Buy High and Sell Low

Kevin Q. Wang*

Joseph L. Rotman School of Management
University of Toronto
105 St George Street
Toronto, Ontario M5S 3E6, Canada

Phone: 416-946-5059
E-mail: kwang@rotman.utoronto.ca

January 9, 2011

*I would like to thank Kalok Chan, Jason Chen, Adlai Fisher (the NFA discussant), Mark Grinblatt (the AFA discussant), Allaudeen Hameed, Joop Huij, Zoran Ivkovich, Raymond Kan, Jonathan Lewellen, Alexander Ljungqvist, Lukasz Pomorski, Douglas Rolph, Jason Wei, Jianguo Xu, Ashraf Zaman for constructive comments, and the Social Sciences and Humanities Research Council of Canada (SSHRC) for financial support. A preliminary draft was posted under the title "Reversal Fear and Momentum."

Buy High and Sell Low

ABSTRACT

Motivated by range-related trading practices, this paper investigates the return-predictive role of relative price level. As the price of a stock moves to an unusually high or low level with respect to a long-term trading range, concern about mean-reversion in the price becomes important. I test this hypothesis using a mean-reversion-based measure to proxy for the relative price level. Tests show that the measure is a significant and robust predictor of cross-sectional variation in stock returns. The results suggest that in the presence of uncertainty about duration of firm-specific shocks, deviation from a perceived range makes investors conservative, which creates abnormal performance of a "buy high and sell low" portfolio strategy. The relative price level effect is not driven by small-cap stocks and it is not a manifestation of momentum, reversal, the 52-week high, and volatility effects.

Key words: Relative price level, mean-reversion, trading range, investor conservatism, underreaction, technical analysis

1. Introduction

Range-related trading strategies are a long-lasting subject in technical analysis and the notion of stock price trading range is extensively applied in practice (e.g., see Murphy (1999), Edwards, Magee, and Bassetti (2007), and Kirkpatrick and Dahlquist (2007)). While illusive, range trading approaches are typically implemented for a horizon of one year or less, such as those using the 52-week high and low to set the price range. Range-related trading practices are often controversial and they raise many intriguing questions. Do investors react to a perceived past trading range or price mean-reversion over a longer-term like a three-year period? Other than a specific point in price (like the 52-week high), does the price level relative to a past range have power in predicting returns? In general, is the notion of range trading useful beyond a short-term anchoring effect? Would any extension of the notion to a longer-term simply lead to some form of the long-run reversal effect of DeBondt and Thaler (1985)?

Investors may perceive a trading range when mean-reversion in the stock price is present over a reasonably long period. Motivated by this intuitive conjecture, I explore a generalized range trading strategy and my results provide interesting answers to the above questions. I construct a mean-reversion-based measure to proxy for the relative price level, which can be interpreted as a reversal probability whenever the mean-reversion continues to exist over some subsequent time period. The measure has significant predictive power for cross-sectional variation in stock returns. I highlight a "buy high and sell low" strategy, which purchases a portfolio of stocks currently at high relative price levels and short-sells a portfolio of stocks now at low relative price levels. For a six-month holding period, the strategy has significantly positive abnormal return, generating an annualized Fama-French alpha (January-excluded) of 11%. These findings suggest that adjustment speed of stock prices in incorporating firm-specific information (about duration of firm-specific shocks in particular) is sluggish such that the current price level relative to a perceived past trading range has predictive power for future returns.

My results shed light on a novel channel to link trading behavior to mean-reversion. Mean-reversion in my framework is driven by transitory firm-specific shocks, and the benchmark path for the mean-reverting price is built upon the market index. A natural hypothesis in this setting is that if mean-reversion existed over some period and investors perceive existence of mean-reversion or a trading range, investors become conservative when the current price level becomes too high (low) relative to the perceived range. Of course, a necessary condition for this to happen is that substantial information uncertainty exists and persists due to slow diffusion or processing of information. In other words, in the presence of uncertainty about duration of firm-specific shocks, deviation from a perceived past range makes investors conservative and creates underreaction. Investor underreaction may take the forms of profit-taking at high price levels and bargain-hunting at low price levels, which are typically associated with creation of a perceived range. The abnormal performance of the "buy high and sell low" strategy then arises from the underreaction. Consistent with this explanation, I find that the strategy's positive abnormal returns persist for about a year but there is no sign of any subsequent reversal.

An impressive feature of the findings is that the predictive power of the relative price level is not a small-cap effect. Stocks of small market-capitalization tend to have low analyst coverage, low institutional ownership, and hence more serious mispricings. Small-cap stocks are more volatile and they are likely to be associated with stronger limits to arbitrage. Indeed, most anomalies documented in the literature are much stronger among small-cap stocks than large-cap stocks. Interestingly, I find that the profitability of a relative price level strategy constructed from stocks in the largest size quintile is only a moderate gap (around or less than 1.5% annually) below that from stocks in the smallest size quintile.[1] This small-cap vs. large-cap result has interesting implications for portfolio management, as institutional portfolios tend to consist of only large-cap stocks. The result also has implications for robustness consideration, since it shows that it is definitely not

[1] The gap is significantly smaller, or even disappeared, in cases where January is not excluded.

the case that my findings are driven by strange unknown features of tiny stocks.

This paper is related to two strands of literature. On the one hand, extreme price levels may be associated with large price changes, and thus the effect of the relative price level seems related to the momentum effect of Jegadeesh and Titman (1993). The momentum effect refers to return continuation at intermediate horizons,[2] and there is now an extensive literature on momentum.[3] On the other hand, a number of studies on nominal stock price from different perspectives have emerged (e.g., see Baker, Greenwood, and Wurgler (2009), Green and Hwang (2009), Huddart, Lang, and Yetman (2009), and Weld et al. (2009)). Among them, George and Hwang (2004) is most related to my paper. Consistent with an anchor-and-adjust bias, George and Hwang show that a measure based on the 52-week high has significant return-predictive power. My tests show that there is no sign that the lagged six-month return and the George-Hwang 52-week-high-based measure can take away the predictive power of my relative price level measure. Intuitively, the relative price level effect is (or can be) different from the momentum and the 52-week high effects since identical large price changes can lead to very different relative price levels and the 52-week high emphasizes only a particular short-term reference point in price.[4]

The rest of the paper is organized as follows. Section 2 presents the hypothesis and the econometric approach to constructing a relative price level measure, which is the basis of my tests. Section 3 reports and discusses the empirical results including the basic findings and potential explanations. Among other things, the tests aim to examine whether the relative price level effect is a manifestation of momentum, the 52-week high, or volatility effects. Section 4 concludes the paper.

[2] Momentum is for a horizon of three to twelve months. For example, a strategy that buys the top decile and short-sells the bottom decile of stocks ranked by the lagged 6-month returns produces an average payoff of about 6% over the next 6-month holding period.

[3] A few examples of the proposed explanations and empirical tests include Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Hong, Lim, and Stein (2000), Jegadeesh and Titman (2001), and Grinblatt and Han (2005).

[4] The three variables are quite different. The cross-sectional correlation between my relative price level measure and the George-Hwang 52-week-high-based measure is 0.41 on average over the sample period, while the average correlation between my measure and the lagged six-month stock return is 0.40.

2. Hypothesis and Econometric Approach

Suppose that traders perceive existence of a trading range or mean-reversion for a stock's price over a past period but the price is now at a relatively high (low) level. What would they do? Of course, that depends on whether they think that the mean-reversion may persist over a subsequent period. If they do, they have incentives to buy low and sell high. In the presence of significant and persistent information uncertainty, such incentives affect adjustment speed of stock prices, and may create mispricings that last for some time.

Hypothesis. *Transitory firm-specific shocks create mean-reversion in stock prices. In the presence of information uncertainty about the duration of the shocks, there is in most time periods a non-zero conditional probability that the mean-reversion may persist. Due to the concern about a potential reversal to the mean, a high (low) price level relative to the mean-reversion benchmark makes traders conservative, which generates underreaction. Thus, a high (low) relative price level predicts positive (negative) abnormal return.*

In this section, I discuss an econometric approach for constructing a relative price level measure, which provides the basis for all my tests. To motivate this empirical device, I first present an example and illustrate the key points with a simplified measure. Then I move to the relative price level measure that I focus on in the empirical analysis.

As an example, suppose that the price of a stock, $P_{i,t}$, and the market index value, $P_{m,t}$, have the same sensitivity to market-wide shocks. For instance, if the market index value goes up by 10% due to such a shock, so does the stock price. In this case, the price ratio $P_{i,t}/P_{m,t}$ is driven by firm-specific shocks. Let $\ln(P_{i,t}/P_{m,t}) = a_i + u_{i,t}$, or equivalently,

$$p_{i,t} = a_i + p_{m,t} + u_{i,t}, \tag{1}$$

where $p_{i,t} \equiv \ln(P_{i,t})$ (i.e., the log of the stock price), $p_{m,t} \equiv \ln(P_{m,t})$, and $u_{i,t}$ stands for the time-t joint effect of firm-specific shocks.

Mean-reversion in the stock price is assumed to have existed for some time before the portfolio formation date, and traders had observed it. Mean-reversion refers to a tendency of the price to revert back to a benchmark. Intuitively, investors may perceive a trading range if there exists mean-reversion in the price over some time period. In turn, a reinforcing effect may arise. Specifically, the perception of a range may reinforce it as traders do profit-taking when the price is near the upper bound of the perceived range and go bargain-hunting when the price approaches to the lower bound.

In this example, I assume that over an interval before the date, the residual term $u_{i,t}$ is stationary, with mean 0 and variance $\sigma^2_{u_i}$ for the marginal distribution. Then, the log price $p_{i,t}$ mean-reverts to the benchmark $a_i + p_{m,t}$. To illustrate, let $u_{i,t}$ follow a moving-average process of order q, i.e., an MA(q) process:

$$u_{i,t} = \varepsilon_{i,t} + \theta_1 \varepsilon_{i,t-1} + \theta_2 \varepsilon_{i,t-2} + \cdots + \theta_q \varepsilon_{i,t-q}, \tag{2}$$

where $\cdots, \varepsilon_{i,t-2}, \varepsilon_{i,t-1}, \varepsilon_{i,t}, \cdots$ is a sequence of $i.i.d.$ normal variables. This is a sequence of temporary firm-specific shocks. The effect of each shock $\varepsilon_{i,t}$ on the stock price is transitory, lasting for at most $q + 1$ periods.

Uncertainty about duration of the ranking period firm-specific shocks is not resolved by the portfolio formation date, or equivalently, at the beginning of the holding period. In the presence of the uncertainty, traders are concerned about whether recent shocks are transitory. In this example, I define a proxy for the relative price level as

$$\phi_{i,t_h} = \Phi\left(\frac{p_{i,t_h} - a_i - p_{m,t_h}}{\sigma_{u_i}}\right), \tag{3}$$

where the time t_h is the starting point of the holding period, and $\Phi(\cdot)$ is the standard normal cumulative distribution function. If the recent firm-specific news are not permanent shocks, and they continue to follow the MA(q) process in (2), then one can show that

$$\phi_{i,t_h} = \text{Prob}\left[\Delta p_{i,t_h+q+1} < \Delta p_{m,t_h+q+1}\right]. \tag{4}$$

where $\Delta p_{i,t_h+q+1} \equiv p_{i,t_h+q+1} - p_{i,t_h}$, $\Delta p_{m,t_h+q+1} \equiv p_{m,t_h+q+1} - p_{m,t_h}$, and $\text{Prob}[\cdot]$ refers to the time-t_h conditional probability.[5]

Thus, ϕ_{i,t_h} is a *reversal probability*, i.e., the probability that stock i will underperform the market index over the interval from t_h to t_h+q+1. For example, when a large transitory shock pushes p_{i,t_h} far above the benchmark a_i+p_{m,t_h}, this is a time that relative price level becomes important. As the transitory effect dies out, the (log) stock price tends to revert back to the benchmark, and thus the stock tends to underperform the benchmark, i.e., the market, over a subsequent period. More specifically, suppose that a stock has a high value of ϕ_{i,t_h}, say 0.8, indicating that the stock price is now at an usually high level. Then there is a large probability that the stock may underperform the market in a subsequent interval, if the mean-reversion persists over the time interval.

Traders may perceive a price trading range due to existence of mean-reversion in the price. It is apparently not feasible to specify all the perceived specific ranges. When using a measure like ϕ_{i,t_h} to proxy for the price level relative to the mean-reversion benchmark, we may view the standard deviation, which in this example is σ_{u_i} in (3), or a multiple of the standard deviation, as a proxy for the width of a perceived trading range.

A simple but potentially confusing point is the term of reversal probability in the low ϕ case. To illustrate, suppose that a stock has a low value of ϕ_{i,t_h}, say 0.2, reflecting that the stock price is at a rather low relative price level. Then if the mean-reversion persists, there is a large probability that the stock may outperform the market in a subsequent interval. Strictly speaking, this reversal probability in this case should be

$$\text{Prob}\left[\Delta p_{i,t_h+q+1} > \Delta p_{m,t_h+q+1}\right] = 1 - \phi_{i,t_h}.$$

Since $1-\phi_{i,t_h}$ and ϕ_{i,t_h} are perfectly collinear, I still refer to ϕ_{i,t_h} as the reversal probability in cases where ϕ_{i,t_h} is low. This will not create any issues in the tests. Thus, both high and

[5] Under the assumption, the transitory effects of the recent shocks last for at most $q+1$ periods. Given normality and that u_{i,t_h} and u_{i,t_h+q+1} are uncorrelated, we have

$$\phi_{i,t_h} = \text{Prob}\left(\frac{u_{i,t_h+q+1}}{\sigma_{u_i}} < \frac{u_{i,t_h}}{\sigma_{u_i}}\right) = \text{Prob}\left(u_{i,t_h+q+1} < u_{i,t_h}\right) = \text{Prob}\left(p_{i,t_h+q+1} - p_{m,t_h+q+1} < p_{i,t_h} - p_{m,t_h}\right).$$

low values of ϕ_{i,t_h}, bounded between 0 and 1, suggest great reversal probabilities under the assumption that the mean-reversion may persist over some subsequent period. Small reversal probabilities are associated with medium values (near 0.5) of ϕ_{i,t_h}.

The benchmark path for the mean-reverting price is constructed using the market index. This is appealing for several reasons. First, nonstationarity of stock prices is a difficult issue. Using the price-to-market ratio, we have a simple way to make the problem tractable. Second, stock prices are driven by both firm-specific shocks and market-wide shocks. The market-based benchmark provides a simple way to proxy for effects of market-wide shocks. With this practical method for separation, mean-reversion due to firm-specific shocks becomes the focus. Third, a stock's performance relative to the market is important to many investors. For a fund manager considering whether to buy a stock, for instance, a high value of ϕ_{i,t_h} suggests that with a good chance the stock may lag behind the market, which should really matter if the manager's goal is to beat the market.

Moving out of the example, it is useful to consider a simple extension of the measure (3). For the mean-reversion that traders have observed or perceived, I assume that the stock price is co-integrated with the market index:

$$p_{i,t} = a_i + b_i p_{m,t} + u_{i,t}, \tag{5}$$

where introducing the coefficient b_i is the only difference from the example. The coefficient b_i measures the stock price sensitivity to the market index.[6] In the example above, $b_i = 1$. But this assumption may be too restrictive in cross-sectional analyses since many stocks have quite different sensitivities to market-wide shocks. The co-integration implies that there exist coefficients a_i and b_i such that $u_{i,t}$ is stationary.

The proxy for relative price level is defined as

$$\phi_{i,t_h} = \Phi\left(\frac{p_{i,t_h} - a_i - b_i p_{m,t_h}}{\sigma_{u_i}}\right), \tag{6}$$

[6] If $u_{i,t}$ is stationary, equation (1) implies that $E(\Delta p_{i,t+1}) = b_i E(\Delta p_{m,t+1})$.

where again, compared to (3), the only difference is that b_i may be different from 1. It should be noted that equations (5) and (6) do not require any specific structure for $u_{i,t}$. With or without further distributional restriction (such as normality or (2)) being imposed on u_{i,t_h}, the value of ϕ_{i,t_h} in (6) reveals whether the deviation of p_{i,t_h} from the benchmark level $a_i + b_i p_{m,t_h}$ is significant relative to σ_{u_i}, where σ_{u_i} serves as a width measure of the stock's regular price range. Either a high or a low value of ϕ_{i,t_h} suggests unusual relative level, as either of them indicates that the stock price is away from its regular range.

The reversal probability interpretation remains valid, if the firm-specific shocks are transitory such that they follow the normal MA(q) process in (2). Under this assumption, it can be easily derived that

$$\phi_{i,t_h} = \text{Prob}\left[\Delta p_{i,t_h+q+1} < b_i \Delta p_{m,t_h+q+1}\right], \tag{7}$$

showing that π_{i,t_h} is a reversal probability, i.e., the probability that after accounting for the sensitivity b_i, the stock underperforms the market over the interval from t_h to $t_h + q + 1$. A subtle point is that even without (7), the nonlinear transformation by $\Phi(\cdot)$ in (6) is appealing. Intuitively, for increasingly large deviations of the price from the benchmark (either up or down), the marginal effect on traders may diminish. For example, in terms of traders' mean-reversion concern, it may make little difference whether the stock price is four or five standard deviations above the benchmark. Being concave (convex) for positive (negative) deviations, the function $\Phi(\cdot)$ serves well to account for the nonlinearity.

The co-integration model (5) is an empirical device to quantify the mean-reversion over a past period, providing an important basis to measure the relative price level. While it serves for empirical purposes, equation (5) is not intended to be a complete model of the stock price throughout all time periods. Most notably, it does not explicitly incorporate permanent firm-specific shocks or structural breaks. In the tests, parameters of (5) are estimated from a past three-year estimate window. Thus, my empirical approach implicitly presumes that structural breaks are rare and that equation (5), with constant coefficients, holds between two structural breaks. This presumption is conceptually comforting, since the existence of permanent shocks, though they may be rare, ensures that (5) will not provide long-term arbitrage opportunities.[7]

Finally, I describe the relative measure that I focus on for the tabulated results in the next section. The measure ϕ in (6) is simple and intuitive, but equation (5) does not explicitly account for stock price dynamics from one period to the next. Importantly, from (5) and (6), one cannot easily check whether there is any sign for existence of mean-reversion. In contrast, the approach below describes explicitly how the stock price moves from one point to the next:

$$\Delta p_{i,t+1} = \lambda_{i0} + \lambda_{i1} p_{i,t} + \lambda_{i2} p_{m,t} + b_i \Delta p_{m,t+1} + \varepsilon_{i,t+1}, \tag{8}$$

where $\Delta p_{i,t+1} = p_{i,t+1} - p_{i,t}$, $\Delta p_{m,t+1} = p_{m,t+1} - p_{m,t}$, and the sequence $\{\varepsilon_{i,t+1}\}$ is *i.i.d.* normal. This specification is similar to that of Balvers, Wu, and Gilliland (2000).[8] The difference is that they set $b_i = 1$, which does not seem plausible in my context since individual stocks have quite diverse exposures to the market. Roughly speaking, we may view $\Delta p_{i,t+1}$ and $\Delta p_{m,t+1}$ as returns on the stock and the market index. Therefore, the coefficient b_i controls for systematic market exposure.

Importantly, a negative sign of the parameter λ_{i1} reflects existence of mean-reversion. If $\lambda_{i1} < 0$, deviations of the log price (p_{it}) from the benchmark value are reversed over time. In (8), the benchmark is a linear function of the log market index, i.e., $-(\lambda_{i0} + \lambda_{i2} p_{m,t})/\lambda_{i1}$. The absolute value of the parameter λ_{i1} reflects the speed of reversion.

Similarly as in (6), I define the relative price level measure as

$$\pi_{i,t_h} = \Phi\left(-\frac{\lambda_{i0} + \lambda_{i1} p_{i,t_h} + \lambda_{i2} p_{m,t_h}}{\sigma_{\varepsilon_i}}\right), \tag{9}$$

[7] To illustrate, suppose that with no change in the parameters a_i and b_i, equation (5) holds forever. Then, extreme values of ϕ_{i,t_h} imply easy "arbitrage" opportunities. For a large value of ϕ_{i,t_h}, for example, one can buy the market and short-sell the stock at the same time. This works if one is patient, willing to wait for the stock price to revert towards the benchmark. However, this strategy is not justified if the parameters a_i and/or b_i for the benchmark may jump to different values due to structural breaks.

[8] Balvers, Wu, and Gilliland study national market indexes. Earlier well-known investigations on mean-reversion include Fama and French (1988) and Poterba and Summers (1988). Unlike my paper, these studies focus on mean-reversion at an aggregate level (e.g., size portfolios or a country's stock market index).

where σ_{ε_i} is the standard deviation of $\varepsilon_{i,t+1}$ and again, the time t_h is the starting point of the holding period. Unlike (5), equation (8) offers a simple way to check existence of mean-reversion for stocks at a high/low price level over the estimation window (i.e., one can test whether $\lambda_{i1} < 0$). Moreover, we can retain the reversal probability interpretation for the proxy in (9) if we assume that the sequence $\{\varepsilon_{i,t+1}\}$ in (8) remains to be *i.i.d.* normal throughout the recent period (including ε_{i,t_h+1}). Intuitively speaking, one can imagine that in the presence of uncertainty about duration of firm-specific shocks, investors may "prepare for the worst" such that they consider the consequences in case that the recent shocks are all transitory. Under this assumption, it can be easily shown that

$$\pi_{i,t_h} = \text{Prob}\left[\Delta p_{i,t_h+1} < b_i \Delta p_{m,t_h+1}\right]. \tag{10}$$

Thus, the relative price level measure π_{i,t_h} of (9) might also be interpreted as a reversal probability. It is the probability that after adjusting for the market exposure, the stock is going to underperform the market index over the next period.[9]

I focus on the relative price level measure π of (9) in the empirical tests. Meanwhile, I use the measure ϕ of (6) for robustness checks. The measure ϕ is simple and thus ideal for introducing the idea. Though not an explicit measure, ϕ may serve as an useful check about possible robustness issues due to specification.

My construction of the measure π (or ϕ) relies on the assumption that recent firm-specific shocks are accompanied by substantial information uncertainty and investors fail to quickly resolve the duration uncertainty about these shocks. When trading the stocks, investors are concerned about consequences in a worst-case scenario that these shocks turn out to be transitory. Without modeling permanent shocks, however, the relative price level measure may be overstated in cases where traders can quickly recognize that some of the recent firm-specific shocks are permanent. Nonetheless, since overstated values of the measure would lead to a weaker predictive relation between the measure and future

[9] For a proof of (10), note that $\Delta p_{i,t_h+1} < b_i \Delta p_{m,t_h+1}$ is equivalent to $(\Delta p_{i,t_h+1} - b_i \Delta p_{m,t_h+1})/\sigma_{\varepsilon_i} < 0$, which is, by (8), equivalent to $\varepsilon_{i,t_h+1}/\sigma_{\varepsilon_i} < -(\lambda_{i0} + \lambda_{i1} p_{i,t_h} + \lambda_{i2} p_{m,t_h})/\sigma_{\varepsilon_i}$.

stock returns, it is informative that my tests still identify significant predictive power of the relative price level proxy. To illustrate, suppose that for some stocks, traders immediately recognize that the recent shocks are permanent. For these stocks, there are no subsequent abnormal returns due to the mean-reversion concern, and hence the overstated values of the relative price level measure are not followed by large abnormal returns. Thus the mismeasurement works against my conclusion since the test results would be less supportive to the predictive ability of the measure. In other words, relative to the predictive power of π (or ϕ) uncovered in my tests, the predictive power of an unbiased (un-overstated) relative price level measure should be even more significant.

3. Empirical Results

3.1 Basic Findings

Monthly stock return and price data from January 1960 to December 2009 are obtained from CRSP. Stocks that are traded on New York Stock Exchange, American Stock Exchange, and NASDAQ are included. Following Jegadeesh and Titman (2001), stocks priced below $5 at the end of the ranking month and stocks with market capitalizations in the smallest decile are excluded. These stocks are excluded to ensure that the results are not driven primarily by small and illiquid stocks or by bid-ask bounces.[10] For the market index value, the level of the Standard & Poor's 500 composite index is used. Importantly, all the stock prices are adjusted to control for distribution events such as splits.

I start with descriptive statistics of the mean-reversion estimates, which are parameter estimates for equations (5) and (8), and also, ϕ and π, given by (6) and (9), respectively. For each stock and for a given month t, the parameters a and b of equation (5) are estimated by regressions over the three-year window from month $t-47$ to month $t-12$. Skipping the

[10] This step seems to be particularly relevant to studies that involve mean-reversion. For example, Conrad and Kaul (1993) suggest that the long-term reversal in DeBondt and Thaler (1985) is due to inclusion of low-priced stocks.

most recent twelve months helps avoid being mixed up with the momentum effect. The relative price level measure, denoted as ϕ (omitting the subscript for simplicity), is then determined by (6) with the regression estimates. This measure will be used for robustness checking purpose.

I focus on the measure π in Tables 2 through 7. Like for parameters in equation (5), the estimates of λ_0, λ_1, λ_2, and b (omitting subscript i for brevity) in equation (8) are obtained from regressions that run over the rolling three-year windows (from month $t-47$ to month $t-12$). The parameter estimates are used to compute π defined by (9).

Table 1 reports the time-series means of the equally-weighted averages of the estimates across stocks. The ϕ estimates are 0.497 on average across all stocks, which is close to 0.5. The mean of the regression slope b for equation (5) is 1.105 and about two standard deviations above zero. The magnitudes of the variables are just as expected.

The estimate of λ_1 is impressive, which has the sign and magnitude that are clearly supportive to existence of mean-reversion in stock prices. The mean of the estimate for λ_1 is negative and its absolute value is more than five standard deviations! Estimates of other parameters are also reasonable. According to (8), the benchmark path for mean-reversion is $-(\lambda_0 + \lambda_2 p_m)/\lambda_1$. Using the estimates in Table 1, one obtains that $-\lambda_0/\lambda_1 = -3.867$ and $-\lambda_2/\lambda_1 = 1.156$, which are similar to the estimates of a and b for equation (5). Finally, the mean of the measure π across all stocks is 0.486, close to 0.5 as expected.

Table 2 presents results about a π-based strategy, which is constructed as follows. Using the measure π, I create portfolios following the procedure of Jegadeesh and Titman (2001). To facilitate comparison with momentum, I use the six-month holding period. Here I take the high π portfolio, the top π decile, to illustrate the portfolio construction. For each of the months $t-4$ through t, stocks are ranked on the basis of the π value at the end of the month, and the stocks in the highest π decile are equally-weighted to form a portfolio, which is being held for six months. The process creates five portfolios, and then they are equally-weighted, each with the weight 1/5, to form the time-t top π decile, which may be referred to as the time-t high π portfolio. At the end of month t, I skip one month and look at performance of the portfolio over month $t+2$.[11] The low π portfolio is constructed in the same way, except that stocks with the lowest π values are used in each step. This procedure is repeated over time throughout the sample period.

For convenience, I use a π strategy to denote a strategy that buys a high π portfolio (top π-ranked decile or quintile) and short-sells a low π portfolio (bottom π-ranked decile or quintile), and the payoff to the π strategy is defined to be the (month $t+2$) return difference between the high π and low π portfolios.

Table 2 shows that the high (low) π decile portfolio has significantly positive (negative) alpha. For the high π portfolio, the monthly alpha from the Fama-French three factor model is 0.51% (0.57%) in the case of January being included (excluded), with a robust t-statistic above 5.0. For the low π portfolio, the alpha is −0.28% (−0.34%) in the case of January being included (excluded), with a robust t-statistic of −2.71 (−3.29). Thus, the alpha of the π strategy ("hi − lo") is significant, 0.79% (0.91%) with a t-value of 5.66 (6.01), in the case with (without) January. These numbers are economically significant. Even without compounding, the annualized January-excluded alpha of the π strategy is about 11%. I replicate the table with the ϕ measure. The results are even slightly stronger. For example, the alpha of the π strategy ("hi − lo") is 0.89% (1.07%) with a t-value of 5.59 (6.23) in the case with (without) January. For brevity, the results based on the ϕ measure are omitted.

It is interesting to note that the Fama-French regressions show that the relative price level effect runs against the book-to-market effect. The low π portfolio has significantly positive book-to-market beta estimate while the high π portfolio does not. Therefore, from findings in the literature on the value premium, one would predict that the low π

[11] Skipping one month after the portfolio formation period is a common practice to mitigate bid-ask bounce effects. Monthly returns, returns over month $t+2$, of such portfolios are used throughout my tests. In Table 2, for example, the month $t+2$ returns are regressed on the contemporaneous Fama-French three factors (see Fama and French (1996)) to obtain the alphas.

portfolio has higher holding period return, which contradicts to the performance of the π strategy. The relative price level effect also runs against the long-term reversal effect of DeBondt and Thaler (1985). The results in this table clearly show that the pattern emerged from the tests is not the reversal effect.

In sum, my basic findings suggest that there exists significant mean-reversion in stock prices and that the measure π for the relative price level has predictive power for abnormal returns. The π strategy between the top and bottom π deciles has large and significant abnormal performance. Both the high π and low π portfolios have significant alphas which are of opposite signs. These results are clearly supportive to the hypothesis stated in Section 2. In the next subsection, I check whether the relative price level effect is different from the momentum effect of Jegadeesh and Titman (1993).

3.2 Is It Just the Momentum Effect?

We focus on price levels relative to observed/perceived mean-reversion over a past period. But high (low) price levels seem to be related to the momentum effect of Jegadeesh and Titman (1993). Another seemingly related issue is the role of the 52-week high, as George and Hwang (2004) suggest that a measure based on the 52-week high helps explain the momentum effect. This subsection aims to address these issues. My tests consist of two steps. First, I proceed with a two-way or bivariate sorting approach. This is an intuitive testing procedure, which examines abnormal returns across portfolios created by two sorting variables: the past six-month return (rlag6) and the relative price level measure (π). The results are reported in Table 3. Second, I run cross-sectional regressions and report the results in Table 4.

Panel A of Table 3 shows that for winner (loser) stocks, those in the high (low) rlag6 quintile, there are clear patterns of abnormal returns when sorting the stocks by π. For the case with January being excluded, sub-panel A1 shows that the strategy of buying the winner stocks with high π and at the same time short-selling the loser stocks with low π has a monthly alpha of 1.16% (= 0.69% – (−0.47%)). In contrast, the strategy of buying the winner stocks with low π while short-selling the loser stocks with high π has a monthly alpha of 0.40% (= 0.27% – (−0.13%)). Overall, there is a monotone relation, for both the winner and loser quintiles, between the abnormal return and π. The results in sub-panel A2, where January is not excluded, are similar. Panel A shows that the π measure has significant alpha-predictive power that is not the same as rlag6, since variation in rlag6 from low π to high π quintiles is moderate in either the loser or the winner case.

Panel B of Table 3 shows that for stocks in the high (low) π quintile, there are clear patterns from the sorting by the past return variable (lag6). For example, as sub-panel B1 shows, when January is excluded, the alpha of the stocks having high π and high rlag6 is much higher than that of the stocks with high π but low rlag6 (0.78% versus 0.15%). In contrast, the alpha of the stocks having low π and low rlag6 is much lower than that of the stocks with low π and high rlag6 (−0.58% versus −0.01%). For the case with January included, the results in sub-panel B2 are similar. Overall, Panel B complements Panel A, showing that the π and rlag6 variables have independent sorting power.

Instead of extending to higher dimensional multivariate sorts, my next step is to carry out cross-sectional regression tests, to include compare more return-forecasting variables (the measure of George and Hwang (2004) in particular) and to incorporate correlations among the variables. Table 4 presents the Fama-MacBeth estimates of monthly cross-sectional regressions. The dependent variable is the monthly stock return. The regressors include the relative price level measure (π), the past 6-month return (rlag6), and the nearness to 52-week high measure (gh52). The dependent variable is measured two months after the independent variables. Specifically, if the regressors are measured by the end of month t, the dependent variable is the stock return over month $t + 2$. The variable gh52, defined as the ratio of current price to the 52-week high, is due to George and Hwang (2004). They aim at testing an anchor-and-adjust hypothesis. Their cross-sectional tests document predictive power of the 52-week-high-based variable.

The results from the cross-sectional regressions in Table 4 suggest that the measure π is a significant determinant of conditional expected returns. The regressions are based on all stocks including those that are neither winners nor losers in the momentum strategies. On the one hand, the significance of the relative price level measure π is robust, whether it is being included alone or along with the variables rlag6 and gh52. The Fama-MacBeth t-statistic for π is the highest among all regressors in all the cases, ranging from 3.87 to 6.78. The coefficient and t-statistic for π are larger when January is excluded. On the other hand, the past 6-month return (rlag6) is also statistically significant. The 52-week high measure (gh52) is sensitive to exclusion of January, and it is significant except in one case. Putting together, neither π nor rlag6 can eliminate the role of the other, and there is no sign that π and gh52 capture the same effect.

Among untabulated results, I have computed cross-sectional correlations between π and rlag6 or gh52. The cross-sectional correlation between the measure π and the past six-month return rlag6 is 0.40 on average over the sample period, while that between π and gh52 is 0.41. These correlations are indeed not very high.

Why does the π-generated effect (i.e.., the relative price level effect) differ from the momentum effect? Figure 1 illustrates that the two can be rather different. In Panel 1, A and B are two winner stocks. Both have large price increases, *identical* in percentage terms, over the six-month momentum ranking period. Stock A reaches an unusually high level now (month 0), surging from its normal price level of 100. In contrast, stock B is now at the normal trading level. If the ranking period firm-specific shocks are transitory, it is scary to hold A. So investor reactions to A and B may be quite different. Empirically, our test results above show that A has larger positive abnormal return than B over the holding period. Panel 2 is the case of two losers, C and D. Both stocks have large price drops, *identical* in percentage terms, over the ranking period. At the end of the ranking period, C is at the normal benchmark level. Therefore, D seems likely to be target for bargain hunting as it is now far below the regular level. In this case, our results above confirm that D has stronger negative abnormal return (larger in absolute value) than C in the holding period.

In short, the measure π maintains its significance and robustness throughout the tests. The π-generated effect and the moment effect are quite different in terms of return-predictive power. In addition, the tests do not suggest that the measure π and the 52-week high measure gh52 capture the same effect.

3.3 Is It a Volatility Effect?

Volatility effects seem to be another potential explanation. Jiang, Lee, and Zhang (2005) and Zhang (2006) find that momentum payoffs are higher among firms with higher information uncertainty. Although still no consensus on the explanation, empirical studies (e.g., Ang et al (2006, 2009) and Fu (2009)) have found that idiosyncratic volatility can affect expected stock returns. There is a chance that some investors may be confused between mean-reversion and return volatility. Thus, it is possible that my findings are related to return volatility or they may even largely reflect a volatility effect.

I carry out a set of tests to check whether the relative price level effect disappears when controlling for volatility. Table 5 presents estimates of the Fama-MacBeth monthly cross-sectional regressions, which are set up in the same way as in Table 4. A new regressor, the variable σ_ε, is introduced. This is an idiosyncratic volatility measure: the monthly excess stock return (i.e.., in excess of the Treasury bill rate) is regressed on the excess market return over the three-year estimation window (from $t-47$ to $t-12$), and σ_ε is the standard deviation of the residual of this regression.

The results from the cross-sectional regressions in Table 5 suggest that there is no sign that the return-predictive power of the measure π can be taken away by including the volatility measure. The measure π remains to be a significant and robust determinant of conditional expected returns. The estimate of π is stable across different specifications and the Fama-MacBeth t-statistic for π is robust in all the cases, ranging from 3.76 to 5.60. In regressions (R2) and (R3), the idiosyncratic volatility measure σ_{ε} is significant in the January-included cases, but not in all other cases. Comparing across cases, the variables gh52 and σ_{ε} are sensitive to the control for the January effect, i.e., whether or not January is excluded from the sample.

I also tried different specifications of the regressions and different volatility measures. The conclusion remains unchanged. In sum, the π-generated effect and volatility effects seem unrelated, and at the least, the results do not suggest that the return-predictive power of the relative price level measure π can be explained by a volatility effect.

3.4 Subsequent Reversal?

Our results show that the π strategy generates positive abnormal return over the holding period. Is there any reversal following the holding period? If there is a subsequent reversal, there exists an additional challenge since a convincing explanation of the effect has to explain the co-existence of return continuation and subsequent reversal.

Table 6 shows the performance of π-sorted portfolios over the two post-holding periods: a six-moth period right after the holding period and a twelve-month period starting at six months after the holding period. In other words, suppose that we form the portfolios in month t and the holding period is from $t+2$ to $t+6$. Then the first post-holding period mentioned above is from $t+7$ to $t+12$ and the second from $t+13$ to $t+24$. In the table, I use "$t+7$ to $t+12$" and "$t+13$ to $t+24$" to denote the two cases respectively.

Note that "$t+7$ to $t+12$" and "$t+13$ to $t+24$" are just for notational convenience. The actual construction of Table 6 is similar to that of Table 2. For the $t+7$ to $t+12$ case, for example, the month-t top π decile is the equally-weighted average of the following five portfolios. For each of the months $t-10$ through $t-6$, stocks are ranked on the basis of the π value at the end of the month, and the stocks in the highest π decile are equally-weighted to form a portfolio, which is being held for six months starting six months later. For the one formed at month $t-6$ for instance, it will be held from month $t+1$ to $t+6$ (not over the six months from $t-5$ to t). The month-t top π portfolio in the second case (from $t+13$ to $t+24$) is constructed similarly, which is the equally-weighted average of the following five portfolios. For each of the months $t-16$ through $t-12$, stocks are ranked on the basis of the π value at the end of the month, and the stocks in the highest π decile are equally-weighted to form a portfolio, which is being held for twelve months starting twelve months later. For the one formed at month $t-12$, for instance, it will be held from month $t+1$ to $t+12$ (not over the twelve months from $t-11$ to t). The construction, repeated over time through the sample period, is otherwise identical to that of Table 2. Again, at the end of month t, there is a one month skip and hence one looks at the performance of the portfolio over month $t+2$.

Table 6 shows that there is return-continuation in the $t+7$ to $t+12$ case, though weaker than that over the holding period ($t+2$ to $t+6$) of the π strategy. The alpha of the π strategy ("hi $-$ lo") is 0.38% with a robust t-statistic of 3.51. However, the continuation is absent when going further to the twelve-month period in the $t+13$ to $t+24$ case. The alpha of the π strategy for the period in the $t+13$ to $t+24$ case is 0.09% with a robust t-statistic of 0.69. In this case, the alphas for both the high π and low π portfolios are positive, but small and insignificant, with the t-values of 1.35 and 0.30, respectively. Thus, there is neither return reversal nor return continuation over the twelve-month post-holding period in the $t+13$ to $t+24$ case. In other words, the return continuation extends up to twelve months and subsequently there is no abnormal return.

Without a subsequent reversal, it is straightforward to provide an explanation for the performance of the π strategy. In particular, the results can be explained by traders' underreaction. Figure 2 presents an illustration of the underreaction framework, using a high π stock and a low π stock. Suppose that before the holding period, the high (low)

π rises (drops), due to positive (negative) news, to a high (low) relative price level. For the high π stock, there is a price run-up. If the price of the high π stock goes up to the right level P_1, there would be no abnormal return in the subsequent period. Due to underreaction, the price surge stops at P_2, and later a correction generates positive abnormal return over the holding period. For the low π stock, the price should plunge to the right level P_4, but it stops at P_3 due to underreaction. A correction in the holding period creates negative abnormal return. The key hypothesis of my paper is that concerns about the stock price mean-reversion created by transitory firm-specific shocks are the source of investor conservatism, which generates the underreaction.

3.5 A Small-Cap Effect?

Are the findings about the relative price level effect mainly driven by small-cap stocks? This is a natural question given that small-cap stocks are associated with low analyst coverage and low institutional ownership. They have large information uncertainty and large pricing errors. Small-cap stocks are highly volatile and they are likely to be associated with strong limits to arbitrage. It is not surprising that most anomalies documented in the literature are much stronger among small-cap stocks than large-cap stocks.

I perform a simple test to check whether my findings are just a small-cap effect. Table 7 presents the results from a bivariate-sorting test. I replace rlag6 in Table 3 by size and then use size and π as the two sorting variables. Table 7 is otherwise identical in construction to Table 3. The test should effectively show whether it makes a big difference to construct a π strategy using large-cap stocks or small-cap ones.

In Panel A, stocks are first sorted on size and then on π. In either the small or the big size quintile, the π-sort creates monotone variation in the alpha. In the small-cap quintile, the payoff for the π strategy is 0.76% $(= 0.45\% - (-0.31)\%)$ in Panel A1 where January is excluded, and 0.64% $(= 0.48\% - (-0.16)\%)$ in Panel A2 where January is included. In the big-cap quintile, the payoff for the π strategy is 0.64% ($= 0.34\% - (-0.30)\%$) in the case without January, and 0.59% ($= 0.31\% - (-0.28)\%$) when January is included. In sum, the performance of the π strategy is stronger among small-cap stocks, but the corresponding performance among stocks in the big-cap quintile is not far below. The annualized value of the difference between the monthly alphas of 0.76% and 0.64% is about 1.5%. Due to the January effect on low π stocks, the performance gap is smaller when January is included. In this case, the annualized value of the "small vs. big" difference between the monthly alphas of 0.64% and 0.59% is only 0.6%.

Sorting on π of course creates monotone variation in the π value, for example, ranging from 0.19 to 0.80 in Panel A1. There is no variation in the size in the small-cap quintile - staying at 0.06 across the π quintiles. (The average size of all stocks included in my sample is about $1.9 billions.) In the big-cap size quintile, there is variation in the size, between 7.69 and 8.62, across the π quintiles. However, the variation is not monotone.

In Panel B, the sorting order is reversed. Without January (Panel B1), the size-sort does not create monotone variation in the alpha in the low π quintile. In Panel B2, the January effect is evident. The low-π small-cap cell has an alpha of -0.11%, while in contrast the corresponding alpha in Panel B1 is -0.27%. In both Panels B1 and B2, the size-sort does not generate variation in π, which shows that the performance difference between the small and large size quintiles is not due to difference in the π value.

The conclusion, perhaps surprising, is that although the abnormal performance, the Fama-French alpha, of the π strategy using stocks in the small-cap quintile is stronger, it does not differ drastically from that using stocks in the big-cap quintile.

3.6 Robustness Checks

Several robustness checks have been performed. At the start, for example, I use the sample to replicate some well-known findings on momentum. For Table 4, I tried various specifications other than the ones reported. Similarly, different idiosyncratic volatility measures were checked for Table 5. I replicate Tables 2 through 7 using the measure ϕ defined in (6) instead of the measure π. In this subsection, I present the replication of Panel A of Table 7 using the ϕ measure, which gives an example of my robustness checks and also re-emphasizes the results of Table 7. Other than Table 8, all robustness checking results are omitted for brevity.

Replacing π by ϕ, I replicate Panel A of Table 7 and report the results in Table 8. The results are quite consistent with those in Table 7. In either the small or the big size quintile, the π-sort creates monotone variation in the alpha. In the small-cap quintile, the payoff for the π strategy is 0.82% (= 0.48% − (−0.34)%) in Panel A1 where January is excluded, and 0.63% (= 0.47% − (−0.16)%) in Panel A2 where January is included. In the big-cap quintile, the payoff for the π strategy is 0.73% (= 0.41% − (−0.32)%) in the case without January, and 0.64% (= 0.37% − (−0.27)%) when January is not excluded.

In sum, the performance of the π strategy is not too different between the small-cap and big-cap quintiles (0.82% versus 0.73% per month) when January is excluded. Due to the January effect on low π stocks, the performance gap between the small-cap and large-cap cases disappears (0.63% vs. 0.64%) when January is not excluded.

4. Conclusion

Range-related trading strategies are a long-lasting subject, which can be dated back to the beginning of technical analysis. The notion of range trading is widely applied in practice. Intuitively, a trading range may be perceived if there is mean-reversion in the price. In turn, the perception of a range may reinforce it as traders do profit-taking when the price is near the upper bound of the perceived range and go bargain-hunting when the price approaches to the lower bound. In practice, the strategies are short-term, focusing on a range over one-year or less, and they emphasize two specific reference points, the upper and lower bounds.

Extending the logic of range trading, a natural conjecture is that perception of mean-reversion over longer horizons may affect traders. My results suggest that investors do react to perceived mean-reversion over longer terms (three or four years) and to the relative price level in general (not just a special anchor like the 52-week high). In other words, the notion of range trading is useful beyond a short-term anchoring effect. Moreover, my extension uncovers a return-continuation pattern that is opposite to the long-run reversal of DeBondt and Thaler (1985). The return-predictive role of the relative price level remains significant after controlling for the momentum effect of Jegadeesh and Titman (1993) and the 52-week-high-based measure of George and Hwang (2004). This relative price level effect remains strong even among stocks in the largest size quintile and it can be combined with momentum to generate enhanced abnormal returns. Further tests suggest that the effect is consistent with an underreaction hypothesis such that in the presence of uncertainty about duration of firm-specific shocks, deviation from a perceived historical range makes investors conservative. The conservatism generates investor underreaction and thus the abnormal performance of the "buy high and sell low" strategy.

It is difficult, if possible at all, to prove the exact cause of traders' underreaction. It is well-known in behavioral finance that empirical research to separate beliefs-based models and preferences-based models is generally inconclusive (Barberis and Thaler (2003)). In this paper, I take the beliefs-based approach assuming that investor underreaction arises from conservatism and slow information diffusion/processing (e.g., Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)), but alternatively one may motivate my study with the disposition effect. Recent theoretical work by Barberis, Huang, and Santos (2001), Grinblatt and Han (2005), and Li and Yang (2009) suggests that preferences specifications based on prospect theory and mental accounting can play an important role in explaining asset pricing dynamics and the cross-sectional variation in stock returns. A combination of prospect theory and mental accounting tends to generate a disposition effect, that is, a tendency to ride losses and realize gains. It seems intuitive to imagine a link between the range trading or the relative price level effect and the disposition effect. However, the trend adjustment in constructing the mean-reversion-based measure of the relative price level makes the issue complicated. Like in other settings, it is likely to be a tough challenge for future research to clearly separate the two alternative explanations of the investor underreaction associated with range trading.

Finally, when traders do not diversify over a large number of stocks in trading, the mean-reversion concern in the presence of substantial uncertainty may be more rational than we think. There do exist empirical evidences that investors do not hold or cannot easily trade large portfolios. On the one hand, a common finding from several papers (see Blume, Crockett, and Friend (1974), Goetzmann and Kumar (2001), Statman (2004), and Polkovnichenko (2005)) is that in general a retail investor holds a small number of stocks (only 3 or 4 stocks on average). For investors with small undiversified portfolios, my mean-reversion-based measure of the relative price level represents a legitimate risk concern that should be priced. On the other hand, Korajczyk and Sadka (2004) and Lesmond, Schill, and Zhou (2004) find that for the Jegadeesh-Titman momentum strategies that involve a large number of stocks, the need for frequent rebalancing (which may occur in the trading of high/low relative price level stocks) creates substantial trading costs that tend to erode away the profitability. Therefore, traders may not pursue diversification in equity trading, and thus it is not necessarily irrational to observe that the relative price level can predict abnormal returns with respect to conventional benchmark models of risk.

References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 1-23.

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2009, Catering through nominal share prices, *Journal of Finance*, forthcoming.

Balvers, Ronald, Yangru Wu, and Erik Gilliland, 2000, Mean reversion across national stock markets and parametric contrarian investment strategies, *Journal of Finance* 55, 745-772.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1-53.

Barberis, Nicholas, and Richard H. Thaler, 2003, A survey of behavioral finance, *Handbook of the Economics of Finance*, North-Holland.

Blume, Marshall, Jean Crockett, and Irwin Friend, 1974, Stock ownership in the United States: Characteristics and trends, *Survey of Current Business* 54, 16-40.

Conrad, Jennifer, and Gautam Kaul, 1993, Long-term overreaction or biases in computed returns? *Journal of Finance* 48, 39-63.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839-1886.

DeBondt, Werner F.M., and Richard H. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793-805.

Edwards, Robert D., John Magee, and W.H.C. Bassetti, 2007, *Technical Analysis of Stock Trends*, (CRC Press).

Fama, Eugene F., and Kenneth R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24-37.

George, Thomas J., and Chuan-yang Hwang, 2004, The 52-week high and momentum investing, *Journal of Finance* 59, 2145-2176.

Goetzmann, William, and Alok Kumar, 2001, Equity portfolio diversification, *NBER* Working Paper 8686.

Green, T. Clifton, and Byoung-Hyoun Hwang , 2009, Price-based return comovement, *Journal of Financial Economics* 93, 37-50.

Grinblatt, Mark, and Bing Han, 2005, Prospect theory, mental accounting and momentum, *Journal of Financial Economics* 78, 311-339.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 54, 2143-2184.

Huddart, Steven, Mark Lang, and Michelle Yetman, 2009, Volume and price patterns around a stock's 52-week highs and lows: Theory and evidence, *Management Science* 55, 16-31.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

Jiang, Guohua, Charles M.C. Lee, and Grace Yi Zhang, 2005, Information uncertainty and expected stock returns, *Review of Accounting Studies* 10, 185-221.

Kirkpatrick, Charles D., and Julie R. Dahlquist, 2007, *Technical Analysis: The Complete Resource for Financial Market Technicians*, (FT Press).

Korajczyk, Robert A., and Ronnie Sadka, 2004, Are momentum profits robust to trading costs?, *Journal of Finance* 59, 1039-1082.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71, 349-380.

Li, Yan, and Liyan Yang, 2009, Prospect theory, the disposition effects and asset prices, Working paper, Temple University and University of Toronto.

Murphy, John J., 1999, *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*, (New York Institute of Finance).

Polkovnichenko, Valery, 2005, Household portfolio diversification: A case for rank-dependent preferences, *Review of Financial Studies* 18, 1467-1501.

Poterba, James, and Lawrence Summers, 1988, Mean reversion in stock prices: Evidence and implications, *Journal of Financial Economics* 22, 27-59.

Statman, Meir, 2004, The diversification puzzle, *Financial Analysts Journal* 60, 44-53.

Weld, William, Shlomo Benartzi, Roni Mechaely, and Richard H. Thaler, 2009, The nominal stock price puzzle, *Journal of Economic Perspectives*, forthcoming.

Zhang, X. Frank, 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105-137.

TABLE 1

Descriptive Statistics for Mean-Reversion Estimates

For stocks on New York Stock Exchange, American Stock Exchange, and NASDAQ, their monthly data from 1960 to 2009 are obtained and used for all tables throughout this paper. Stocks priced below $5 at end of the portfolio formation month and those with market capitalizations in the smallest decile are excluded. This table reports statistics for the parameter estimates for equations (5) and (8) and the relative price level measures ϕ of (6) and π of (9) in section 2. For each stock for month t, the parameters of equations (5) and (8) are estimated by regressions over the three-year window from month $t-47$ to month $t-12$. The values of ϕ and π are then determined by (6) and (9) with the regression estimates. Reported is the time-series mean of the equally-weighted average of the estimates across all stocks. In parentheses is the time-series standard deviation. For the market index value, the level of the S&P 500 composite index is used. For all stocks, the prices are adjusted to control for distribution events such as splits.

Estimating (5) and ϕ of (6)			Estimating (8) and π of (9)				
a	b	ϕ	λ_0	λ_1	λ_2	b	π
−3.536	1.105	0.497	−0.870	−0.225	0.260	1.058	0.486
(3.005)	(0.553)	(0.135)	(0.678)	(0.039)	(0.126)	(0.204)	(0.082)

TABLE 2

Relative Price Level Strategies

Relative price level strategies are constructed following the approach of Jegadeesh and Titman (2001). The measure π replaces the past 6-month return (rlag6) for the sorting variable, but otherwise the construction is identical to that of the Jegadeesh-Titman momentum strategy (with the six-month holding period). Details of the construction are provided in Section 3.1. This table reports the mean excess returns (in excess of the T-bill rate) on the portfolios and the Fama-French regression results, where α is the regression intercept. Parameters b, s, and h are the loadings for the market, size, and book-to-market factors, respectively. The top (bottom) π decile is denoted as the "high (low) π" portfolio. The π strategy, the one that buys the high π portfolio and short-sells the low π portfolio, is denoted by "hi − lo." Reported in parentheses are robust t-statistics, i.e., they are adjusted for autocorrelation and heteroskedasticity.

		mean	α	b	s	h	R^2
High π	Jan. Incl.	0.0106	0.0051	0.9633	0.5717	0.0026	0.9125
		(4.82)	(5.82)	(39.44)	(10.47)	(0.06)	
	Jan. Excl.	0.0098	0.0057	0.9748	0.6164	0.0277	0.9197
		(4.62)	(5.83)	(34.79)	(14.36)	(0.55)	
Low π	Jan. Incl.	0.0047	−0.0028	1.0156	0.5133	0.4433	0.8340
		(2.24)	(−2.71)	(26.62)	(4.49)	(4.05)	
	Jan. Excl.	0.0022	−0.0034	1.0135	0.4736	0.4490	0.8275
		(1.00)	(−3.29)	(25.18)	(4.08)	(3.75)	
H − L	Jan. Incl.	0.0059	0.0079	−0.0523	0.0584	−0.4408	0.1308
		(4.13)	(5.66)	(−1.03)	(0.37)	(−3.03)	
	Jan. Excl.	0.0077	0.0091	−0.0387	0.1428	−0.4213	0.1535
		(5.50)	(6.01)	(−0.71)	(0.96)	(−2.62)	

TABLE 3

Two-way Sorts

This table present results from two-way sorts. The portfolios are created by two sorting variables, the relative price level measure π defined in (9) and the lagged six-month return rlag6. The construction is similar to that for Table 2, which is the overlapping procedure of Jegadeesh and Titman (2001). In Table 2, stocks are sorted into deciles with one ranking variable. In this table, each of the two sorting variables divides stocks into 5 quintiles, and the combination leads to 25 portfolios. Stocks are sorted first by rlag6 and then by π in Panel A, but first by π and then by rlag6 in Panel B. Both Panels A and B are divided to cover the cases with and without January. "High (low) π" refers to the highest (lowest) π quintile, and similarly, "high (low) rlag6" refers to the highest (lowest) rlag6 quintile. The ahphas from the Fama-French three factor model are reported, with robust t-statistics (i.e., adjusted for autocorrelation and heteroskedasticity) in parentheses. For each of the portfolios in the table, the average values of π and rlag6 for the portfolio are reported, which are calculated at the end of the portfolio formation month.

TABLE 3 (Continued)

Panel A. Two-way sort: first by rlag6 then by π

A1. January excluded

		π				
		low	2	3	4	high
rlag6						
low	α (%)	−0.47	−0.39	−0.31	−0.27	−0.13
	$t(\alpha)$	(−3.67)	(−2.79)	(−2.56)	(−2.41)	(−1.24)
	π	0.10	0.20	0.31	0.43	0.60
	rlag6	−0.08	−0.07	−0.06	−0.06	−0.05
high	α (%)	0.27	0.52	0.53	0.55	0.69
	$t(\alpha)$	(2.97)	(5.44)	(5.05)	(4.38)	(4.57)
	π	0.37	0.53	0.66	0.78	0.89
	rlag6	0.25	0.26	0.28	0.29	0.32

A2. January included

		π				
		low	2	3	4	high
rlag6						
low	α (%)	−0.40	−0.33	−0.24	−0.19	−0.03
	$t(\alpha)$	(−3.28)	(−2.45)	(−1.98)	(−1.60)	(−0.32)
	π	0.10	0.20	0.31	0.43	0.60
	rlag6	−0.09	−0.07	−0.07	−0.06	−0.05
high	α (%)	0.22	0.45	0.47	0.50	0.61
	$t(\alpha)$	(2.58)	(5.37)	(5.15)	(4.06)	(4.64)
	π	0.37	0.54	0.66	0.78	0.89
	rlag6	0.25	0.26	0.27	0.28	0.32

TABLE 3 (Continued)

Panel B. Two-way sort: first by π then by rlag6

B1. January excluded

		rlag6				
		low	2	3	4	high
π						
low	α (%)	−0.58	−0.34	−0.20	−0.13	−0.01
	$t(\alpha)$	(−3.86)	(−3.03)	(−2.12)	(−1.53)	(−0.15)
	π	0.14	0.16	0.18	0.21	0.24
	rlag6	−0.12	−0.03	0.01	0.06	0.15
high	α (%)	0.15	0.32	0.41	0.56	0.78
	$t(\alpha)$	(1.66)	(4.72)	(5.53)	(4.96)	(4.07)
	π	0.73	0.77	0.80	0.82	0.85
	rlag6	0.01	0.09	0.14	0.21	0.40

B2. January included

		rlag6				
		low	2	3	4	high
π						
low	α (%)	−0.49	−0.30	−0.18	−0.12	−0.03
	$t(\alpha)$	(−3.42)	(−2.76)	(−1.88)	(−1.35)	(−0.30)
	π	0.14	0.16	0.18	0.21	0.24
	rlag6	−0.12	−0.03	0.01	0.06	0.15
high	α (%)	0.18	0.29	0.36	0.50	0.73
	$t(\alpha)$	(2.03)	(4.02)	(4.90)	(5.01)	(4.02)
	π	0.73	0.77	0.80	0.82	0.85
	rlag6	0.01	0.09	0.14	0.21	0.39

TABLE 4

Fama-MacBeth Regressions

This table presents the Fama-MacBeth estimates of monthly cross-sectional regressions, using all the stocks included in Table 1. The regression equations are $r_{i,t+2} = c_{0,t} + c'_{1,t} z_{i,t} + \varepsilon_{i,t+2}$, where $z_{i,t}$ is a vector of regressors. The dependent variable is the monthly stock return for month $t+2$. The regressors include the relative price level measure (π), the past 6-month return (rlag6), and the nearness to the 52-week-high measure (gh52) which is the ratio of the current price to the 52-week high. The month-t stock return (rlag1) and the market capitalization (size) are used as control variables. The extra time gap between the dependent variable (time $t+2$) and the regressors (time t) corresponds to the common practice of skipping one month between the holding period and the ranking period. The Fama-MacBeth t-statistics are in parentheses, and for the ease of reporting, the coefficient estimates are multiplied by 100.

Reg.		π	rlag6	gh52	rlag1	size	adj.R^2
(R1)	Jan. Incl.	0.75			−0.26	−0.03	1.79
		(5.25)			(−0.66)	(−3.07)	
	Jan. Excl.	0.93			−0.08	−0.01	1.68
		(6.78)			(−0.20)	(−1.58)	
(R2)	Jan. Incl.	0.52	0.64		−0.90	−0.03	2.76
		(4.43)	(2.89)		(−2.49)	(−2.90)	
	Jan. Excl.	0.63	0.90		−0.92	−0.01	2.61
		(5.58)	(4.15)		(−2.52)	(−1.32)	
(R3)	Jan. Incl.	0.61		0.95	−0.58	−0.03	3.11
		(4.37)		(2.11)	(−1.63)	(−3.62)	
	Jan. Excl.	0.65		1.74	−0.80	−0.02	2.91
		(4.51)		(3.96)	(−2.23)	(−2.36)	
(R4)	Jan. Incl.	0.46	0.77	0.29	−1.00	−0.03	3.91
		(3.87)	(3.51)	(0.54)	(−3.20)	(−3.37)	
	Jan. Excl.	0.50	0.75	1.10	−1.20	−0.02	3.73
		(4.12)	(3.31)	(2.05)	(−3.83)	(−2.05)	

TABLE 5

Is It a Volatility Effect?

This table presents results from checking whether stock volatility can take away the relative price level effect. Reported are estimates of the Fama-MacBeth cross-sectional regressions, which are set up in exactly the same way as in Table 4. One new regressor, σ_ε, is introduced. The variable is an idiosyncratic volatility measure: for the period from $t-47$ to $t-12$, the monthly excess stock return is regressed on the excess market return and σ_ε is the standard deviation of the residual of this regression. For other details, see Table 4.

Reg.		π	rlag6	gh52	σ_ε	rlag1	size	adj.R^2
(R1)	Jan. Incl.	0.42	0.69		2.74	−0.93	−0.02	4.58
		(4.16)	(3.50)		(1.60)	(−3.03)	(−2.95)	
	Jan. Excl.	0.54	0.94		0.23	−0.97	−0.01	4.41
		(5.60)	(4.95)		(0.13)	(−3.09)	(−1.80)	
(R2)	Jan. Incl.	0.49		1.30	3.99	−0.79	−0.02	4.64
		(4.46)		(3.46)	(2.41)	(−2.66)	(−3.23)	
	Jan. Excl.	0.56		1.92	2.21	−0.93	−0.01	4.43
		(5.12)		(5.29)	(1.30)	(−3.12)	(−2.23)	
(R3)	Jan. Incl.	0.37	0.58	0.71	3.18	−1.10	−0.02	5.11
		(3.76)	(3.13)	(1.77)	(2.08)	(−3.85)	(−3.11)	
	Jan. Excl.	0.43	0.63	1.27	1.27	−1.26	−0.01	4.92
		(4.42)	(3.43)	(3.22)	(0.81)	(−4.39)	(−2.07)	

TABLE 6

Testing for Subsequent Reversal

Relative price level strategies are constructed as in Table 2, except that two different post-holding periods are used. The π-strategy's holding period is of six months. The first post-holding period is the six-moth interval right after the holding period and the second post-holding period is a twelve-month interval starting at six months after the holding period. In other words, suppose that we form the portfolios in month t and the holding period is from $t+2$ to $t+6$. Then the first post-holding period mentioned above is from $t+7$ to $t+12$ and the second from $t+13$ to $t+24$. In the table, "$t+7$ to $t+12$" and "$t+13$ to $t+24$" are used to denote the two cases respectively. See Section 3.4 for description about the construction. Reported are cases where January is excluded. Reported in parentheses are t-statistics that are adjusted for autocorrelation and heteroskedasticity.

		mean	α	b	s	h	R^2
high π	$t+7$ to $t+12$	0.0064	0.0024	1.0127	0.4838	0.0316	0.9253
		(3.17)	(3.14)	(30.83)	(8.82)	(0.57)	
	$t+13$ to $t+24$	0.0056	0.0011	1.0204	0.4109	0.1672	0.9139
		(2.77)	(1.35)	(27.07)	(5.11)	(1.87)	
low π	$t+7$ to $t+12$	0.0042	−0.0014	1.0286	0.4814	0.5230	0.8853
		(1.95)	(−1.56)	(32.64)	(5.83)	(4.15)	
	$t+13$ to $t+24$	0.0057	0.0003	1.0069	0.4887	0.4779	0.9084
		(2.63)	(0.30)	(42.31)	(8.57)	(4.51)	
hi − lo	$t+7$ to $t+12$	0.0022	0.0038	−0.0159	0.0024	−0.4915	0.2478
		(1.43)	(3.51)	(−0.38)	(0.04)	(−3.29)	
	$t+13$ to $t+24$	−0.0001	0.0009	0.0135	−0.0778	−0.3108	0.1560
		(−0.08)	(0.69)	(0.31)	(−1.58)	(−3.72)	

TABLE 7

Is It a Small-Cap Effect?

This table presents two-way sorting results, just like Table 3. The ranking variable rlag6 in Table 3 is replaced by the market-cap or "size." Tables 3 and 7 are otherwise identical in construction.

Panel A. Two-way sort: first by size then by π

A1. January excluded

		π				
		low	2	3	4	high
size						
small	α (%)	−0.31	0.00	0.21	0.32	0.45
	$t(\alpha)$	(−2.59)	(0.02)	(2.04)	(3.48)	(4.39)
	π	0.19	0.34	0.47	0.61	0.78
	size	0.06	0.06	0.06	0.06	0.06
big	α (%)	−0.30	−0.11	0.07	0.14	0.34
	$t(\alpha)$	(−3.74)	(−1.70)	(1.38)	(2.13)	(3.09)
	π	0.20	0.36	0.50	0.64	0.80
	size	7.89	7.92	7.69	7.77	8.62

A2. January included

		π				
		low	2	3	4	high
size						
small	α (%)	−0.16	0.08	0.29	0.37	0.48
	$t(\alpha)$	(−1.49)	(0.72)	(2.99)	(4.19)	(4.43)
	π	0.19	0.34	0.47	0.61	0.78
	size	0.06	0.06	0.06	0.06	0.06
big	α (%)	−0.28	−0.12	0.05	0.12	0.31
	$t(\alpha)$	(−3.11)	(−1.56)	(0.80)	(1.88)	(3.23)
	π	0.20	0.36	0.50	0.64	0.80
	size	7.88	7.90	7.71	7.77	8.62

TABLE 7 (Continued)

Panel B. Two-way sort: first by π then by size

B1. January excluded

		size				
		small	2	3	4	big
π						
low	α (%)	−0.27	−0.24	−0.22	−0.24	−0.30
	$t(\alpha)$	(−2.19)	(−2.07)	(−2.01)	(−2.41)	(−3.43)
	π	0.20	0.19	0.19	0.19	0.19
	size	0.06	0.12	0.27	0.71	7.01
high	α (%)	0.49	0.49	0.50	0.41	0.34
	$t(\alpha)$	(4.53)	(5.52)	(5.09)	(4.82)	(3.62)
	π	0.80	0.79	0.79	0.79	0.79
	size	0.07	0.18	0.42	1.09	9.52

B2. January included

		size				
		small	2	3	4	big
π						
low	α (%)	−0.11	−0.21	−0.24	−0.26	−0.28
	$t(\alpha)$	(−0.91)	(−1.91)	(−2.24)	(−2.37)	(−2.98)
	π	0.19	0.19	0.19	0.19	0.19
	size	0.06	0.12	0.27	0.71	7.01
high	α (%)	0.51	0.44	0.42	0.36	0.30
	$t(\alpha)$	(4.55)	(5.28)	(4.74)	(4.54)	(3.69)
	π	0.80	0.79	0.79	0.79	0.79
	size	0.07	0.18	0.42	1.08	9.52

TABLE 8

Replacing π by ϕ: A Robustness Check

This table presents two-way sorting results. Stocks are sorted first by size then by ϕ given by (6). Replacing π by ϕ, Table 8 is otherwise identical in construction to Panel A of Table 7.

January excluded

		ϕ				
		low	2	3	4	high
size						
small	α (%)	−0.34	−0.01	0.20	0.34	0.48
	$t(\alpha)$	(−2.75)	(−0.12)	(1.87)	(3.28)	(4.47)
	ϕ	0.07	0.24	0.46	0.68	0.90
	size	0.06	0.06	0.06	0.06	0.06
big	α (%)	−0.32	−0.10	0.03	0.12	0.41
	$t(\alpha)$	(−4.25)	(−1.27)	(0.53)	(2.08)	(4.24)
	ϕ	0.06	0.26	0.53	0.79	0.95
	size	7.95	7.58	7.53	8.07	8.76

January included

		ϕ				
		low	2	3	4	high
size						
small	α (%)	−0.16	0.08	0.27	0.37	0.47
	$t(\alpha)$	(−1.37)	(0.75)	(2.74)	(3.54)	(4.27)
	ϕ	0.07	0.24	0.46	0.68	0.90
	size	0.06	0.06	0.06	0.06	0.06
big	α (%)	−0.27	−0.09	−0.01	0.07	0.37
	$t(\alpha)$	(−3.41)	(−1.17)	(−0.12)	(1.15)	(4.37)
	ϕ	0.06	0.26	0.53	0.79	0.95
	size	7.95	7.57	7.52	8.08	8.77

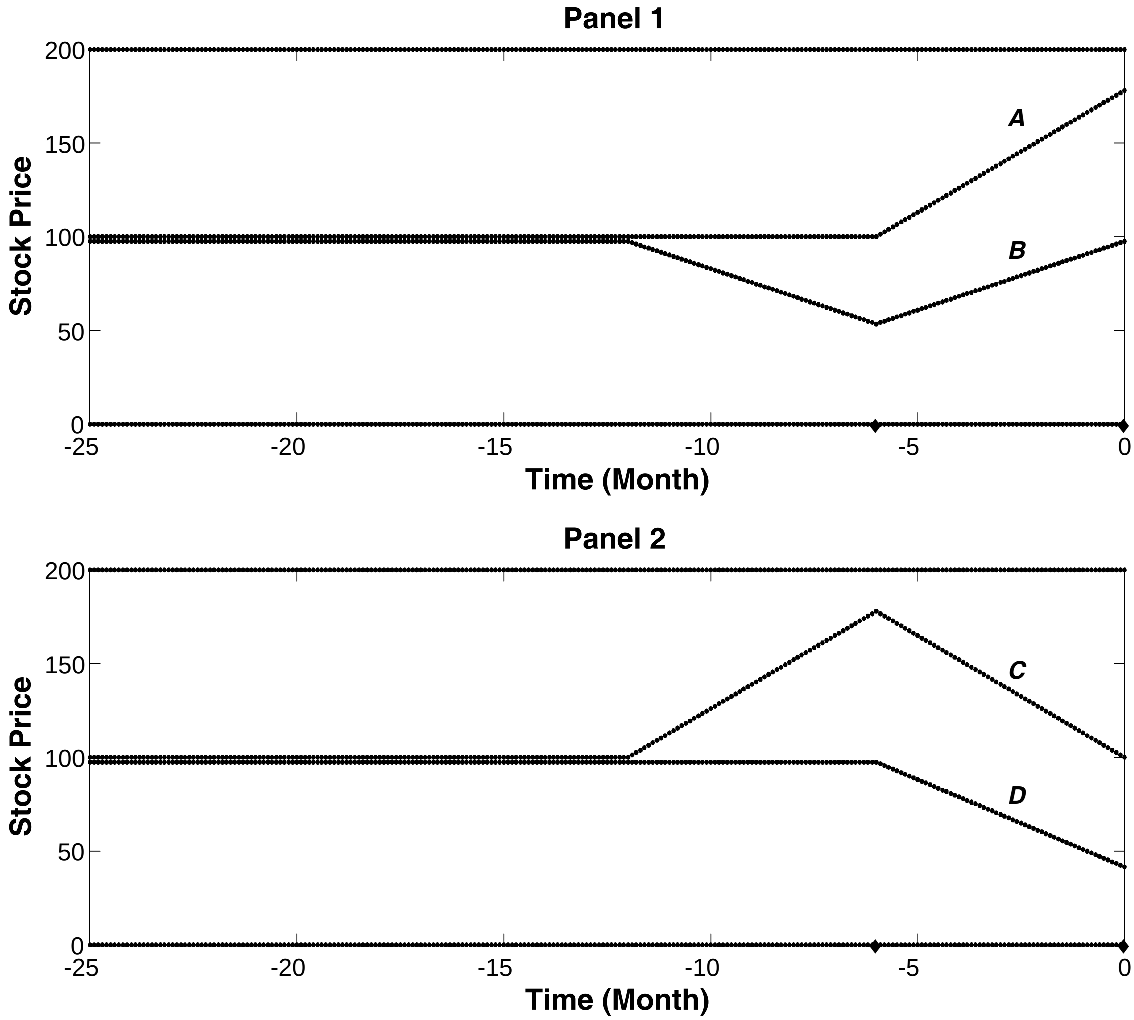

Figure 1. Why is it different from momentum?

The ranking period is from month -6 to month 0. In Panel 1, stock A and stock B have the same price changes (relative changes, $\Delta P/P$) over the ranking period, but they are at different price levels at time 0. In Panel 2, stock C and stock D have the same price changes (relative changes, $\Delta P/P$) over the ranking period, but they are at different price levels at time 0. The benchmark price level of all the four stocks, A, B, C, and D, is assumed to be flat at 100.

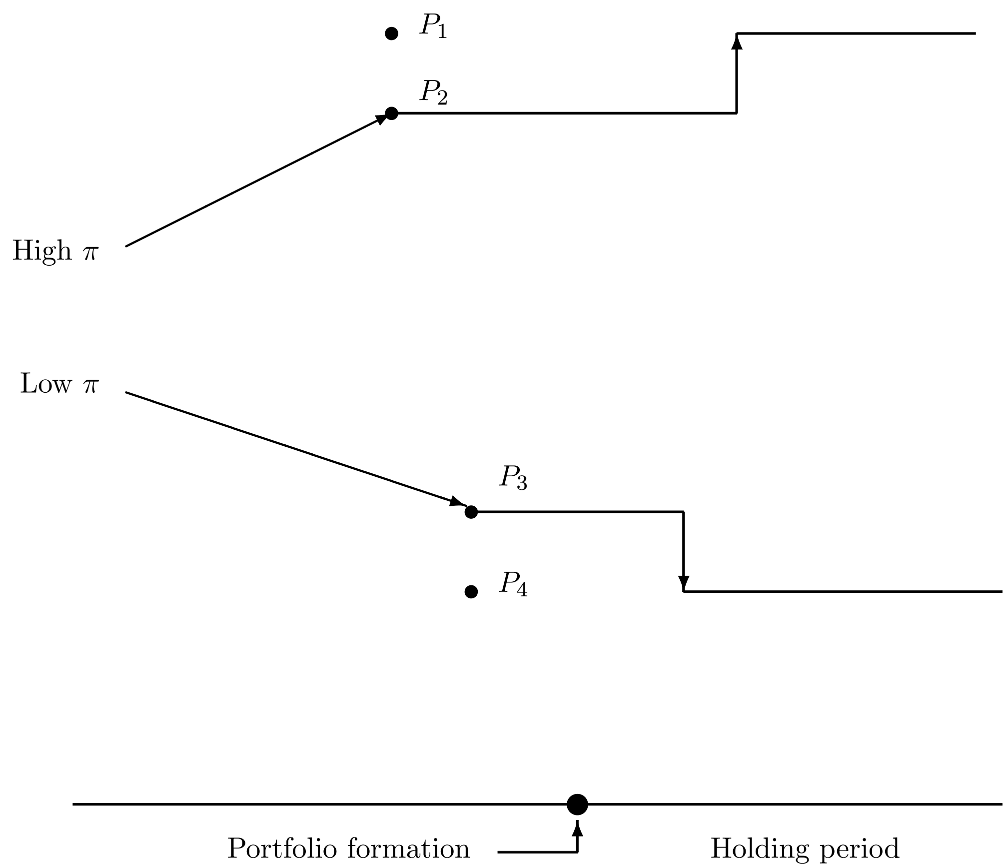

Figure 2. An illustration of the underreaction explanation

This diagram is an illustration for the underreaction explanation. Price movements are presented for a high π stock and a low π stock. The two stocks are associated with investor underreaction. The initial underreaction is corrected in the holding period.