Long-Term Momentum Hypothesis: New Contrarian Strategy*

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ABSTRACT

This paper proposes a new hypothesis that price momentum becomes stronger as the history of a trend in stock price is longer. It, referred to the long-term momentum hypothesis, provides two key predictions. First, the contrarian strategy, suggested by the previous studies, will not obtain profits *in the short run*. On the other hand, Barberis et al. (1988) predicts that it will earn profits even in the short run. Second, a new contrarian strategy, designed for exploiting long-term momentum, will be *short-term profitable*. Empirical results established by this study are consistent with the long-term momentum hypothesis. However, other hypotheses fail to explain them.

Financial literature documents two stylized facts such as long-term reversal and short-term momentum in stock prices. Evidence on these two anomalies is strong, but what causes them is still controversial. On the side of market efficiency, behavioral finance theories successfully explain those anomalies by using established psychological behaviors of investors. However, some scholars cast doubt on the validity of their theories. For example, Fama (1998) point out that while behavioral models do well in explaining anomalies that they are designed to explain, they fail to explain other anomalies. He argues that as a rule of scientific endeavor, the effectiveness of a model should be evaluated on the basis of a rejectable prediction that has not yet been tested. This paper attempts to challenge Fama's argument by providing a new behavioral hypothesis and performing new rejectable tests that have not been tested.

This paper proposes a new hypothesis that price momentum becomes stronger as the history of a trend in stock price is longer. This hypothesis, referred to the long-term momentum hypothesis, provides a new prediction of short-term profitability on contrarian strategies, while it also successfully explains the long-term reversal and short-term momentum.

DeLong et al. (1990) and Daniel et al. (1998) explain two stylized facts by using price momentum. They argue that overreaction has two phases. In the initial overreaction phase, overreaction continues, leading to short-term momentum. In the following correction phase, the initial overreaction is gradually reversed in the long run, causing long-term reversal in stock price. Such an overreaction pattern successfully accounts for short-term momentum as well as long-term reversal. Thus, if their arguments are right, price momentum is more likely to occur in the short run rather than in the long run.

Their arguments, however, do not seem to be consistent with the experimental evidence of Andressen and Kraus (1988). They find that when the stock price exhibits a trend, subjects tend to chase the trend; they begin to buy more when prices rise and sell when prices fell. Such trend chasing appears to be a virtually universal phenomenon among the subjects in their experiment. It is noteworthy that this momentum trading appears to occur only in response to significant changes in the price level over a substantial number of observations, not in response to the most recent price changes alone. This result suggests that momentum trading is more likely to occur in the long run than in the short run, which is

opposite of interpretation by DeLong et al. (1990) and Daniel et al. (1998). In fact, financial literature implicitly limits the possibility of continuing overreaction to a short-term period, probably for the lack of evidence on long-term momentum.

This paper develops a simple model that allows the activities of momentum trading to increase with the length of a period in which stock price consistently shows a trend. In this model, price momentum becomes stronger as the length of the trend in past returns is longer. Thus, it predicts that the original contrarian strategy, used by previous studies, will obtain negative returns in the short run. Such a prediction is the opposite of the common belief implied by the existing behavioral finance. For example, Barberis et al. (1998)' model predicts that it is profitable even in the short run as well as in the long run. Our simulation results confirm their predictions. This paper also suggests a new contrarian strategy. If our model holds, the new contrarian strategy, referred to the trend-bucking contrarian strategy, will be short-term profitable.

In general, our empirical results are consistent with the predictions of our model. After controlling risks, the trend-bucking contrarian strategy is short-term profitable, while the original contrarian strategy does not yield any return in the short run. Further tests show that other hypotheses for contrarian profits fail to explain our main results.

Our results appear to be related to short-term momentum in stock prices. Thus, one may argue that our results are simply due to the existing short-term momentum phenomenon. However, they do not simply rely on the short-term momentum in stock prices. Subperiod analysis of this paper shows that the trend-buckling contrarian strategy earns higher returns than any other in the first period of 1931 through 1947 when short-term momentum does not appear.

Our model and the model of Barberis et al. (1988) are discussed and their simulations are implemented in Section I. In Section II, the empirical designs and our main tests are discussed. In Section III, we describe the data used in the analysis, present the basic empirical results of the tests, and determine which of the behavioral models better explains the observed short-term profits on each of the three contrarian strategies including the original contrarian strategies. Section IV examines the possibility that

the results could be explained in terms of various risk-based hypotheses**.** This analysis indicates that the results cannot be explained by any of the risk-based hypotheses. In Section V, we address the issue of robustness by examining contrarian profits in four subperiods. Only one of the tree contrarian strategies, the trend-buckling strategy, is profitable in all four subperiods. Section VI examines the seasonality of the profits of the contrarian strategies. Section VII provides implications of the analyses.

I. Long-Term Momentum Hypothesis versus BSV Model

This paper compares our model with the model of Barberis et al. (1988; henceforth BSV) and simulates how their predictions of the short-term profitability are different. Except the BSV model, other behavioral models do not contain any specific predictions on the short-term profitability on contrarian strategies. In Daniel et al. (1998)'s model, a single piece of initial private information drives short-term momentum and long-term reversal. Since their model can not specify how long overreaction continues, it is impossible to predict when it ends and get corrected. Thus, we can only predict the long-term profitability of a contrarian strategy, of longing the long-term loser portfolio and shorting the long-term winner portfolio. This is also true for Hong and Stein (1999) and DeLong et al. (1990). However, the framework of the BSV model allows for prediction of its short-term profitability. By this reason, it is compared with our model.

A. Long-term Momentum Hypothesis

This paper develops a simple model that allows the activities of momentum trading to increase with the length of a period in which stock price consistently shows a trend. It considers multi-periods and two assets, cash and stock. Cash is in perfectly elastic supply and pays no net return. Stock is in zero net supply. It includes two types of investors: momentum traders and passive rational investors. Momentum traders use simple strategies. Their stock demand at time t is a simple function of just price change from *t*-2 to *t*-1. They do not condition on any public information except the price change. At every time *t*, a new

generation of momentum traders enters the market and transacts against passive rational investors. Every trader in this generation holds position for j periods. The demand DM_t of all generations of momentum traders at time t is described as follow:

$$DM_t = \sum_{k=1}^{j} m(t-k+1) \times (P_{t-k} - P_{t-k-1}) \qquad (1)$$

where P_t is the stock price at time t. $m(t)$ is the momentum trading coefficient at time t, depending on the previous price changes as follows:

If sign ($P_{t-1} - P_{t-2}$) = sign($P_{t-2} - P_{t-3}$), then $m(t) = (1+n)\, m(t-1)$

Otherwise, $m(t) = (1-n)\, m(t-1)$ (2)

where $0 < n < 1$ and n is the adjustment of the momentum coefficient. Equation (2) indicates that the momentum coefficient increases as price change exhibits a trend, consistent with experimental results suggested by Andressen and Kraus (1988). Thus, the demand of momentum traders gradually increases as the trend of price change lasts until j periods.

DM_t in equation (1) must be absorbed by passive rational investors so that the excess demand in the market may be cleared. Passive rational investors are rational in that they fairly forecast stock price based on all available information about the stream of the firm's earnings. However, they are boundedly rational because they do not learn from the order flow of momentum traders. They are passive because they always treat the order flow of momentum traders as an uninformative supply shock. At every time t, passive rational investors choose their demand DR_t for the stock by maximizing mean-variance utility function with risk aversion coefficient γ. DR_t is given by

$$DR_t = \frac{(\theta - P_t)}{2\gamma\sigma_{\vartheta}^2} \quad , \qquad (3)$$

where θ is the fair value that we discuss below and σ_{θ}^2 is the variance of θ.[1]

The assumptions about earnings' distribution here are exactly same to those of the BSV model. These same assumptions enable us to simulate a single data set of earnings commonly used to test both

the BSV model and our model. Earnings for a stock are distributed as $N_{t+1} = N_t + y_{t+1}$. y_{t+1} takes one of two values, +y or -y, following a random walk. If the current earnings are assumed to be paid out to shareholders, the fair value of the stock price at time t is equal to θ_t = E_t $(N_{t+1}/(1+\delta) + N_{t+2}/(1+\delta)^2 + ---) = N_t/\delta$ at the time t where δ is a discount factor.

The market clearing condition with equation (1) and (3) determines the current stock price P_t as follows:

$$P_t = \theta + \sum_{k=1}^{j} g(t-k+1) \times (P_{t-k} - P_{t-k-1}) \qquad (4)$$

where $g(t-k+1) = 2\gamma\sigma_\theta\, m(t-k+1)$.

If stock price tends to increase over periods from t-1 to t-j, the demand of momentum traders will be positive. The market clearing condition makes P_t rise above the fair value so that the demand of passive rational investors may be negative. Likewise, if stock price tends to decrease from t-1 to t-j, P_t need drop below the fair value. The longer the stock price in history shows a trend, the stronger the activities of momentum trading become. Thus, deviation of the current price from the fair value will increase with the length of periods exhibiting a trend. We test this implication using simulated data sets of earnings.

We fix parameter values, setting an initial earnings, earnings' shock at every time t and the discount factor to N_1=100, y_t = ±10 and δ = 0.12. g(3) is set to 1/5.[2] g(1) and g(2) are equal to zero, because momentum trading does not exist until P_1 and P_2 are determined by passive rational investors alone. We fix the adjustment of the momentum coefficient to n = 1/10.

We simulate 50,000 independent earnings sequences, each one starting with N_1 =100. Each sequence represents a different firm and contains 10 earnings realization. What we are interested in is to calculate returns following particular realizations of earnings. Long-term winner (loser) portfolio is defined as consisting of all stocks with positive (negative) earnings changes in each of 6 periods.

Figure 1 shows the price path of long-term winner portfolio, formed in time -1. After particular realization of earnings changes in periods from time -6 through time -1, they follow the random walk distribution. Thus, the fair value of the long-term loser portfolio tends to be flat after time -1. its actual price is determined by interaction of both rational investors and momentum traders. The positive demand of momentum traders in time 1 becomes larger as its price continues to increase by five sequent positive earnings changes from time -6 to -1. Thus, an increase in the demand raises the price of long-term winner portfolio in time 1. However, the excess demand by momentum traders gradually declines in the long run by two reasons. First, the positive demand of old momentum traders gradually fades as they exit the market. Second, more importantly, new generations of momentum traders entering the market gradually weaken momentum trading because price changes of long-term winner portfolio, triggering momentum trading, become smoother after time -1. Gradual decline in momentum trading puts more weight to pricing power of passive rational investors over times, explaining why the price of long-term winner portfolio approaches its fair value in the long run. Thus, it claims that it obtains positive returns in the long run, leading to long-term reversal.

Panel A of Table I shows the simulation results. A contrarian strategy, of longing a long-term loser portfolio and shorting a long-term winner portfolio, initially obtains a return of -7.08%. We refer it to the traditional contrarian strategy. On the contrary, it yields positive returns in the long run because an initial negative return is outweighed by substantial positive returns from time 2 through time 4. Further, Panel B of Table I documents that the momentum strategy, of longing a short-term winner portfolio and shorting a short-term loser portfolio formed in time -1, earns 4.58 % return in time 1. The short-term winner (negative) portfolio consists of all firms which earnings changes are positive (negative) in time -1. Thus, our simulation results also documents short-term momentum.

Our model suggests that the price path of the long-term winner (loser) portfolio has two phases in the test period such as an overreaction phase and a correction phase. In an overreaction phase, price overreaction continues and thereafter gets corrected in a correction phase. The traditional contrarian strategy obtains profits in the correction phase. Moreover, any contrarian strategy will be profitable in the

short run, if it avoids the overreaction phase and capture the correction phase. For example, the traditional contrarian strategy will be short-term profitable if it begins being used not in time 1 but in time 2. However, it is difficult to predict when the overreaction phase ends because we do not know how long it will continue. For example, when the adjustment of the momentum coefficient n is changed to 1/5 from 1/10 in our model, the simulation results indicate that the correction phase begins in time 4. In reality, the overreaction phase may vary across stocks or over times because of differences in creditability of information, the amounts and the contents of information, the extent of analyst's attention and other conditions of the market. This is why the traditional contrarian strategy should not be used to obtain short-term profits, if the long-term momentum hypothesis holds.

We design a new contrarian strategy that is able to identify not only overvalued (undervalued) stocks but also their correction phase. It longs the portfolio consisting of all stocks with four consecutive negative signals of earnings changes followed by a positive signal. This portfolio is denoted as 'LW' portfolio. Four consecutive negative signals increase downward momentum trading that undervalues the portfolio up to time -2. However, the most recent positive signal increases the price of LW portfolio in time -1, bucking against the trend of downward momentum. Such a trend bucking belittles an effect of downward momentum on stock prices and strengthens pricing powers of passive rational investors. Thus, LW portfolio can yield positive returns immediately after time -1. Similarly, the portfolio, consisting of stocks with four positive signals followed by a negative signal, obtains negative returns immediately after time -1. Thus, the strategy, of longing LW portfolio and shorting WL portfolio, is able to earn short-term profits. It is denoted as the trend bucking contrarian strategy.

Panel C of Table I shows returns on the trend bucking contrarian strategy, using the previous simulated data. Its initial return is 9 % and smoothly rises up to time 4. Thus, its returns are positive not only in the short run but also in the long run. The big difference between the traditional contrarian strategy and the trend bucking contrarian strategy lies in their short-term profitability.

New arguments that our model suggests are referred to as of the long-term momentum hypothesis. The first long-term momentum hypothesis is that the traditional contrarian strategy loses money in the

short run immediately after formation period. The second hypothesis is that the trend-bucking contrarian strategy is profitable in the short run as well as in the long run.

B. BSV model

Barberis, Schleifer, and Vishny (1998; henceforth BSV) develop a model based on two established psychological biases: representativeness (Kahneman and Tversky 1982) and conservatism (Edward 1968). Representative bias is the tendency of people to view individual events as typical or representative of some specific class and to ignore the laws of probability in the process. Conservatism bias is the psychological bias of people to update slowly prices in the face of new evidence. BSV develop a model of security pricing that incorporates these biases.[3] The conservative bias causes *momentum* in stock prices, while the representative bias eventually results in *price reversals*, and hence contrarian profits.

As we mentioned in A of Section I, the signals of earnings change are assumed to follow a random walk. However, when investors receive a string of positive (negative) signals for the long-term winner (loser) portfolio, the representative bias tends to increase the likelihood of the trending regime, which suggests that upcoming signals will be also positive (negative). Thus, investors overvalue (undervalue) the long-term winner (loser) portfolio.

The fundamental difference in overreaction between the BSV model and our model lies in what investors extrapolate to forecast the prices of long-term winners or losers. Momentum traders in our model extrapolate price changes by using simply the past price changes. This is why a new signal does not affect the activities of momentum trading. In the BSV model, investors extrapolate price levels by predicting a stream of a firm's cash flows. A new signal affects stock prices because it leads them to update predicting a stream of cash flows.

The BSV model predicts that a new signal, on average, will begin correcting stock prices immediately after the formation period. When investors receive a series of positive signals, they increase the likelihood that a positive signal is more likely to arrive in the next period than a negative signal. Thus, they are not surprised at a positive signal following a series of positive signals. On the contrary, a

negative signal will surprise them because it is against their expectation. Thus, a new signal, on average, will decrease the price of the long-term winner portfolio. On the contrary, a new signal following a string of negative signals, on average, will increase the price of the long-term loser portfolio.

Using the same simulated data set about earnings changes, we test the short-term profitability of contrarian strategies in BSV model. Our parameter setting is basically same to that of the BSV model except that the regime switching parameters are set to λ_1 =0.1 and λ_2 = 0.1 and the formation requires 5 periods.[4] BSV set λ_2 = 0.3 so that underreaction is more dominant than overreaction. In such situation, the overreaction regime is easily changed to the underreaction regime, leading to a very short correction phase. In fact, the test period in BSV's simulation is only one period, while its formation periods are four periods. By changing λ_2 to 0.1 from 0.3, we consider the situation in which overreaction and underreaction are equally dominant. This change extends the periods of a correction phase.

Figure 2 shows that the price of the long-term winner portfolio declines immediately after the formation period. Its price path in the BSV model is obviously different from that in our model. The BSV model predicts that the long-term winner portfolio will obtain a negative return in time 1, while our model predicts the opposite.

Panel A of Table II documents that the traditional contrarian strategy earns 8.74% profit in time 1, confirming that the BSV model and the long-term momentum hypothesis have opposite predictions about the short-term profitability of the traditional strategy. However, both BSV's model and our model agree that it earns profits in the long run. Panel A shows that its returns are all positive in all test periods, although they gradually decline from time 1 to time 4.

The result of Panel A is consistent with the implicit common interpretation of the financial literature about the overreaction argument, which suggests that the contrarian strategy is profitable not only in the long run but also in the short run. For example, Fama and French (1996) test the three-factor model versus the overreaction argument by examining profits of a contrarian strategy. They use a month as a holding period to calculate its returns. Using such a short horizon reflects their implicit interpretation that

the contrarian strategy should be profitable even over a short horizon like a month if the overreaction argument accounts for long-term reversal in stock prices. Thus, the BSV model supports this interpretation but the long-term momentum hypothesis does not.

The Panel B of Table II documents that the momentum strategy earns a positive return of 3.19%, confirming that the BSV model explains short-term momentum.[5] The Panel C of Table II shows that the trend bucking contrarian strategy also earns a positive return of 1.26% in time 1 but a negative return of -4.47% in time 2. According to the BSV model, its positive return is due to overvaluation of the LW portfolio and undervaluation of the WL portfolio, while its reversal in time 2 is due to correction of them.[6] The BSV model, therefore, predicts the same short-term profitability of the trend-bucking contrarian strategy as the second long-term momentum hypothesis. However, it results from overreaction rather than correction of overreaction unlike the long-term momentum hypothesis.

II. Empirical Designs

A. Empirical Tests

This paper provides two main empirical tests to investigate the validity of our model versus the BSV model. The first test is to examine the short-term profitability of the traditional contrarian strategy. As we see in Chapter I, the first long-term momentum hypothesis predicts that it earns a positive return in the short run, while the BSV model predicts the opposite. Thus, such opposite predictions may provide a good test to examine the validity of two models.

However, it is not easy to accomplish this test because inaccurate measure of risk factors may make the result obscure. Both the time varying risk hypothesis (Ball and Kothari (1989)) and financial distressed premium hypothesis (Fama and French (1992,1993,1996)) argue that the expected return of the long-term loser portfolio is higher than that of the long-term winner portfolio. If we do not properly measure their risks, the result of the first test may be misleading. In order to implement the first test, we control the risk factors by using the methodologies of these two risk-based hypotheses.

The second test of this paper is to examine whether the trend bucking strategy earns a positive return in the short run and its return is reversed in the long run. The BSV model predicts its return reversal in the long run, while the long-term momentum hypothesis predicts that it is profitable in the long run.

Further, we implement additional tests to investigate whether other hypotheses may explain the results of these two tests. First, the measurement error hypothesis suggested by Conrad and Kaul (1993) argue that microstructure factors systematically upwardly bias measured raw returns, especially for low-priced stocks, which can overstate contrarian strategy profits. To reduce these biases, they suggest compounded returns, instead of cumulative returns. We use these two returns to examine how two different measures affect profits of two contrarian strategies.

Second, most importantly, we test whether the data snooping hypothesis may explain the results of the two tests. It is noteworthy that the short-term momentum phenomenon may drive the results of two tests in favor of the long-term momentum hypothesis. For example, suppose that momentum phenomenon is simply due to the data snooping. If then, the traditional contrarian strategy may obtain short-term negative returns because of short-term momentum. Furthermore, the trend bucking contrarian strategy may be short-term profitable because of the same reason. To exclude this possibility, we investigate sub-periods when short-term phenomenon is not found at all.

Additionally, we examine the seasonality of returns on the contrarian strategies to see whether the seasonal pattern like January effect may explain their returns. The previous studies document that most of CAPM anomalies such as long-term reversal, size and the book to market effect concentrate in January. Analysis on the seasonality may provide a clue of identifying the relation between our results and the CAPM anomalies.

B. Two Testable Contrarian Strategies

Two contrarian strategies are required for testing our empirical tests. In order to form these strategies, our simulation sorts stocks by using a series of earnings changes. In both BSV model and our model, earnings

changes stand for all information affecting stock prices. In reality, however, news of earnings changes is simply one of important signals that affect stock prices. Thus, stock prices themselves may be a good proxy for all valuable information. Further, the previous studies generally use past returns to form contrarian strategies. By these reasons, we use past returns to form two strategies.

For the trend bucking contrarian strategy, two stage-sorting periods are needed to form the LW and WL portfolios. In the first stage, stocks are sorted by a relative long-term past return matching four consecutive signals in our model. In the second stage, these stocks are resorted by a relative short-term past return that matches a signal bucking the past series of signals.

On the other hand, if the traditional contrarian strategy is formed by one stage sorting period, stocks are sorted by the long-term past returns matching the five consecutive signals in our model. In this case, we refer the traditional contrarian strategy to the original contrarian strategy because it is exactly same contrarian strategy used by previous studies such as DeBondt and Thaler (1985). One problem with the original contrarian strategy is that it is not mutually exclusive with the trend bucking contrarian strategy. For example, long-term winner stocks for the original contrarian strategy can be WL stocks for the trend bucking contrarian strategy. Since the long-term momentum hypothesis predicts opposite predictions about the short-term profitability of two strategies, they need be mutually exclusive. Therefore, it is desirable to use two stage-sorting methodology to form the traditional contrarian strategy. We refer it to as of the doubly extreme contrarian strategy. In this case, the long-term loser portfolio for the traditional contrarian strategy turns out to be the 'LL' portfolio for the doubly extreme contrarian strategy.

We provide empirical tests for two mutually exclusive contrarian strategies such as the trend-bucking contrarians strategy and the doubly-extreme contrarians strategy. In addition, the original contrarian strategy is tested to compare our results with those of other studies.

Ⅲ. The Basic Empirical Evidence

A. Sample and Methodology

The universe of stocks for the empirical analyses consists of all NYSE stocks listed on the Center for Research in Security Prices (CRSP) monthly tape from 1926 to 1996. From this universe, we exclude stocks that do not have at least 5 years of data prior to the portfolio formation date. NYSE stocks are chosen exclusively for two reasons. It is well known that returns on low priced stocks are very sensitive to microstructure-induced biases related to bid-ask spread, non-synchronous trading, and price discreteness. Since AMEX and NASDAQ stocks tend to be low priced, the exclusion of these stocks will mitigate the effects of such biases.[7] Second, many empirical studies on long-term reversal use the NYSE stocks (e.g. DeBondt and Thaler (1985, 1987), Chopra et al. (1992) and Fama and French (1996)). For the purposes of comparison, the NYSE stocks are appropriate.

The sorting procedure is as follows. At the end of every month *t-2*, stocks are ranked according to two consecutive compound returns: long-term compounded returns from *t-60* through *t-8* and short-term compounded returns from *t-7* through *t-2*.[8] Long-term compounded returns are denoted as (60-8), and short-term compounded returns as (7-2). One month is skipped between the portfolio formation date and the test starting date to reduce microstructure biases.

Stocks are sorted into deciles in ascending order on the basis of (60-8) returns and then again into quintiles based on (7-2) returns within each (60-8) portfolio decile. This two-stage sorting procedure produces 50 portfolios. The highest (lowest) decile portfolio is referred to the (60-8) winner (loser), while the highest (lowest) quintile portfolio is referred to the (7-2) winner (loser). The (60-8) winner plus the (7-2) loser is denoted as WL. Earlier studies have often used deciles for contrarian strategy portfolios. For comparison with their results, stocks are ranked to deciles on the basis of (60-8) past returns. The portfolios, formed at the end of the portfolio formation date *t-2*, are invested for 12 months from *t* through *t+11*.

Following Ball, Kothari, and Shanken (1995), firms delisted during the postranking period are included. When stocks are delisted on CRSP tape, their monthly returns are replaced with their postdelisting returns.[9] If these are not available on the CRSP monthly tape, average postdelisting returns

corresponding to their CRSP delisting codes are included as the monthly returns on delisted stocks.[10] For the remaining holding period, returns on delisted stocks are replaced with NYSE value-weighted returns.

The average postdelisting return for financial-distress-related delisted stocks is -21.7% for January 1931 through June 1963 and -25.9% for July 1963 through December 1996. Including the postdelisting returns mitigates upward survivorship biases, especially for losers, since they tend to be delisted for financial-distress reasons. Postdelisting returns on stocks delisted for other reasons are not significant. For example, the average postdelisting return on merger-related stocks is 2% for January 1931 through June 1963 and 2.8% for July 1963 through December 1996.

Since portfolios are formed every month and their holding period is 12 months, their returns overlap, which causes positive autocorrelation. Standard errors are calculated using Newey and West's (1987) methodology to adjust bias caused by their autocorrelations.

B. Compounded and Cumulative Returns on Contrarian Strategies

Blume and Stambaugh (1983) document that bid-ask spread or price discreteness causes an upward bias in the single-period return. Conrad and Kaul (1993) point out that this upward bias becomes more severe for low priced stocks when returns are cumulated. They suggest a compounded return to mitigate this upward bias.[11] This section compares a compounded return with a cumulative return to investigate whether this upward bias seriously affects a cumulative return or an average monthly return.

Panel A and B in Table III provide an annual compounded returns and an annual cumulative return for each of the 50 portfolios. They show that average annual returns decrease with the rank of (60-8), while they increase with the rank of (7-2). These results confirm the previous findings of long-term reversal and short-term momentum in stock prices. As shown in Panel A, the LW portfolio yields the highest annual compounded return of 27.53 among 50 portfolios, while the WL portfolio earns the lowest annual compounded return of 8.83%. Panel B shows that the annual cumulative returns on 50 portfolios produce similar results.

However, there is a large difference between the compounded return (19.89%) and the cumulative return (25.05%) for portfolio LL. This result is consistent with Conrad and Kaul's (1993) measurement error hypothesis that cumulating monthly returns causes serious upward bias, especially for low priced stocks such as long-term losers. However, this measurement bias does not appear to affect the average annual return on portfolio LW, which is 26.80% on a cumulative basis and 27.53% on a compounded basis. Other portfolios are similarly unaffected.

These findings suggest that the return metric significantly affects magnitudes of measured returns on extreme losers. Since cumulating returns appears to aggravate upward biases, compounded returns are more likely to be reliable than cumulative returns as a measure of contrarian strategy returns. Further, cumulative returns implicitly assume monthly portfolio rebalancing, which incurs substantial transaction costs for low priced stocks. For these reasons, compounded returns are more likely to approximate returns from actual investments.

Panel C of Table III provides the results of the three contrarian strategies. The original strategy is included to compare the results of the earlier studies with those of this study. The trend-bucking strategy has the highest return in terms of both the annual compounded return and the annual cumulative return. It produces an annual compounded return of 18.7% and an annual cumulative return of 17.71%. The original contrarian strategy (L-W) earns an annual compounded return of 7.2% and an annual cumulative return of 10.6%. The doubly-extreme contrarian strategy yields an annual compounded return of 0.73% and an annual cumulative return of 8.20%.

The trend-bucking strategy appears to yield much higher return than the other two contrarian strategies. This seems to be consistent with the long-term momentum hypothesis. However, the non-negative returns to both the original and the doubly-extreme contrarian strategy do not appear to be consistent with the long-term momentum hypothesis. However, risk adjustment is required to determine whether these results are consistent with either the BSV model or the the long-term momentum hypothesis. Risk factors will be considered in Section IV.

C. Contrarian Strategies and the Basic Characteristics of 50 Portfolios

Table IV reports the compounded returns on the trend-bucking and doubly-extreme contrarian strategies at various horizons. Given 59-month past returns, stocks are sorted on the basis of (59-*j*) and *j*-month past returns and held for *h* months. Table IV displays the results for *j* = 3, 6, 9, 12 and *h* = 3, 6, 9, 12 strategies.

Panel A shows that the highest monthly return is realized with the trend-bucking strategy at *j*=9 and *h*=6, which earns 1.97% per month. The *j*=3 and *h*=3 strategy earns 1.05% per month, which is the lowest. The return on the *j*=3 trend-bucking strategy increases with the holding period *h*, while that on the *j*=12 strategy decreases with *h*. Panel B displays that the returns on the doubly-extreme contrarian strategy are negligible and some are even negative. In general, the results of Table IV confirm those of Table III. The returns on the trend-bucking contrarian strategy appear strong at various horizons.

Table V reports the basic characteristics of the 50 portfolios. Panel A reports the time series average of the size of the firms in each portfolio (in million) at time *t-2*. Average firm size tends to increase with (60-8) rank, up to decile 8, and then decreases. Average firm size also increases with (7-2) rank up to quintile 4, and then decreases. These nonlinear relations between the firm size and the rank of past returns suggest that the size effect (Banz (1981) and Zarowin (1990)) does not explain the annual compounded returns on the 50 portfolios. For example, WL, which has the lowest annual return, does not include the largest firms. Similarly, LW, which has the highest annual return, does not include the smallest firms. In general, the annual returns on the 50 portfolios are not closely related to firm size.

Panel B shows the average share prices of the 50 portfolios. Generally, average share prices are positively related to both (60-8) rank and (7-2) rank. They are negatively related to annual returns across (60-8) ranks. This negative relation is consistent with the transaction cost hypothesis (Stoll and Whaley (1983)) and the possible effects of illiquidity (Ahmid and Mendelson (1986)). However, average share prices are positively related to annual average returns on portfolios across the (7-2) ranks, a result that is inconsistent with these hypotheses.

Panel B also reports that the average share price of portfolio LW ($16.11) is higher than that of the portfolio LL ($10.45). The high share price of LW may at least partially explain why the problem of

upward biases does not appear in the annual cumulative return on LW. Ball, Kothari, and Shanken (1995) question the implementability of the original contrarian strategy, which assumes that the position can be established at CRSP closing prices and thus ignores bid-ask spreads, illiquidity, and other transaction costs. However, compared with the original or the doubly-extreme contrarian portfolio, the trend-bucking portfolio does not comprise either extremely small or low-priced stocks. Thus, microstructure bias should not be a deep concern for the trend-bucking strategy.

Panel C reports the average (60-2) past compounded returns on the 50 portfolios. Like share prices, they are positively related to the (60-8) rank and the (7-2) rank. LL has the lowest (60-2) past compounded returns, and WW has the largest. In terms of (60-2) past returns, LL is the worst (60-2) long-term loser and WW is the best (60-2) long-term winner among the 50 portfolios. This relation confirms that the doubly-extreme contrarian strategy is very similar to the original contrarian strategy.

Panel D displays average (60-8) compounded returns for the 50 portfolios. Within each row from (60-8) decile 2 to decile 9, there is little variation in (60-8) compounded past returns across (7-2) portfolio quintiles. However, the (60-8) returns on (60-8) long-term losers and winners vary widely across (7-2) ranks. For example, among the (60-8) long-term winners, WL and WW have higher (60-8) past compounded returns than any other.

Panel E reports (7-2) past returns for the 50 portfolios. LL has the lowest (7-2) past returns among the 50 portfolios, and LW has the highest. (7-2) past returns are positively related to annual returns on portfolios across (7-2) portfolio quintiles, which constitutes the evidence of short-term momentum.

Table V confirms that portfolio LW tends to consist of value stocks in terms of size, share price, or (60-2) long-term past returns, while portfolio WL tends to consist of glamour stocks. Thus, it is reasonable to classify the strategy of buying LW and shorting WL as a contrarian strategy. However, the returns on the trend-bucking contrarian strategy do not appear to be fully accounted for by the firms characteristics reported in Table V.

Ⅳ. Risk Based Hypotheses

Contrarian strategies are designed to buy value stocks and short glamour stocks. Although the evidence indicates the trend-bucking strategy is not comprised of extreme-value stocks or glamour stocks, its position of longing LW and shorting WL may nevertheless be risky. In order to price their risks, this paper employs the postranking beta regression used by Ball, Kothari, and Shanken (1995) as well as the three-factor model of Fama and French (1993). These studies document that the abnormal return on the original contrarian strategy disappears after controlling for risk.

A. Postranking Beta and Jensen's Alpha

Ball, Kothari, and Shanken (1995) document that contrarian profits are largely due to measurement problems involved in extremely low priced stocks. It is well known that microstructure-related biases in measured returns are most pronounced at the calendar year-end when earlier studies (DeBondt and Thaler (1985, 1987) and Chopra et al. (1992)) typically form contrarian portfolios. Ball, Kothari, and Shanken (1995) show that a contrarian portfolio formed at June-end earns negative abnormal returns, in contrast with the December-end portfolio. We follow their methodology to examine whether it accounts for our basic results in Section III.

They claim that the contrarian portfolio's beta should vary systematically over time, depending on the realized market risk premium over the ranking period. The argument is that if the realized premium in the ranking period is positive, the loser portfolio tends to consist of low-beta stocks. Likewise, if the realized premium is negative, the loser portfolio tends to contain more high-beta stocks. The postranking beta is allowed to be a function of the market return over the ranking period, estimated by the following model:

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \delta_p [R_m(t-5, t-1) - \text{Avg}\, R_m] R_{mt} + \varepsilon_{pt} \qquad (1)$$

In equation (1), calendar year t indicates the test period after the portfolio formation date. R_{pt} is the annual buy-and-hold excess return on portfolio p, and R_{mt} is the equal-weighted annual excess return on

NYSE stocks in year *t*, obtained by subtracting the annual return on Treasury bills (Ibbotson Associates 1997). α_p is the abnormal return, β_p is the relative risk of portfolio *p*, and Avg R_m is the time series average of annual excess returns on R_{mt} for the entire period, while $R_m(t-5, t-1)$ is the average excess return on R_{mt} over year *t-5* through *t-1*. The deviation of a portfolio's beta in year *t* from its average beta is given by product of δ_p and the unexpected market excess return over the relevant ranking period.

If this model is true and the market index R_{mt} adequately proxies for the market portfolio, the efficient market hypothesis requires that the intercept (Jensen alpha) should be zero. Thus, the estimated alpha indicates an abnormal return, unexplained by the time series regression. Beta captures postranking risk, while delta captures changes in risk conditional on the realized market risk premium over the ranking period. Delta is expected to be negative for loser portfolios.

Table VI reports the estimated alphas, betas, and deltas for various contrarian portfolios, based on the postranking beta regressions. The portfolios are formed at the end of May each year. They are held from July through June of the next year so that there is no overlap. For the original contrarian portfolios, the estimated alpha of portfolio L is –1.25% (*t*= -0.33), while that of portfolio W is 2.10% (*t*=1.20). Thus, the original strategy is not profitable after controlling for risk, yielding –3.35% (*t*= -0.75). This result is similar to that obtained by Ball, Kothari, and Shanken (1995).[12]

In contrast, the estimated alpha of the doubly-extreme contrarian strategy (LL-WW) is –9.57% (*t*=-2.15). Therefore, the evidence contradicts the prediction of the BSV model. However, it is consistent with the prediction of the long-term momentum hypothesis that LL (WW) has the negative (positive) abnormal return in the short term immediately after portfolio formation. The results in Table VI indicate that the estimated alpha of the LL portfolio is –5% (*t*=-1.41) and of the WW portfolio is 4.57% (*t*=1.99). Although these estimated alphas are not statistically reliable, the abnormal return of the doubly-extreme strategy is reliably negative.

The trend-bucking contrarian strategy earns the annual abnormal return of 10.38% (t=2.30). The estimated alpha of LW is 4.66% (t=1.21), and of WL is -5.72% (t= -2.86). The signs of these estimated alphas are also consistent with the long-term momentum hypothesis, which predict the positive (negative) abnormal return on LW (WL) as a result of the price correction for undervalued (overvalued) stocks.

The systematic risk estimates behave as documented in the earlier studies.[13] The betas of loser portfolios (L, LL or LW) exceed those of winner portfolios (W, WW, WL), consistent with the time varying risk hypothesis (Ball and Kothari (1989)). However, it is difficult to interpret the signs of the estimated deltas. The positive deltas of loser portfolios such as LL or LW are not consistent with the prediction of the time varying risk hypothesis. They do not appear to be riskier when the premium realized over the ranking period is negative. However, the deltas of all three contrarian strategies are negative, and two of them are reliable.

In summary, the trend-bucking contrarian strategy has a highly positive abnormal return, even after controlling for risk by using the time series beta regression. However, both the doubly-extreme strategy and the original strategy yield negative risk-adjusted abnormal returns. These results are consistent with the long-term momentum hypothesis, but not with the BSV model.

B. Three-Factor Regression

Fama and French (1992) show that beta cannot account for anomalies in stock returns associated with size, book-to-market ratio, or earnings per share. They attribute this result to the failure of beta as a risk measure. Instead, they suggest a three-factor model that can capture most of the anomalies in stock returns:

$$R_{pt} - R_f = \alpha_p + \beta_p (R_{mt} - R_f) + s_p \, SMB_t + h_p \, HML_t + \varepsilon_{pt} \qquad (2)$$

In equation (2), R_{pt} is the average monthly return on the portfolio in month t, α_p measures the abnormal return, R_f is one- month Treasury bill rate observed at the beginning of the month t, R_{mt} is the value-weighted average return, and SMB_t is the monthly return on the mimicking portfolio for size in month t.

The mimicking portfolio is constructed by buying the small-firm portfolio and shorting the large-firm portfolio. HML_t is the monthly return on the mimicking portfolio for the book-to-market ratio. The mimicking portfolio is constructed by buying the high-book-to-market portfolio and shorting the low-book-to-market portfolio.[14]

For this analysis, portfolios are formed every month. The holding period is 12 months. The monthly returns are calculated only for surviving stocks, instead of replacing missing returns with the value-weighted NYSE return. The results of the three-factor regressions are displayed in Table VII.[15] Their test period is from July 1963 through December 1996.

Consistent with the results of the previous studies, loser portfolios such as LL, L, and LW tend to load highly on SMB and HML. In contrast, winner portfolios such as WW, W, and WL tend to load less on SMB and HML. For example, all winner portfolios have negative loadings on HML. Thus, if HML or SML captures a financial distress-premium as Fama and French (1993, 1996) argue, this result indicates that returns on LL, LW and L behave like those of small distressed firms. Thus, loading patterns of the three-factor premium are consistent with their financial distress-premium hypothesis.

However, the estimated alphas do not appear to be consistent with this hypothesis. Although the estimated alphas for LL and L are not significantly negative, those for LW and WW (WL) are reliably positive (negative). The trend-bucking contrarian strategy earns 12.72% per year (1.06% per month, t=5.46). In contrast, the doubly-extreme contrarian strategy yields -11.4% per year (-0.95% per month, t=-2.20). The signs of these estimated alphas are inconsistent with the BSV model but are consistent with the long-term momentum hypothesis.

The trend-bucking contrarian strategy consists of stocks which prices have recently reversed the trend, while the traditional contrarian strategy consists of stocks which prices have continued the trend. As far as the loser stocks are concerned, the latter tends to include more financially distressed stocks or stocks with higher debt/equity ratio. Thus, we can conjecture, based on risk-based hypotheses, that the

traditional strategy seems to be riskier than the trend bucking strategy. The results that we get here are consistent with this conjecture.

C. The Long-term Performance of Postranking Return over 36 Months

The failure of these two asset-pricing models does not necessarily indicate that asset pricing is irrational. Instead, their failure may simply indicate the shortcomings of these models. As an additional test, this subsection examines the long-term return behavior of contrarian portfolios, which can provide additional insight into the sources of profits or losses from contrarian strategies. According to the long-term momentum hypothesis, LL (WW) tends to consist of stocks that continue to be under- (over-) valued. However, this continuing overreaction is temporary. A series of new information about firm's value in the future will finally begin to correct the price errors over time. Thus, the negative abnormal return to the doubly-extreme contrarian strategy should be short-lived and reversed in the long-term as our simulation result shows.

Figure 3 displays the long-term time series of postranking compounded raw returns on each of the three contrarian portfolios tested in this paper. For the doubly-extreme contrarian strategy, the compounded raw return 'bottoms out' at –1.8% in month 9 and then gradually increases to 23.7% in month 36. This reversal is impressive, and is consistent with the long-term momentum hypothesis. However, the result is inconsistent with both the BSV model and the risk-based hypotheses.

Meanwhile, the trend-bucking contrarian portfolio fairly steadily accumulates positive returns through month 36. Moreover, it steadily outperforms the original contrarian portfolio throughout this period. According to the long-term momentum hypothesis, the LW portfolio consists of undervalued stocks whose prices are corrected in the postranking period, while the WL portfolio consists of overvalued stocks whose prices are also corrected in the postranking period. Thus, the persistence of the positive return from the trend-bucking contrarian portfolio is consistent with slow correction of price errors in both the LW and WL stocks. This persistence is not consistent with the prediction of the BSV model but with the long-term momentum hypothesis.

The different return behaviors of the doubly-extreme strategy and the trend-bucking strategy provide a possible explanation about the recent empirical findings of Lee and Swaminathan (1999). Their *early strategy*, of buying low volume short-term winners and shorting high volume short-term losers, continues to earn a positive return in four years after portfolio formation. In contrast, their *late strategy*, defined as buying high volume short-term winners and shorting low volume short-term losers, earns a short-term positive return but immediately begins losing in subsequent years. They argue that the existing behavioral models cannot account for these findings. However, their findings may indeed be consistent with the long-term momentum hypothesis.

According to their evidence, high volume stocks tend to be glamour stocks and low volume stocks tend to be value stocks. Thus, high (low) volume winners are similar to WW (LL). Their late strategy is comparable to the opposite of the doubly-extreme contrarian strategy. Likewise, their early strategy is comparable to the trend-bucking contrarian strategy. Therefore, the long-term momentum hypothesis may be able to explain the patterns of long-term performance for Lee and Swaminathan's early and late strategies as it does for the trend-bucking and doubly-extreme strategies, respectively.

Ⅴ. Subperiod Analysis

The results of the previous section suggest that the risk-based hypotheses cannot account for the return behavior of contrarian portfolios. However, this evidence does not necessarily imply that the abnormal return of the trend-bucking strategy is due to overreaction. As Black (1993) and Mackinlay (1995) argue, anomalies may be the results of data snooping. If the results reported in this paper are simply due to data snooping, they are likely to be sample specific.

The possibility of data snooping is especially important with respect to the trend-bucking contrarian strategy, because this strategy is related to the short-term momentum phenomenon on whose robustness some researchers have cast doubt.[16] For example, LW is a short-term winner portfolio, while WL is a short-term loser portfolio. The trend-bucking contrarian strategy might have higher abnormal returns than

others simply because of the short-term momentum phenomenon, and such momentum may be due to data snooping. If that is so, it should not yield higher returns than the original or the doubly-extreme contrarian strategy in a period without short-term momentum.

Table VIII provides a subperiod analysis. The entire period is divided into four subperiods as follows: January 1931 through March 1947 (207 months), April 1947 through June 1963 (207 months), July 1963 through September 1979 (207 months), and October 1979 through December 1996 (207 months)

Table VIII reports that the trend-bucking contrarian strategy provides much higher compounded return than the doubly-extreme or the original contrarian strategy in all four subperiods. Furthermore, this strategy earns reliably positive return except in the second subperiod. Hence, the trend-bucking contrarian strategy yields the reliably highest returns among the three contrarian strategies in all subperiods. These strong results are hardly attributable to chance (i.e. data snooping).

The trend-bucking contrarian strategy earns an annual compounded return of 34.52% (t=2.47) in the first subperiod (January 1931 through March 1947) when short-term momentum, as Jegadeesh and Titman (1993) and Conrad and Kaul (1998) report, does not appear. This return is much higher than that of any other, confirming that the outperformance of the trend-bucking strategy over other strategies is not a simple representation of short-term return momentum.

Panel A also highlights how measurement errors can be serious in calculating average returns on extreme loser portfolios. In the first period, LL has an average compounded return of 40.65% and an average cumulative return of 54.11%. The difference is about 13.46%. Microstructure-induced upward biases are likely to be responsible for this difference. The reason is that the large difference is found only for low-priced stocks like LL and L. In the case of the trend-bucking contrarian strategy, there is no significant difference between cumulative returns and compounded returns in all subperiods.

The original and the doubly-extreme contrarian strategies appear to lose money in the second and fourth subperiods, even without risk adjustment. The long-term momentum hypothesis predict that these

strategies will lose money in the short-term. Thus, their negative returns in the two subperiods are not surprising at all.

Ⅵ. Seasonality of Contrarian Strategies

For the final analysis, we examine the seasonality of the returns on the three contrarian strategies examined in this paper. In particular, we focus on the return of each strategy in January versus non-January months. DeBondt and Thaler (1985, 1987) and Chopra et al. (1992) note that the returns of contrarian strategies accrue primarily in January. While they attribute contrarian returns, concentrated in January, to overreaction, they do not provide answer to the question of why return reversal occurs only in January? In other word, why does the market correct price errors only in January?

The results of the seasonality analysis in Table IX show that the positive returns on both the original strategy and doubly-extreme contrarian strategy are realized only in January, consistent with the earlier studies. However, the trend-bucking contrarian strategy earns positive returns both in January and in non-January months. It earns 5.61% in January and 1.15% per month in the other months, producing 76% of its average annual returns in non-January months.[17] Thus, the trend-bucking strategy is unique among contrarian strategies in that its returns do not appear to be simply a manifestation of the January effect.[18] This evidence suggests more reasonable implication that the market corrects price errors not only in January but also in non-January if overreaction and its correction cause return reversal.

Ⅶ. Conclusions

This paper adds three contributions to the finance literature. First, this paper tests the validity of two behavioral models and other hypotheses that attempt to explain long-term reversal in stock prices. Our empirical tests favor the long-term momentum hypothesis over the BSV model. Further, other possible hypotheses for contrarian returns fail to explain short-term returns on the trend-bucking contrarian strategy, consistent with the long-term momentum hypothesis.

Secondly, this paper provides a new contrarian strategy, called as the trend-bucking contrarian strategy. It may be a good strategy to implement by two reasons. First, it appears to yield high abnormal return. Second, it seems to require lower transaction costs than the other contrarian strategies. It is well known that trading extremely low priced stocks requires substantial transaction costs. However, it does not appear to consist of extremely low priced stocks as shown in Panel B of Table V.

Lastly, the long-term momentum hypothesis suggests a new condition for capturing contrarian profits. In other word, it claims that we should identify not only price errors but also the correction phase to pursue short-term profits. Although the doubly-extreme contrarian strategy may be good for identifying price errors, it appears to lose money. The momentum hypothesis attributes its losses to the failure of identifying the correction phase. Identifying the correction phase may be an important condition for exploiting other anomalies related to long-term reversal such as the size effect, the book-to-market effect, the price effect, if they result from price errors.

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Footnotes

[1] Refer to DeLong et al. (1990b) for the derivation of stock demand with the mean-reverting utility function.

[2] The fair value's variance σ_θ is equal to 6944.44 based on the distribution of earnings with $y_t = \pm 10$. Thus, the risk aversion factor γ and the momentum coefficient $m(3)$ should be altogether adjusted to generate $g(3) = 1/5$.

[3] In the BSV model, investors believe that the world has only two regimes. Under the trending regime, caused by the representative bias, earnings tend to be trending. In contrast, under the mean reverting regime, caused by the conservative bias, earnings are more likely to be mean reverting. Two regimes are ruled by Markov process. The regime switching process is specified also as Markov process.

[4] λ_1 is the probability of switching Regime 1 to Regime 2 and λ_2 is that of switching Regime 2 to Regime 1. Regime 1 is the state of a mean reverting for earnings, while Regime 2 is the state of trend for earnings. The BSV model sets λ_1=0.1 and λ_2=0.3 so that switching to mean reverting regime may be more frequent.

[5] BSV's simulation contains 6 earnings realization. They sort stocks by the first earnings realization to form the short-term winner and loser portfolios and test returns on these portfolios in the period after formation. In terms of our version, they would form the short-term portfolios in time -6 and test their returns in time -5, which is different from our methodology. Our formation for short-term portfolios is more general because it contains all cases of earnings realization before the formation period.

[6] Four consecutive negative signals undervalue the LW portfolio in time -2 because the representative bias of investors increases the likelihood of the trending regime that the following signal is more likely to be negative. However, the positive signal in time -1 decreases the likelihood of the trending regime. If the next signal is positive in time 1, two consecutive positive signals increase again the likelihood of the trending regime. However, in this case, the trending regime means that the following signal is more likely to be positive. Thus, the positive signal in time 1 overvalues the LW portfolio. If the negative signal

arrives in time 1, investors increase the likelihood of the mean reverting regime is stronger. In other words, investors underreact to the negative signals because they expect that the next signal in time 2 will be positive. In other word, the negative signal in time 1 also overvalues the LW portfolio. Thus, the LW portfolio is overvalued in time 1 regardless of the sign of the signal. Such overvaluation is reversed in time 2.

[7] Ball, Kothari, and Shanken (1995) report that AMEX stocks are more sensitive to microstructure-induced biases than NYSE stocks.

[8] The earlier studies typically use 5 year past returns for long-term reversal (DeBondt and Thaler (1985), Ball and Kothari (1989), Ball, Kothari, Shanken (1995) and Fama and French (1996)). For short-term momentum, 6 month past returns are used (Jegadeesh and Titman (1993) and Chan, Jegadeesh, Lakonishok (1996))

[9] According to CRSP, their postdelisting return is calculated by comparing the value after delisting against the price on the last date. The value after delisting can include a delisting price or the amount from a final distribution.

[10] Average postdelisting returns are calculated both for the January 1931-June 1963 period and for the July 1963-December 1996 period.

[11] The example of Berkey Inc. illustrates how substantially the compounded returns on the low priced stocks can be different from their cumulative returns. The share price of Berkey Inc. was $ 5.125 in January 1985 and declined to $ 0.03125 in December 1989. This extreme low price increased to $ 0.375 in January 1990. Thus, it had 1100% monthly return in January 1990 by an increase of $0.34375 in the share price. The stock of Berkey Inc. was delisted from NYSE by the reason of bankruptcy in February just after this event. Its annual cumulative return from February 1989 through January 1990 was 941.82% while its annual compounded return for the same period is $ 71.43%.

[12] Table Ⅴ of Ball, Kothari, and Shanken (1995) shows that the estimated alpha of the June-end portfolio L (W) is negative (positive) in the first year of the postranking period.

[13] Chopra et al. (1992) and DeBondt and Thaler (1987) criticize asymmetry of market beta in a sense that the beta is high in up-markets and low in down markets, indicating a desirable form of risk. On the other hand, Ball et al. (1995) point out that this attractive market beta is accompanied by an unappealing negative alpha for contrarian returns. Jones (1993) reports that the seemingly desirable up- and down-market beta behavior largely disappears over the post-war period.

[14] See Fama and French (1996).

[15] We thank Jinho Byun for providing the data on the factor mimicking portfolio returns.

[16] Jegadeesh and Titman (1993) and Conrad and Kaul (1998) report that short-term momentum does not exist in the pre-1940s period. Fama and French (1996), and Fama (1988) argue that short-term momentum in stock prices may be due to data snooping because they do not strongly appear in the pre-1963 period. On the contrary, Haugen and Baker (1996) and Rowenhorst (1998) show that short-term momentum universally exists in European stock markets. However, their test period is limited to the recent period such as the post-1980 period.

[17] The anomalies related to long-term reversal include the size effect (Keim (1983), the book-to-market effect (Loughran (1997)), the long-term past return effect (DeBondt and Thaler (1985, 1987) and Chopra et al. (1992)), the price effect (Bhardwaj and Brooks (1992)). For example, Fama and French (1992) report that the book-to-market effect appears in non-January months. However, Loughran (1997) documents that the book-to-market effect is driven exclusively by January returns when small, young and growth stocks like IPO stocks are excluded.

[18] We examine whether this result is consistent with the rational tax-loss selling hypothesis of Chan (1986). The results, not reported here, show that LW is a short-term winner and WL is a short-term loser for 6 to 12 months near the tax year. Thus, the positive January return from the trend-bucking contrarian strategy is not consistent with the tax-loss selling hypothesis. However, this January profit appears to be consistent with the argument that the January effect is a low price effect.

Table I
Returns on Contrarian and Momentum Strategies in Long-term Momentum Model

Panel A. Returns on the Traditional Contrarian Strategy in Long-term Momentum Hypothesis

Time	Long-term Loser Portfolio	Long-term Winner Portfolio	Traditional Contrarian Strategy
1	-5.96 %	1.12 %	-7.08 %
2	1.68 %	-1.42 %	3.10 %
3	7.36 %	-2.12 %	9.48 %
4	6.13 %	-3.39 %	9.52 %

Panel B. Returns on the Momentum Strategy in Long-term Momentum Hypothesis

Time	Short-term Loser Portfolio	Short-term Winner Portfolio	Momentum Strategy
1	-2.40 %	2.18 %	4.58 %
2	-0.68 %	-0.83 %	-0.15 %
3	0.10 %	0.36 %	0.26 %
4	0.11 %	0.19 %	0.08 %

Panel C. Returns on the Trend Bucking Contrarian Strategy in the Long-term Momentum Hypothesis

Time	LW	WL	Trend Bucking Contrarian Strategy
1	6.53 %	-2.47 %	9.00 %
2	6.37 %	-2.68 %	9.05 %
3	6.10 %	-3.20 %	9.30 %
4	6.02 %	-3.49 %	9.51 %

Table II

Returns on Contrarian and Momentum Strategies in the BSV Model

Panel A. Returns on the Traditional Contrarian Strategy in the BSV Model

Time	Long-term Loser Portfolio	Long-term Winner Portfolio	Traditional Contrarian Strategy
1	6.16 %	-2.58 %	8.74 %
2	4.58 %	-1.26 %	5.84 %
3	3.19 %	0.67 %	2.52 %
4	0.84 %	-0.09 %	0.93 %

Panel B. Returns on the Momentum Strategy in the BSV Model

Time	Short-term Loser	Short-term Winner	Momentum Strategy
1	-1.15 %	2.04 %	3.19 %
2	2.04 %	-1.68 %	-3.72 %
3	0.89 %	-0.16 %	-1.05 %
4	0.22 %	0.21 %	-0.01 %

Panel C. Returns on the Trend Bucking Contrarian Strategy in the BSV Model

Time	LW	WL	Trend Bucking Contrarian Strategy
1	1.53 %	0.27 %	1.26 %
2	-2.55 %	1.92 %	-4.47 %
3	0.30%	0.29 %	0.01 %
4	0.29 %	0.13 %	0.16 %

Table III

Annual Compounded and Cumulative Returns on 50 Portfolios in Contrarian Strategies: January 1931 through December 1996

At the end of each month *t-1*, NYSE stocks are allocated to deciles based on their compounded returns from *t-60* though *t-8*. These compounded past returns are denoted as (60-8). Decile 1 contains the stocks with the lowest (60-8) returns and is called the (60-8) long-term loser, while decile 10 is called the (60-8) long-term winner. Within each (60-8) portfolio decile, stocks are sorted into quintiles based on their (7-2) compounded returns. Quintile 1 contains the stocks with the lowest (7-2) compounded returns (the (7-2) short-term loser), while quintile 5 contains those with the highest (7-2) compounded returns (the(7-2) short-term winner). This two-stage sorting method creates 50 portfolios. Each of these portfolios is held for 12-months from *t* through *t+11*. For example, a portfolio formed in January 1963 is held from March 1963 through February 1964. One month is skipped between the formation period and the test period to avoid microstructure and other biases. Panels A and B show annual compounded and cumulative returns on each portfolio. When return information stock is missing during the test period, its post-delisting return is used in the first missing month. If the post-listing return is not available, an average of post-delisting returns is used. For the remaining holding period, returns on delisted stocks are replaced with the value-weighted return on NYSE stocks. Figures in parenthesis in Panel C are Newey and West (1987) autocorrelation-consistent *t*-values.

Panel A. Time Series Average Annual Compounded Returns (%)

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	19.89	23.20	23.54	25.45	27.53	22.54
D2	16.88	19.27	21.70	21.36	24.80	19.95
D3	16.73	18.21	19.50	19.79	20.83	19.21
D4	16.42	17.43	17.80	17.99	20.70	18.38
D5	16.61	17.48	17.63	18.02	20.43	17.33
D6	14.95	16.33	16.62	17.69	19.86	17.27
D7	15.02	16.41	16.74	17.37	19.23	16.98
D8	14.20	14.81	15.79	16.81	19.09	16.23
D9	12.09	13.58	14.50	15.82	18.85	15.63
Long-term winner	8.83	12.32	13.81	14.98	19.16	15.35

Panel B. Time Series Average Annual Cumulative Returns (%)

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	25.05	25.40	24.18	24.96	26.80	24.50
D2	18.91	20.44	20.81	20.59	22.40	20.01
D3	17.39	18.18	18.82	18.74	19.65	18.66
D4	16.90	17.33	17.18	17.16	19.51	17.62
D5	16.35	17.08	16.66	17.10	19.23	16.70
D6	15.26	15.95	16.09	16.40	18.66	16.39
D7	14.76	15.38	15.67	16.16	17.88	16.05
D8	13.83	14.09	14.82	15.76	17.49	15.35
D9	12.00	13.02	13.65	14.57	17.17	14.62
Long-term winner	9.09	11.50	12.53	13.65	16.85	13.89

Panel C. Annual Returns from Contrarian Strategies (%)

Portfolio	Compounded Returns	Cumulative Returns
LL portfolio	19.89	25.05
LW portfolio	27.53	26.80
(60-2) Long-term loser (L)	22.54	24.50
WW portfolio	19.16	16.85
WL portfolio	8.83	9.09
(60-2) Long-term winner (W)	15.35	13.89
Trend-bucking contrarian strategy (LW – WL)	18.70 (t=4.55)	17.71 (t=4.64)
Doubly-extreme contrarian strategy (LL-WW)	0.73 (t=0.14)	8.20 (t=1.78)
Original contrarian strategy (L-W)	7.20 (t=1.61)	10.60 (t=2.51)

Table IV

Compounded Returns to Contrarian Portfolios at Other Horizons: January 1931-December 1996

At the end of each month *t-1*, NYSE stocks are allocated to deciles based on their compounded returns from *t-60* though *t-(j+2)*. Decile 1 (10) contains the NYSE stocks with the lowest (highest) compounded past returns. Within each decile, stocks are again assigned to quintiles based on *j*-month compounded returns beginning from (*t*-(j+1)). Quintile 1 (5) contains the stocks with the lowest (highest) *j*-month compounded returns. The portfolio of stocks in Decile 1 (10) and quintile 5 (1) is denoted as LW (WL), while the portfolio of stocks in decile 1 (10) and quintile 1 (5) is denoted as LL (WW). These portfolios are held for *h*-months from *t* through *t+(h-1)*. One month is skipped between the formation period and the test period to mitigate microstructure and other biases. Panel A (B) shows *h*-month compounded returns to the trend-bucking (doubly-extreme) contrarian portfolios. When return information stock is missing during the test period, its post-delisting return is used in the first missing month. If the post-listing return is not available, an average of post-delisting returns is used. For the remaining holding period, returns on delisted stocks are replaced with the value-weighted return on NYSE stocks. Figures in parenthesis are Newey and West (1987) autocorrelation-consistent *t*-values.

Panel A. Compounded Raw Returns to Trend-Bucking Contrarian Portfolios

j-month short-term past return	*h*-month holding period =	3	6	9	12
3	LW	5.48	11.52	18.51	26.60
	WL	2.32	4.76	7.05	10.03
	LW-WL	3.16	6.76	11.46	16.57
		(*t*=3.04)	(*t*=3.55)	(*t*=3.88)	(*t*=3.72)
	Avg. (month)	1.05	1.13	1.27	1.38
6	LW	6.47	13.73	20.98	27.53
	WL	2.27	3.59	5.49	8.83
	LW-WL	4.20	10.14	15.49	18.70
		(*t*=4.20)	(*t*=4.59)	(*t*=4.85)	(*t*=4.55)
	Avg. (month)	1.40	1.69	1.72	1.56
9	LW	7.33	14.61	20.74	26.88
	WL	1.60	2.77	5.19	9.02
	LW-WL	5.73	11.84	15.55	17.86
		(*t*=4.96)	(*t*=5.18)	(*t*=5.00)	(*t*=4.44)
	Avg. (month)	1.91	1.97	1.73	1.49
12	LW	7.21	13.69	18.94	24.70
	WL	1.61	3.28	6.10	10.00
	LW-WL	5.61	10.41	12.84	14.70
		(*t*=4.45)	(*t*=5.17)	(*t*=4.69)	(*t*=4.07)
	Avg. (month)	1.87	1.74	1.43	1.23

Panel B. Compounded Raw Returns on Doubly-Extreme Contrarian Portfolios

L	H =	3	6	9	12
3	LL	5.17	9.13	13.64	20.05
	WW	4.75	9.38	14.27	18.50
	LL-WW	0.42	-0.25	-0.63	1.55
		(*t*=0.30)	(*t*=-0.10)	(*t*=-0.17)	(*t*=0.29)
	Avg. (month)	0.14	-0.04	-0.07	0.13
6	LL	4.83	8.50	12.73	19.89
	WW	5.09	10.12	14.86	19.16
	LL-WW	-0.26	-1.62	-2.13	0.73
		(*t*=-0.19)	(*t*=-0.73)	(*t*=-0.62)	(*t*=0.14)
	Avg. (month)	-0.09	-0.27	-0.24	0.06
9	LL	4.84	8.72	13.68	20.87
	WW	5.24	10.05	14.71	18.56
	LL-WW	-0.39	-1.33	-1.03	2.31
		(*t*=-0.29)	(*t*=-0.58)	(*t*=-0.28)	(*t*=0.41)
	Avg. (month)	-0.13	-0.22	-0.11	0.19
12	LL	5.13	9.50	15.10	22.42
	WW	4.86	9.53	13.95	17.76
	LL-WW	0.26	-0.03	1.16	4.66
		(*t*=0.20)	(*t*=-0.01)	(*t*=0.28)	(*t*=0.77)
	Avg. (month)	0.09	-0.01	0.13	0.39

Table V

Basic Statistics of 50 Portfolios: January 1931 through November 1995

At the end of each month *t-1*, NYSE stocks are allocated to deciles based on their compounded returns from *t-60* though *t-8*. These compounded past returns are called (60-8) compounded returns. Decile 1 contains the NYSE stocks with the lowest (60-8) compounded past returns. Decile 1 is called the(60-8) long-term loser, while decile 10 is called the (60-8) long-term winner. Within each portfolio decile, stocks are sorted into quintiles based on their (7-2) compounded returns. Quintile 1 (quintile 5) contains the stocks with the lowest (highest) (7-2) compounded returns. Quintile 1 is called the (7-2) short-term loser, while quintile 5 is called the (7-2) short-term winner. This double-sorting method creates 50 portfolios. For each portfolio, the average size, the price per share at *(t-2)*, (60-2), (60-8) and (7-2) compounded past returns are calculated. The test period is January 1931 through November 1995. For the original contrarian strategy portfolios, all stocks are ranked into deciles based on compounded returns from *t-60* through *t-2*. For each (60-2) portfolio, basic statistics are also calculated.

Panel A. Time Series Average of Size ($ millions)

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	104.72	168.58	191.18	192.07	163.62	152.88
D2	201.98	288.70	320.43	358.86	316.05	280.32
D3	276.41	401.76	466.28	531.58	412.31	420.77
D4	319.76	460.49	511.25	614.12	500.79	475.73
D5	379.79	552.02	585.53	689.37	594.98	560.90
D6	401.41	601.08	665.90	772.83	724.08	648.05
D7	437.31	695.27	776.35	859.95	719.04	728.60
D8	509.52	708.99	826.59	892.73	706.76	773.75
D9	508.77	756.22	903.81	892.44	649.31	804.67
Long-term winner	415.23	641.76	779.36	800.55	609.47	653.71

Panel B. Time Series Average of Share Price

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	10.45	14.08	15.46	15.77	16.11	13.44
D2	16.18	20.53	22.18	23.00	23.34	20.08
D3	18.40	23.69	26.24	27.05	27.37	24.33
D4	21.25	26.31	27.90	30.56	29.64	27.00
D5	22.24	27.94	30.12	31.98	32.50	28.95
D6	24.18	29.06	31.40	33.66	35.22	30.63
D7	25.07	30.88	33.93	36.51	38.59	33.15
D8	26.86	32.54	36.87	38.75	44.44	36.15
D9	28.59	36.77	46.87	45.48	53.75	43.78
Long-term winner	31.85	40.67	47.45	46.66	48.69	46.45

Panel C. Time Series Average of (60-2) Past Returns (%)

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	-55.47	-44.47	-38.75	-34.10	-21.84	-44.13
D2	-27.40	-14.88	-7.57	1.02	22.27	-9.84
D3	-9.35	5.80	15.10	25.62	50.64	13.50
D4	7.25	24.06	35.18	47.48	75.62	34.40
D5	22.70	42.34	54.97	69.33	102.10	55.36
D6	40.04	62.06	76.59	92.83	130.03	78.26
D7	60.73	85.62	102.46	121.05	163.43	105.77
D8	87.36	117.19	136.98	159.20	209.43	142.81
D9	131.38	169.45	193.80	221.77	287.58	204.27
Long-term winner	312.77	362.86	403.78	456.88	617.17	451.69

Panel D. Time Series Average of (60-8) Past Returns (%)

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	-45.43	-42.49	-41.55	-42.15	-44.83	-40.32
D2	-12.05	-11.65	-11.73	-11.54	-11.78	-8.07
D3	9.68	10.03	10.01	10.12	9.97	13.39
D4	29.36	29.12	29.31	29.28	29.18	32.29
D5	48.31	48.40	48.41	48.58	48.35	50.65
D6	69.20	69.31	69.36	69.33	69.25	71.44
D7	94.73	94.39	94.41	94.23	94.42	95.72
D8	128.20	127.89	127.88	127.90	128.44	127.67
D9	184.14	183.36	182.73	182.87	184.30	180.27
Long-term winner	425.98	389.88	386.09	389.25	414.25	388.71

Panel E. Time Series Average of (7-2) Past Returns

(60-8) Portfolio Decile	(7-2) Portfolio Quintile					(60-2) Portfolio Decile
	Short-term Loser	Q2	Q3	Q4	Short-term winner	
Long-term loser	-22.00	-3.92	5.52	16.07	52.66	-1.87
D2	-18.90	-3.67	5.59	16.09	43.86	2.98
D3	-18.17	-3.63	5.53	15.88	41.34	4.66
D4	-17.51	-3.56	5.58	15.91	39.50	5.84
D5	-17.39	-3.50	5.55	15.83	39.54	7.52
D6	-17.16	-3.52	5.52	15.75	38.90	8.67
D7	-17.11	-3.53	5.56	15.77	35.15	10.01
D8	-17.28	-3.59	5.50	15.75	38.25	11.77
D9	-17.55	-3.59	5.57	15.88	38.46	13.93
Long-term winner	-19.10	-3.65	5.58	15.66	39.05	19.43

Table VI

Regressions of Equally Weighted Market Returns on Annual Compounded Returns on Contrarian Portfolios: July 1931 through June 1996

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \delta_p [R_m(t-5,t-1) - \text{Avg}\, R_m] R_{mt} + \varepsilon_{pt}$$

For portfolio construction and notation, see Table Ⅰ. R_{pt} is an annual buy-and-hold excess return beginning July through June every year. R_{mt} is the equally weighted excess return on NYSE stocks. Excess returns are obtained by subtracting the annual return on Treasury bills (Ibbotson Associates 1997). Avg R_m is the time series average of annual excess return on R_{mt}. $R_m(t-5,t-1)$ is the average excess return on the market index over years *t-y* through *t-1*. Figures in parenthesis are Newey and West (1987) autocorrelation-consistent *t*-values.

Portfolio	α_p	β_p	δ_p	*adj-* R^2
LL	-5.00 (*t*=-1.41)	1.22 (*t*=12.69)	0.23 (*t*=0.83)	0.84
LW	4.66 (*t*=1.21)	1.20 (*t*=11.47)	0.60 (*t*=2.02)	0.79
WL	-5.72 (*t*=-2.86)	0.82 (*t*=15.22)	0.90 (*t*=5.81)	0.83
WW	4.57 (*t*=1.99)	0.86 (*t*=13.73)	1.32 (*t*=7.39)	0.77
L	-1.25 (*t*=-0.33)	1.28 (*t*=12.47)	-0.01 (*t*=-0.05)	0.85
W	2.10 (*t*=1.20)	0.80 (*t*=16.72)	1.30 (*t*=9.56)	0.83
Doubly-extreme contrarian strategy (LL-WW)	-9.57 (*t*=-2.15)	0.37 (*t*=3.03)	-1.09 (*t*=-3.14)	0.55
Trend-bucking contrarian strategy (LW-WL)	10.38 (*t*=2.30)	0.38 (*t*=3.07)	-0.30 (*t*=-0.85)	0.33
Original contrarian strategy (L-W)	-3.35 (*t*=-0.75)	0.48 (*t*=3.95)	-1.32 (*t*=-3.81)	0.66

Table VII

Three-Factor Regressions for Monthly Excess Returns: July 1963 through December 1996

$$R_{pt} - R_f = \alpha_p + \beta_p (R_{mt} - R_f) + s_p\ SMB_t + h_p\ HML_t + \varepsilon_{pt}$$

For portfolio construction and notation, see Table Ⅰ. Portfolios are formed every month. For the 12-month holding period, portfolios are rebalanced monthly to maintain equal weight for each of the surviving stocks. For each month t, 12 portfolio returns are included, one for each of the 12 calendar months. Each portfolio has a 1/12 weight in producing average monthly returns on the portfolio in month *t*. R_{pt} is average monthly return on the portfolio at time *t*, R_f is one- month Treasury bill rate observed at the beginning of the month, R_{mt} is the value-weighted average return, and SMB_t is the return on the mimicking portfolio for size, defined by buying a portfolio of small-firm stocks and selling a portfolio of large-firm stocks. HML_t is the return on a mimicking portfolio defined by buying a portfolio of high-book-to-market stocks and selling a portfolio of low book-to-market stocks. The formation of SMB_t and HML_t follows Fama and French (1996).

Portfolio	α_p	β_p	s_p	h_p	$adj\text{-}R^2$
LL	-0.50 (*t*=-1.26)	1.13 (*t*=11.12)	1.82 (*t*=13.49)	1.04 (*t*=6.43)	0.52
LW	0.34 (*t*=2.43)	1.19 (*t*=32.98)	1.10 (*t*=23.02)	0.49 (*t*=8.58)	0.86
WL	-0.72 (*t*=-6.54)	1.19 (*t*=41.87)	0.73 (*t*=19.47)	-0.11 (*t*=-2.36)	0.90
WW	0.45 (*t*=3.96)	1.13 (*t*=38.96)	0.49 (*t*=12.73)	-0.48 (*t*=-10.40)	0.89
L	-0.16 (*t*=-0.89)	1.15 (*t*=23.47)	1.36 (*t*=20.90)	0.81 (*t*=10.33)	0.78
W	0.11 (*t*=1.57)	1.14 (*t*=62.44)	0.47 (*t*=19.55)	-0.33 (*t*=-11.24)	0.95
Doubly-extreme contrarian strategy (LL-WW)	-0.95 (*t*=-2.20)	-0.06 (*t*=-0.01)	1.33 (*t*=9.08)	1.53 (*t*=8.67)	0.27
Trend-bucking contrarian strategy (LW-WL)	1.06 (*t*=5.46)	-0.00 (*t*=-0.03)	0.37 (*t*=5.52)	0.60 (*t*=7.52)	0.17
Original contrarian strategy (L-W)	-0.28 (*t*=-1.29)	0.01 (*t*=0.19)	0.88 (*t*=11.91)	1.13 (*t*=12.7)	0.42

Table VIII

Subperiod Average 1-Year Compounded Returns and Cumulative Returns on Component Portfolios and Contrarian Strategy Portfolios

For portfolio construction, notation, and other details, see Table Ⅰ. Each portfolio is held for 12 months from *t* through *t+11*. Autocorrelation-consistent standard errors (see Newey and West (1987)) are used to calculate *t* value.

Panel A. 1931.1-1947.3 (207 months)

Portfolio	Compounded Returns	Cumulative Returns
LL portfolio	40.65	54.11
LW portfolio	46.45	48.91
(60-2) Long-term loser (L)	40.28	48.25
WW portfolio	19.83	17.91
WL portfolio	11.93	15.65
(60-2) Long-term winner (W)	15.15	14.82
Trend-bucking contrarian strategy (LW – WL)	34.52 (*t*=2.47)	33.26 (*t*=2.54)
Doubly-extreme contrarian strategy (LL-WW)	20.83 (*t*=1.27)	36.20 (*t*=2.97)
Original contrarian strategy (L-W)	25.13 (*t*=1.63)	33.44 (*t*=2.50)

Panel B. 1947.4-1963.6 (207 months)

Portfolios	Compounded Returns	Cumulative Returns
LL portfolio	13.70	13.26
LW portfolio	16.27	14.59
(60-2) Long-term loser (L)	14.90	14.09
WW portfolio	20.56	17.47
WL portfolio	12.60	11.10
(60-2) Long-term winner (W)	17.71	15.54
Trend-bucking contrarian strategy (LW – WL)	3.66 (*t*=1.11)	3.49 (*t*=1.34)
Doubly-extreme contrarian strategy (LL-WW)	-6.86 (*t*=-1.87)	-4.20 (*t*=-1.23)
Original contrarian strategy (L-W)	-2.81 (*t*=-0.86)	-1.45 (*t*=-0.52)

Panel C. 1963.7 – 1979.9 (207 months)

Portfolios	Compounded Returns	Cumulative Returns
LL portfolio	20.10	21.08
LW portfolio	24.76	23.92
(60-2) Long-term loser (L)	21.22	21.31
WW portfolio	13.68	12.54
WL portfolio	2.17	1.73
(60-2) Long-term winner (W)	9.22	8.36
Trend-bucking contrarian strategy (LW – WL)	22.59 (*t*=7.67)	22.19 (*t*=7.45)
Doubly-extreme contrarian strategy (LL-WW)	6.42 (*t*=1.16)	8.54 (*t*=1.88)
Original contrarian strategy (L-W)	12.00 (*t*=3.97)	12.96 (*t*=5.07)

Panel D. 1979.10-1996.12 (207 months)

Portfolios	Compounded Returns	Cumulative Returns
LL portfolio	7.00	14.60
LW portfolio	23.76	21.33
(60-2) Long-term loser (L)	15.49	16.58
WW portfolio	23.15	20.27
WL portfolio	10.19	9.69
(60-2) Long-term winner (W)	20.10	17.87
Trend-bucking contrarian strategy (LW – WL)	13.57 (*t*=3.21)	11.64 (*t*=3.50)
Doubly-extreme contrarian strategy (LL-WW)	-16.15 (*t*=-2.57)	-5.67 (*t*=-0.88)
Original contrarian strategy (L-W)	-4.61 (*t*=-0.96)	-1.29 (*t*=-0.31)

Table IX

Average Monthly Return of Contrarian Strategies in January and Non-January Months: January 1931 through December 1996

For portfolio construction, notation, and other details, see Table Ⅰ. Each portfolio is held for 12 months from *t* through *t+11*. The portfolio formation by the past return is described in Table Ⅰ. Portfolios are formed every month. For 12-month holding period, they are rebalanced monthly to maintain equal weight for each of surviving stocks. The test period is January 1931 through December 1996. All months are divided into January and non-January months. The table shows the averages of time series of monthly returns in January and non-January months. Parenthesis in the portfolios indicates the standard deviation of a monthly return. Parenthesis in the contrarian strategies indicates *t*-value. Autocorrelation-consistent standard errors (see Newey and West (1987)) are used to calculate *t* values.

Portfolios	January	Non-January months	Average
LL portfolio	18.62 (22.99)	0.66 (13.54)	2.16 (15.36)
LW portfolio	9.32 (12.89)	1.62 (10.13)	2.26 (10.60)
(60-2) Long-term loser (L)	12.92 (15.90)	1.09 (11.41)	2.07 (12.28)
WW portfolio	1.90 (6.24)	1.35 (6.84)	1.40 (6.79)
WL portfolio	3.71 (7.15)	0.48 (8.50)	0.75 (8.45)
(60-2) Long-term winner (W)	2.22 (5.99)	1.05 (6.82)	1.15 (6.76)
Trend-bucking contrarian strategy (LW – WL)	5.61 (*t*=4.55)	1.15 (*t*=4.97)	1.52 (*t*=6.36)
Doubly-extreme contrarian strategy (LL-WW)	16.72 (*t*=6.01)	-0.68 (*t*=-1.69)	0.77 (*t*=1.64)
Original contrarian strategy (L-W)	10.71 (*t*=6.12)	0.04 (*t*=0.13)	0.93 (*t*=2.84)

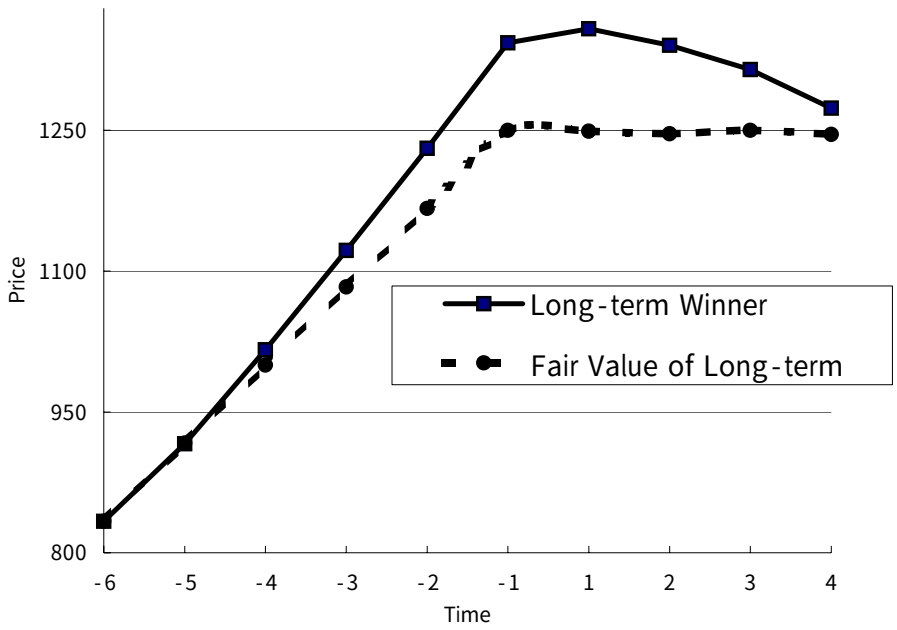

Figure 1

The Long-term Momentum Hypothesis

The figure features the predicted price paths of the long-term winner portfolio with its fair value using our simulation. The dashed lines indicate fair values throughout the figure. The solid lines in the sorting period indicate realized stock prices. Time -6 is the beginning of the sorting period and time -1is the end of the sorting period. Time 1 through time 4 is the test period.

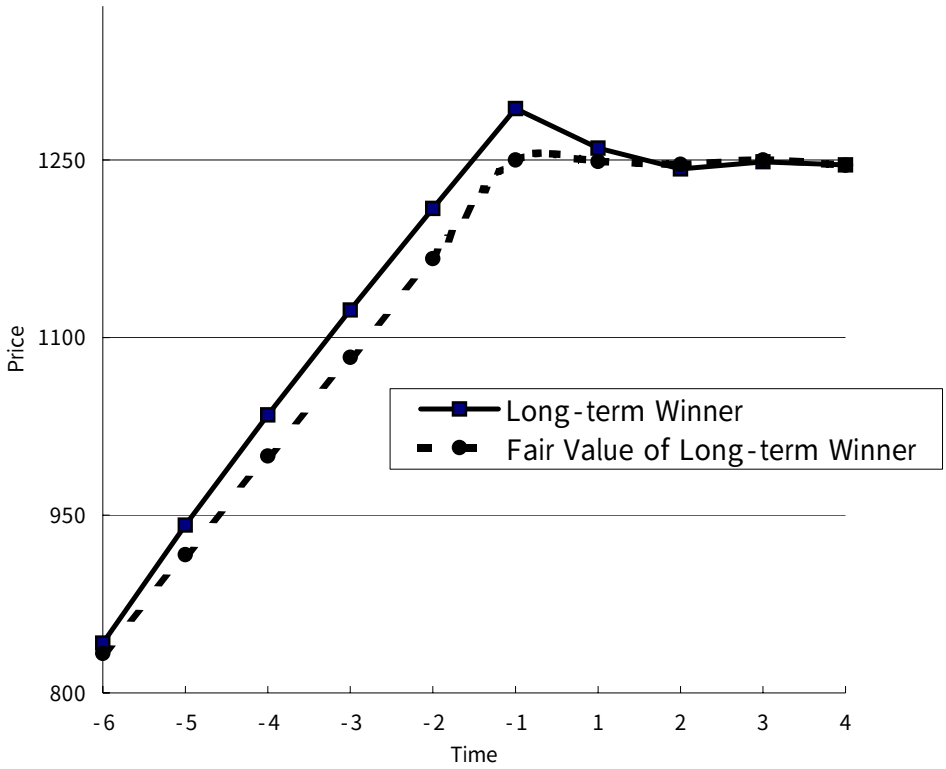

Figure 2

The BSV model

The figure features the predicted price paths of the long-term winner portfolio with its fair value using our simulation. The dashed lines indicate fair values throughout the figure. The solid lines in the sorting period indicate realized stock prices. Time -6 is the beginning of the sorting period and time -1is the end of the sorting period. Time 1 through time 4 is the test period.

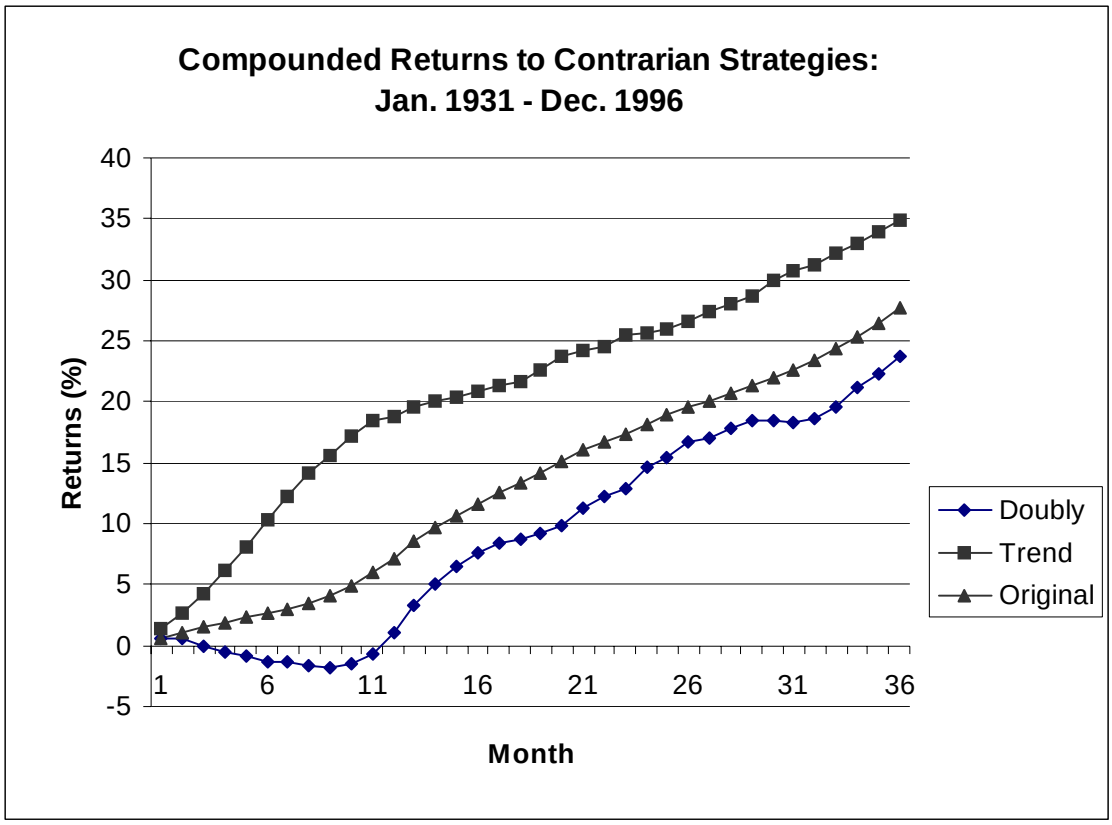

Figure 3

36 Month Compounded Raw Returns to Contrarian Strategies

This figure shows 36 month average compounded raw returns on three contrarian strategies: the original contrarian strategy, the doubly-extreme contrarian strategy, and the trend-bucking contrarian strategy.