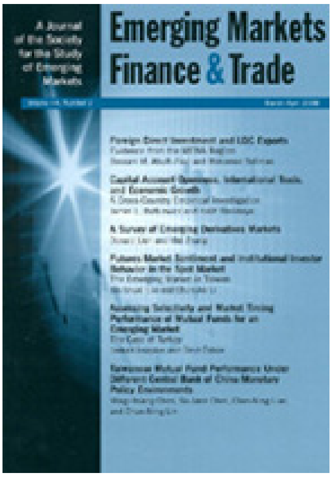

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Behavioral Investment Strategy Matters: A Statistical Arbitrage Approach

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Behavioral Investment Strategy Matters: A Statistical Arbitrage Approach

David S. Sun, Shih-Chuan Tsai, and Wei Wang

ABSTRACT: In this study, we employ a statistical arbitrage approach to demonstrate that momentum strategies work only in longer formation and holding periods, a result more conclusive than standard parametric tests can offer. Disposition and overconfidence effects are important factors contributing to the phenomenon. The overconfidence effect seems to dominate the disposition effect, especially in an up market. Moreover, the overconfidence investment behavior of institutional investors is the main cause for significant momentum returns observed in an up market. In a down market, the institutional investors tend to adopt a contrarian strategy while the individuals are still maintaining momentum behavior within shorter periods.

KEY WORDS: disposition effect, market state, momentum strategy, statistical arbitrage.

Equilibrium models have been widely used to examine the efficient market hypothesis but are, however, subject to the potential problem of "joint hypotheses," as pointed out in Fama (1998). Abnormal returns may indicate the equilibrium model adopted is inappropriate, instead of implying market inefficiency. Extending the prospect theory of Kahnman and Tversky (1979), Jegadeesh and Titman (1993) proposed a model of momentum to examine market efficiency and found that stock prices are predictable under the momentum model. The extension of prospect theory by Daniel and Titman (1999) on overconfidence also indicates that certain stocks could generate greater overconfidence among investors, resulting in a stronger momentum effect. Other studies argue that momentum returns only appear in up markets rather than in down markets.

To the extent that the momentum strategy has been supported by various works based on the equilibrium concept regardless of the joint-hypothesis criticism, this study intends to examine momentum-related effects through an alternative model based on the concept of statistical arbitrage. As statistical arbitrage is a long-horizon trading strategy that generates riskless profits in the limit, it is seen as a natural candidate for extending the findings in the existing empirical literature on anomalies due to disposition and overconfidence effects. Tests of market efficiency based on the statistical arbitrage approach avoid the joint-hypothesis problem of equilibrium models.

Based on this difference, we examine momentum effects on excess stock returns under up- or down-market states utilizing the strategy proposed in Cooper et al. (2004) to test market efficiency in the Taiwanese stock market. Under the test of statistical arbitrage with

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a constrained mean, only strategies with matching forming and holding periods generate significant excess returns. The pattern of profitability from statistical arbitrage examination is more consistent and general, leaning toward long-term strategies, than what the raw momentum returns exhibit. The comparison between constrained and unconstrained trading profit means indicates that loosening the constraint on the profit path allows us to further conclude that momentum strategies are profitable only in an up market, which is more conclusive than the traditional *t*-test can offer. Although traditional models support short-term momentum strategies to generate significantly positive profits even in a down market, especially in the emerging markets, statistical arbitrage models suggest that they are not valid if risks are properly taken into account.

More specifically, our statistical arbitrage approach explores the disposition and overconfidence effects for possible causes of tested results. We found significant momentum effects as in Cooper et al. (2004), but we proceed further to conclude that investor overconfidence is the primary factor causing the up-market momentum effects, while a negative disposition effect results in mixed and insignificant momentum effects in a down market. The significant momentum returns found in this study can be considered as driven mainly by the follow-on trading pattern of institutional investors, which dominates the moderate disposition effect. The significant up-market momentum phenomenon is a result of the similar behavior of the two major investor groups, while the absence of down-market momentum is due to the difference between their trading patterns there. Market frictions, size effects, overlapping periods, and market-state definition are also examined in robustness tests, and our main results remain unchanged.

Findings of this paper contribute to the understanding of long-term market anomalies and their major driving factors, as compared to results derived through cross-sectional approaches. Our model-free statistical arbitrage analysis adds to those analyses based on equilibrium asset prices in providing conclusions free of Fama's joint-hypothesis problem. Our study of the Taiwanese market is a helpful reference for studies on return anomalies in the emerging stock markets.

Literature and Methodology

Statistical arbitrage represents a zero cost, self-financing trading opportunity that has positive expected cumulative trading profits with a declining time-averaged variance and a probability of loss that converges to zero. The statistical arbitrage analysis is designed to exploit persistent anomalies and was first introduced by Bondarenko (2003) and Hogan et al. (2004), and later improved by Jarrow et al. (2005) in a study on stock markets. Hogan et al. (2004) analyzes momentum and value trading strategies, while Jarrow et al. (2005) extends the analysis to stock liquidity and industry momentum strategies. Both studies find that these strategies generate statistical arbitrage opportunities even after adjusting for market frictions such as transaction costs, margin requirements, and liquidity buffers for the marking-to-market of short sales and borrowing rates, although momentum and value strategies offer the most profitable trading opportunities.

There are several types of statistical arbitrage strategies commonly adopted. The first type is pair or basket trading, or spread trading, which allows the trader to capture anomalies, relative strengths, or even fundamental differences on two stocks or baskets of stocks while maintaining a market neutral position. Profits come from the changes in spread between the two. Gatev et al. (2006) summarize a comprehensive list of market-neutral strategies in practice. The second one is a multifactor model, which is based on the correlations of stock returns with several factors chosen, as in arbitrage pricing theory. The third type falls on the category of mean-reverting strategies, assuming stock prices to be mean reverting. According to the strategy, the winning or outperforming stock, which is expected to decrease in the future, should be sold short while the underperforming stock should be bought. One example of this type is contrarian trading. Triantafyllopoulos and Montana (2011) employ a state-space framework for modeling spread under a mean-reverting process. The fourth kind is related to the econometric relation of cointegration, relying on mean reverting tracking errors. Dunis and Ho (2005) outline many applications of cointegration such as index replication, which exploits long-term qualities of cointegration requiring only occasional portfolio rebalancing.

We use for our statistical arbitrage model a behavioral-type strategy such as the momentum investment introduced by Jegadeesh and Titman (1993). We use stock prices from firms listed on the Taiwan Stock Exchange (TSE) from January 1, 1998, to August 31, 2008. The number of stocks ranges from 462 to 711 over the data period. Market index for the analysis of momentum returns is the Taiwan Weighted Stock Index, which covers all stocks listed on TSE within the same period. The short-term interest rate for the statistical arbitrage approach is the overnight interbank money market rate. Balances for margin trading by individual investors in the data period are obtained from the Securities and Futures Institute in Taiwan. Number of shares purchased and sold by institutional investors is from the *Taiwan Economic Journal (TEJ).* Corporate characteristics such as book-to-market ratio and sales growth are also obtained from *TEJ.*

Logarithmic returns of stocks are computed weekly while portfolios are constructed with equal weights for all stocks. An investment portfolio of momentum strategy is defined as longing a portfolio of winning stocks and shorting another portfolio of losing stocks. So the momentum portfolio return is calculated as

$$R_{p,t} = \frac{\sum_{i=1}^{n} R_{i,t}^{W}}{n} - \frac{\sum_{i=1}^{n} R_{i,t}^{L}}{n}, \tag{1}$$

where p denotes a certain portfolio, $R_{i,t}^{W}$ is the return of the ith stock at the tth period within the winning portfolio, $R_{i,t}^{L}$ is the return of a stock in the losing portfolio. Twenty stocks are selected for each of the winning and losing portfolios to achieve the momentum portfolio returns. In order to compare long- versus short-term investment strategy, the geometric average of consecutive weekly returns are used.

An up market is defined, following Cooper et al. (2004), as a one-year period (from the last day of the forming period of a specific portfolio going back one year) during which the periodic return of the closing market index is positive, whereas a down market is one in which the periodic index return is negative. To gauge the disposition effect of Shefrin and Statman (1985), we utilize the measure proposed by Weber and Camerer (1998), which is

$$\alpha = \frac{S_{+} - S_{-}}{S_{+} + S_{-}}, \tag{2}$$

where S_{+} is the quantity of stocks disposed of when the previous return is positive. In the case of individual investors, it would be the margin sell quantity, given previously positive returns, minus the buyback quantity on shorted stocks given a negative previous return. For institutional investors, it would be the sell quantity given previously positive returns. When categorized by corporate characteristics, this measure would be the sum of the individuals and the institutional investors. S_- is the quantity of stocks sold when the previous return is negative. In the case of individual investors, it would be the margin sell quantity, given previously negative returns, minus the buyback quantity on shorted stocks given a positive previous return. For institutional investors, it would be the sell quantity given previously negative returns. If $\alpha > 0$, investors sell more on profits than on losses. The closer this measure is to 1, the more the investor is exhibiting disposition effect.

The overconfidence measure, also following Weber and Camerer (1998), is given by

$$\beta = \frac{B_+ - B_-}{B_+ + B_-}, \tag{3}$$

where B denotes buys rather than sells as compared to Equation (3). So Equation (4) measures buy moves following positive or negative previous period returns. The overconfidence measure also reflects momentum buying behavior. If $\beta > 0$, investors buy more on profits than on losses. The closer this measure is to 1, the more investors exhibit overconfidence or momentum effect.

Based on the measures listed above, we examine if (1) momentum strategy profits more in an up market, (2) momentum strategy is consistent with statistical arbitrage, and (3) the disposition or overconfidence effect is capable of explaining the difference in momentum returns. According to Jarrow et al. (2005), if a minimum t-statistic is utilized for statistical inferences, both constrained means (profits in all periods must be fixed and positive) and unconstrained means (profits across periods can take on various paths) can be tested. The critical value for the minimum t-test is the maximum value among all possible critical values. So we employ Monte-Carlo simulation as well as bootstrapping methods to obtain critical values for this test.

Momentum Strategy

We start out with twenty winners and twenty losers instead of the top or bottom 10 percent to maintain the number of stocks in the portfolios. There are ten forming periods and ten holding periods, with both being one of 1, 2, 3, 4, 6, 8, 12, 24, 36, or 48 weeks. Losers are the ones with the lowest returns in the respective holding interval, while winners are those with the second highest returns to avoid frequently unexpected reversals happening in the most profitable stocks. In order to increase statistical power, an overlapping execution strategy is conducted such that a strategy for a given week is repeated in the next week. When the forming and holding periods are one week, there are 504 observations, while for the 48-week forming and holding periods, there are 457 observations. Equal weights are used in forming momentum portfolios. All winning and losing stocks are purchased initially with NT$100, under the assumption that each stock is divisible infinitely, consistent with a self-financing principle. A momentum strategy is to buy winning stocks and sell losing stocks on the day the portfolio is constructed. The portfolio is closed out at the end of the holding period, and an average weekly return is computed by subtracting the average losing stock returns from the average winning stock returns and then dividing by the total number of weeks within the holding period. In general, those doing better in the forming period also perform better in the subsequent holding periods. But the longer the holding period is, the more likely it is for the most winning portfolios to lose. This pattern is much more pronounced for the portfolios formed using eight-week returns than for those formed using one-week returns. This outcome implies that it is more likely for the most winning stocks to reverse their returns in the long run.

Statistical Arbitrage

We modify the definition of statistical arbitrage in Jarrow et al. (2005) as follows:

$$\begin{gathered} v(0)=0 \\ \lim_{t\to\infty} E^{p}\left[v(t)\right]>0 \\ \lim_{t\to\infty} P\left[v(t)<0\right]=0, \text{ or} \\ \lim_{t\to\infty} Var\left[v(t)\middle|v(t)<0\right]=0. \end{gathered} \tag{4}$$

where $v(0)$ is the up-front cost of the investment strategy, and $E^{p}[]$ stands for the expectation under probability measure P, with $P[]$ as the probability under that measure. The term $v(t)$ denotes cumulated discounted trading profits. In the fourth condition, only the variance of having a loss is considered rather than defining all scenarios. A profit model of constrained mean is defined as

$$\Delta v_i = \mu + \sigma i^{\lambda} Z_i \text{ and } v(t_n) = \sum_{i=1}^{n} \Delta v_i \sim N\left(\mu n, \sigma^2 \sum_{i=1}^{n} i^{2\lambda}\right), \tag{5}$$

while a model of unconstrained mean is

$$\Delta v_i = \mu i^{\theta} + \sigma i^{\lambda} Z_i \text{ and } v(t_n) = \sum_{i=1}^{n} \Delta v_i \sim N\left(\mu \sum_{i=1}^{n} i^{\theta}, \sigma^2 \sum_{i=1}^{n} i^{2\lambda}\right). \tag{6}$$

In Equation (5), μ is the mean of trading profits and λ is the growth rate of volatility. In Equation (6), θ is the growth rate of profit means. Discounted trading profits under Equation (5) of all periods are fixed at μ, hence confining possible trading paths as well as available strategies. Equation (6) relaxes the restriction and allows a more general class of statistical arbitrage strategies. Applying log likelihood function on Δv_i, we can solve for the four parameters with first-order conditions. According to the specification of Jarrow et al. (2005), statistical inferences are done with a minimum t-test. The inference statistic of an unconstrained mean model is given by

$$S_{UM} = \text{Min}\left\{t(\hat{u}), t\left(\hat{\theta} - \hat{\lambda} + \frac{1}{2}\right), t\left(\hat{\theta}+1\right), \text{Max}\left[t\left(-\hat{\lambda}\right), t\left(\hat{\theta}-\hat{\lambda}\right)\right]\right\}, \tag{7}$$

while the statistic for a constrained mean model is

$$S_{CM} = \text{Min}\left\{t(\hat{u}), t\left(-\hat{\lambda}\right)\right\}. \tag{8}$$

If either of the minimum t-test statistics is greater than its respective critical value, then any t-statistic for the inference would be significant to reject the null hypothesis (Equation (8)), and there is statistically significant room for statistical arbitrage to counter market efficiency. The critical values t_c is the maximum of all the achievable critical values. But the minimum t-test statistics follow a joint distribution rather than a standard normal distribution; t_c has to be obtained through a Monte Carlo simulation in the absence of sample autocorrelation.

Monte Carlo Simulation

The simulated parameters should generate a proportion, which is smaller than the significance level α, where the null hypothesis is rejected, or

$$\Pr\left\{S_{UM} > t_c \left|\mu, \lambda, \theta, \sigma\right.\right\} \le \alpha.$$

So the maximum critical value t_c needs the biggest parameter space for the null hypothesis. Jarrow et al. (2005) suggest using the space

$$(\mu, \lambda, \theta) = \left(-1 \times 10^{-6}, -\frac{1}{2}, -1\right).$$

We simulate 500 discounted trading profit results and calculate parameters based on the maximum likelihood principle. Out of the four t-values corresponding to the null hypothesis, the largest one is set to be the critical value t_c. The process is repeated a thousand times, and the ranked t_c at the percentile of $100(1 - \alpha)$, for a single-tailed statistical arbitrage test, is the minimum t-test critical value used for inferences in our results.

Empirical Results

Traditional t-Tests on Original Returns

A standard t-test is conducted first to compare original momentum returns with results under all market states in Table 1. Out of the 100 momentum strategies, fifty-four exhibit positive average weekly returns at the 1 percent significance level, while another fifteen produce significantly positive returns at 5 percent and the other eight are significant at 10 percent. If samples are further divided according to up or down market, in an up market seventy-six momentum strategies out of 100 achieve significantly positive average weekly returns at 1 percent, with another eleven significant at 5 percent and seven significant at 10 percent. Only six strategies are unable to produce significant positive returns. In a down market, only six out of 100 produce significantly positive average weekly returns at 1 percent, and one is significantly positive at 5 percent and two at 10 percent. There is also one producing significantly negative average weekly returns at 5 percent, and another significantly negative one at 10 percent. Our results are consistent with Cooper et al. (2004), who conclude that momentum returns are significant in an up market, but not so in a down market.

Under all market states, for all strategies holding longer than eight weeks, there are always significantly positive returns, suggesting that momentum strategies tend to produce excess returns in longer holding periods. This phenomenon holds, however, only for those formed on average returns that are two weeks or shorter, or thirty-six weeks or longer. But if the forming period is between three and twenty-four weeks, yet the holding period is shorter than four weeks, there are no significant returns for momentum strategies. This is consistent with the prediction of Jegadeesh and Titman (1993) on reversals due to overreaction for very short (within a month) and very long (more than fifteen months) holding periods. But our study, which is based on weekly return data, shows that reversals do not happen immediately and they last for a period of time.

Testing Statistical Arbitrage

Following basic tests on sample momentum returns, we proceed with tests based on statistical arbitrage models. In addition to constrained-mean and unconstrained-mean

Table 1. Returns on momentum strategies: all market states

	Portfolio holding periods									
	1 week	2 weeks	3 weeks	4 weeks	6 weeks	8 weeks	12 weeks	24 weeks	36 weeks	48 weeks
1 week	0.3033	0.313	0.235	0.2081	0.1259	0.1677	0.1643	0.1012	0.1168	0.1179
	(2.03)**	(3.05)***	(2.79)***	(2.85)***	(2.07)**	(3.14)***	(3.65)***	(3.59)***	(5.88)***	(6.6)***
2 weeks	0.3634	0.3275	0.2336	0.1925	0.153	0.2021	0.1771	0.1369	0.1388	0.1468
	(2.43)**	(3.3)***	(2.96)***	(2.79)***	(2.71)***	(3.92)***	(4.02)***	(4.77)***	(6.89)***	(8.3)***
3 weeks	0.2512	0.1986	0.1193	0.0848	0.0999	0.1398	0.1281	0.1334	0.1476	0.1562
	(1.66)*	(2)**	(–1.46)	(–1.16)	(–1.64)	(2.61)***	(2.86)***	(4.36)***	(6.89)***	(8.47)***
4 weeks	0.2655	0.1322	0.1101	0.0912	0.1346	0.1785	0.1218	0.1316	0.1426	0.1527
	(1.67)*	(1.22)	(1.24)	(1.20)	(2.07)**	(3.12)***	(2.59)***	(4.28)***	(6.56)***	(8.03)***
6 weeks	0.1517	0.113	0.0696	0.0502	0.1142	0.1285	0.0998	0.1267	0.1617	0.183
	(0.93)	(1.05)	(0.77)	(0.62)	(1.69)*	(2.18)**	(2.08)**	(3.94)***	(7.47)***	(9.46)***
8 weeks	0.1935	0.1179	0.0856	0.1142	0.1178	0.1348	0.1268	0.1163	0.1673	0.1921
	(1.17)	(1.05)	(0.93)	(1.44)	(1.73)*	(2.27)**	(2.57)**	(3.54)***	(7.45)***	(9.71)***
12 weeks	0.3153	0.1351	0.0904	0.0833	0.1057	0.1185	0.1134	0.1151	0.1854	0.1789
	(1.86)*	(1.17)	(0.94)	(1.01)	(1.53)	(1.95)*	(2.24)**	(3.34)***	(8.15)***	(9.09)***
24 weeks	0.1468	0.1537	0.1399	0.1391	0.1459	0.1598	0.1666	0.2748	0.2927	0.2465
	(0.85)	(1.23)	(1.37)	(1.54)	(1.88)*	(2.3)**	(2.84)***	(7.5)***	(11.9)***	(12.05)***
36 weeks	0.2143	0.2636	0.2463	0.2775	0.2965	0.3106	0.3286	0.3582	0.3099	0.2706
	(1.25)	(2.1)**	(2.34)**	(2.97)***	(3.66)***	(4.4)***	(5.72)***	(9.85)***	(13.26)***	(14.96)***
48 weeks	0.2993	0.2449	0.2413	0.2733	0.2917	0.2905	0.3027	0.28	0.2696	0.2433
	(1.86)*	(2.05)**	(2.31)**	(2.87)***	(3.6)***	(4.14)***	(5.41)***	(8.08)***	(10.86)***	(12.46)***

* Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

models, we also applied correlations on these two models. The uncorrelated models, with assumed normally distributed residuals, are simulated Monte Carlo method models designed to generate critical values. The 1 percent and 5 percent critical values are, respectively, 5.01 and 3.27. Under the constrained-mean model, out of the 100 momentum strategies, as shown in Table 1, there are seventeen with significant profits given all market states. In an up market, the number of significant strategies increases to fifty-eight, while in a down market there are only eleven with significant profits. For strategies with matching forming and holding periods, significant profits fall on those with both forming and holding periods longer than twenty-four weeks. Only long-term momentum strategies can win persistent profits in a constrained-mean model. For the unconstrained-mean model, the critical value is 181.46 at 1 percent and 157.77 at 5 percent. Profitable strategies appear only in an up market. In Table 2, almost all strategies with matching, long- or short-term forming and holding periods are significantly profitable in the sense of statistical arbitrage.

Correlated models are assumed to have autoregressive residuals, so a bootstrapping method is used to draw residuals for respective momentum strategies. Critical values are identified with one thousand repetitive draws, as described in the previous section. Each strategy, therefore, has its own critical values as a result of the nature of drawing. In general, standard deviations are larger and t-statistics tend to be smaller. Under a correlated constrained-mean model, there are twelve strategies with significant statistical arbitrage profits in all market states. In an up market, there are fifty-five significantly profitable strategies, while the number decreases to only nine in a down market. In such a market, only long-term strategies make profits, regardless of market states. Under a correlated unconstrained-mean model, profitable strategies (numbering fifty-seven) appear only in an up market. These results, from inferences based on statistical arbitrage, are consistent in general with those in Table 1, based on traditional t-tests. However, there are two basic differences. The first one is that the pattern of profitability from statistical arbitrage examination is more consistent and general, leaning toward long-term strategies, than the pattern exhibited by the raw momentum returns. The other difference is that statistical arbitrage inferences offer much stronger statistical power, as they are independent of potential distribution and pricing assumptions. The comparison between constrained and unconstrained trading profit means indicates that loosening the constraint on the profit path allows us to further conclude that momentum strategies are profitable only in an up market, which is more conclusive than the traditional t-test can offer. Although traditional models support the ability of short-term momentum strategies to generate significantly positive profits even in a down market, especially in the emerging markets, statistical arbitrage models suggest that those short-term momentum strategies may not have been that great if risks are properly taken into account.

Disposition and Overconfidence Effects

To explore the asymmetric pattern of profits from a momentum strategy, we further examine the effects of disposition and overconfidence under different market states. The examination is done from the dimensions of investor type, market-to-book ratio, sales growth, liquidity, and market capitalization. As the disposition effect defined in Equation (3) and the overconfidence effect defined in Equation (4) do not necessarily

Table 2. Tests on disposition and overconfidence effects on momentum strategies

Entire sample	1 week	2 weeks	3 weeks	4 weeks	6 weeks
Disposition effect:	0.097	0.1504	0.1854	0.1985	0.2144
all market states	(19.24)***	(23.72)***	(29.38)***	(28.65)***	(26.81)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Disposition effect:	0.1309	0.194	0.2349	0.2596	0.2893
up market	(24.01)***	(29.I5)***	(34.75)***	(37.16)***	(40.24)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Disposition effect:	0.051	–0.033	–0.018	–0.034	–0.055
down market	(–6.47)***	(–3.37)***	(–1.75)*	(–3.12)***	(–4.49)***
	[< 0.0001]	[0.454]	[0.3239]	[0.8076]	[0.1416]
Overconfidence effect:	0.153	0.2104	0.2428	0.2562	0.2671
all market states	(27.32)***	(31.4)***	(36.48)***	(34.77)***	(31.84)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Overconfidence effect:	0.1853	0.2475	0.2851	0.3108	0.3349
up market	(31.28)***	(35.42)***	(38.97)***	(42.62)***	(44.58)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Overconfidence effect:	0.0003	0.0269	0.0396	0.0183	–0.006
down market	(–0.04)	(2.71)***	(3.84)***	–1.61	(–0.46)
	[0.0117]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]

(continues)

Table 2. Continued

Entire sample	8 weeks	12 weeks	24 weeks	36 weeks	48 weeks
Disposition effect:	0.2378	0.2468	0.2326	0.2221	0.2343
all market states	(30.5)***	(26.47)***	(21.2)***	(17.07)***	(15.92)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Disposition effect:	0.3094	0.3179	0.2967	0.3297	0.3514
up market	(38.79)***	(34.57)***	(27.71)***	(25.3)***	(23.94)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Disposition effect:	–0.067	–0.055	–0.035	–0.207	–0.273
down market	(–5.22)***	(–3.97)***	(–2.24)**	(–11.4)***	(–14.17)***
	[0.0033]	[0.0318]	[0.1907]	[< 0.0001]	[< 0.0001]
Overconfidence effect:	0.2917	0.2925	0.2656	0.2535	0.2631
all market states	(36.34)***	(30.24)***	(24.07)***	(19.54)***	(17.71)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Overconfidence effect:	0.3548	0.363	0.331	0.3526	0.3716
up market	(42.79)***	(39.67)***	(32.11)***	(27.33)***	(25.47)***
	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]	[< 0.0001]
Overconfidence effect:	–0.02	–0.021	–0.022	–0.187	–0.246
down market	(–1.49)	(–1.43)	(–1.35)	(–10.1)***	(–12.18)***
	[0.4593]	[0.6775]	[0.5669]	[< 0.0001]	[< 0.0001]

Notes: T-values are in parentheses. Values in brackets are p-values of Wilcoxon sign tests. * Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

follow a normal distribution, a Wilcoxon sign test is also conducted to determine if the median of either effect is different from zero.

Table 2 shows that, regardless of market states, both effects are significantly positive for all of the ten holding period strategies. Both measures increase roughly with the length of the holding period, with the strongest effects taking place at the eight- and twelve-week holding periods. Looking at the measures in an up market, both effects are further magnified. But the strongest effects appear instead in the longest holding period: forty-eight weeks. When both effects are significantly positive, the overconfidence effect is greater than the disposition effect uniformly across all holding periods. The returns momentum strategy found previously is supported by the two effects. When the market is down, the disposition effect tends to be significantly negative, suggesting investors sell more losing stocks than winning ones. The overconfidence effect in a down market is significantly negative only in the longer holding periods, meaning investors buy losing stocks and sell winning stocks there. The disposition effect is stronger than the overconfidence one, indicating that investors tend not to sell winning stocks. The absence of the momentum effect found previously is consistent with this phenomenon.

Breaking samples into individual and institutional investors allows us to distinguish how investor preference affects the disposition and overconfidence effects. When the market is up, individuals dispose of winning stocks earlier than the institutional investors. But the overconfidence behavior of institutional investors is uniformly stronger than individuals across all holding periods. So the significant momentum returns in Taiwan discussed in the earlier part of this section can be considered as driven mainly by the follow-on trading pattern of institutional investors, which dominates the moderate disposition effect. When the market is down, individuals exhibit a certain degree of momentum drive in the short to medium holding periods, while institutional investors practice a contrarian trading behavior all the time. In other words, the significant up-market momentum phenomenon is a result of the similar behavior of the two major investor groups, while the absence of down-market momentum is due to the difference between their trading patterns.

Comparing stocks with market-to-book ratio we find that investors as a whole chase stocks in a bull market more than they of dispose them, especially those with higher market-to-book (M/B) ratios. But in a bear market, losing stocks that have high a M/B ratio are sold only in the short term, but in the long term only stocks having low M/B ratios are the subject of stop-loss moves. High M/B stocks suffering losses are almost never targets of follow-on buying in a bear market. However, low M/B stocks are the targets of contrarian trading patterns during longer holding periods.

Robustness Discussions

The first robustness check is on firm size. Based on ranked firm size, from high to low, one year prior to forming periods of respective strategies, we keep only firms ranked in the top 50 percent. Portfolio returns on momentum strategies applied only on stocks of larger firms are shown in Table 3. Results of regressions of momentum returns on market returns for strategies with different portfolio forming- and holding-period combinations are given in Table 4 and show that thirty-four out of 100 strategies exhibit significantly positive returns and six strategies generate negative returns. In an up market, forty strategies produce positive returns, but none have significantly negative returns. In a

Table 3. Returns on momentum strategies of larger firms: all market states

	Portfolio holding periods									
	1 week	2 weeks	3 weeks	4 weeks	6 weeks	8 weeks	12 weeks	24 weeks	36 weeks	48 weeks
1 week	0.4213	0.3844	0.1903	0.0546	–0.04	0.0006	0.005	0.0107	0.0271	0.0364
	(2.4)**	(3.32)***	(1.99)**	(0.65)	(–0.59)	(0.01)	(0.10)	(0.33)	(1.13)	(1.74)*
2 weeks	0.5772	0.4184	0.2122	0.0591	–0.042	0.02	0.0215	0.037	0.0466	0.0616
	(2.97)***	(3.37)***	(2.11)**	(0.69)	(–0.61)	(0.33)	(0.43)	(1.08)	(1.96)**	(2.9)***
3 weeks	0.3023	0.1333	–0.034	–0.132	–0.11	–0.021	–0.032	0.0234	0.0419	0.0638
	(1.51)	(1.06)	(–0.34)	(–1.51)	(–1.5)	(–0.33)	(–0.61)	(0.65)	(1.65)	(2.78)***
4 weeks	0.1692	–0.03	–0.149	–0.227	–0.146	–0.071	–0.084	0.0027	0.0292	0.0576
	(0.86)	(–0.23)	(–1.4)	(–2.47)**	(–1.89)*	(–1.11)	(–1.63)	(0.07)	(1.17)	(2.48)**
6 weeks	–0.028	–0.117	–0.182	–0.189	–0.1	–0.071	–0.087	0.0079	0.0476	0.078
	(–0.13)	(–0.87)	(–1.67)	(–1.99)**	(–1.3)	(–1.11)	(–1.68)*	(0.21)	(1.83)*	(3.21)***
8 weeks	–0.069	–0.102	–0.146	–0.157	–0.136	–0.096	–0.095	0.0046	0.0751	0.0925
	(–0.33)	(–0.73)	(–1.3)	(–1.63)	(–1.72)*	(–1.44)	(–1.75)*	(0.12)	(2.8)***	(3.7)***
12 weeks	0.0487	–0.093	–0.175	–0.186	–0.169	–0.129	–0.091	0.0293	0.117	0.0963
	(0.24)	(–0.69)	(–1.58)	(–1.95)*	(–2.18)**	(–1.91)*	(–1.58)	(0.71)	(4.03)***	(3.68)***
24 weeks	–0.039	–0.014	–0.057	–0.068	–0.032	0.0099	0.0552	0.2033	0.2312	0.1339
	(–0.18)	(–0.09)	(–0.45)	(–0.59)	(–0.34)	(0.12)	(0.80)	(4.69)***	(7.17)***	(4.92)***
36 weeks	0.0738	0.0235	0.0113	0.02	0.0608	0.1021	0.189	0.2615	0.2054	0.1417
	(0.35)	(0.15)	(0.09)	(0.17)	(0.64)	(1.27)	(2.99)***	(6.23)***	(6.82)***	(5.96)***
48 weeks	0.2532	0.255	0.2346	0.2302	0.2462	0.2549	0.2598	0.2411	0.2005	0.1382
	(1.24)	(1.70)	(1.78)*	(1.94)*	(2.51)**	(3.1)***	(4.01)***	(5.43)***	(5.93)***	(5.02)***

* Significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Table 4. Regression of momentum returns on market returns

Strategies	Intercept	Market return	Market return²
1_1	0.2498712	0.262	0.1231881
	(1.79)*	(0.29)	(0.50)
1_4	0.2413212	0.714	–0.3460990
	(3.31)***	(1.71)*	(–1.86)*
1_12	0.1486686	0.139	–0.0872980
	(3.27)***	(0.52)	(–0.36)
1_24	0.107822	0.017	–0.0037053
	(3.75)***	(0.06)	(–0.01)
1_48	0.1133613	0.022	–0.0083140
	(5.88)***	(0.18)	(–0.3)
4_1	0.263267	2.234	–0.7401640
	(1.34)	(3.4)***	(–3.39)***
4_4	0.1269084	1.391	–1.9551600
	(–1.39)	(2.13)**	(–2.55)**
4_12	–0.0670368	0.61	–0.7535500
	(–1.33)	(1.81)*	(–1.89)*
4_24	0.489883	0.42	–0.1875300
	(1.36)	(1.54)	(–0.4)
4_48	0.0615068	0.018	–0.0455228
	(2.5)**	(0.18)	(–0.19)
12_1	0.0068538	2.722	–0.7795330
	(–0.03)	(1.32)	(–1.27)
12_4	–0.191473	1.659	–1.2292200
	(–2.06)**	(2.37)**	(–2.33)**
12_12	–0.0632049	0.045	–0.9705130
	(–1.12)	(0.17)	(–2.4)**
12_24	0.0874891	0.742	–0.2707670
	(2.06)*	(2.98)***	(–2.42)**
12_48	0.0953588	0.029	–0.3643893
	(3.27)***	(0.24)	(–0.32)
24_1	–0.0748871	2.374	–0.7030960
	(–0.36)	(1.01)	(–1)
24_4	0.037323	1.857	–0.6061520
	(–0.35)	(2.45)**	(–2.51)**
24_12	0.1149979	1.168	–0.4160660
	(1.74)*	(4.16)***	(–4.27)***
24_24	0.2598451	0.692	–0.2626140
	(5.78)***	(3)***	(–3.72)***
24_48	0.1422263	0.048	–0.0213390
	(4.72)***	(0.77)	(–1.05)
48_1	0.3054744	2.853	–0.9330760
	(1.57)	(1.42)	(–1.54)
48_4	0.2736304	2.835	–0.5682803
	(2.46)**	(4.2)***	(–4.22)***
48_12	0.2707832	1.968	–0.7000060
	(4.11)***	(7.87)***	(–7.6)***
48_24	0.2333171	1.162	–0.2320725
	(4.84)***	(8.93)***	(–8.66)***
48_48	0.1382632	0.102	–0.0442220
	(4.49)***	(0.99)	(–1.03)

Note: T-statistics are in parentheses.

down market, only seven strategies render positive returns, but there are thirty-two with significantly negative returns. Compared with the results for the whole sample discussed in the previous section, momentum strategies on stocks of larger firms produce fewer cases of positive returns and more cases of negative returns. When the market is up, fewer strategies generate negative returns, while more negative returns appear in a down market. The comparison suggests part of the momentum effect is caused by trading stocks of smaller firms, which is excluded in this robustness check. This indicates that a momentum phenomenon exists in all stocks, and size is not a factor.

The definition of market states may play a role in causing the momentum effect. The strongest momentum effects appear in the medium range, rather than in the state in which market return is the highest. The state with the worst market return does show more negative strategies. However, this verification suggests that the original halving classification is appropriate, as it segregates the situation in which more strategies with momentum returns cluster. To further determine how market states affect momentum returns, we conduct a regression of returns on the level market returns and the squared market returns. The results, shown in Table 4, suggest that the level market returns affects momentum returns positively, but the squared market returns have a negative influence on momentum returns. This nonlinear relationship between market and momentum returns reflect that a finer division of market states does not help much in analyzing momentum returns or how they are driven by overconfidence effects.

Conclusion

This study employs the concept of statistical arbitrage to analyze the momentum phenomenon in the Taiwanese market. We extend the analysis with statistical arbitrage to situations under different market states, which allows us to relate the momentum effects to other behavioral facts, namely the disposition effect and the overconfidence effect. The method of statistical arbitrage frees us from getting benchmark returns from an equilibrium model susceptible to the joint hypothesis criticism. The statistical arbitrage analysis, carried out through a long-horizon trading strategy, identifies momentum effect and helps us perform subsequent examinations and explorations.

The approach of statistical arbitrage reassures our preliminary finding with raw portfolio returns. The distinction between the constrained and the unconstrained profit path, as well as the inclusion of autocorrelation, causes the original results on raw portfolio returns to change. The spirit of the main findings, however, remains. The momentum strategies are seen to prevail especially in an up market but behave inconclusively in a down market. The introduction of the disposition effect and the overconfidence effect helps greatly in identifying the overconfidence effect as a major driving factor of the momentum effect. Coupled with further categorizations of investor type, market-to-book ratio, sales growth, liquidity, and market cap, the analysis of the disposition and overconfidence effects tells how the two factors affect momentum returns in more detail and with greater clarity. Our findings are also robust to firm size, overlapping executions, alternative market-state definitions, and market friction.

The study of momentum effect in this study benefits from the understanding of trading behavior especially in the emerging markets. Our adoption of statistical arbitrage is also more desirable in markets where high volatilities strongly twist the distribution of equilibrium returns. There are more behavioral factors that can be extended in studying the momentum phenomenon. This study serves as a fruitful step in that continuum.

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