The Moving Average Ratio and Momentum

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I show the ratio of the short-term moving average to the long-term moving average (*moving average ratio*, MAR) has significant predictive power for future returns. The MAR combined with nearness to the 52-week high explains most of the intermediate-term momentum profits. This suggests that an anchoring bias, in which investors use moving averages or the 52-week high as reference points for estimating fundamental values, is the primary source of momentum effects. Momentum caused by the anchoring bias do not disappear in the long-run even when there are return reversals, confirming that intermediate-term momentum and long-term reversals are separate phenomena.

Keywords: momentum; moving average; 52-week high; anchoring bias; behavioral theory; efficient market hypothesis

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1. Introduction

This paper finds that the ratio of two variables commonly used in technical analysis – short- and long-term moving averages – has significant predictive power for future returns, and that this predictive power is distinct from the predictive power of either past returns, first reported by Jegadeesh and Titman (1993), or nearness of the current price to the 52-week high, reported by George and Hwang (2004). Further, the predictive power of past returns becomes insignificant once future returns are controlled for the moving average ratio and nearness to the 52-week high. These findings are consistent with George and Hwang's argument that momentum in stock market is caused by investors' anchoring bias. Investors may use the long-term moving average as a reference point for long-term fundamental value and use the short-term moving average when they evaluate the appropriateness of the current price level.

One of the most puzzling phenomena in financial markets is the intermediate-term momentum in stock prices reported by Jegadeesh and Titman (1993). Jegadeesh and Titman show that the self-financing strategy that buys winners and sells losers based on the previous three- to 12-month returns, and holds the position for the following three to 12 months, generates positive profits. Rouwenhorst (1998) finds that momentum phenomena are not restricted to the U.S. market, prevailing in 12 other countries. Also, Jegadeesh and Titman (2001) report that momentum strategies continue to be profitable in the 1990s. These results suggest that the initially reported profitability of momentum strategies is not the result of data-snooping biases. In addition to intermediate-term momentum, DeBondt and Thaler (1985), Lee and Swaminathan (2000), and Jegadeesh and Titman (2001) report long-term reversals in stock returns. For instance, Jegadeesh and Titman (2001) find that profits from a momentum strategy with a six-month formation period, over a 48- month period beginning with the thirteenth month after the momentum portfolio formation period, are significantly negative. They also report that momentum profits over a 12-month period immediately following the formation period are significantly positive for the sample period 1965 to 1997. However, Jegadeesh and Titman also show that the long-term reversal is both time dependent and stronger among small firms, while momentum is persistent regardless of sample period and firm size.

Some explanations for intermediate-term momentum in stock prices are consistent with the efficient market hypothesis. For instance, Berk, Green, and Naik (1999) develop a theoretical model that predicts intermediate-term momentum profits. In their model, time-varying but persistent systematic risk generates momentum profits. Conrad and Kaul (1998) show that intermediate-term momentum profits come primarily from the cross-sectional dispersion of unconditional expected returns, while Jegadeesh and Titman (2001) argue that the Conrad and Kaul results are driven by errors in the estimation of unconditional expected returns. Finally, Chordia and Shivakumar (2002) argue that a set of macroeconomic variables can predict expected stock returns.

Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) present behavioral models to explain the coexistence of intermediate-term momentum and long-term reversals in stock returns. In sum, under Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999), investors tend to underreact to new information, resulting in intermediate-term momentum, but they subsequently overcorrect previous mispricing, leading to long-term reversals. Under Daniel, Hirshleifer, and Subrahmanyam (1998), momentum is a consequence of investors' tendency to overreact to prior information, and reversals occur when they correct the mispricing. Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) attribute the mispricing to psychological biases, such as conservatism and representativeness heuristics or overconfidence that leads to momentum or reversals, while Hong and Stein (1999) emphasize slow diffusion of information to explain momentum.

In addition to the above behavioral theories, George and Hwang (2004, GH hereafter) find that the nearness of current price to the 52-week high price explains a large portion of profits derived from momentum strategies. Specifically, GH show that the investment strategy that buys stocks with a high ratio of current price to 52-week high and sells stocks with a low ratio produces statistically significantly positive profits. More importantly, profits from Jegadeesh and Titman's (1993) style momentum strategy are significantly reduced once stock returns are controlled for returns forecasted by nearness to the 52-week high. GH suggest that investors are subject to an anchoring bias whereby they use the 52-week high as a reference point against which they evaluate the potential impact of news. When good news has pushed a stock's price to or near a new 52-week high, investors are reluctant to bid the price of the stock higher even if the information warrants it. On the other hand, when bad news pushes a stock's price far from its 52-week high, investors are initially unwilling to sell the stock at prices that are as low as the information implies. The subsequent corrections of these mispricings generate momentum profits.

GH find, however, that nearness to the 52-week high fails to explain negative profits from Jegadeesh and Titman's (1993) momentum strategy over the post-holding periods. This, together with results described above, suggests that a large portion of intermediate-term momentum is a consequence of investors' anchoring bias on the 52-week high in estimating the current fundamental value, but the anchoring bias is independent of long-term reversals in stock returns. Therefore, in contrast to Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), or Hong and Stein (1999), GH conclude that intermediate-term momentum and long-term reversals are separate phenomena.

More recent research identifies determinants of momentum and reversal phenomena. For example, Arena, Haggard, and Yan (2008) show that momentum is stronger among high idiosyncratic volatility stocks, and stocks with high idiosyncratic volatility experience faster and larger reversals. Arena, Haggard, and Yan (2008) argue that the findings are consistent with the view that momentum profits result from underreaction to firm-specific information, for which idiosyncratic volatility can be viewed as a proxy for firm-specific information. Zhang (2006) shows that greater information uncertainty produces higher momentum profits. Zhang also shows that the initial market reaction to new public information is incomplete, and that the degree of incompleteness of the market reaction increases with information uncertainty. These findings suggest that investors' underreaction to new information causes momentum.

The primary contribution of this paper to the momentum literature is the finding that the ratio of a short-term moving average to a long-term moving average has significant predictive power for future returns distinct from either past returns or nearness to the 52-week high. Particularly, an investment strategy that ranks stocks based on the ratio of the 50-day moving average to the 200-day moving average, buys the top 10% (or 30%) of stocks, and sells the bottom 10% (or 30%) of stocks, produces profits over the subsequent six-month holding period that are substantially greater than profits generated by either Jegadeesh and Titman's (1993) momentum strategy or GH's 52-week high strategy. Further, the predictive power of stock returns for the previous 12 months becomes insignificant once future returns are controlled for the moving average ratio and nearness to the 52-week high.

The predictive power of the moving average ratio is not restricted to the 50/200 parameterization. When I use one, two, five, or 20 days for the short-term moving average~~s~~, and 200 or 250 days for the long-term moving average~~s~~, each of the moving average ratio combinations generates statistically significant profits, even when controlling for momentum and the 52-week high. For all short- and long-term moving average combinations tested, the moving average ratio has more significant predictive power than the past 12-month return. For some combinations, the moving average ratio and nearness to the 52-week high completely explain the momentum phenomenon.

One of the technical trading rules introduced in Reilly and Norton (2003) suggests that investors buy stocks when the short-term moving average (MA) line crosses the long-term MA line from below, and sell stocks when the short-term MA line crosses the long-term MA line from above. Further, this rule suggests that, if the short-term MA is substantially greater than the long-term MA (which occurs when there is a rapid run-up in price), a technician might consider this an indication that the stock is temporarily overbought which is bearish for the short-run. Similarly, if the short-term MA is substantially less than the long-term MA, it might be considered a signal of an oversold stock, which is bullish for the short-run. I do not test the usefulness of the buy or sell signal when the short- and long-term MA lines cross. Rather, I test whether the difference between the short- and long-term MAs has predictive power for future returns, as the technical trading rule suggests. My results are opposite those suggested by the trading rule: stocks with a short-term MA that is much greater than the long-term MA tend to perform better over the following six-month period than stocks with the opposite MA relation.

These findings, together with those of George and Hwang, can be explained by investors' anchoring bias as summarized by Kahneman, Slovic, and Tversky (1982). Investors may use the long-term moving average as a reference point for long-term fundamental value. Next, they may use a shorter-term moving average as a reference point for current price in order to eliminate noise that might be included in the current price. Investors anchor on the long-term moving average when they evaluate the appropriateness of the current price level. This anchoring on moving averages is a bias since, if the fundamental value follows a random walk process, as financial theories generally assert, then time-series averages do not have predictive power for future values. When recent good news has boosted the short-term MA substantially above the long-term MA, demand for a stock would be less than the information warrants because investors incorrectly believe that the current price is too high given their anchor, the long-term MA. This reduced demand results in underreaction to the information. However, the information eventually prevails so that the mispricing is corrected in the subsequent period, resulting in momentum profits. The underreaction is most significant when the difference between the short- and long-term MAs is largest. Similarly, when recent bad news has pushed the short-term MA below the long-term MA, demand for the stock would be greater than the information warrants because investors incorrectly believe that the current price is too low given their anchor, leading to underreaction and momentum. If some investors regard the 52-week high as their reference point for estimating fundamental value, as George and Hwang (2004) argue, it can also be true that these investors, or other investors, use moving averages as their reference points.

Jegadeesh and Titman (2001) show that return reversals are much stronger for 1965 to 1981 than for 1982 to 1998, while return momentum is stronger in the later period. Also, they show that, when only large firms are included in the sample, the reversals become much weaker while momentum for large firms is still strong. These results suggest that intermediate-term momentum and long-term reversals might be separate phenomena, as George and Hwang (2004) argue. Further, these results are more supportive of the argument that momentum returns are due to anchoring (which is a form of underreaction) rather than overreaction and subsequent correction. My analysis of long-term reversals shows that future return forecasts based on the moving-average ratio do not reverse in the long run, even when there exist long-term reversals, if past performance is measured by the previous twelve-month returns. This is consistent with George and Hwang (2004), who show that returns forecasts based on 52-week high do not reverse in the long run, and confirms George and Hwang's argument that intermediate-term momentum and long-term reversals are not likely to be components of the same phenomenon, as modeled by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999).

2. Methods and data

2.1. Investment strategies and variables

I compare three trading strategies, each of which uses a different variable. The first strategy is denoted *JT* (*p*, *J*, *D*, *K*), which, following Jegadeesh and Titman (1993), buys the top *p*% of stocks and sells the bottom *p*% based on the previous *J*-month returns (denoted "*J*-return" hereafter) and holds the portfolio for *K* months. There is a *D*-month gap between the portfolio formation period and the holding period. The second strategy is denoted *GH* 52*HI* (*p*, *D*, *K*), which, following George and Hwang (2004), buys the top *p*% of stocks and sells the bottom *p*% based on the ratio of a stock's current price to its highest price during the previous 12 months ("52HIR" hereafter) and holds the portfolio for the next *K* months. Finally, an investment strategy based on the ratio of the 50-day moving average to the 200-day MA ("MAR" hereafter) is denoted as *MAR* (*p*, *D*, *K*).[1]

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[1] I use 50/200 parameterization for most t. In addition, I report results for other combinations (i.e., 1/200, 5/200, 20/200, 20/250, and 50/250), as a robustness check in Table 6.

2.2. Data

I use two different samples from the CRSP U.S. stock database for July 1962 through December 2004. The first sample includes all stocks traded on the NYSE, AMEX, and Nasdaq, except that I exclude stocks priced below $5 at the end of the formation period and stocks with market capitalizations that would place them in the smallest NYSE decile. These are the same screenings used by Jegadeesh and Titman (2001). The second sample is the same as the first except that price and size screening are not applied, so that this sample is the same as the George and Hwang (2004) sample over a different period. I use these two samples in order to determine the impact of small and illiquid stocks on profits from the investment strategies.

When constructing a winner or loser portfolio for each of the three investment strategies at the beginning of month t, I exclude stocks meeting any of the following criteria: stocks missing any monthly returns for the previous J-month period (t-J, t-1); stocks with less than 200 daily observations for the previous one-year period (t-12, t-1); stocks with less than 160 daily observations for the previous 200-day period ending on the last trading day of month t-1; and stocks with less than 40 daily observations for the previous 50-day period ending on the last trading day of month t–1. If a stock is excluded from the formation of a JT momentum strategy, it is also excluded from the other investment strategies even if the stock meets the observation requirement for those strategies. In some cases, a stock is included in a winner or loser portfolio but is subsequently delisted or has missing observations during the holding period. If a stock is delisted during a holding period, until and during the month of delisting I use the CRSP returns, and then, after the delisting, I assume that the return is the same as the average for those stocks in its portfolio. If a stock has missing observations for a holding period, I assume that its return is the same as the average return for the stocks in the portfolio.

2.3. Fama-MacBeth (1973) regressions

To simultaneously compare the profitability of the three strategies, *JT* (*p*, *J*, *D*, *K*), *GH* 52*HI* (*p*, *D*, *K*), and *MAR* (*p*, *D*, *K*), after controlling for potential market microstructure and size effects, I implement Fama-MacBeth (1973) style cross-sectional regressions in a manner similar to George and Hwang (2004). For each month *t*, I implement *K* cross-sectional regressions as follows;

$$\begin{aligned} R_{it} &= b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} \ln\left(size_{it-1}\right) + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} FHH_{it-D-k} \\ &\quad + b_{6kt} FHL_{it-D-k} + b_{7kt} MAH_{it-D-k} + b_{8kt} MAL_{it-D-k} + e_{it} \end{aligned} \tag{1}$$

for $k = 1, \ldots, K$, where K is the holding period for the investment strategy, R_{it} and $R_{it\text{-}1}$ are stock *i*'s returns for month *t* and month *t* -1, respectively, ln ($size_{it\text{-}1}$) is the natural logarithm of the market capitalization of stock *i* at the end of month *t* - 1, and all other independent variables are dummy variables that depend on the stock's inclusion in the portfolio for each strategy. For instance, $JH_{it\text{-}D\text{-}k}$ equals one if stock *i* belongs to the winner portfolio for the *JT* momentum strategy formed at the beginning of month ($t - D - k + 1$) and zero otherwise. For *JT* (30, 6, 0, 6), $JH_{it\text{-}D\text{-}k}$ equals one if stock *i* belongs to the top 30% based on the six-month return from ($t - k - 5$) to ($t - k$). $JL_{it\text{-}D\text{-}k}$ equals one if ~~the~~ stock *i* belongs to the loser portfolio for the *JT* momentum strategy. Similarly, $FHH_{it\text{-}D\text{-}k}$ and $FHL_{it\text{-}D\text{-}k}$ take one or zero, respectively, depending on whether stock *i* belongs to the winner or loser portfolio for the GH investment strategy based on the nearness of the stock's price to the 52-week high. Finally, MAH_{it-D-k} and MAL_{it-D-k} equal one or zero, respectively, depending on whether stock *i* belongs to the winner or loser portfolio for the investment strategy based on the moving average ratio.

Once the coefficients, b_{lkt} for $l = 0, \ldots, 8$, are estimated for $k = 1, \ldots, K$, I then calculate the average for each estimated coefficient for each *l*, so $\hat{b}_{lt} = 1/K \sum_{k=1}^{K} \hat{b}_{jkt}$ for $l = 0, \ldots, 8$. Also, I calculate $\hat{b}_{3t} - \hat{b}_{4t}$, $\hat{b}_{5t} - \hat{b}_{6t}$, and $\hat{b}_{7t} - \hat{b}_{8t}$ to determine month-*t* profits for the pure *JT, GH* 52*HI* and *MAR* strategies, respectively. Finally, the time-series averages of $\hat{b}_{lt}$'s and $\hat{b}_{3t} - \hat{b}_{4t}$, $\hat{b}_{5t} - \hat{b}_{6t}$, and $\hat{b}_{7t} - \hat{b}_{8t}$, and associated *t*-statistics are used to test for the profitability of each of the three investment strategies and for market microstructure effects and size effects.

3. Results

3.1. Summary statistics

Panel A of Table 1 presents time-series averages of cross-sectional means and standard deviations for the previous 12- and six-month returns (12-return and 6-return), 52HIR, and MAR over the period January 1964 to December 2004. I exclude stocks priced below $5 and stocks with market capitalization that would place them in the smallest NYSE decile. Panel A shows that grand averages of 6-return, 12-return, 52HIR and MAR are 6.64%, 12.92%, 0.82 and 1.03, respectively. Panel B of Table 1 reports time-series averages of the estimates of pairwise correlation coefficients among the four variables. As expected, MAR is positively correlated with each of the other variables, 6-return, 12-return and 52HIR. Given this high correlation with variables previously shown to have predictive power for future returns, it would not be surprising if MAR predicts future returns, because MAR might be a proxy for past returns or for 52HIR. However, the results below indicate that past returns seem to have predictive power for future returns because they are proxies for MAR or 52HIR, and MAR has predictive power distinct from that of 52HIR.

3.2. Raw and risk-adjusted profits from the three investment strategies

Table 2 presents average monthly raw and risk-adjusted returns of winners, losers, and winner minus loser portfolios for the three investment strategies, *JT* (*p*, *J*, *D*, *K*), 52*HI* (*p*, *D*, *K*), and *MAR* (*p*, *D*, *K*), for p = 10% or p = 30%, J = 6 months or J = 12 months, D = 0, and K = 6 for the 41-year period 1964 to 2004. All stocks on the NYSE, AMEX, and Nasdaq are included except stocks priced below $5 and stocks that would be in the smallest NYSE decile at the end of the formation period.

Panel A of Table 2 shows that profits from both Jegadeesh and Titman (1993) momentum strategies are economically and statistically significant. For instance, average monthly profit from *JT*(10,6,0,6) is 1.23% for the entire sample, the same value reported by Jegadeesh and Titman (2001) for 1965 to 1998, using the same screening criteria. This profit is economically and statistically significantly greater than that originally reported by Jegadeesh and Titman (1993), who exclude Nasdaq stocks for 1965 to 1989 but do not use price or size screening. Perhaps this difference results from the fact that small or illiquid stocks are more vulnerable to short-term (weekly or monthly) reversals caused by bid-ask bounce and liquidity effects, so that excluding small stocks in the sample reduces these market microstructure effects. For the entire sample period and for all months, the six-month holding period return is slightly greater when the formation period is six months rather than 12 months, for p = 10%, while the Jegadeesh and Titman (1993) momentum strategy with a twelve-month formation period is more profitable for p = 30%. Monthly profits from Jegadeesh and Titman (1993) strategies for both subsample periods are similar in both magnitude and statistical significance. This suggests that intermediate-term momentum is not the result of data snooping, as Jegadeesh and Titman (2001) argue, and that arbitrageurs do not exploit this predictable price behavior once they come to know the arbitrage opportunities, as argued by Shleifer and Vishny (1997).

Panel A of Table 2 also shows that two other investment strategies, *GH 52HI* (p, 0, 6) and *MAR* (p, 0, 6), produce economically and statistically significant profits for both p = 10% and p = 30%. Further, the moving-average ratio strategy is the most profitable strategy, with the highest t value, for all subsample periods. For example, when p = 10%, monthly profit from *MAR* (10, 0, 6) is 1.45% with t-statistic equal to 6.02. The next most profitable strategy is *JT* (10, 6, 0, 6), which produces 1.23% per month with t-statistic equal to 5.16, followed by *JT* (10, 12, 0, 6) (1.21% per month and t-statistic of 4.94). *GH 52HI* (10, 0, 6) is the least profitable strategy, although these profits are also economically and statistically significant (1.15% per month and t-statistic of 4.49). The order of profitability is the same for p = 30%, with the exception that *JT* (30, 12, 0, 6) is more profitable than *JT* (30, 6, 0, 6). It appears that the success of the 52-week high and moving-average strategies is not restricted to a specific sample period.

When Januarys are excluded from the holding periods in Panel B of Table 2, profits from each of the three investment strategies are larger than those with Januarys included in the sample. This is consistent with previous studies. Panel B also shows that *GH* 52*HI* strategies are slightly more profitable than *JT* momentum strategies for non-Januarys, while *MAR* strategies remain the most profitable.

I regress returns for winner and loser portfolios and profits from the three investment strategies on the Fama-French (1996) factors to determine whether the risk factors can explain the profits from the investment strategies. Panel C of Table 2 presents the estimates of alphas of the Fama-French three-factor regression. The alpha for profit from each strategy is positive and statistically significant, and even larger and more statistically significant than the corresponding raw profit in Panel A. This indicates that the Fama-French factors, if anything, contribute negatively to the profits from the momentum strategies.

Table 3 presents pairwise comparisons of profitability for the three investment strategies, *MAR* (*p*,0,6), *GH* 52*HI* (*p*,0,6) and *JT* (*p*,12,0,6), first for p = 10% and then for p = 30%. The *MAR* strategy is statistically significantly more profitable than the *JT* momentum strategy when p = 10%. The difference in profit is 0.24% per month, with *t*-statistic equal to 2.45. This difference derives from both winner and loser portfolios. The return on the *MAR* winner portfolio is higher by 0.13% (*t*-statistic is 2.55) on average than the return on the *JT* winner portfolio and the return on the *MAR* loser portfolio is lower by 0.11% (*t*-

statistic is -2.02) on average than the return on the *JT* loser portfolio. Also, the *MAR* winner portfolio generates a statistically significantly greater return than the *GH* 52*HI* winners, while the difference in returns between the *MAR* loser and the *GH* 52*HI* loser portfolios is not significant. Finally, the *GH* 52*HI* losers have statistically significantly lower returns than the *JT* loser portfolios, but the difference in returns between the *GH* 52*HI* winners and the *JT* winners is not significant. However, when p = 30%, none of the differences in profits between any pair of investment strategies is statistically significant.

3.3. Comparisons of profitability: two-way sorted portfolios

As seen in Panel B of Table 1, the moving average ratio (MAR) is positively correlated with 52HIR, 12-return and 6-return. Therefore, the predictive power of MAR for future returns may derive from the predictive power of these variables. To investigate whether MAR is an independent signal for future returns, I calculate holding period returns for the double-sorted portfolios based on MAR and 12-return, and on MAR and 52HIR, respectively. In Panel A of Table 4, at the beginning of each month, all stocks are first sorted by 12-return into quintiles. Stocks in each quintile are assigned to one of five equal-sized portfolios based on MAR. The double-sorted portfolios are held for the next six months. Also, risk-adjusted profit from the *MAR* strategy within each 12-return portfolio is presented. The monthly profit from the *MAR* strategy within each 12-return portfolio is regressed on the Fama-French (1996) factors. In Panel B, the stocks are sorted first by MAR and then by 12-return.

If the MAR appears to have predictive power for future returns in Table 2 simply because it is correlated to 12-return, then the difference in holding-period returns between the highest 12-return and lowest 12-return portfolios within each MAR portfolio should be greater than, and more statistically significant than, the difference between the highest-MAR and the lowest-MAR portfolios within each 12-return portfolio. However, Panel A of Table 4 shows that the *MAR* strategy within the lowest 12-return quintile generates 0.78 (0.94) percent profit with *t*-statistic of 4.39 (5.64) when Januarys are included (excluded) in the sample, while Panel B shows that the *JT* strategy within the lowest MAR quintile generates 0.53 (0.74) percent with *t*-statistic of 3.08 (4.23). This suggests that the MAR has more predictive power within the lowest 12-return quintile than does the 12-return variable within the lowest MAR quintile. Comparison of Panels A and B shows that regardless of whether Januarys are included in the sample, the *MAR* strategy within each 12-return quintile generates larger and more statistically significant profits than the *JT* strategy within all of corresponding MAR quintiles. Therefore, the MAR variable within 12-return quintiles has greater predictive power than the 12-return variable within MAR quintiles, indicating that MAR is an independent signal from, and has greater predictive power than, the 12-return.

When profits are adjusted with the Fama-French factors, the results are not consistent in Panels A and B of Table 4. Alphas for the profit from the *MAR* strategy are larger and more statistically significant for the extreme (first and fifth quintiles) 12-return portfolios than those for the profit from the *JT* strategy for corresponding MAR portfolios. However, alphas from the *MAR* strategy are smaller and less statistically significant for the middle 12-return portfolios.

Comparison of MAR and 52HIR in Panels C and D of Table 4 also shows that the MAR within 52HIR quintiles has greater predictive power than 52HIR within MAR quintiles based on raw returns. Panel C shows that the difference in holding period return~~s~~ between the highest and lowest MAR portfolios within each 52HIR quintile is statistically significant regardless of whether Januarys are included. In Panel D, the difference in returns between the highest and lowest 52HIR portfolios within the second, third and fourth MAR quintiles is insignificant when the sample includes Januarys. The return differences between the highest and lowest 52HIR portfolios within the first and fifth MAR quintiles are smaller than the return differences between the highest and lowest MAR portfolios within the first and fifth 52HIR quintiles. However, if Januarys are excluded from the sample, neither variable seems to dominate the other in predicting future returns. The difference between the highest MAR (52HIR) quintile and the lowest MAR (52HIR) quintile within each 52HIR (MAR) quintile is economically and statistically significant for non-Januarys. These results suggest that MAR has predictive power distinct from 52HIR. Also, results from Panels E and F fail to show that either 12-return or 52HIR contains more information for future returns than the other. Repeating the analysis with 6-return, MAR, and 52HIR produces qualitatively similar results (not tabulated).

3.4. Comparisons of profitability: Fama-MacBeth style regressions

Although Table 2 shows that the winners from the three strategies significantly outperform losers over the subsequent six months after the portfolios are formed, these results do not allow us to distinguish among the underlying forces driving the return continuation. Stocks that outperformed other stocks for the previous six or 12 months tend to be priced close to the 52-week high and also have a higher ratio of 50-day moving average to 200-day moving average. In order to identify the marginal effect of belonging to the winner or loser portfolio under a given investment strategy, while controlling for the effect of being in a winner or loser portfolio under other investment strategies, I implement the Fama-MacBeth style cross-sectional regression analysis of Equation (1) in Subsection 2.3.

In Tables 5 and 6, I compare *JT* (30, 12, 1, 6), *GH* 52*HI* (30, 1, 6), and *MAR* (30, 1, 6). Here, the *JT* momentum strategy has a 12-month formation period, holding periods for all strategies are six months, and there is a one-month gap between the formation period and the holding period. I use the *JT* momentum strategy with a 12-month formation period, rather than a six-month formation period, because the *GH* 52*HI* and *MAR* strategies use much more than six months of historical price information to form portfolios, and because the *JT* strategy with a 12-month formation period produces slightly greater momentum profit than the *JT* strategy with a six-month formation period in Table 2. However, when I repeat this analysis with *JT* (30, 6, 1, 6), I obtain similar results (not tabulated).

Table 5 presents the time-series averages of the estimated coefficients of Equation (1), and the differences between estimated coefficients on winner and loser dummies from the investment strategies and associated *t*-statistics as described in Subsection 2.3. In addition to the winner and loser dummy variables, I include one-month lagged returns and the natural logarithm of market capitalization in order to control for market microstructure and size effects. In addition, I separately present time-series averages and *t*-statistics for the coefficient estimates for all months and for January excluded. In Panel A, winner and loser dummy variables for each of the three investment strategies are included in Equation (1), while dummy variables for two or three investment strategies are included in Panel B. Panel C separately presents results for two subsample periods. The sample period is 1964 through 2004. In Panels A through C of Table 5, price and size screenings are applied, while all stocks are included in Table 6.

Panel A of Table 5 confirms the results in Table 2, showing that profit for each of the three investment strategies is significantly positive even if profit is controlled for one-month lagged return and firm size, when winner and loser dummy variables from only one investment strategy are included in Equation (1). For example, the coefficients of the winner and loser dummies from the *JT* strategy are 0.27% (*t*-statistic of 2.46) and -0.32% (*t*-statistic of -3.42) per month, respectively, for the sample period including Januarys. This means that a stock that belongs to the *JT* winner portfolio, on average, performs better by 0.27% per month over the next six months compared to a stock with the same size and last-month return belonging to the middle portfolio, and by 0.60% per month compared to a stock with the same size and last-month return belonging to the loser portfolio. Therefore, the coefficient of winner dummy minus the coefficient of loser dummy can be regarded as the return difference resulting purely from the stock’s membership in the winner or loser portfolio. The size and statistical significance of the profit for each of the three strategies increase when Januarys are excluded from the holding period. Panel A also shows that profit from the *JT* strategy is smallest in both the economic and statistical sense among the three investment strategies, regardless of whether Januarys are included in the sample period.

The new findings of this paper are in Panel B of Table 5, where the winner and loser dummies for the *MAR* strategy play significant roles even after controlling for the *JT* and *GH* 52*HI* strategies. Furthermore, profits from the pure *MAR* strategy are more statistically significant than profits from either the pure *JT* or the pure *GH* 52*HI* strategies. Also, profit from the pure *JT* strategy becomes insignificant when winner and loser dummy variables for all three investment strategies are included in the regression analysis for the sample period including Januarys. Columns two and three include winner and loser dummies for all three strategies as well as the natural logarithm of market capitalization and one-month lagged return in the regression. In this case, the pure *JT* momentum strategy does not produce statistically significant profits at conventional significance levels (i.e., 10% significance level) when Januarys are included in the holding periods; the monthly profit is only 0.13% per month with a *t*-statistic of 1.10. Both the coefficients of the winner and loser dummies from the *JT* strategy are insignificant. When Januarys are excluded, the monthly profit is marginally significant at the 10% level; monthly profit is 0.21% with a *t*-statistic of 1.74. Profit from the pure *JT* strategy comes only from the winner portfolio, which generates 0.15% (*t*-statistic of 1.71) monthly profit, while the loser portfolio contributes only 0.06% (*t*-statistic of -1.19) profit. However, both the pure *GH* 52*HI* and

MAR strategies produce significant profits, at the 1% significance level, regardless of whether Januarys are included. These results suggest that a substantial portion of the predictive power of past 12-month returns for future returns derives from either nearness to the 52-week high price or the moving average ratio. These results are consistent with George and Hwang's (2004) argument that a theory in which current price relative to an anchor plays a role explains the data better than do existing theories that focus on price changes based on overconfidence, conservatism, or slow diffusion of information. Columns two and three also suggest that the predictive power for future return of both nearness to the 52-week high and the moving average ratio are distinct, and that investors regard both the moving averages and the 52-week high as their anchor.

The second and third columns in Panel B of Table 5 also demonstrate that profits from the pure *GH* 52*HI* strategy derive only from the loser portfolios. The coefficient of the winner dummy variable from the pure 52*HI* strategy is only 0.03% (with *t*-statistic of 0.49) for all months, while the coefficient of the loser dummy is -0.40% (with *t*-statistic of -3.92). Even when Januarys are excluded from the sample, the coefficient of the winner dummy is not significant. Therefore, the 52-week high seems to explain only half of the momentum phenomenon. The result suggests that investors who are subject to the anchoring bias and who use the 52-week high as their reference point when evaluating current stock price tend to have a greater bias towards stocks that have performed poorly in the recent past than for stocks that have performed well. Perhaps investors subject to this bias believe that stocks with current prices so low compared to the 52-week high are undervalued, and therefore, these investors want to buy more of these stocks, or sell fewer, than if there were no such bias, while they do not think that stocks with current prices close to the 52-week high are overvalued. However, the fact that profits from the pure *MAR* strategy come from both the winner and loser portfolios, with similar statistical significance, suggests that investors who are subject to the anchoring bias and who use moving averages as their reference points tend to use them for both winners and losers.

In columns four through nine in Panel B of Table 5, dummy variables for the two investment strategies are included in order to determine whether one investment strategy dominates another. The results indicate that none of the three pure investment strategies completely dominates any other strategy. However, only the *MAR* strategy produces significant profits from both winner and loser portfolios in all cases. When dummy variables for the *JT* and *MAR* strategies are included in the regression in columns four and five, the coefficients of the *JT* winner portfolios become insignificant regardless of whether Januarys are included. Columns six and seven show that the coefficient of the winner dummy for the 52*HI* strategy is insignificant for all months when dummy variables for the 52*HI* and *MAR* strategies are included. Also, the coefficients of the loser dummy for the *JT* strategy and the winner dummy for the 52*HI* strategy are insignificant for the all-month sample in the second and third columns.

Panel C of Table 5 displays results for analogous regressions over two subsample periods, 1964 through 1983, and 1984 through 2004. When only *JT* winner and loser dummies are included in equation (1), six-month holding period profits are statistically significantly positive for both subperiods. However, when all winner and loser dummy variables for the three strategies are included, profit from the pure *JT* strategy becomes insignificant when Januarys are included for both subperiods: 0.17% per month with *t*-statistic of 1.14 for the first subperiod, and 0.09% per month with *t*-statistic of 0.52 for the second subperiod. Further, for the second subperiod, even when Januarys are excluded, the pure *JT* strategy fails to generate significant profit: profit is 0.14% per month with *t*-statistic of 0.75. However, profits from both the *GH* 52*HI* strategy and the *MAR* strategy are statistically significantly positive regardless of whether Januarys are included in the subperiods. Perhaps one can conclude from these results that behavioral theories based on conservatism, overconfidence or slow diffusion of information can, at best, partially explain the momentum phenomenon in the first sample period, and theory based on anchoring bias can better explain momentum in both subsample periods.

Panel C of Table 5 also demonstrates that only the *MAR* strategy generates symmetric profits from both winner and loser portfolios with similar levels of statistical significance in both subperiods, while the 52-week high strategy generates significant profits only from the loser portfolios. The pure *JT* strategy does not produce statistically significant profits from either the winner or loser portfolios for both subperiods when Januarys are included. Even when Januarys are excluded, the pure *JT* strategy produces marginal profits from the winner portfolio only in the first subperiod.

In order to determine whether the results in Panels A and B of Table 5 are driven primarily by the exclusion of small and low-priced stocks, the regression analyses are repeated in Panel D for the entire sample of NYSE, AMEX and Nasdaq stocks. The results in Panel D are qualitatively similar to those of Panels A and B. Column four of Panel D shows that average monthly profit from the pure *JT* strategy (0.04% with *t*-statistic of 0.34) is less than the corresponding profit in Panel B, while average monthly profit from the pure 52*HI* and the *MAR* strategies is greater than the corresponding profit reported in Panel B. This suggests that, even when small and low-priced stocks are included, past returns do not explain return continuation if Januarys are included in the holding period. As in Panel B, when Januarys are excluded from the holding periods, average monthly profit for the pure *JT* strategy is marginally significant at the 10% level, while average monthly profit for both the pure 52-week high and MAR strategies is statistically significantly positive.

Relative to the results in Panels A and B of Table 5, the coefficients of one-month lagged returns and size are much greater in absolute value in Panel D. For example, for all months, the coefficient estimate on $R_{it\text{-}1}$ is -6.29 (*t*-statistic is -15.81) when all stocks are included in the sample, while the coefficient is -3.79 (*t*-statistic is -8.69) when small or low priced stocks are excluded. This suggests that small or illiquid stocks are more vulnerable to short-term (one-month) return reversals, consistent with the argument that short-term return reversals are caused by market microstructure effects. Also, coefficients on the natural logarithm of market capitalization are negative and statistically significant regardless of whether Januarys are included in the holding period. These results, along with those of Panels A, B, and C, suggest that the size effect in non-Januarys derives from small or low priced stocks.

3.5. Robustness tests: different moving average ratios

While some textbooks introduce technical trading rules using 50- and 200-day moving averages to represent short- and long-term moving averages, respectively, few academic researchers investigate the significance of this parameterization.[2] (See Park and Irwin, 2007 for a survey.) Table 6 repeats columns two and three from Panel B of Table 5, with the exception that different parameterizations for short- and long-term moving averages are used; specifically, one, five or twenty days for the short-term moving average and 200 or 250 days for the long-term average.[3] The combinations of short- and long-term moving averages analyzed here are: 1/200, 5/200, 20/200, 20/250, and 50/250. Since the 50- and 150-day moving averages contain~~s~~ much less information than the past 12-month return or 52HIR, these long-term moving averages are not included in the analysis.

The results in Table 6 suggest that the significant and distinct predictive power of the moving average ratio for future returns is not restricted to the 50/200 parameterization. Profits from the pure *MAR* strategies with all moving average combinations under consideration are significant, even after controlling for profits from the pure *JT* and 52*HI* strategies. Further, for the all months including Januarys, profit from the pure *MAR* is most statistically significant for each combination. However, the combination of a very short-term moving average (one-day or five-day) with a 200-day moving average results in a profit from the *JT* strategy that is still significantly positive regardless of whether Januarys are included, even though the significance level here is the least among the three investment strategies. When we use the 20/200 combination for the moving average ratio,

[2] Examples include Bodie, Kane and Marcus (2004), Jones (2004), and Reilly and Norton (2003).
[3] Results when the short-term MA is represented by a two-day period are very similar to those using a one-day period.

the pure *JT* strategy generates insignificant profits for the all-month sample. Finally, when the 250-day MA is used for the long-term MA with 20-day or 50-day short-term moving averages, the profit from the pure *JT* strategy is insignificant regardless of whether Januarys are included in the sample. This table suggests that a broad range of moving average ratios has a significant and distinct predictive power for future returns, and further, that the main results are not driven by data-snooping biases.

3.6. Long-term reversals

To investigate the time dependence of return reversals, I measure long-term returns from the *JT* strategy for two subsample periods, June 1968 through December 1983, and January 1984 through December 2004. In Panels A and B of Table 7, the regression includes dummy variables only for the *JT* strategy, and inserts 12-, 24-, 36- and 48-month gaps between the formation and holding periods. Also, the holding period is lengthened to 12 months for consistency with Jegadeesh and Titman (2001) and George and Hwang (2004). In Panel A, all stocks are included in the analysis, while price and size screenings are applied in Panel B. Panel A shows that, in general, the *JT* strategy generates negative profits for the four-year period occurring 12 months after the formation period, and that return reversals are stronger for the first sample period, consistent with Jegadeesh and Titman (2001). Specifically, the *JT* strategy profits during the 12-month period occurring 12, 24, 36, or 48 months after the formation are all statistically significantly negative for the first subperiod, but these profits are statistically insignificant when the gap is 24 or 36 months in the second subperiod. Further, when there are 36-month gaps between the formation and holding periods, the *JT* strategy generates a positive profit in the second subperiod, although this profit is not statistically significant. Return reversals become weaker when small stocks and stocks with price under $5 are excluded in Panel B. The 12-month holding period losses for the period 48 months after formation become insignificant for both subsample periods. This is consistent with Jegadeesh and Titman (2001), who argue that long-term return reversals are much weaker among large companies.

Panel C of Table 7 presents results for Equation (1) comparable to those of Panel C in Table 5, except that there are 12-, 24-, 36-, or 48-month gaps between portfolio formation periods and holding periods. If intermediate-term return continuation and long-term return reversals are linked, as suggested by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), then the investment strategy that contributes most to intermediate-term return continuation should contribute most to long-term return reversals, at least for the period when return reversals are observed in Panels A and B of Table 7. Given the results in Table-5, where the pure 52*HI* and pure MAR strategies contribute most, and the pure *JT* strategy contributes least, to intermediate-term momentum, long-term return reversals should derive primarily from the pure 52*HI* or pure *MAR* strategy if intermediate-term return continuation is linked to long-term return reversals.

However, Panel C of Table 7 shows that neither the moving average ratio nor the 52 week high ratio is related to return reversals even when we observe the reversals. This is consistent with George and Hwang (2004), who do not separate the sample period. For example, Panel C of Table 7 shows that, when there is a 12-month gap between formation and holding periods, the differences between winner and loser portfolios from the pure *JT* strategy are statistically significantly negative for both subsample periods even when price and size screenings are applied. Also, return reversals are observed when there are 24- or 36-month gaps during the first sample period. However, neither the pure 52*HI* strategy nor the *MAR* strategy contributes this negative profit during these subperiods. When there is a 12-month gap, profit from the *JT* strategy is -0.31% (*t*-statistic of -2.58) and -0.35% (*t*-statistic of -2.69) for the first and second subsample periods, respectively, but profits from both the 52*HI* and *MAR* strategies are not significant. Results are similar for the first subperiod for either 24- or 36-month gaps.

In Jegadeesh and Titman (2001), long-term reversals do not seem as strong as intermediate-term momentum since the reversals seem time dependent and less significant among large companies. Also, George and Hwang show that, even though the 52*HI* strategy contributes more to intermediate-term momentum, this strategy contributes little to long-term reversals. I show that, even when we observe return reversals, the *MAR* and 52*HI* strategy, which together contribute most of the intermediate-term momentum, contribute nothing to the long-term return reversals. These pieces of evidence suggest that intermediate-term momentum profits stem primarily from an anchoring bias whereby investors regard the 52-week high price or moving averages as their reference for estimating current prices, but the anchoring bias is not related to long-term reversals, and further, that intermediate-term momentum and long-term reversals are separate phenomena if there is return reversal as George and Hwang (2004) argue.

4. Conclusions

The ratio of a short-term moving average to a long-term moving average along with the ratio of the current price to the 52-week high seem to explain most of the intermediate-term momentum reported by Jegadeesh and Titman (1993). This suggests that an anchoring bias to the 52-week high or moving averages in estimating the current stock price is more likely to be the driving force for intermediate-term momentum, rather than investors' conservatism (Barberis, Shleifer and Vishny, 1998), overconfidence (Daniel, Hirshleifer, and Subrahmanyam, 1998) or slow diffusion of information (Hong and Stein, 1999). Also, the predictive ability of the moving average ratio for future returns is distinct from, and as significant as, the ratio of current price to the 52-week high. This suggests that some investors regard moving average prices and some the 52-week high as their reference prices; however, the extent to which these investor groups overlap is unclear. Finally, I show that neither the pure 52-week high nor the *MAR* strategy contributes to long-term reversals even when long-term reversals measured by past returns are observed. This suggests that intermediate-term return continuation and long-term return reversals are separate phenomena and that separate theories for long-term reversals should be developed.

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Table 1. Summary statistics

At the beginning of each month, returns over the past six and 12 months (6-return and 12-return), the ratios of current price to 52-week high (52HIR), and the ratios of the 50-day moving average to the 200-day moving average (MAR) are calculated for all stocks traded on the NYSE, AMEX, and Nasdaq over the period January 1964 to December 2004. Panel A presents the time-series averages of the cross-sectional averages and standard deviations of the returns and ratios. In Panel B, time-series averages of the estimates of the pairwise correlation coefficients between two variables are reported.

Stocks priced below $5 and stocks with market capitalizations that would place them in the smallest NYSE decile are excluded.

Panel A: Mean and standard deviation

	6-return	12-return	52HIR	MAR
Mean	6.64%	12.92%	0.82	1.03
Standard Deviation	24.34%	35.01%	0.14	0.13

Panel B: Correlation coefficient

	12-return	52HIR	MAR
6-return	0.72	0.65	0.89
12-return		0.62	0.78
52HIR			0.59

Table 2. Raw and risk-adjusted profits from three investment strategies

Average monthly returns for winner and loser portfolios and average monthly profits (with associated *t*-statistics) for three investment strategies are presented. The three investment strategies, *JT*(*p*, *J*, *D*, *K*), *52HI*(*p*, *D*, *K*), and *MAR*(*p*, *D*, *K*) are defined in subsection 2.1. For example, at the beginning of each month *t*, *JT*(*p*, *J*, *D*, *K*) sorts all stocks in the sample based on buy-and-hold returns for the *J* months from *t*-*D*-*J* to *t*-*D*-1, buys equally the top *p*% of stocks (winners) and sells equally the bottom *p*% of stocks (losers), and holds this position for the next *K* months. This strategy is the same as that of Jegadeesh and Titman (1993) where there is a *D*-month gap between formation and holding period. *52HI*(*p*, *D*, *K*) is defined similarly to *JT*(*p*, *J*, *D*, *K*) except that stocks are sorted by the ratio of current price to the 52-week high price instead of past returns. *MAR*(*p*, *D*, *K*) is the same as *52HI*(*p*, *D*, *K*) except that stocks are sorted by the ratio of the 50-day moving average to the 200-day moving average. All stocks traded on the NYSE, AMEX and Nasdaq are included, but stocks priced below $5 at the end of the formation period and stocks with market capitalization that would place them in the smallest NYSE decile are excluded. The sample period is January 1964 to December 2004. Panel A presents the results when Januarys are included in the holding period, and Panel B shows the results for only non-Januarys.

Panel C presents estimated alphas from the Fama-French three factor model. Returns of winner and loser portfolios and profits for each of the three strategies are regressed on the three Fama-French (1996) factors.

Panel A: All months

	P = 10%				*P* = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	1.68	1.72	1.43	1.81	1.51	1.48	1.39	1.54
Loser	0.47	0.49	0.28	0.36	0.79	0.82	0.73	0.75
Winner – Loser	1.21	1.23	1.15	1.45	0.72	0.66	0.66	0.80
	(4.94)	(5.16)	(4.39)	(6.02)	(4.34)	(4.27)	(3.79)	(5.03)
1/64 – 12/83								
Winner	1.78	1.72	1.43	1.81	1.56	1.50	1.37	1.55
Loser	0.55	0.62	0.43	0.48	0.84	0.90	0.87	0.82
Winner – Loser	1.23	1.10	1.00	1.33	0.72	0.60	0.50	0.73
	(3.83)	(3.82)	(3.37)	(4.46)	(3.21)	(2.98)	(2.44)	(3.44)
1/84 – 12/04								
Winner	1.59	1.72	1.43	1.82	1.47	1.47	1.42	1.54
Loser	0.39	0.36	0.14	0.25	0.74	0.74	0.60	0.67
Winner – Loser	1.20	1.35	1.29	1.57	0.73	0.72	0.81	0.87
	(3.23)	(3.60)	(3.03)	(4.17)	(2.96)	(3.08)	(2.92)	(3.68)

Table 2 continued

Panel B: January excluded

	P = 10%				P = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	1.52	1.55	1.37	1.65	1.35	1.32	1.29	1.39
Loser	0.01	0.05	-0.23	-0.09	0.44	0.48	0.33	0.39
Winner – Loser	1.52	1.50	1.60	1.74	0.92	0.85	0.97	0.99
	(6.17)	(6.57)	(6.57)	(7.43)	(5.47)	(5.61)	(5.82)	(6.38)
1/64 – 12/83								
Winner	1.62	1.55	1.34	1.64	1.37	1.30	1.23	1.36
Loser	0.04	0.15	-0.11	0.01	0.42	0.50	0.40	0.42
Winner – Loser	1.58	1.39	1.44	1.63	0.94	0.80	0.82	0.94
	(5.10)	(5.05)	(5.43)	(5.64)	(4.31)	(4.12)	(4.45)	(4.58)
1/84 – 12/04								
Winner	1.43	1.56	1.40	1.67	1.34	1.35	1.36	1.41
Loser	-0.03	-0.05	-0.35	-0.18	0.45	0.45	0.26	0.37
Winner – Loser	1.46	1.61	1.75	1.85	0.89	0.90	1.10	1.04
	(3.84)	(4.45)	(4.34)	(5.04)	(3.53)	(3.88)	(4.05)	(4.48)

Table 2 continued

Panel C: Risk-adjusted returns and profits

	P = 10%				P = 30%			
	JT(10,12,0,6)	*JT*(10,6,0,6)	*52HI*(10,0,6)	*MAR*(10,0,6)	*JT*(30,12,0,6)	*JT*(30,6,0,6)	*52HI*(30,0,6)	*MAR*(30,0,6)
1/64 – 12/04								
Winner	1.10	1.07	0.87	1.17	0.88	0.81	0.80	0.88
Loser	-0.44	-0.33	-0.59	-0.47	-0.05	0.04	-0.11	-0.04
Winner – Loser	1.53	1.40	1.46	1.64	0.93	0.77	0.91	0.92
	(6.37)	(5.79)	(6.74)	(6.69)	(5.68)	(4.89)	(6.45)	(5.69)
1/64 – 12/83								
Winner	1.21	1.11	0.99	1.21	0.99	0.90	0.87	0.96
Loser	-0.37	-0.21	-0.52	-0.37	0.04	0.14	0.01	0.06
Winner – Loser	1.59	1.33	1.51	1.58	0.95	0.75	0.87	0.90
	(4.96)	(4.50)	(6.59)	(5.20)	(4.22)	(3.63)	(5.45)	(4.18)
1/84 – 12/04								
Winner	0.98	1.03	0.80	1.13	0.81	0.75	0.77	0.81
Loser	-0.6	-0.54	-0.77	-0.65	-0.17	-0.10	-0.28	-0.16
Winner – Loser	1.59	1.57	1.58	1.79	0.97	0.85	1.06	0.98
	(4.43)	(4.16)	(4.47)	(4.71)	(4.09)	(3.57)	(4.60)	(4.12)

Table 3. Pairwise comparisons of profitability from three investment strategies

This table presents pairwise comparisons of profitability for the three investment strategies, *MAR* (p,0,6), *JT* (p,12,0,6) and 52*HI* (p,0,6). For each month t, returns are calculated for winner and loser portfolios and profits from the three investment strategies for p = 10% and 30%. Then, the differences in returns for winner and loser portfolios, and momentum profits for each pair of investment strategies are obtained. This table presents the time-series averages and t-statistics (in parentheses) of the differences. All stocks traded on the NYSE, AMEX and Nasdaq are included, but stocks priced below $5 at the end of the formation period and stocks with market capitalizations that would place them in the smallest NYSE decile are excluded. The sample period is January 1964 to December 2004.

		MAR – JT	*MAR – 52HI*	52*HI – JT*
P = 10%	Winner	0.13	0.38	-0.25
		(2.55)	(2.57)	(-1.48)
	Loser	-0.11	0.08	-0.19
		(-2.02)	(1.23)	(-2.24)
	Winner-loser	0.24	0.30	-0.06
		(2.45)	(1.49)	(-0.26)
P = 30%	Winner	0.03	0.15	-0.12
		(0.97)	(1.77)	(-1.20)
	Loser	-0.04	0.01	-0.06
		(-1.25)	(0.25)	(-0.82)
	Winner-loser	0.07	0.14	-0.06
		(1.14)	(0.97)	(-0.37)

Table 4. Raw and risk-adjusted returns for two-way sorted portfolios

This table presents holding period returns for double-sorted portfolios based on two of the three investment strategies, *JT*, *GH* 52*HI*, and *MAR*. In Panel A (B), stocks are first sorted into quintiles by 12-return (MAR) at the beginning of each month. Stocks in each quintile are then assigned to one of five equal-sized portfolios based on the MAR (12-return). The double-sorted portfolios are held for the subsequent six months. Time-series averages of returns on the 25 portfolios and return differences between the lowest and highest MAR (12-return) portfolios within each *JT* (*MAR*) quintile are presented. The risk-adjusted profits from *MAR* (*JT*) strategy within each *JT* (*MAR*) quintile are measured by alphas from the Fama-French three factor model. The return difference between the lowest and highest MAR (12-return) portfolios within each *JT* (*MAR*) quintile is regressed on the three Fama-French (1996) factors. The sample period is from 1964 to 2004, and price and size screenings are applied. Returns and profits for all months and for non-Januarys are presented separately. The results for all months are reported ~~in~~ the columns titled "*All*" and the results for non-Januarys are reported in the columns titled "*NJ*".

Panel A: Sorted first by 12-return and then by MAR

	1(low return)		2		3		4		5(high return)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low MAR)	0.10	-0.40	0.78	0.48	0.94	0.69	1.09	0.87	1.13	0.90	1.02	1.30	(4.76)	(6.12)
2	0.60	0.18	1.08	0.82	1.16	0.97	1.27	1.12	1.44	1.30	0.84	1.12	(4.07)	(5.38)
3	0.82	0.45	1.12	0.88	1.19	1.01	1.34	1.21	1.60	1.49	0.79	1.04	(3.90)	(5.15)
4	0.91	0.57	1.14	0.91	1.19	1.02	1.39	1.25	1.79	1.66	0.88	1.08	(4.12)	(4.99)
5(high MAR)	0.89	0.55	1.11	0.87	1.30	1.13	1.50	1.33	1.99	1.82	1.11	1.28	(4.66)	(5.16)
(5)-(1)	0.78	0.94	0.32	0.39	0.37	0.44	0.41	0.47	0.87	0.92				
t-stat	(4.39)	(5.64)	(3.33)	(4.13)	(3.97)	(4.88)	(3.86)	(4.60)	(5.42)	(5.64)				
Alpha	0.79	0.92	0.29	0.34	0.34	0.39	0.36	0.42	0.85	0.89				
t-stat (alpha)	(4.78)	(6.05)	(2.94)	(3.58)	(3.52)	(4.26)	(3.34)	(4.18)	(5.63)	(6.18)				

Panel B: Sorted first by MAR and then by 12-return

	1(low MAR)		2		3		4		5(high MAR)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low return)	0.19	-0.34	0.90	0.56	0.98	0.71	1.08	0.84	1.31	1.09	1.13	1.43	(4.90)	(6.56)
2	0.63	0.22	1.11	0.84	1.14	0.93	1.22	1.06	1.58	1.43	0.94	1.21	(4.80)	(6.33)
3	0.72	0.36	1.11	0.87	1.19	1.01	1.34	1.20	1.68	1.55	0.96	1.19	(4.78)	(5.99)
4	0.80	0.48	1.10	0.88	1.23	1.08	1.40	1.28	1.80	1.67	0.99	1.18	(4.82)	(5.66)
5(high return)	0.71	0.40	1.08	0.87	1.27	1.11	1.40	1.25	1.89	1.74	1.18	1.35	(5.26)	(5.96)
(5)-(1)	0.53	0.74	0.19	0.31	0.28	0.40	0.32	0.41	0.58	0.65				
t-stat	(3.08)	(4.23)	(1.63)	(2.67)	(2.59)	(3.68)	(2.66)	(3.39)	(3.01)	(3.26)				
Alpha	0.78	0.91	0.37	0.44	0.45	0.50	0.50	0.54	0.77	0.81				
t-stat (alpha)	(4.75)	(5.49)	(3.29)	(3.79)	(4.17)	(4.71)	(4.42)	(4.83)	(4.89)	(5.05)				

Table 4 continued

Panel C: Sorted first by 52HIR and then by MAR

	1(low 52HIR)		2		3		4		5(high 52HIR)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low MAR)	0.07	-0.44	0.88	0.63	1.05	0.87	1.05	0.90	1.03	0.91	0.96	1.35	(3.16)	(4.60)
2	0.54	0.09	1.11	0.84	1.22	1.03	1.19	1.05	1.16	1.08	0.63	1.00	(2.73)	(4.50)
3	0.65	0.22	1.16	0.88	1.28	1.10	1.31	1.18	1.34	1.27	0.68	1.05	(3.50)	(5.70)
4	0.72	0.30	1.18	0.89	1.34	1.12	1.47	1.33	1.57	1.50	0.84	1.20	(4.55)	(7.01)
5(high MAR)	0.78	0.35	1.37	1.06	1.66	1.44	1.80	1.64	1.95	1.86	1.16	1.52	(6.33)	(8.90)
(5)-(1)	0.72	0.78	0.48	0.43	0.60	0.57	0.75	0.74	0.92	0.95				
t-stat	(4.41)	(4.95)	(2.90)	(2.43)	(3.37)	(3.01)	(3.99)	(3.74)	(4.76)	(4.63)				
Alpha	0.72	0.81	0.42	0.43	0.51	0.53	0.64	0.70	0.85	0.91				
t-stat (alpha)	(4.31)	(5.09)	(3.58)	(3.52)	(4.38)	(4.60)	(5.47)	(5.92)	(6.79)	(7.46)				

Panel D: Sorted first by MAR and then by 52HIR

	1(low MAR)		2		3		4		5(high MAR)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low 52HIR)	0.06	-0.50	0.81	0.41	1.00	0.66	1.08	0.78	1.32	1.02	1.25	1.52	(5.21)	(6.70)
2	0.49	0.03	1.16	0.87	1.26	1.05	1.33	1.13	1.68	1.46	1.19	1.46	(5.60)	(7.00)
3	0.73	0.34	1.18	0.95	1.25	1.07	1.39	1.26	1.78	1.65	1.05	1.31	(5.33)	(6.70)
4	0.86	0.55	1.10	0.91	1.18	1.04	1.35	1.24	1.74	1.65	0.88	1.10	(4.69)	(5.94)
5(high 52HIR)	0.91	0.69	1.04	0.88	1.12	1.02	1.29	1.22	1.74	1.68	0.83	0.99	(4.64)	(5.47)
(5)-(1)	0.84	1.19	0.23	0.48	0.13	0.37	0.20	0.44	0.42	0.67				
t-stat	(3.22)	(4.71)	(1.32)	(2.77)	(0.83)	(2.45)	(1.39)	(3.09)	(3.02)	(4.91)				
Alpha	1.05	1.26	0.50	0.61	0.38	0.48	0.40	0.52	0.58	0.70				
t-stat (alpha)	(5.37)	(6.96)	(4.64)	(5.66)	(4.43)	(5.55)	(4.62)	(6.06)	(5.66)	(7.27)				

Table 4 continued

Panel E: Sorted first by 12-return and then by 52HIR														
	1(low return)		2		3		4		5(high return)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low 52HIR)	0.09	-0.46	0.82	0.45	1.01	0.70	1.10	0.81	1.22	0.89	1.13	1.35	(4.77)	(5.70)
2	0.56	0.09	1.12	0.84	1.27	1.06	1.41	1.23	1.64	1.45	1.08	1.36	(4.95)	(6.20)
3	0.79	0.42	1.16	0.93	1.26	1.07	1.46	1.32	1.70	1.57	0.91	1.15	(4.33)	(5.40)
4	0.91	0.58	1.10	0.88	1.16	1.01	1.35	1.24	1.70	1.61	0.79	1.03	(4.12)	(5.31)
5(high 52HIR)	0.97	0.72	1.02	0.85	1.08	0.96	1.26	1.19	1.70	1.65	0.73	0.93	(3.99)	(5.07)
(5)-(1)	0.88	1.18	0.20	0.40	0.08	0.26	0.15	0.38	0.48	0.76				
t-stat	(3.65)	(5.08)	(1.29)	(2.59)	(0.50)	(1.72)	(0.94)	(2.44)	(2.79)	(4.64)				
Alpha	1.03	1.22	0.41	0.48	0.28	0.35	0.28	0.40	0.57	0.74				
t-stat (alpha)	(5.59)	(7.11)	(3.82)	(4.63)	(3.12)	(3.83)	(2.67)	(4.07)	(4.44)	(6.40)				

Panel F: Sorted first by 52HIR and then by 12-return														
	1(low 52HIR)		2		3		4		5(high 52HIR)		(5) – (1)		*t*-statistic	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
1(low return)	0.17	-0.37	0.96	0.68	1.08	0.87	1.04	0.88	1.01	0.90	0.84	1.26	(2.83)	(4.35)
2	0.61	0.16	1.10	0.81	1.17	0.96	1.15	1.00	1.16	1.07	0.55	0.91	(2.53)	(4.27)
3	0.65	0.22	1.15	0.88	1.27	1.08	1.30	1.17	1.37	1.30	0.72	1.08	(3.63)	(5.88)
4	0.62	0.21	1.19	0.91	1.41	1.22	1.53	1.40	1.58	1.52	0.96	1.31	(4.77)	(6.98)
5(high return)	0.71	0.29	1.31	1.03	1.62	1.42	1.78	1.65	1.91	1.83	1.20	1.55	(6.18)	(8.64)
(5)-(1)	0.53	0.65	0.35	0.35	0.54	0.56	0.74	0.77	0.89	0.94				
t-stat	(2.99)	(3.51)	(1.96)	(1.85)	(2.91)	(2.86)	(3.83)	(3.81)	(4.42)	(4.42)				
Alpha	0.70	0.80	0.41	0.44	0.54	0.60	0.70	0.78	0.87	0.94				
t-stat (alpha)	(3.95)	(4.46)	(3.04)	(3.24)	(4.26)	(4.70)	(5.62)	(6.27)	(6.49)	(7.16)				

Table 5. Comparisons of *JT*, *GH* 52*HI*, and *MAR* strategies

The basic functional form of the regression equation is

$$R_{it} = b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} \ln(size_{it-1}) + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} FHH_{it-D-k} + b_{6kt} FHL_{it-D-k} + b_{7kt} MAH_{it-D-k} + b_{8kt} MAL_{it-D-k} + e_{it} \text{ ,}$$

for k = 1, …, 6, and D=1, where R_{it} and $R_{it\text{-}1}$ are stock i's returns for month t and t-1, respectively, ln($size_{it\text{-}1}$) is the natural logarithm of stock i's market capitalization at the end of month t-1, $JH_{it\text{-}k}$ is a dummy variable that equals one if stock i's past performance over the 12-month period (t-D-k-11, t-D-k-1) is in the top 30% when measured by the JT momentum strategy performance criterion, and is zero otherwise; $JL_{it\text{-}k}$ equals one if stock i's past performance over the same period is in the bottom 30% as measured by the *JT* momentum strategy performance criterion, and is zero otherwise. The dummy variables, $FHH_{it\text{-}k}$, $FHL_{it\text{-}k}$, $MAH_{it\text{-}k}$, and $MAL_{it\text{-}k}$ are similarly defined except that $FHH_{it\text{-}k}$ and $FHL_{it\text{-}k}$ use the *GH* 52*HI* strategy criterion, and $MAH_{it\text{-}k}$ and $MAL_{it\text{-}k}$ use the *MAR* strategy criterion.

For each month, regressions are estimated for k=1,…, 6, and the coefficients averaged. This table presents time-series averages and associated t-statistics. Also, in the bottom part of each panel, the time-series averages of differences in the coefficient estimates between winner and loser dummies for the investment strategies are presented. For example, the the row titled "JT winner dummy – JT loser dummy" represents the time-series average of the difference between the coefficient estimates for the JT winner and loser dummies.

Panel A presents results with winner and loser dummy variables for each of the three investment strategies included in the regression. Dummy variables for two or three investment strategies are included in Panel B. Panel C separately presents results from two subperiods, 1964 – 1983 and 1984 – 2004. Columns under the title "*JT*" include only JT momentum strategy dummies, columns under the title "*JT-52HI*" include only *JT* and *GH* 52*HI* strategy dummies, and so on. In Panels A, B, and C, the same price and size screenings as in Table 1 are applied to the sample data. The price and size screenings are not applied in Panel D.

Table 5 continued

Panel A: One strategy is included. (with price and size screening)

	JT		*52HI*		*MAR*	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*
Intercept	1.80	0.55	2.18	1.01	1.82	0.58
	(3.41)	(1.13)	(4.19)	(2.05)	(3.43)	(1.16)
R_{it-1}	-3.47	-2.80	-3.48	-2.82	-3.42	-2.75
	(-7.46)	(-6.03)	(-7.31)	(-5.89)	(-7.30)	(-5.86)
ln(size)	-0.05	0.03	-0.07	0.01	-0.05	0.03
	(-1.46)	(1.10)	(-2.20)	(0.16)	(-1.51)	(1.06)
JT winner dummy	0.27	0.30				
	(2.46)	(2.61)				
JT loser dummy	-0.32	-0.45				
	(-3.42)	(-4.81)				
52HI winner dummy			0.14	0.22		
			(2.71)	(4.19)		
52HI loser dummy			-0.57	-0.73		
			(-5.14)	(-6.65)		
MAR winner dummy					0.33	0.36
					(3.36)	(3.43)
MAR loser dummy					-0.40	-0.52
					(-4.40)	(-5.82)
JT winner dummy –	0.60	0.76				
JT loser dummy	(4.09)	(5.10)				
52HI winner dummy –			0.72	0.95		
52HI loser dummy			(4.73)	(6.44)		
MAR winner dummy –					0.74	0.88
MAR loser dummy					(5.49)	(6.55)

Table 5 continued

Panel B: Two or three strategies are included. (with price and size screening)

	JT-52HI-MAR		*JT-MAR*		*52HI-MAR*		*JT–52HI*	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
Intercept	2.05	0.89	1.87	0.67	2.08	0.91	2.08	0.91
	(4.19)	(1.97)	(3.67)	(1.40)	(4.18)	(1.97)	(4.19)	(1.97)
R_{it-1}	-3.79	-3.11	-3.62	-2.95	-3.66	-2.99	-3.69	-3.02
	(-8.70)	(-7.17)	(-8.04)	(-6.56)	(-8.16)	(-6.66)	(-8.33)	(-6.82)
ln(size)	-0.07	0.01	-0.05	0.03	-0.07	0.01	-0.07	0.01
	(-2.10)	(0.36)	(-1.64)	(0.91)	(-2.12)	(0.33)	(-2.13)	(0.32)
JT winner dummy	0.12	0.15	0.10	0.13			0.25	0.27
	(1.46)	(1.71)	(1.17)	(1.43)			(2.29)	(2.34)
JT loser dummy	-0.01	-0.06	-0.13	-0.23			-0.06	-0.12
	(-0.15)	(-1.19)	(-1.83)	(-3.16)			(-1.11)	(-2.03)
52HI winner dummy	0.03	0.08			0.05	0.12	0.06	0.11
	(0.49)	(1.45)			(1.01)	(2.40)	(1.04)	(2.06)
52HI loser dummy	-0.40	-0.52			-0.42	-0.56	-0.49	-0.61
	(-3.92)	(-4.98)			(-3.73)	(-5.00)	(-4.56)	(-5.68)
MAR winner dummy	0.25	0.23	0.26	0.26	0.30	0.30		
	(3.75)	(3.35)	(4.05)	(3.82)	(2.97)	(2.78)		
MAR loser dummy	-0.17	-0.18	-0.33	-0.39	-0.18	-0.20		
	(-4.19)	(-4.42)	(-4.74)	(-5.88)	(-3.83)	(-4.25)		
JT winner dummy –	0.13	0.21	0.23	0.36			0.32	0.39
JT loser dummy	(1.10)	(1.74)	(2.00)	(3.03)			(2.14)	(2.52)
52HI winner dummy –	0.43	0.60			0.47	0.68	0.55	0.73
52HI loser dummy	(2.86)	(3.95)			(3.01)	(4.41)	(3.54)	(4.69)
MAR winner dummy –	0.41	0.41	0.59	0.65	0.48	0.50		
MAR loser dummy	(4.69)	(4.46)	(6.25)	(7.04)	(3.65)	(3.62)		

Table 5 continued

Panel C: For subsample periods (with price and size screening)

	JT				*JT-52HI-MAR*			
	1/64 – 12/83		1/84 – 12/04		1/64 – 12/83		1/84 – 12/04	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
Intercept	2.71	1.02	0.93	0.11	2.94	1.31	1.21	0.49
	(3.10)	(1.27)	(1.54)	(0.19)	(3.62)	(1.77)	(2.16)	(0.91)
R_{it-1}	-4.98	-4.33	-2.04	-1.35	-5.27	-4.59	-2.38	-1.71
	(-7.69)	(-6.78)	(-3.11)	(-2.04)	(-8.45)	(-7.49)	(-3.99)	(-2.84)
ln(size)	-0.13	-0.01	0.02	0.07	-0.14	-0.03	0.00	0.05
	(-2.30)	(-0.15)	(0.58)	(1.94)	(-2.78)	(-0.63)	(0.11)	(1.28)
JT winner dummy	0.28	0.36	0.26	0.25	0.13	0.18	0.11	0.11
	(2.12)	(2.61)	(1.49)	(1.36)	(1.24)	(1.70)	(0.89)	(0.85)
JT loser dummy	-0.30	-0.42	-0.34	-0.49	-0.04	-0.10	0.02	-0.03
	(-2.88)	(-4.05)	(-2.20)	(-3.12)	(-0.59)	(-1.56)	(0.26)	(-1.31)
52HI winner dummy					0.05	0.09	0.01	0.07
					(0.65)	(1.37)	(0.12)	(0.79)
52HI loser dummy					-0.32	-0.41	-0.48	-0.62
					(-3.08)	(-4.00)	(-2.76)	(-3.48)
MAR winner dummy					0.18	0.19	0.31	0.27
					(2.23)	(2.35)	(3.01)	(2.44)
MAR loser dummy					-0.16	-0.14	-0.18	-0.21
					(-2.76)	(-2.40)	(-3.15)	(-3.84)
JT winner dummy –	0.59	0.78	0.61	0.74	0.17	0.28	0.09	0.14
JT loser dummy	(3.06)	(4.12)	(2.76)	(3.24)	(1.14)	(1.92)	(0.52)	(0.74)
52HI winner dummy –					0.36	0.50	0.49	0.69
52HI loser dummy					(2.26)	(3.21)	(1.97)	(2.69)
MAR winner dummy –					0.33	0.33	0.49	0.48
MAR loser dummy					(2.84)	(2.75)	(3.73)	(3.52)

Table 5 continued

Panel D: Without price and size screening

	JT		*JT-52HI-MAR*	
	All Months	Jan. Excl.	All Months	Jan. Excl.
Intercept	3.75	1.92	4.08	2.44
	(6.58)	(3.81)	(7.91)	(5.33)
R_{it-1}	-6.07	-5.09	-6.29	-5.34
	(-14.46)	(-14.01)	(-15.81)	(15.47)
ln(size)	-0.21	-0.08	-0.24	-0.13
	(-5.15)	(-2.23)	(-6.32)	(-3.67)
JT winner dummy	0.26	0.29	0.08	0.09
	(2.63)	(2.82)	(1.05)	(1.25)
JT loser dummy	-0.32	-0.64	0.04	-0.10
	(-2.42)	(-5.29)	(0.69)	(-1.82)
52HI winner dummy			0.15	0.23
			(2.21)	(3.24)
52HI loser dummy			-0.34	-0.61
			(-2.82)	(-5.30)
MAR winner dummy			0.24	0.21
			(3.80)	(3.19)
MAR loser dummy			-0.24	-0.30
			(-4.99)	(-6.52)
JT winner dummy –	0.58	0.93	0.04	0.19
JT loser dummy	(3.55)	(5.95)	(0.34)	(1.81)
52HI winner dummy –			0.50	0.84
52HI loser dummy			(2.76)	(4.79)
MAR winner dummy –			0.48	0.51
MAR loser dummy			(5.63)	(5.83)

Table 6. Various *MAR* strategies (with price and size screening)

This table repeats columns two and three of Table 5, Panel B, except that various moving average ratio combinations are used here. *S*/*L* MAR represents the ratio of the *S*-day moving average to the *L*-day moving average.

	1/200 MAR		5/200 MAR		20/200 MAR		20/250 MAR		50/250 MAR	
	All	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*	*All*	*NJ*
Intercept	2.04	0.88	2.04	0.88	2.04	0.88	2.05	0.89	2.06	0.90
	(4.19)	(1.95)	(4.19)	(1.95)	(4.18)	(1.94)	(4.19)	(1.95)	(4.20)	(1.97)
R_{it-1}	-3.78	-3.10	-3.78	-3.10	-3.78	-3.10	-3.77	-3.09	-3.77	-3.09
	(-8.71)	(-7.19)	(-8.70)	(-7.17)	(-8.69)	(-7.16)	(-8.65)	(-7.12)	(-8.63)	(-7.11)
ln(size)	-0.07	0.01	-0.07	0.01	-0.07	0.01	-0.07	0.01	-0.07	0.01
	(-2.06)	(0.41)	(-2.07)	(0.40)	(-2.07)	(0.40)	(-2.09)	(0.37)	(-2.12)	(0.33)
JT winner dummy	0.15	0.18	0.15	0.18	0.13	0.16	0.09	0.12	0.08	0.10
	(1.91)	(2.24)	(1.86)	(2.18)	(1.68)	(1.96)	(1.27)	(1.61)	(1.00)	(1.24)
JT loser dummy	-0.05	-0.11	-0.05	-0.10	-0.03	-0.09	0.00	-0.05	0.03	-0.02
	(-0.99)	(-2.05)	(-0.89)	(-1.94)	(-0.61)	(-1.66)	(0.01)	(-1.04)	(0.56)	(-0.45)
52HI winner dummy	-0.02	0.04	-0.01	0.05	0.00	0.06	0.01	0.06	0.04	0.09
	(-0.24)	(0.65)	(-0.21)	(0.72)	(0.06)	(1.00)	(0.13)	(1.04)	(0.66)	(1.60)
52HI loser dummy	-0.42	-0.54	-0.41	-0.53	-0.41	-0.52	-0.40	-0.52	-0.41	-0.52
	(-3.75)	(-4.78)	(-3.76)	(-4.78)	(-3.82)	(-4.85)	(-3.72)	(-4.73)	(-3.92)	(-4.96)
MAR winner dummy	0.23	0.20	0.23	0.21	0.24	0.22	0.27	0.25	0.27	0.27
	(2.74)	(2.32)	(2.85)	(2.42)	(3.24)	(2.82)	(3.54)	(3.13)	(4.17)	(3.85)
MAR loser dummy	-0.10	-0.10	-0.11	-0.11	-0.13	-0.14	-0.16	-0.16	-0.18	-0.20
	(-2.00)	(-1.82)	(-2.24)	(-2.17)	(-2.88)	(-2.90)	(-3.26)	(-3.34)	(-4.45)	(-4.76)
JT winner dummy –	0.20	0.29	0.19	0.28	0.17	0.25	0.09	0.18	0.05	0.12
JT loser dummy	(1.74)	(2.44)	(1.67)	(2.36)	(1.44)	(2.09)	(0.87)	(1.59)	(0.45)	(1.09)
52HI winner dummy –	0.40	0.58	0.40	0.58	0.41	0.59	0.41	0.59	0.45	0.61
52HI loser dummy	(2.32)	(3.35)	(2.36)	(3.40)	(2.57)	(3.62)	(2.55)	(3.58)	(2.93)	(3.99)
MAR winner dummy –	0.33	0.30	0.34	0.32	0.37	0.36	0.43	0.41	0.46	0.46
MAR loser dummy	(2.75)	(2.38)	(2.96)	(2.62)	(3.58)	(3.27)	(3.87)	(3.60)	(4.98)	(4.86)

Table 7. Long-term reversals from the *JT*, *GH* 52*HI*, and *MAR* strategies

The basic functional form of the regression equation is

$$R_{it} = b_{0kt} + b_{1kt} R_{it-1} + b_{2kt} \ln\left(size_{it-1}\right) + b_{3kt} JH_{it-D-k} + b_{4kt} JL_{it-D-k} + b_{5kt} FHH_{it-D-k} + b_{6kt} FHL_{it-D-k} + b_{7kt} MAH_{it-D-k} + b_{8kt} MAL_{it-D-k} + e_{it} ,$$

for k = 1, …, 12, (holding period is 12 months) and D=12, 24, 36, or 48, where R_{it} and $R_{it\text{-}1}$ are stock i's returns for month t and t-1, respectively, ln($size_{it\text{-}1}$) is the natural logarithm of stock i's market capitalization at the end of month t-1, $JH_{it\text{-}k}$ is a dummy variable that equals one if stock i's past performance over the 12-month period (t-D-k-11, t-D-k-1) is in the top 30% when measured by the JT momentum strategy performance criterion, and is zero otherwise; $JL_{it\text{-}k}$ equals one if stock i's past performance over the same period is in the bottom 30% as measured by the *JT* momentum strategy performance criterion, and is zero otherwise. The dummy variables, $FHH_{it\text{-}k}$, $FHL_{it\text{-}k}$, $MAH_{it\text{-}k}$, and $MAL_{it\text{-}k}$ are similarly defined except that $FHH_{it\text{-}k}$ and $FHL_{it\text{-}k}$ use the *GH* 52*HI* strategy criterion and $MAH_{it\text{-}k}$ and $MAL_{it\text{-}k}$ use the *MAR* strategy criterion.

In Panels A and B, dummy variables for the *JT* strategy only are included in the regression, while dummy variables for all strategies are included in Panel C. The one-month lagged return and size are included in the regressions but not reported in Panels A and B.

	D = 12			*D* = 24			*D* = 36			*D* = 48		
	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04
Panel A: Without price and size screening												
JT winner dummy	-0.25	-0.28	-0.23	-0.13	-0.18	-0.09	-0.04	-0.26	0.12	-0.13	-0.19	-0.09
	(-3.29)	(-2.70)	(-2.12)	(-1.81)	(-1.82)	(-0.92)	(-0.65)	(-2.95)	(1.19)	(-1.85)	(-2.15)	(-0.83)
JT loser dummy	0.21	0.10	0.29	0.13	0.14	0.13	0.00	0.08	-0.05	0.08	0.05	0.10
	(1.77)	(0.86)	(1.56)	(1.29)	(1.54)	(0.77)	(0.03)	(1.00)	(-0.39)	(1.06)	(0.59)	(0.88)
JT winner dummy - JT loser dummy	-0.46	-0.38	-0.52	-0.27	-0.32	-0.23	-0.05	-0.34	0.17	-0.21	-0.24	-0.19
	(-3.68)	(-2.48)	(-2.80)	(-2.48)	(-2.59)	(-1.39)	(-0.61)	(-3.74)	(1.48)	(-3.05)	(-2.34)	(-2.02)
Panel B: With price and size screening												
JT winner dummy	-0.22	-0.27	-0.18	-0.12	-0.19	-0.07	0.00	-0.21	0.16	-0.07	-0.13	-0.02
	(-2.32)	(-2.27)	(-1.31)	(-1.36)	(-1.67)	(-0.52)	(0.03)	(-2.02)	(1.33)	(-0.80)	(-1.31)	(-0.16)
JT loser dummy	0.14	0.16	0.13	0.12	0.12	0.12	0.02	0.08	-0.03	0.09	0.04	0.12
	(1.72)	(1.74)	(1.02)	(1.59)	(1.52)	(1.01)	(0.24)	(1.16)	(-0.32)	(1.58)	(0.60)	(1.49)
JT winner dummy - JT loser dummy	-0.36	-0.43	-0.31	-0.24	-0.31	-0.18	-0.01	-0.29	0.19	-0.16	-0.17	-0.14
	(-3.47)	(-2.88)	(-2.17)	(-2.55)	(-2.30)	(-1.44)	(-0.18)	(-2.69)	(1.91)	(-2.03)	(-1.59)	(-1.33)

Table 7. Continued

Panel C: Results from *JT*, *GH* 52*HI*, and *MAR* strategies (with price and size screening)

	D = 12			*D* = 24			*D* = 36			*D* = 48		
	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04	6/68 - 12/04	6/68 - 12/83	1/84 - 12/04
Intercept	0.85	1.58	0.31	1.56	2.22	1.07	2.12	2.64	1.74	2.37	3.02	1.89
	(1.40)	(1.46)	(0.45)	(2.40)	(1.93)	(1.43)	(3.17)	(2.29)	(2.18)	(3.56)	(2.67)	(2.36)
$R_{it\text{-}1}$	-4.86	-6.61	-3.57	-5.20	-7.03	-3.84	-5.32	-7.06	-4.03	-5.56	-7.14	-4.39
	(-9.68)	(-8.10)	(-5.75)	(-10.47)	(-8.65)	(-6.20)	(-10.74)	(-8.85)	(-6.53)	(-11.40)	(-9.13)	(-7.17)
ln(size)	0.03	-0.03	0.07	-0.02	-0.09	0.02	-0.07	-0.12	-0.03	-0.08	-0.15	-0.04
	(0.67)	(-0.48)	(1.53)	(-0.56)	(-1.11)	(0.39)	(-1.46)	(-1.54)	(-0.52)	(-1.85)	(-1.93)	(-0.68)
JT winner dummy	-0.17	-0.19	-0.16	-0.11	-0.17	-0.07	-0.01	-0.14	0.10	-0.05	-0.07	-0.03
	(-2.48)	(-2.09)	(-1.58)	(-1.68)	(-2.08)	(-0.79)	(-0.09)	(-1.78)	(1.10)	(-0.78)	(-0.91)	(-0.34)
JT loser dummy	0.16	0.11	0.19	0.07	0.09	0.04	-0.01	0.04	-0.05	-0.05	0.03	0.07
	(4.09)	(2.27)	(3.40)	(1.80)	(1.78)	(0.89)	(-0.46)	(0.89)	(-1.23)	(1.86)	(0.76)	(1.76)
52HI winner dummy	0.01	-0.07	0.07	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.07	-0.05	-0.09
	(0.20)	(-1.16)	(0.99)	(-0.68)	(-0.51)	(-0.49)	(-0.70)	(-0.53)	(-0.50)	(-1.72)	(-0.83)	(-1.53)
52HI lower dummy	-0.03	0.00	-0.05	0.07	0.05	0.08	0.07	0.05	0.09	-0.01	-0.07	0.03
	(-0.32)	(-0.02)	(-0.35)	(0.73)	(0.52)	(0.56)	(0.74)	(0.51)	(0.58)	(-0.14)	(-0.74)	(0.25)
MAR winner dummy	-0.07	-0.09	-0.06	-0.02	-0.03	-0.02	-0.01	-0.07	0.03	0.03	-0.05	0.08
	(-1.18)	(-1.18)	(-0.65)	(-0.34)	(-0.37)	(-0.17)	(-0.22)	(-1.01)	(0.39)	(0.47)	(-0.69)	(1.00)
MAR loser dummy	-0.01	0.00	-0.02	-0.01	-0.04	0.02	-0.02	0.02	-0.04	-0.01	0.04	-0.04
	(-0.38)	(0.09)	(-0.57)	(-0.28)	(-1.12)	(0.58)	(-0.22)	(0.56)	(-1.49)	(-0.23)	(0.93)	(-1.04)
JT winner dummy -	-0.33	-0.31	-0.35	-0.18	-0.27	-0.11	0.01	-0.18	0.15	-0.10	-0.10	-0.10
JT loser dummy	(-3.68)	(-2.58)	(-2.69)	(-2.24)	(-2.33)	(-1.02)	(0.12)	(-1.81)	(1.38)	(-1.39)	(-1.09)	(-0.96)
52HI winner dummy -	0.04	-0.07	0.13	-0.10	-0.08	-0.12	-0.10	-0.08	-0.12	-0.06	0.02	-0.12
52HI lower dummy	(0.29)	(-0.45)	(0.57)	(-0.75)	(-0.55)	(-0.56)	(-0.77)	(-0.55)	(-0.59)	(-0.51)	(0.15)	(-0.68)
MAR winner dummy -	-0.06	-0.09	-0.04	-0.01	0.01	-0.03	0.00	-0.09	0.08	0.03	-0.08	0.12
MAR loser dummy	(-0.84)	(-0.96)	(-0.36)	(-0.20)	(0.13)	(-0.34)	(0.07)	(-1.02)	(0.84)	(0.47)	(-0.92)	(1.18)