Financial Management

A Test of Technical Analysis: Matching Time Displaced Generalized Patterns

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We use a least squares metric to match the return pattern of a target stock with that of an out-of-sample-twin. The twin with the smallest metric is found by a comprehensive period-by-period search of stocks in the Center for Research in Security Prices data set extending back to 1926. If technical analysis has value, targets of twins producing the highest returns in the twin postperiod should also have the highest performance in the target postperiod. Using a randomly selected sample of 66,000 return patterns, we find higher means for targets corresponding to the highest returning twin quintile. We also use regressions to risk adjust target returns and find that twin returns in the postmatch period significantly predict risk-adjusted target returns.

The historical price graph may be the most recognizable of all forms of information considered by the ordinary investor. However, financial academics, relying on the logic of the efficient markets theorem and exhaustive empirical investigations, largely contend that the information contained in past stock prices is of little value to the investor. Conversely, technical analysts embrace the idea that past patterns are informative. Malkiel (1981) states "... technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) the method is patently false and (2) it easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember it is your money we are trying to save." Technical analysts counter that academic studies can never capture every nuance of the stock chart. In addition, if technical analysis is of no value, it is puzzling why it is still prevalent in the marketplace. Why would a rational economic agent engage in such activity and why would firms pay for this form of human capital? Lo, Mamaysky, and Wang (2000) characterize the difference between technical analysis and quantitative finance as follows: "Technical analysis is primarily *visual*, whereas quantitative finance is primarily algebraic and numerical." And "technical analysis has survived through the years, perhaps because its visual model of analysis is more conducive to human cognitions ...." Menkhoff (2010) finds that the vast majority of 692 fund managers in five market (the United States, Germany, Switzerland, Italy, and Thailand) trading countries rely heavily on technical analysis. He concludes that "At a forecasting horizon of weeks, technical analysis is the most important form of analysis and up to this horizon it is thus more important than fundamental analysis."

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A significant problem in technical analysis is the precise mathematical definition and prespecification of the patterns or rules. Neftci (1991) addresses the problem of the precise mathematical definition of technical rules and notes that any well defined rule must pass the test of being defined in Markov time. In short, at time t, the rule must give buy and sell signals without using information from times $\tau > t$. Further, he notes that according to the Wiener-Kolmogorov prediction theory, vector autoregressions (VARs) should yield the optimal linear forecast. Hence, any forecast that improves on VARs must be based on nonlinear methods.

Another problem confronting technical analysis is that of data snooping. Data snooping occurs when the same data set is used repeatedly to investigate different models of pricing or selection rules. Since there are no equilibrium models of technical analysis, efforts to find profitable trading rules are necessarily ad hoc. Thus, the significance levels are suspect and almost certainly overstated. Sullivan, Timmermann, and White (1999) use White's (2000) reality check bootstrap methodology to develop data snooping adjustments in the context of technical analysis.

Our approach satisfies the Neftci (1991) criterion and largely avoids the issue of data snooping since we do not prespecify patterns or selection rules. Using a database of daily and monthly stock returns from the Center for Research in Securities Prices (CRSP) stocks, we randomly choose target stocks and, via exhaustive search, compare their (normalized) price pattern with the price pattern of stocks at an earlier period. The stock and interval with the best matching pattern is referred to as the "twin." The selected twin can be a previous pattern of the target stock, but it is more likely to be a pattern from some other stock in the universe.

There are four relevant intervals in the target-twin paradigm: 1) the match period of the target, 2) the match period of the twin, 3) the postmatch period of the twin, and 4) the postmatch period of the target. All match and postperiods of the twin precede in time and do not intersect the match and postperiods of the target. The out-of-sample performance of the target (target postmatch period) is inferred from the out-of-sample, but from the known performance of the twin (twin postmatch period). If the twin pattern is informative, twins that perform well in the twin postperiod will significantly explain the performance of the target in the postmatch period. We use regressions and the target/twin paradigm to test the hypothesis that price patterns are informative.

The paper is organized as follows. We review the literature in Section I. Section II develops the model, while Section III documents the data and screens. Section IV outlines the regression models and Section V provides our conclusions.

I. Background

An early form of technical analysis was formulated by Charles Dow (1851-1902), founder of Dow Jones & Company and the *Wall Street Journal*. The Dow theory, popularized in *Wall Street Journal* editorials, is developed in Robert Rhea's book (1932) and in Murphy (1986). Following Dow, Alfred Cowles (1933) demonstrated that the Dow Theory, as interpreted, would earn less than a well diversified buy and hold portfolio. In more recent years, the use of technical trading rules and pattern identification techniques have been proposed and tested extensively by a number of scholars including Alexander (1961), Brock, Lakonishok, and LeBaron (1992), and Lo et al. (2000) to name just a few. Alexander's (1961) filter rule was first shown to produce returns greater than buy and hold, but Fama and Blume (1966), using the 30 stocks in the Dow Jones Industrial Average and the filter rule, found that when transaction costs were taken into account, only two of the 30 stocks in the Dow Jones Industrial Average (DJIA) would have bested buy and hold. Sweeney (1988), using the filter rule and transaction costs available to floor traders, finds that 14 of the surviving stocks in the Dow beat buy and hold for the period 1970-1982. Brock et al. (1992)

investigate a variety of moving average and channel break techniques. They find that a set of 26 trading rules applied to the DJIA outperform a benchmark portfolio. Sullivan et al. (1999) expand Brock et al.'s (1992) set of 26 technical rules to 7,846 trading rules and find profitable trading opportunities. However, in the 1987-1996 out-of-sample period, the best performing trading rules are not significant. Marshall, Cahan, and Cahan (2010) explore technical trading rules on 49 stocks around the world found in the Morgan Stanley Capital Index. They find that when data snooping is taken into account, over 5,000 trading rules do not add value beyond that expected by chance.

Some anomalies have also been noted in connection with momentum strategies. However, the short-term positive autocorrelation reported by Lo and MacKinlay (1988) is not enough to overcome trading costs faced by investors. Findings of long-term negative autocorrelation have also been reported. For example, DeBondt and Thaler (1987) note that portfolios of previous winning stocks are beaten by a portfolio of losing stocks in out-of-sample tests.

Lo et al. (2000) use kernel regressions to extract and evaluate 10 well known patterns used in technical analysis. They do not test trading profitability, stating that such tests necessarily involve specifying a fully articulated dynamic general asset pricing model. Instead, they focus on whether patterns can be informative. If patterns are informative, conditioning on them should alter the distribution of returns. Indeed, using χ^2 and the Kolmogorov-Smirnov test, they find that some patterns are informative. Using stocks in the CRSP database that traded from 1962 to 1996, they find that seven of 10 patterns are informative for NYSE/AMEX stocks and all 10 patterns are informative for NASDAQ stocks. Jegadeesh (2000) points out, however, that conditional means are not different and that the difference in the distributions are due to differences in higher moments.

In several respects, our approach is like that of Lo et al. (2000). We examine patterns and provide evidence that the distributions conditional on previous patterns is different from that of unconditional returns. However, we use regressions with controls to demonstrate that the conditional differences are due to differences in means. Our approach also differs from that of Lo et al. (2000) in that we do not prespecify patterns, but search for twins with patterns that match those of the target.

Regression control variables include loadings on Fama and French (1993) risk factors and Carhart (1997) momentum, match period average excess returns as a proxy for overreaction explored by DeBondt and Thaler (1987), the firm's own momentum as in Jegadeesh and Titman (1993), and the standard error of residuals similar to the idiosyncratic volatility measure used by Ang et al. (2006, 2009). Thus, the control variables adjust for known proxies for risk, momentum, and overreaction.

We find evidence that five year monthly patterns are informative, even after adjustment for risk, momentum, and overreaction. We do not find that daily patterns evolving over 150 days are informative when returns are adjusted by the controls. For the monthly patterns, out-of-sample target returns are significantly related to the 12, 24, and 36 month returns of the twin. When analyzed by quintiles, we also find evidence that targets corresponding to twins in the best performing quintile postmatch are informative. While target regressions on posttwin returns are significant, adjusted R^2s are usually less than 4%.

II. The Model

Consider a stock x in the universe of stocks Ω. Observations on x are in the interval $I_x = [t_{\min(x)}, t_{\max(x)}]$ where $t_{\min(x)}$ is the time of the first recorded trade and $t_{\max(x)}$ is the time of the last recorded trade. The target stock is denoted by subscript a and the twin stock by subscript w. The dividend adjusted price of the target stock at time t is $P_a(t)$ and the price of the twin stock at time s is $P_w(s)$. The target match period is the interval $[t, t + \tau] = T_a$. Similarly, the twin match period is the interval $[s, s + \tau] = T_w$.

To allow for out-of-sample evaluation, postmatch periods are defined for both the target and the twin. The target postmatch period is of length Δ_a and is defined by $(t + \tau, t + \tau + \Delta_a]$. Thus, data set limitations require that $t + \tau + \Delta_a \leq t_{\max(a)}$.

The twin postmatch period is of length Δ_w. To prevent the twin postmatch period from intersecting with the target match period, we require that $s + \tau + \Delta_w < t$.

To determine the best twin, we normalize the initial target and twin prices and minimize a difference metric between the target and twin stock price over all feasible twin stocks and intervals. The stock universe is the set Ω stocks in the CRSP database after screening. For target stock a and match period T_a, the twin is the stock $w \in \Omega$ satisfying

$$\min_{w \in \Omega, s \in I_w} \int_0^\tau \left| \frac{P_a(t+v)}{P_a(t)} - \frac{P_w(s+v)}{P_w(s)} \right|^\alpha dv, \alpha > 0, \tag{1}$$

where $I_w = [t_{\min(w)}, t - \tau - \Delta_w)$. In some cases, the twin and target can be the same stock. Typically, the stock a is not the same as the stock w. This reflects the logic that over a previous and nonintersecting interval, the pattern of a stock is more likely to match the pattern of one of a large number of stocks rather than its own pattern.

Since we use discrete data, we implement Equation (1) by summing the metric over all stocks and displacements. Both $\alpha = 1$ and $\alpha = 2$ metrics were evaluated and found to produce almost identical results. Consequently, we focused on the usual squared metric. The algorithm begins with the random selection of a target a at prespecified time t, with an interval of length τ, and a candidate twin w with a match period beginning at $s = t_{\min(w)}$. The metric is evaluated and s is increased by one period until all feasible periods are evaluated (until $s = t\text{-}\tau\text{-}\Delta_w\text{-}1$). This means that for a single stock w, we evaluate each possible interval prior to intersection with the match period of the target. The twin w and the metric is saved and other twins are successively evaluated for all $w \in \Omega_w$ and integers $s \in I_w$. The twin and the match interval are the w and s minimizing the discrete form of Equation (1).

To highlight the intuition underlying the target-twin methodology, selected examples are displayed in Figures 1 and 2. All prices are inclusive of dividends and normalized to one at the start of the match period and the postmatch period. Figures 1 and 2 are matches using monthly prices where the match period is 60 months and the postperiod is 24 months. The Nike match period begins in January 2000. By exhaustive search, the stock and the interval with prices closest to that of Nike is determined using a squared metric. Nike's twin is 3M with a match period beginning on January 31, 1979. The postperiod prices of 3M begin on the first trading day in February, 1984 and the postperiod prices for Nike begin on the first trading day in February, 2005. The Nike and 3M prices remain closely coupled in their postperiods. Over the 24 month postperiod, Nike's holding period return is 12.2% and 3M's holding period return is 18.7%.

Figure 2 is a plot of the prices for the target Greif, Inc. and its twin, Xerox. The Xerox twin interval begins in July 1967. In this plot, the match period prices are closely coupled, but there is an obvious divergence in their postperiods. Twin prices are generally decreasing in the postperiod, while the target prices are generally increasing. After 24 months in their postmatch period, Greif's holding period return is 100%, while Xerox's holding period return is –36%.

Figure 1. Nike and Twin Returns: Monthly Data

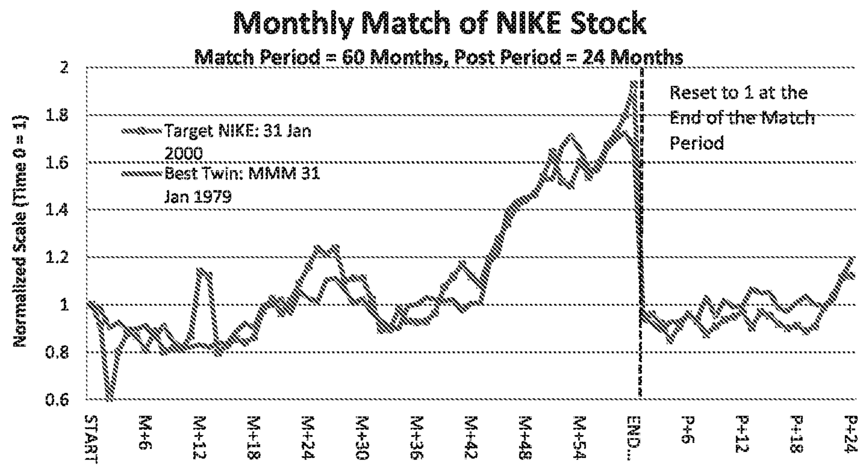
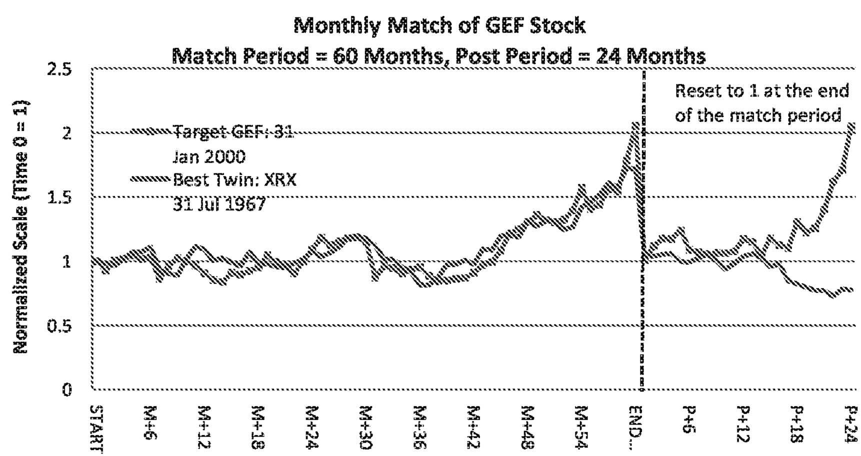


Figure 2. Greif and Twin Returns: Monthly Data



A. Hypothesis

If technical analysis has information not embedded in the prices, the postmatch returns of the twin will contain information about the out-of-sample target returns. The out-of-sample period of length Δ_w for the twin is the interval $(s + \tau,\ s + \tau + \Delta_w] = \Phi_w$. The out-of-sample period for the target is the interval $(t + \tau,\ t + \tau + \Delta_a] = \Phi_a$. We define r_a to be the vector of the target returns in Φ_a and r_w to be the vector of twin returns in Φ_w. Instead of testing for the equality of the distributions as in Lo et al. (2000), we impose a stricter standard and test the null hypothesis that the conditional out-of-sample target returns are independent of the postperiod twin returns. Our null is

$$E\left[r_a | r_w, \theta\right] = E\left[r_a | \theta\right], \tag{2}$$

where θ is a vector of proxies for risk, momentum, and overreaction. We test the null hypothesis using linear regressions with parameters estimated by the Generalized Method of Moments (GMM).

III. Data

We evaluate both daily and monthly returns using the CRSP database from 1926 to 2008. The database was preprocessed to remove observations that could confound the matching or postmatch evaluation process. We removed randomly chosen target-match interval pairs, (a,T_a), if the target fails to maintain a listing during the postmatch period. In addition, to avoid anomalies caused by the discrete quantization of prices, we removed records where the target was valued at less than \$2 per share for any 12 consecutive holding periods. Similarly, we removed targets with unknown returns, and targets with no trades or zero returns for at least 12 of the previous 24 holding periods. In each case, we did not remove the stock, but only the stock-interval pair, (a,T_a), that violates one or more of these screens.

A. Performance Quintiles

For daily data, performance quintiles are formed each year beginning January 2, 1968 and ending January 2, 2008. One thousand targets are randomly chosen on the first trading day of each year. Each target is matched with a twin, providing a total of 41,000 observations. The match period is 150 days in length and the postmatch period, in some cases, extends up to an additional 75 days. Therefore, the data on the target extend up to 225 trading days into 2008.

For monthly data, performance quintiles are formed each year beginning January 31, 1955 and ending January 31, 2001. Targets are chosen randomly in January of each year. Each target is matched with a twin, providing a total of 25,000 observations. It was not possible to find 1,000 twins for each year back to 1955 due to data screens. Years 1989-2001 have 1,000 observations (target-twin matches) per year or a total of 12,000 observations. Targets in years 1955-1988 sometimes have fewer than 1,000 observations and produce a total of 13,000 observations. The minimum number of matches in any year was 200 (years 1955-1964). The match period for monthly data is 60 months and the postmatch period extends up to an additional 36 months. Therefore, the data on targets extend up to January 31, 2009.

Quintiles are formed each year for each set of targets. For example, if 1,000 targets are selected for a match period beginning in 2001, quintiles of 200 stocks each are formed during this match period. Similarly, moving back one year, quintiles of 200 stocks are formed for the stocks with a match period beginning in the year 2000. This process continues until the quintiles are formed for each year back until 1955 (monthly data) or 1968 (daily data). We refer to the stocks with a matching period beginning in year 2001 as the year 2001 data set.

Quintile performance is measured by the holding period returns at a number of horizons. For monthly returns, we sort twins in the postperiod based on holding period returns at 12, 18, and 24 months. For daily returns, we consider horizons of 25, 50, and 75 days in the postperiod. Target membership is determined by the quintile of their twin. If the twin in the postperiod is in the n^{th} quintile, Q_n, then the target is also placed in quintile Q_n. The smallest returns are in Quintile One and the larger returns are ordered monotonically by increasing return with the highest returns in Quintile Five. If the twin is informative, the target postperiod returns will be significantly different across quintiles. We form 25 sets of quintiles for monthly data and 41 sets of quintiles for daily data. Each target stock in a set (e.g., the year 2001 set) is uniquely assigned to a quintile.

We analyze both holding period returns and average adjusted returns. Holding period returns for an m period horizon are computed as

$$r_i(m) = \prod_{j=1}^{m} \left(1 + r_{ij}\right)^{m} - 1, \tag{3}$$

where $r_i(m) \equiv r_i$ when the holding period is clear from the context. The returns include dividends.

We compute adjusted returns for target stocks in the postperiod in the year t (e.g., year 2001) data set. We subtract the average postmatch return of all targets in that data set from the raw return of the target. The averaged adjusted return for stock j from the year t data set is computed as

$$r_{adj(jt)} = r_{jt} - \bar{r}_t, \tag{4}$$

where r_{jt} is the postperiod return for target j in the year t data set and $\bar{r}_t$ is the overall mean return for all target stocks in the year t data set. Equivalently, $r_{adj(jt)}$ is the postmatch return from a long position in stock j and a short position in an equally weighted portfolio of targets. The portfolio requires zero net investment.

One advantage of using adjusted returns is that it nulls the effect of survival bias. Survival bias is otherwise present since we select only those targets that have CRSP returns through the postmatch period.

Timely evaluation of the set of records for the best match is a computational challenge. There are a total of over 900,000 records for the monthly data set and 17 million records in the daily data set. Since we search over all time increments to find the best twin interval combination, a single match can require the evaluation of nearly 1,000,000 twins for monthly data and almost 20,000,000 twins for daily data. In addition, we evaluate a total of 41,000 targets using daily data and 25,000 targets using monthly data, increasing the total number of computations by a multiple of roughly 61,000. Using efficient programming techniques, a single match over monthly intervals can be made in a fraction of a second.

B. Plots and Descriptive Statistics

Adjusted return plots from 25,000 matches are illustrated in Figure 3 . The twins were matched over 60 months and the returns were sorted at 12 months in the postperiod. The highest twin returns are in Quintile Five. In the postperiod, the adjusted returns of the target in Quintile Five dominate other quintiles at all horizons. The quintile returns were not monotonic. The second best quintile was Quintile One.

Daily adjusted return plots derived from 41,000 matches are provided in Figure 4 . The match period was 150 days and the twin returns were sorted at 75 days. Quintile Five target returns were generally higher, but other quintiles were better at 5 and 25 days.

Quintile statistics for adjusted monthly returns are provided in Table I . All returns are computed in their respective postmatch periods. Twin returns are sorted and target returns are computed for holding periods of 12, 18, and 24 months. In Panel A, the twin sort and target holding period is 12 months. Quintile Five has the highest adjusted return at 0.0276 followed by Quintile One at 0.0080. All other quintiles have negative adjusted returns. Similarly, Quintile Five also has the largest standard deviation followed by Quintile One. We compute medians of the adjusted returns to see if the quintile results are driven by large outliers. We do not find that to be the case as medians are algebraically larger for Quintile Five. Adjusted return medians are negative for all

Figure 3. Adjusted Target Return by Quintiles: Monthly Data

Stock returns in all quintile are adjusted by average returns for the year.

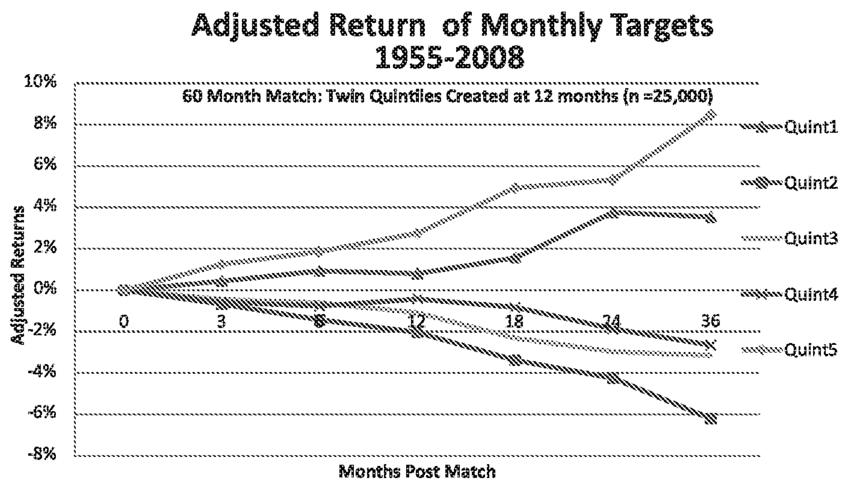
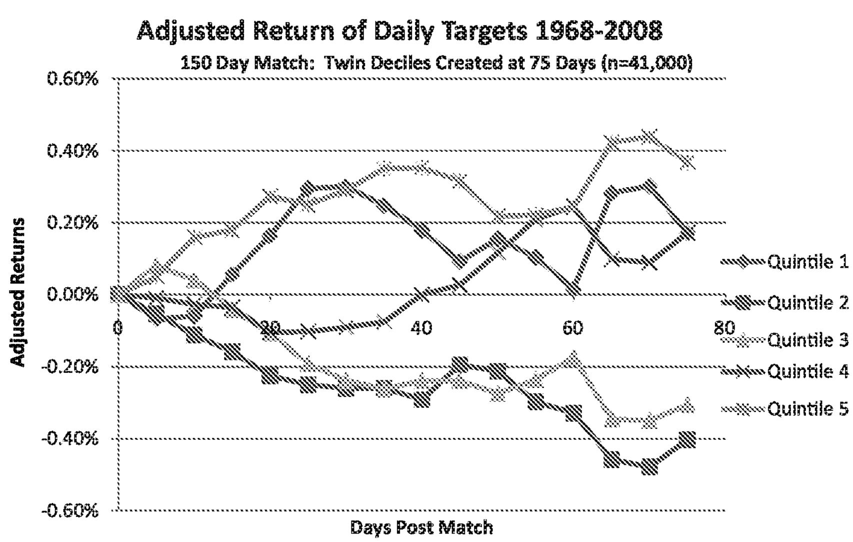


Figure 4. Adjusted Target Return by Quintiles: Daily Data

Stock returns in all quintiles are adjusted by average returns for the year.



quintiles due to positive skewness. The results are similar for Panels B and C where the respective mean adjusted returns and medians are higher for Quintile Five.

Table II reports adjusted holding period returns when quintile sorts are based on daily matches. Quintile Five still has the highest returns when twins are sorted at 25, 50, or 75 days. Quintile Five (second best) adjusted returns are 0.0021 (0.0010), 0.0018 (0.005), and 0.0037 (0.0017). Quintile

Table I. Statistics for Target Adjusted Holding Period Returns by Quintile: Monthly Data

Our sample consists of 25,000 observations for the period from January 31, 1955 to January 31, 2001. The target and twin match period is 60 months. Quintiles are formed each year based on twin holding period returns at 12 months in Panel A, 18 months at Panel B, and 24 months in Panel C. The quintiles are arrayed from the lowest twin return, Quintile 1 to highest twin return, Quintile 5. Target quintile membership is determined by the quintile of the twin. We adjust postperiod target returns by average returns (Adj HPR) in the year *t* dataset. Sample averages, standard deviations, medians, and skewness are computed from adjusted target returns.

Adj. HPR Postmatch		Quintile 1	2	3	4	5
		Panel A. Twin Sort at 12 Months				
12	Average	0.0080	−0.0204	−0.0109	−0.0043	0.0276
	Std dev	0.4313	0.3502	0.3925	0.4080	0.4979
	Medians	−0.0499	−0.0591	−0.0589	−0.0536	−0.0416
	Skew	2.5556	3.0216	4.7742	6.2473	5.0098
		Panel B. Twin Sort at 18 Months				
18	Average	0.0082	−0.0127	−0.0315	−0.0079	0.0439
	Std dev	0.6098	0.5444	0.5625	0.5359	0.8140
	Medians	−0.1026	−0.0973	−0.1044	−0.0912	−0.0802
	Skew	3.9678	4.5597	6.8906	4.1862	11.4997
		Panel C. Twin Sort at 24 Months				
24	Average	0.0228	−0.0273	−0.0231	−0.0210	0.0486
	Std dev	0.9640	0.7853	0.7862	0.6909	0.9342
	Medians	−0.1299	−0.1296	−0.1355	−0.1346	−0.1008
	Skew	12.2913	13.0209	10.6193	4.2210	7.8454

Five does not have the highest medians suggesting that these daily results may be driven by large outliers. In addition, the returns in Quintile Five have the second highest estimated return standard deviation of all three panels implying that perhaps the twins with the highest volatility matches the target with the highest volatility. Thus, the higher return of the target is a compensation for risk and is not related to the information provided by the twin.

Returns are not controlled for risk, momentum, or overreaction. We examine these adjustments in the next section.

IV. Regression Models

The information presented in the tables and plots seems to indicate that twin returns are informative. These results are consistent with the logic that higher twin returns predict higher target returns in the postperiod. However, the focus thus far has been on point estimates that are not adjusted for risk or other documented factors. These issues are examined in more detail in this section.

Excess target returns in the postperiod are adjusted using seven factors available during the target match period. From Dr. Kenneth French's website, we obtain the Fama French (1993) and Carhart (1997) factors: 1) mkt, 2) hml, 3) smb, and mom, 4) corresponding to excess market

Table II. Statistics for Average Adjusted Holding Preturns by Quintile: Daily Data

Our sample consists of 41,000 observations from January 2, 1968 to January 2, 2008. The target and twin match period is 150 days. Quintiles are formed each year based on twin holding period returns at 25 days in Panel A, 50 days in Panel B, and 75 day in Panel C. The quintiles are arrayed from lowest twin return, Quintile 1, to highest twin return, Quintile 5. Target quintile membership is determined by the quintile of the twin. We adjust postperiod target returns by average returns (Adj HPR) in the year t data set. Sample averages, standard deviations, medians, and skewness are computed from adjusted target returns.

Adj. HPR Postmatch		Quintile				
		1	2	3	4	5
		Panel A. Twin Sort at 25 Days				
25	Average	0.0002	−0.0006	−0.0028	0.0010	0.0021
	Std dev	0.1202	0.1000	0.0908	0.1009	0.1159
	Medians	−0.0096	−0.0082	−0.0094	−0.00572	−0.0074
	Skew	1.4370	1.8987	1.1202	1.3350	1.0335
		Panel B. Twin Sort at 50 Days				
50	Average	−0.0004	0.0005	−0.0012	−0.0006	0.0018
	Std dev	0.1719	0.1493	0.1324	0.1403	0.1691
	Medians	−0.0122	−0.0111	−0.0096	−0.0086	−0.0107
	Skew	1.3217	1.9377	0.9717	1.1335	1.2050
		Panel C. Twin Sort at 75 Days				
75	Average	0.0017	−0.0040	−0.0031	0.0017	0.0037
	Std dev	0.2216	0.1802	0.1702	0.1802	0.2159
	Medians	−0.0200	−0.0188	−0.0120	−0.0109	−0.0158
	Skew	1.6580	1.9408	1.4427	1.7338	2.0434

return, 5) high minus low portfolio return, 6) small minus big portfolio return, and 7) a high minus low momentum portfolio. Target returns during the match period are regressed on these factors to provide firm loadings. We also use the idiosyncratic volatility estimated from the residuals. Idiosyncratic volatility has been found to be important when explaining cross-sectional volatility in Ang et al. (2006, 2009). We compute own stock momentum during the match period following the approach of Jegadeesh and Titman (1993). For monthly data, own momentum is computed as the last six months return during a five year match period. For daily data, own momentum is computed as the last 75 days of a 150 day match period. Finally, we also included, as a control variable, average excess return (alpha) obtained from Fama-French-Carhart (FF4) regressions during the match period. Inclusion of alpha is consistent with the overreaction hypothesis of DeBondt and Thaler (1987).

A. Quintile Regressions

We use GMM to fit postmatch target excess returns to a seven factor model plus target quintile dummies. The model is

$$r_i - r_f = \delta_0 + \sum_{k=1}^{4} \delta_k \beta_{jk} + \delta_5 \alpha_j + \delta_6 v_j + \delta_7 \sigma_j + \sum_{i=1, i \neq 3}^{5} \gamma_i d_{ji} + \varepsilon_j, i \neq 3, \tag{5}$$

where $j = 1 \ldots$,25,000 for monthly data and $j = 1, \ldots 41,000$ for daily data. Further:

r_{aj} = the target holding period return in the target postperiod.
r_f = the risk-free holding period return corresponding the horizon of the target return.
δ_0 = the intercept constant.
β_{jk} = the FF4 loadings during the target match period for firm j and factor k.
α_j = the α (average excess return) determined using the FF4 model in the match period for target j.
ϵ_j = the stock's own momentum equal to the holding period yield during the target's last six months (150 days) in the target match period.
σ_j = the idiosyncratic volatility estimated from the FF4 model fit during the target's match period.
d_{ji} = the intercept dummy. The intercept dummy is $d_{ji} = 1$ if the target return is in quintile j and zero otherwise.

The hypothesis that the pattern is not informative is rejected if there is sufficient evidence to conclude that the coefficient of d_{ji} is significantly different from zero.

1. Monthly Data

Regression results for raw returns based on monthly data are provided in Tables III-V. Table III reports quintile regressions when twin holding period returns are sorted at 12 months in the postperiod. Dummies are assigned depending upon quintile membership. The Quintile Five target return dummy (corresponding to the highest twin return) is significant and positive for target holding periods of 3, 6, and 18 months. Respective significance levels are 0.0109, 0.0850, and 0.0249. The adjusted R^2s are 0.0252, 0.0298, and 0.385, respectively. The controls that are significant at all these horizons are smb, mom, alpha, and stderr with p-values less than 0.0001. The mom and alpha coefficients are negative, while the smb and stderr coefficients are positive.

Regression results when twin holding period returns are sorted at 18 and 24 months are provided in Tables IV and V, respectively. The results are similar to those in Table III, with twin dummies significant and positive at 3, 6, 12, and 18 months in both tables. The same control variables, smb, mom, alpha and stderr, are consistently significant. They have the same signs as in Table III.

If meaningful patterns exist, one might expect that the significance of that information would tend to attenuate at the beginning of the target's postmatch period. That seems to be the case as the significance levels of the d_5 coefficient are highest at the shortest postmatch horizon. Specifically, the significance levels at the three month horizon are 0.0109, 0.0006, and 0.009 for dummies corresponding to twin sorts at 12, 18, and 24 months, respectively. Likewise, postmatch returns at 24 months are not significant for any twin sorts.

We also sorted twin postmatch returns into deciles and regressed target returns on decile dummies. The regression setup was otherwise identical to the quintile setup. The results were consistent with results using quintiles, both in levels of significance and R^2s. Tables with decile regressions are available from the authors.

2. Daily Data

Tables VI-VIII report results for daily data when twin returns are sorted at 25, 50, and 75 days postmatch. In each table, excess target returns are computed at 5, 10, 25, 50, and 75 days. A priori, one might expect that daily patterns would be more informative than monthly patterns because the data are more timely. However, the daily data may be more greatly influenced by

Table III. Quintile Regressions When Twin Holding Period Returns Are Sorted at 12 Months in the Twin Post Period

This table reports GMM regressions using 25,000 observations. The dependent variable is the target excess holding period return (Target XHPR) at 3, 6, 12, 18, and 24 months in the target post period when twin returns are sorted into quintiles at 12 months in the twin post match period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), and mom (momentum). Other factors include alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period), and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	3 Month		6 Month		12 Month		18 Month		24 Month	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
Intercept	0.0174	<0.0001	0.0149	0.0063	0.0269	0.0045	0.0339	0.0125	0.0432	0.0139
Market	0.0013	0.6436	−0.0099	0.0208	−0.0300	0.0001	−0.0223	0.0389	−0.0455	0.0039
Hml	−0.0083	0.0002	−0.0011	0.7508	0.0057	0.3834	0.0116	0.1365	0.0164	0.1946
Smb	0.0185	<0.0001	0.0148	<0.0001	0.0060	0.3334	0.0325	0.0001	0.0291	0.0246
Mom	−2.3121	<0.0001	−3.4615	<0.0001	−4.2159	<0.0001	−6.8777	<0.0001	−5.8584	0.0022
Alpha	−1.5790	<0.0001	−1.9129	<0.0001	−2.5388	<0.0001	−4.0818	<0.0001	−5.3915	<0.0001
Firm mom	−0.0166	0.0348	−0.0252	0.0540	−0.0143	0.6797	−0.1355	<0.0001	−0.1701	0.0010
Std error	0.3373	<0.0001	0.9465	<0.0001	1.7888	<0.0001	2.6457	<0.0001	3.7056	<0.0001
d1	0.0030	0.4240	0.0024	0.6686	−0.0023	0.7966	0.0000	0.9995	0.0189	0.3141
d2	−0.0020	0.5381	−0.0080	0.1009	−0.0089	0.2654	−0.0119	0.2738	−0.0130	0.3804
d4	−0.0019	0.5721	−0.0031	0.5379	0.0040	0.6373	0.0090	0.4275	0.0046	0.7681
d5	0.0096	0.0109	0.0096	0.0850	0.0142	0.1323	0.0307	0.0249	0.0284	0.1156
Adj-R^2	0.0252		0.0298		0.0259		0.0385		0.035	

Table IV. Quintile Regressions When Twin Holding Period Returns Are Sorted at 18 Months in the Twin Post Period

The table presents GMM regressions using 25,000 observations. The dependent variable is target excess holding period return (Target XHPR) at 3, 6, 12, 18, and 24 months in the target post period when twin returns are sorted into quintiles at 18 months in the twin post match period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), mom (momentum). Other factors include alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period), and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	3 Month		6 Month		12 Month		18 Month		24 Month	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
Intercept	0.0127	0.0005	0.0069	0.2047	0.0172	0.0686	0.0233	0.1001	0.0326	0.0703
Market	0.0014	0.6190	−0.0096	0.0259	−0.0299	0.0001	−0.0220	0.0406	−0.0440	0.0047
Hml	−0.0083	0.0002	−0.0011	0.7421	0.0058	0.3794	0.0116	0.1368	0.0161	0.2034
Smb	0.0184	<0.0001	0.0149	<0.0001	0.0060	0.3385	0.0325	0.0001	0.0297	0.0216
Mom	−2.3123	<0.0001	−3.4560	<0.0001	−4.2052	<0.0001	−6.8694	<0.0001	−5.8244	0.0024
Alpha	−1.5779	<0.0001	−1.9053	<0.0001	−2.5294	<0.0001	−4.0796	<0.0001	−5.3595	<0.0001
Firm mom	−0.0167	0.0335	−0.0253	0.0539	−0.0142	0.6828	−0.1355	<0.0001	−0.1705	0.0010
Std error	0.3410	<0.0001	0.9555	<0.0001	1.7926	<0.0001	2.6599	<0.0001	3.7419	<0.0001
d1	0.0069	0.0580	0.0057	0.3043	0.0045	0.6107	0.0078	0.5271	0.0057	0.7484
d2	0.0059	0.0770	0.0053	0.2713	0.0089	0.2545	0.0175	0.1246	0.0215	0.2132
d4	0.0048	0.1471	0.0110	0.0292	0.0168	0.0473	0.0135	0.2352	0.0135	0.3952
d5	0.0127	0.0006	0.0136	0.0139	0.0233	0.0122	0.0353	0.0107	0.0289	0.1145
Adj-R^2	0.0252		0.0297		0.0256		0.0388		0.0349	

Table V. Quintile Regression When Twin Holding Period Returns are Sorted at 24 Months in the Twin Post Period

The table reports GMM regressions with 25,000 observations. The dependent variable is the target excess holding period return (Target XHPR) at 3, 6, 12, 18, and 24 months in the target post period when twin returns are sorted into quintiles at 24 months in the twin pos tmatch period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), and mom (momentum). Other factors are alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period), and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on the target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	3 Months		6 Months		12 Months		18 Months		24 Months	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
Intercept	0.0136	0.0001	0.0100	0.0642	0.0189	0.0430	0.0296	0.0325	0.0445	0.0093
Market	0.0013	0.6418	−0.0097	0.0244	−0.0306	0.0001	−0.0230	0.0335	−0.0447	0.0045
Hml	−0.0083	0.0002	−0.0011	0.7482	0.0059	0.3662	0.0118	0.1293	0.0163	0.1967
Smb	0.0184	<0.0001	0.0149	<0.0001	0.0057	0.3660	0.0320	0.0002	0.0294	0.0236
Mom	−2.3202	<0.0001	−3.4648	<0.0001	−4.2383	<0.0001	−6.9146	<0.0001	−5.8572	0.0022
Alpha	−1.5799	<0.0001	−1.9062	<0.0001	−2.5482	<0.0001	−4.1134	<0.0001	−5.3759	<0.0001
Firm Mom	−0.0166	0.0342	−0.0253	0.0536	−0.0142	0.6827	−0.1355	<0.0001	−0.1706	0.0010
Std error	0.3402	<0.0001	0.9547	<0.0001	1.7833	<0.0001	2.6458	<0.0001	3.7286	<0.0001
d1	0.0062	0.0909	0.0027	0.6219	0.0109	0.2091	0.0178	0.1493	0.0055	0.7611
d2	0.0045	0.1715	0.0036	0.4662	0.0103	0.1868	0.0027	0.8036	−0.0049	0.7577
d4	0.0031	0.3537	0.0024	0.6232	0.0051	0.5282	0.0028	0.7976	−0.0057	0.7075
d5	0.0123	0.0009	0.0122	0.0258	0.0264	0.0034	0.0309	0.0198	0.0189	0.2903
Adj-R^2	0.0252		0.0296		0.0256		0.0383		0.0348	

Table VI. Quintile Regressions When Twin Holding Period Rreturns are Sorted at 25 Days in the Twin Post Period

This table reports GMM regressions with 41,000 observations. The dependent variable is target excess holding period return (Target XHPR) at 5, 10, 25, 50, and 75 days in the target post period when twin returns are sorted into quintiles at 25 days in the twin post match period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), and mom (momentum). Other factors are alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period), and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	5 Days		10 Days		25 Days		50 Days		75 Days	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
Intercept	0.0003	0.6860	0.0040	0.0003	0.0034	0.0513	0.0040	0.1275	−0.0049	0.1424
Market	−0.0007	0.2403	−0.0002	0.8011	−0.0015	0.2267	−0.0036	0.0527	−0.0127	<0.0001
Hml	−0.0008	0.0432	−0.0015	0.0033	0.0052	<0.0001	−0.0035	0.0039	0.0027	0.0804
Smb	0.0009	0.0346	0.0023	0.0002	0.0047	<0.0001	0.0053	0.0004	0.0034	0.0674
Mom	−0.0002	0.7337	0.0010	0.1089	0.0002	0.8713	0.0028	0.0625	0.0050	0.0066
Alpha	−1.6853	<0.0001	−1.4554	<0.0001	−2.9950	<0.0001	0.3079	0.7075	2.4157	0.0181
Firm Mom	0.0097	<0.0001	0.0033	0.2162	0.0316	<0.0001	0.0364	<0.0001	0.0187	0.0171
Std error	0.0907	0.0169	0.0397	0.4769	0.3238	0.0004	0.1321	0.3202	0.6031	0.0004
d1	−0.0013	0.1092	−0.0004	0.7418	0.0003	0.8939	0.0012	0.6782	0.0015	0.6746
d2	−0.0005	0.4730	0.0011	0.2899	0.0017	0.3273	0.0031	0.2324	0.0063	0.0573
d4	0.0010	0.1872	0.0015	0.1299	0.0034	0.0487	0.0011	0.6672	0.0034	0.3056
d5	0.0001	0.8612	0.0007	0.5254	0.0022	0.2433	0.0006	0.8378	0.0004	0.9175
Adj-R^2	0.0028		0.0017		0.0057		0.0032		0.0029	

Table VII. Quintile Regressions When Twin Holding Period Returns are Sorted at 50 Days in the Twin Post Period

This table presents GMM regressions with 41,000 observations. The dependent variable is target excess holding period return (Target XHPR) at 5, 10, 25, 50, and 75 days in the target post period when twin returns are sorted into quintiles at 50 days in the twin post match period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), and mom (momentum). Other factors are alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period) and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	**5 Days**		**10 Days**		**25 Days**		**50 Days**		**75 Days**	
	Coef.	***p*-value**	**Coef.**	***p*-value**	**Coef.**	***p*-value**	**Coef.**	***p*-value**	**Coef.**	***p*-value**
Intercept	0.0008	0.2889	0.0051	<0.0001	0.0045	0.0110	0.0048	0.0680	−0.0033	0.3163
Market	−0.0006	0.3222	−0.0001	0.8994	−0.0015	0.2462	−0.0036	0.0534	−0.0127	<0.0001
Hml	−0.0008	0.0349	−0.0015	0.0027	−0.0052	<0.0001	−0.0035	0.0039	0.0027	0.0822
Smb	0.0010	0.0293	0.0023	0.0001	0.0047	<0.0001	0.0053	0.0004	0.0034	0.0669
Mom	−0.0001	0.7621	0.0010	0.1048	0.0002	0.8700	0.0028	0.0632	0.0050	0.0067
Alpha	−1.6931	<0.0001	−1.4610	<0.0001	−2.9952	<0.0001	0.3105	0.7052	2.4157	0.0181
Firm Mom	0.0097	<0.0001	0.0033	0.2244	0.0315	<0.0001	0.0363	<0.0001	0.0185	0.0180
Std error	0.1030	0.0067	0.0498	0.3725	0.3291	0.0003	0.1303	0.3235	0.5976	0.0004
d1	−0.0026	0.0020	−0.0023	0.0467	−0.0008	0.6690	−0.0006	0.8319	−0.0013	0.7249
d2	−0.0006	0.4146	−0.0007	0.5047	0.0010	0.5758	0.0013	0.6299	0.0019	0.5740
d4	0.0000	0.9967	−0.0001	0.9561	0.0009	0.6093	0.0003	0.8971	0.0023	0.4757
d5	−0.0019	0.0211	−0.0014	0.2372	0.0003	0.8646	0.0014	0.6302	0.0014	0.6895
Adj-R^2	0.0033		0.0017		0.0057		0.0032		0.0028	

Table VIII. Quintile Regressions When Twin Holding Period Returns are Sorted at 75 Days in the Twin Post Period

This table reports GMM regressions with 41,000 observations. The dependent variable is target excess holding period return (Target XHPR) at 5, 10, 25, 50, and 75 days in the target post period when twin returns are sorted into quintiles at 75 days in the twin post match period. Target quintile membership is determined by the quintile of the twin. The independent variables include the four Fama-French-Carhart factors, market (market minus the risk free rate), hml (high minus low), smb (small minus big), and mom (momentum). Other factors are alpha (the average excess return of the target during the match period), firm mom (the firm's own momentum computed from holding period returns during the last six months of the match period), and stderr (the standard error of the residuals computed during the match period). The coefficients d1-d5 are the loadings on target dummies corresponding to Quintiles 1-5. The mid quintile (d3) is omitted to avoid the dummy variable trap.

Target XHPR	5 Days		10 Days		25 Days		50 Days		75 Days	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*P*-value
Intercept	0.0012	0.1143	0.0054	<0.0001	0.0049	0.0052	0.0037	0.1603	−0.0038	0.2554
Market	−0.0006	0.2596	−0.0002	0.7985	−0.0016	0.2010	−0.0038	0.0457	−0.0130	<0.0001
Hml	−0.0008	0.0405	−0.0015	0.0034	−0.0052	<0.0001	−0.0034	0.0045	0.0028	0.0700
Smb	0.0009	0.0327	0.0023	0.0002	0.0046	<0.0001	0.0053	0.0005	0.0033	0.0737
Mom	−0.0002	0.7372	0.0010	0.1096	0.0002	0.8727	0.0028	0.0637	0.0050	0.0069
Alpha	−1.6861	<0.0001	−1.4486	<0.0001	−2.9771	<0.0001	0.3213	0.6954	2.4469	0.0167
Firm Mom	0.0096	<0.0001	0.0032	0.2337	0.0316	<0.0001	0.0364	<0.0001	0.0185	0.0180
Std error	0.0923	0.0146	0.0361	0.5175	0.3044	0.0009	0.1100	0.4040	0.5565	0.0009
d1	−0.0021	0.0139	−0.0018	0.1263	0.0021	0.2986	0.0032	0.2750	0.0035	0.3410
d2	−0.0015	0.0461	−0.0017	0.0908	−0.0012	0.4980	0.0005	0.8529	−0.0010	0.7640
d4	−0.0010	0.1785	−0.0008	0.4333	0.0004	0.8312	0.0036	0.1637	0.0044	0.1794
d5	−0.0010	0.2424	0.0004	0.7318	0.0015	0.4422	0.0034	0.2344	0.0055	0.1321
Adj-R^2	0.0028		0.0017		0.0057		0.0032	.	0.0029	

noise components that may make it difficult to extract useful information. Our regressions seem to suggest that the latter explanation is more plausible.

We find nothing remarkable in Tables VI-VIII. Quintile dummies are significant in only one case. Specifically, the coefficient on d_5 is significant ($p = 0.0211$) for five day target returns in Table VII. However, the coefficient is negative suggesting that the tendency of posttarget returns is to move in an opposite direction from that of the twin. The maximum R^2 found in any of the daily tables is 0.0058.

These results are interesting in light of the statistics presented in Table II. Specifically, point estimates of mean returns in Table II indicated that the highest returns are in Quintile Five. However, quintile returns are not significantly different when adjustments are made for risk and other controls. This seems to suggest that incrementally higher returns from daily charts may be primarily due to risk-bearing and/or behavioral factors.

B. Stock Return Regressions

In this section, we investigate individual stock returns as explained by market factors and twin returns. The setup is similar to the quintile regressions, but actual twin returns are used as regressors instead of dummies. The regression equation is

$$r_{aj} - r_f = \delta_0 + \sum_{k=1}^{4} \alpha_k \beta_{jk} + \delta_5 \alpha_j + \delta_6 \upsilon_j + \delta_7 \sigma_j + \gamma_i r_{\omega_{ji}} + \varepsilon_j, \tag{6}$$

where $j = 1\ldots, 25{,}000$ for monthly data and $j = 1, \ldots 41{,}000$ for daily data. The twin's return in the posttwin period is $r_{w_{ji}}$, where $i = 1$ corresponds to 12 month twin returns in the postmatch period, $i = 2$ corresponds to 24 month twin returns in the postmatch period, and $i = 3$ corresponds to 36 month twin returns in the postmatch period. The null hypothesis is that $\gamma_i = 0,\ i = 1, 2{,}3$.

1. Monthly Data

The results using monthly data are provided in Tables IX and X. Excess target holding period returns are regressed against the control variables and twin holding period returns at all twin horizons. In Table IX, Panel A, three month target returns in the target postperiod are regressed against the control variables and twin returns at 12, 18, and 24 months. The twin return coefficients are positive and significant. The respective significance levels are 0.0012, 0.0191, and 0.0016. The control variables smb, mom, alpha, and stderr remain significant at 0.0001. In Panel B, excess target returns at six months are regressed against the same factors and the significance levels of the twins are 0.0008, 0.0036, and 0.0011, respectively. R^2s generally remain between about 2.5% to 3%. Target holding period returns at 12 and 18 months in the posttarget period are found in Table X. The results are similar to those in Table IX: All twins are significant at better than the 1% level. Since we have adjusted for risk, momentum, and overreactions, we view these results to be strong evidence that patterns are informative.

2. Daily Data

The results for regressions on twin returns using daily data are reported in Tables XI and XII. In addition to the control variables, the regressors are twin returns at 25, 50, and 75 days. The results here are similar to the regressions using quintile data. Namely, there is insufficient evidence to conclude that twin returns are informative in the daily data. The only exception is in Table XI, Panel B, where target returns at 10 days are regressed on controls and the 75 day twin return in the postperiod. In that specification, the twin coefficient is positive and significant at 0.0939.

Table IX. Target Excess Holding Period Returns at Three and Six Months Regressed Against Controls and Twin Returns at 12, 18, and 24 Months

This table presents GMM regression based on 25,000 observations from 1955 to 2001. In each year, excess target holding period returns (XHPR) at three and six months in the post period are regressed against control variables from the target match period and twin returns in the twin post period. The control variables are loadings on four Fama-French-Carhart factors, the alpha, the firm's own momentum, and standard errors, all computed during the target's match period.

XHPR	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*P*-value
	Panel A. Three Month Target HPR in the Post Period						*Panel B. Six Month Target HPR in the Post Period*					
Intercept	0.0156	<0.0001	0.00160	<0.0001	0.0154	<0.0001	0.0101	0.0314	0.0102	0.0305	0.0098	0.0376
Market	0.0020	0.4879	0.0018	0.5182	0.0018	0.5242	−0.0091	0.0345	−0.0092	0.0311	−0.0093	0.0299
Hml	−0.0083	0.0001	−0.0083	0.0001	−0.0083	0.0002	−0.0011	0.7400	−0.0011	0.7524	−0.0011	0.7541
Smb	0.0187	<0.0001	0.0186	<0.0001	0.0187	<0.0001	0.0151	<0.0001	0.0150	<0.0001	0.0151	<0.0001
Mom	−2.2898	<0.0001	−2.2941	<0.0001	−2.2918	<0.0001	−3.4298	<0.0001	−3.4306	<0.0001	−3.4325	<0.0001
Alpha	−1.5543	<0.0001	−1.5612	<0.0001	−1.5532	<0.0001	−1.8763	<0.0001	−1.8803	<0.0001	−1.8741	<0.0001
Firm mom	−0.0168	0.0316	−0.0165	0.0366	−0.0165	0.0356	−0.0255	0.0505	−0.0250	0.0570	−0.0251	0.0556
Std error	0.3396	<0.0001	0.3438	<0.0001	0.3401	<0.0001	0.9474	<0.0001	0.9513	<0.0001	0.9479	<0.0001
Twin12	0.0158	0.0012					0.0234	0.0008				
Twin18			0.0078	0.0191					0.0140	0.0036		
Twin24					0.0081	0.0016					0.0122	0.0011
Adj-R^2	0.0256		0.0252		0.0255		0.0303		0.0301		0.0302	

Table X. Target Excess Holding Period Returns at 12 and 18 Months Regressed Against Controls and Twin Returns at 12, 18, and 24 Months

This table presents GMM regressions based on 25,000 observations from 1955 to 2001. In each year, excess target holding period returns (XHPR) at 12 and 18 months in the post period are regressed against control variables from the target match period and twin returns in the twin post period. The control variables are loadings on four Fama-French-Carhart factors, the alpha, the firm's own momentum, and standard errors, all computed during the target's match period.

XHPR	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
	Panel A. Twelve Month Target HPR in the Post Period						*Panel B. Eighteen Month Target HPR in the Post Period*					
Intercept	0.0224	0.0074	0.0218	0.0105	0.0218	0.0100	0.0278	0.0281	0.0278	0.0331	0.0270	0.0378
Market	−0.0293	0.0002	−0.0295	0.0002	−0.0296	0.0002	−0.0207	0.0558	−0.0211	0.0503	−0.0214	0.0479
Hml	0.0058	0.3802	0.0059	0.3702	0.0059	0.3727	0.0116	0.1346	0.0118	0.1293	0.0118	0.1294
Smb	0.0063	0.3133	0.0061	0.3266	0.0062	0.3218	0.0331	<0.0001	0.0328	0.0001	0.0329	0.0001
Mom	−4.1748	<0.0001	−4.1679	<0.0001	−4.1782	<0.0001	−6.7954	<0.0001	−6.7950	<0.0001	−6.8048	<0.0001
Alpha	−2.4972	<0.0001	−2.4944	<0.0001	−2.4932	<0.0001	−3.9990	<0.0001	−4.0072	<0.0001	−3.9953	<0.0001
Firm mom	−0.0146	0.6729	−0.0136	0.6940	−0.0139	0.6885	−0.1362	<0.0001	−0.1345	<0.0001	−0.1349	<0.0001
Std error	1.7804	<0.0001	1.7828	<0.0001	1.7808	<0.0001	2.6328	<0.0001	2.6425	<0.0001	2.6351	<0.0001
Twin12	0.0349	0.0015					0.0662	0.0004				
Twin18			0.0244	0.0030					0.0408	0.0026		
Twin24					0.0184	0.0037					0.0337	0.0016
Adj-R^2	0.0260		0.0260		0.0259		0.0393		0.0389		0.0390	

Table XI. Target Excess Holding Period Returns at Five and Ten Days Regressed Against Controls and Twin Returns at 25, 50, and 75

This table reports GMM regressions based on 41,000 observations from 1968 to 2008. In each year, excess target holding period returns (XHPR) at five and ten days in the post period are regressed against control variables from the target match period and twin returns in the twin post period. The control variables are loadings on four Fama-French-Carhart factors, the alpha, the firm's own momentum, and standard errors, all computed during the target's match period.

XHPR	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*P*-value	Coef.	*p*-value
	Panel A. Five Day Target HPR in the Post Period						*Panel B. Ten Day Target HPR in the Post Period*					
Intercept	0.0003	0.6073	0.0004	0.5806	0.0003	0.6463	0.0047	<0.0001	0.0047	<0.0001	0.0046	<0.0001
Market	−0.0007	0.2117	−0.0007	0.2132	−0.0007	0.2111	−0.0002	0.7849	−0.0002	0.7845	−0.0002	0.7809
Hml	−0.0008	0.047	−0.0008	0.0466	−0.0008	0.0472	−0.0015	0.0034	−0.0015	0.0034	−0.0015	0.0035
Smb	0.0009	0.0353	0.0009	0.0357	0.0009	0.035	0.0023	0.0002	0.0023	0.0002	0.0023	0.0002
Mom	−0.0002	0.7292	−0.0002	0.7253	−0.0002	0.7305	0.0010	0.1107	0.0010	0.1106	0.0010	0.1097
Alpha	−1.6813	<0.0001	−1.6838	<0.0001	−1.6796	<0.0001	−1.4525	<0.0001	−1.4521	<0.0001	−1.4461	<0.0001
Firm mom	0.0097	<0.0001	0.0097	<0.0001	0.0097	<0.0001	0.0033	0.2197	0.0033	0.2202	0.0032	0.2351
Std error	0.0836	0.0254	0.0844	0.0239	0.0829	0.0264	0.0345	0.5300	0.0344	0.5308	0.0322	0.5576
Twin25	0.0000	0.9896					−0.0001	0.9820				
Twin50			−0.0016	0.4842					0.0002	0.9496		
Twin75					0.0013	0.5174					0.0045	0.0939
Adj-R^2	0.0027		0.0027		0.0027		0.0017		0.0017		0.0018	

Table XII. Target Excess Holding Period Returns at 25 and 50 Days Regressed Against Controls and Twin Returns at 25, 50, and 75 Days

GMM regression based on 25,000 observations beginning in 1968 and ending in 2008. In each year, excess target holding period returns (XHPR) at 20 and 50 days in the post period are regressed against control variables from the target match period and twin returns in the twin post period. The control variables are loadings on four Fama-French-Carhart factors, the alpha, firm's own momentum and standard error, all computed during the target's match period.

XHPR	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
	Panel A. 25 Day Target HPR in the Post Period						*Panel B. 50 Day Target HPR in the Post Period*					
Intercept	0.0049	0.0017	0.0048	0.0022	0.0048	0.0022	0.0052	0.0232	0.0051	0.0266	0.0053	0.0232
Market	−0.0015	0.2260	−0.0015	0.2272	−0.0015	0.2296	−0.0036	0.0522	−0.0036	0.0518	−0.0036	0.0524
Hml	−0.0052	<0.0001	−0.0052	<0.0001	−0.0052	<0.0001	−0.0035	0.0039	−0.0035	0.0039	−0.0035	0.0039
Smb	0.0047	<0.0001	0.0047	<0.0001	0.0047	<0.0001	0.0053	0.0004	0.0053	0.0004	0.0053	0.0004
Mom	0.0002	0.8726	0.0002	0.8640	0.0002	0.8721	0.0028	0.0631	0.0028	0.0622	0.0028	0.0631
Alpha	−2.9874	<0.0001	−2.9778	<0.0001	−2.9853	<0.0001	0.3087	0.7066	0.3186	0.6977	0.3073	0.7080
Firm mom	0.0316	<0.0001	0.0315	<0.0001	0.0315	<0.0001	0.0364	<0.0001	0.0363	<0.0001	0.0364	<0.0001
Std error	0.3193	0.0004	0.3178	0.0004	0.3202	0.0004	0.1295	0.3196	0.1265	0.3306	0.1303	0.3166
Twin25	0.0096	.02177					0.0021	0.8571				
Twin50			0.0090	0.1221					0.0071	0.4058		
Twin75					0.0044	0.3475					−0.0004	0.9554
Adj-R^2	0.0058		0.0058		0.0057		0.0032		0.0033		0.0032	

V. Conclusions

We examine a large number of possible stock price patterns. Using the target-twin methodology and data from an exhaustive search, we find that the patterns provide information beyond that explained by other factors. The relationship between targets and twins is stronger when data and patterns are evaluated using monthly data. A possible implication is that charts based on monthly data are more informative than charts based on possibly noisy daily data.

Patterns based on daily data are interesting in another respect. Point estimates of mean returns based on 41,000 observations indicate that the highest returns are in Quintile Five. However, quintile returns are not significantly different when adjustments are made for risk and other controls. This seems to suggest that incrementally higher returns from charting may be primarily a reward for risk bearing and/or behavioral factors.

Our regressions use proxies to adjust for the effect of risk, momentum, and over reaction. The adjusted regressions provide consistent evidence that twin returns at 12, 18, and 24 months postmatch are significant explanatory variables for postmatch target returns at 3, 6, 12, and 18 months. It is tempting to conclude that technical analysis can produce average excess returns. However, we do not explicitly test a trading strategy and due to obvious research limitations, we do not claim that statistically significant abnormal returns will result from an operational pattern matching strategy. The regression R^2s are small and the results are based on transaction data. We do not account for bid-ask spreads or other forms of transaction costs. Furthermore, there is a selection bias since prospective targets selected during the match period are required to have data in the postmatch period.

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