.136)**	(7.434)**	
CL	0.011	-0.052	0.293	-0.007	0.038	0.280	-0.004	0.015	0.140
	(1.242)	(-6.335)**		(-1.136)	(6.282)**		(-0.974)	(3.998)**	
CR	-0.005	-0.002	-0.003	-0.173	0.008	-0.005	0.178	-0.006	-0.005
	(-2.129)*	(-0.596)		(-10.44)**	(0.451)		(10.619)**	(-0.350)	
CT	-0.058	-0.182	0.511	-0.000	0.148	0.457	0.059	0.034	0.205
	(-3.340)**	(-11.47)**		(-0.011)	(9.671)**		(7.959)**	(4.182)**	
DM	-0.044	-0.243	0.342	-0.001	0.148	0.382	0.045	0.095	0.204
	(-1.406)	(-8.603)**		(-0.084)	(9.459)**		(2.360)*	(5.262)**	
FC	0.081	-0.006	-0.003	0.063	0.094	0.275	-0.144	-0.088	0.190
	(5.308)**	(-0.342)		(5.095)**	(8.105)**		(-8.335)**	(-5.209)**	
GC	-0.059	-0.266	0.510	0.001	0.185	0.484	0.058	0.081	0.351
	(-2.639)**	(-12.13)**		(0.035)	(11.550)**		(5.766)**	(7.464)**	
HG	-0.174	-0.148	0.316	0.083	0.131	0.449	0.091	0.017	0.025
	(-7.019)**	(-7.276)**		(5.426)**	(9.888)**		(7.866)**	(1.746)	
HO	-0.094	-0.068	0.363	0.015	0.048	0.431	0.079	0.020	0.106
	(-11.18)**	(-9.450)**		(3.308)**	(10.249)**		(12.882)**	(4.058)**	
HU	-0.061	-0.065	0.265	0.042	0.049	0.296	0.019	0.016	0.084
	(-6.490)**	(-5.923)**		(6.672)**	(6.466)**		(4.223)**	(3.459)**	
JO	-0.120	-0.031	0.007	0.044	0.080	0.184	0.076	-0.048	0.085
	(-3.643)**	(-0.928)		(2.475)*	(4.739)**		(4.296)**	(-2.530)*	
JY	0.098	-0.346	0.540	-0.064	0.216	0.508	-0.034	0.130	0.444
	(3.678)**	(-13.57)**		(-3.597)**	(11.447)**		(-2.731)**	(11.613)**	
KC	-0.212	-0.113	0.391	0.090	0.105	0.450	0.122	0.008	0.020
	(-18.47)**	(-9.637)**		(10.059)**	(10.666)**		(26.025)**	(2.006)*	
KW	-0.019	-0.053	0.112	0.030	0.057	0.345	-0.010	-0.004	-0.003
	(-1.237)	(-4.170)**		(4.301)**	(8.915)**		(-0.854)	(-0.429)	
LB	-0.091	-0.077	0.138	0.031	0.056	0.107	0.060	0.021	0.018
	(-4.646)**	(-3.806)**		(2.074)*	(3.584)**		(3.985)**	(1.608)	

Table 10 (cont.)

	Commercial Traders			Non-Commercial Traders			Non-Reporting Traders		
	B_0	B_1	R^2	B_0	B_1	R^2	B_0	B_1	R^2
LC	-0.081 (-6.099)**	-0.078 (-5.346)**	0.243	0.059 (5.494)**	0.085 (7.671)**	0.344	0.022 (1.754)	-0.007 (-0.453)	-0.002
LH	0.004 (0.427)	-0.082 (-7.466)**	0.381	0.048 (4.395)**	0.123 (11.548)**	0.522	-0.052 (-6.386)**	-0.041 (-4.459)**	0.188
NG	-0.080 (-8.742)**	-0.054 (-6.942)**	0.334	0.018 (2.758)**	0.053 (8.170)**	0.439	0.062 (11.579)**	0.001 (0.343)	-0.005
O-	-0.353 (-18.97)**	0.011 (0.633)	-0.000	0.102 (12.141)**	0.029 (3.678)**	0.108	0.251 (15.362)**	-0.040 (-2.702)**	0.067
PA	-0.332 (-8.913)**	-0.030 (-0.882)	0.006	0.163 (6.874)**	0.039 (1.719)	0.037	0.169 (9.596)**	-0.009 (-0.582)	-0.001
PB	-0.027 (-1.640)	-0.015 (-0.945)	0.005	-0.027 (-1.713)	0.124 (8.699)**	0.376	0.054 (2.806)**	-0.109 (-7.072)**	0.290
PL	-0.355 (-16.70)**	-0.173 (-8.493)**	0.384	0.202 (11.240)**	0.158 (8.402)**	0.401	0.153 (14.099)**	0.015 (1.445)	0.021
RR	-0.058 (-2.408)*	-0.089 (-3.943)**	0.166	0.004 (0.336)	0.043 (3.447)**	0.131	0.054 (2.699)**	0.046 (2.634)**	0.071
S-	-0.146 (-8.957)**	-0.124 (-9.319)**	0.385	0.086 (8.064)**	0.108 (12.671)**	0.500	0.060 (7.245)**	0.016 (2.177)*	0.036
SB	-0.209 (-10.26)**	-0.184 (-9.878)**	0.494	0.089 (7.445)**	0.132 (11.448)**	0.558	0.120 (10.860)**	0.052 (5.449)**	0.228
SE	-0.017 (-2.765)**	-0.000 (-0.021)	-0.007	-0.004 (-2.069)*	0.000 (0.311)	-0.007	0.021 (3.557)**	-0.000 (-0.024)	-0.007
SF	0.058 (2.523)*	-0.399 (-16.59)**	0.585	-0.043 (-2.873)**	0.228 (12.478)**	0.524	-0.015 (-1.190)	0.171 (14.203)**	0.528
SI	-0.430 (-26.43)**	-0.089 (-5.828)**	0.239	0.204 (12.538)**	0.101 (7.168)**	0.320	0.225 (30.523)**	-0.012 (-1.762)	0.025
SM	-0.135 (-11.69)**	-0.126 (-12.14)**	0.520	0.043 (6.043)**	0.088 (13.194)**	0.559	0.092 (15.177)**	0.038 (6.690)**	0.277
W-	-0.128 (-8.255)**	-0.073 (-4.883)**	0.182	0.069 (6.115)**	0.087 (7.959)**	0.372	0.059 (5.772)**	-0.014 (-1.564)	0.018

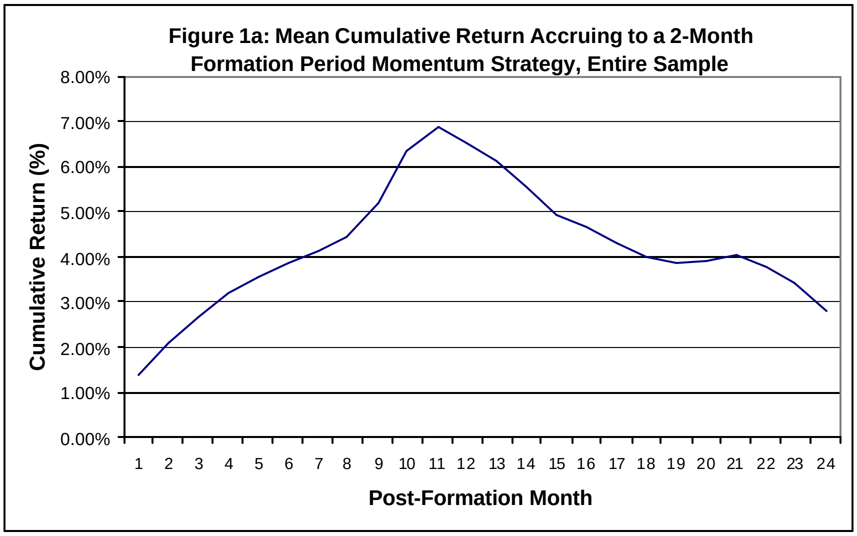
Figure 1a: Mean Cumulative Return Accruing to a 2-Month Formation Period Momentum Strategy, Entire Sample
Cumulative Return (%)
Post-Formation Month
0.00%
1.00%
2.00%
3.00%
4.00%
5.00%
6.00%
7.00%
8.00%

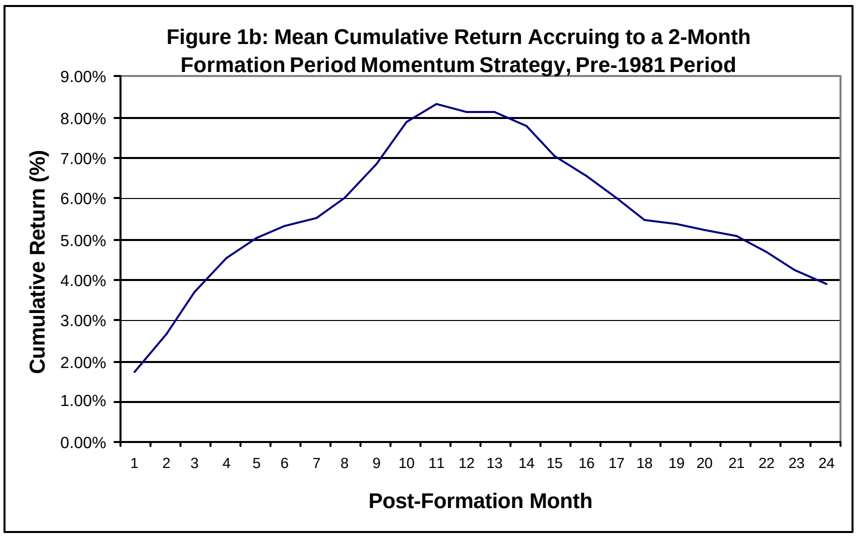
Figure 1b: Mean Cumulative Return Accruing to a 2-Month Formation Period Momentum Strategy, Pre-1981 Period
Cumulative Return (%)
Post-Formation Month
0.00%
1.00%
2.00%
3.00%
4.00%
5.00%
6.00%
7.00%
8.00%
9.00%

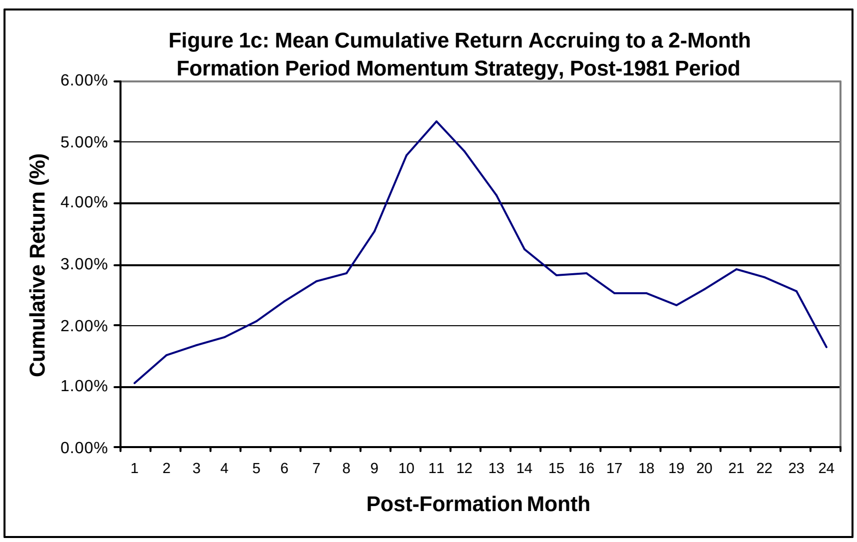
Figure 1c: Mean Cumulative Return Accruing to a 2-Month Formation Period Momentum Strategy, Post-1981 Period
Cumulative Return (%)
Post-Formation Month
0.00%
1.00%
2.00%
3.00%
4.00%
5.00%
6.00%

Figure 2a: Mean Cumulative Return Accruing to a 1m / 6m /.025 Dual Moving Average Crossover Strategy: Entire Sample

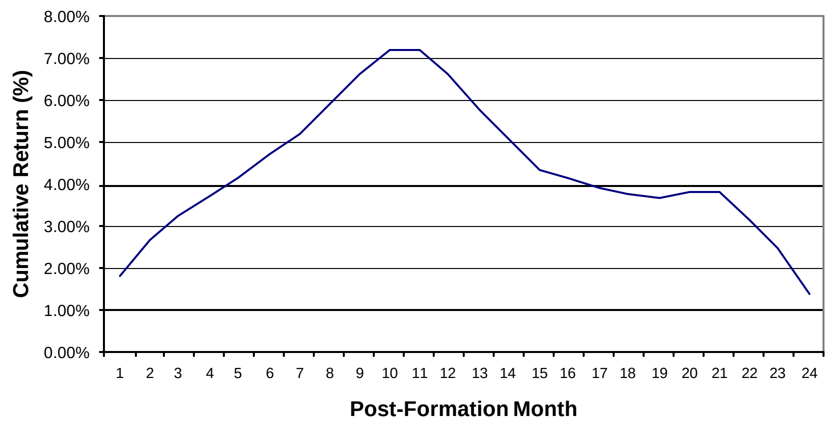

Figure 2b: Mean Cumulative Return Accruing to a 1m /6m /.025 Dual Moving Average Crossover Strategy: Pre-1981 Period

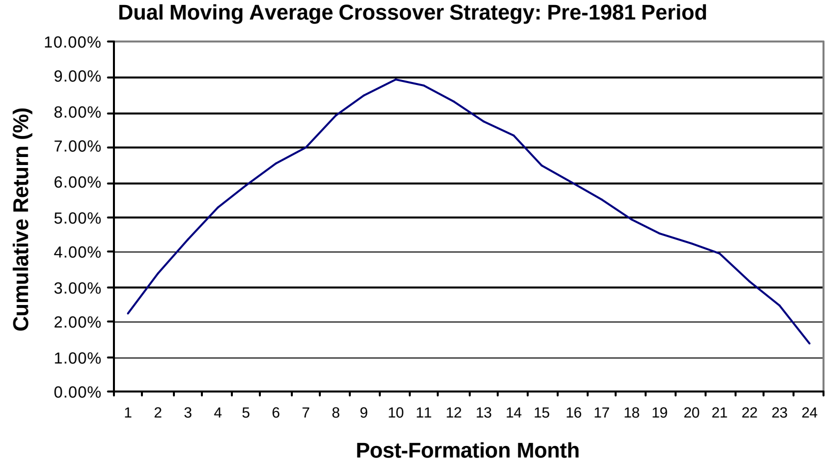

Figure 2c: Mean Cumulative Return Accruing to a 1m / 6m /.025 Dual Moving Average Crossover Strategy: Post-1981 Period