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The Mean Reversion Characteristic of P/E Ratio and the Application in Investment Practice: Evidence from Taiwan

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Abstract

The purpose of the current study is to investigate the mean reversion characteristic in firm-specific price-to-earnings ratio (P/E ratios), and to employ it for investment practice. Existing studies related to the mean reversion feature in P/E ratio has focused on US and non-US market-wise data, but overlooked individual stocks. The findings and implications might not be generalized insofar as individual stocks. We differentiate our study from other research by analyzing firm-specific time series data. However, negative P/E ratio is meaningless, and P/E ratio will diverge when the denominator (EPS) is close to zero. To overcome the two flaws, we adopt E/P ratio in our following tests. The results show that not all E/P time series of individual stocks exhibit a mean reversion feature. Among the 1,156 non-finance firms listed on TSE and OTC in Taiwan in 2006, the E/P ratios of 516 firms (about 45%) exhibit the tendency of mean reversion. In addition, the current study makes an effort to combine the mean reversion theory with investment practice. We design an investment strategy based on the detected mean reversion feature of E/P ratio, and report the dominant investment performance.

Key Words: P/E ratio, E/P ratio, Mean Reversion, Investment Strategy, Time series analysis

1. Introduction

The use of price-to-earnings ratio (P/E ratio) as a forecasting variable for subsequent stock returns has been documented by many studies (e.g., Campbell and Shiller, 1988, 1998 and 2001; Bhargava and Malhotra, 2006; Campbell and Yogo, 2006; Weigand and Irons, 2007)[1]. Cross-sectional regressions (hereafter, the predictive regressions) are adopted to validate the relationship between P/E ratio and subsequent stock returns. P/E ratio appears to be negatively related to subsequent stock returns. The negative relationship implies that a firm's stock prices will eventually fall in the future, while the firm's P/E ratio is relatively high, to bring the P/E ratios back to a long-run average level, and vice versa.

The mean reversion theory proposed by Campbell and Shiller (1998, 2001) and Carlson et al. (2002) asserts that it is reasonable to assume stock prices to be less likely to deviate far from normal levels of fundamental values, such as earnings. The existence

[1] Goyal and Welch (2006) argue that the predictive regressions adopted in the related literature often perform poorly with out-of-sample forecasts. Nonetheless, Campbell and Thompson (2008), against to Goyal and Welch (2006), show that many predictive regressions could still work even in an out-of-sample analysis.

of a normal P/E ratio implies that a company's P/E ratios tend to revert to a specific long-run equilibrium level when deviating away. In other words, the stock prices maintain a rational relationship with earnings. However, no research has discussed the mean reverting *behavior* as well as the rational levels of P/E ratios. With the evidence on the negative relationship between P/E and subsequent returns, previous studies reached the conclusion that P/E ratio regresses to mean. Nevertheless, this evidence is indirect evidence. One of the purposes of this study is to provide direct evidence on the mean reversion feature of P/E ratio. We make an effort to capture the mean reverting processes as well as the long-run equilibrium levels of P/E ratios. In addition, negative P/E ratio is meaningless, and P/E ratio will diverge when the denominator (EPS) is close to zero. To overcome the two flaws, we adopt E/P ratio in our following tests.

Existing studies related to the mean reversion theory has focused on U.S. and non-U.S. market-wise data but overlooked individual stocks. The findings and implications might not be generalized insofar as individual stocks. By extending research sample from market indices to individual stocks, we are given a better understanding of the behavior of individual stock E/P ratios. To come to this goal, firm specific E/P time series are adopted as the sample in the current study.

Regarding the methodology, there might be what Granger and Newbold (1974) call a spurious regression relationship, if we carry out the predictive regressions to individual stocks. This is because not all firm specific E/P ratios are stationary. In our opinions, stationary autoregressive and moving average (ARMA) models have an advantage over the predictive regressions in observing the mean reverting processes of firm specific E/P ratios. ARMA models, therefore, are adopted as our research tool.

Campbell and Shiller (1988) adopt a first-order vector autoregression model (VAR) to examine the power of P/E ratios in predicting stock returns. Although the relationship between current and lagged P/E ratios has been involved in the structural estimation system in Campbell and Shiller (1988), they do not shed light on the autoregression characteristic of P/E ratio. In other words, they do not pay much attention to the mean reverting behavior of P/E ratios. Similarly, Bhargava and Malhotra (2006) concern about the relationship between subsequent stock prices and P/E ratios, but overlooked the autoregressive relationship of P/E ratios.

Taiwan is well known for its information and electronics technology. The Economist on May 27, 2010, reports that "Taiwan is now the home of many of the world's largest makers of computers and associated hardware. …". More than half of the listed firms in Taiwan are electronic firms, and therefore the stock market of Taiwan is an electronics-dominated market as well as an emerging market. Recently, for many emerging markets, including Taiwan, a body of research retests the performance of several investment strategies which have been examined for the practicability with U.S data. For example, the success of several technical trading strategies has been validated in many emerging markets (e.g., Ito, 1999; Ahmed et al. 2000; Askoy and Saglam, 2006; McKenzie, 2007). Evidence of significant profits to the momentum and the contrarian strategies are found in several emerging markets, such as Asian and Latin American markets (e.g., Rouwenhorst, 1999; Kang et al. 2002; Hong et al. 2007; Muga, 2007; Krausz et al. 2009; Zhou et al. 2010). However, the strategies are proposed by previous literature. The current study contributes to the finance literature by providing an innovative strategy according to the detected mean reversion feature of E/P ratio. We reveal the dominant performance of the strategy in Taiwan stock market.

2. Methodology

2.1 Why ARMA models?

A stationary ARMA model has a good feature to capture the mean reverting process of a firm-specific E/P ratio. From the following derivation, the adequacy of adopting ARMA models as our research tool is revealed. Consider an AR(1) model, and denote an initial value of the time series as y_0:

$$y_1 = a_0 + a_1 y_0 + \varepsilon_1 \qquad \cdots\cdots\cdots\cdots (1)$$

where ε_1 is a white noise disturbance term, and a_0 and a_1 are the intercept and the autoregressive coefficient of one-lagged term, respectively. By forward iteration, we could obtain Equation (2), Equation (3) and Equation (4), respectively.

$$\begin{aligned} y_2 &= a_0 + a_1 y_1 + \varepsilon_2 = a_0 + a_1(a_0 + a_1 y_0 + \varepsilon_1) + \varepsilon_2 \\ &= a_0(1 + a_1) + a_1^2 y_0 + a_1\varepsilon_1 + \varepsilon_2 \qquad \cdots\cdots\cdots\cdots (2) \end{aligned}$$

$$\begin{aligned} y_3 &= a_0 + a_1 y_2 + \varepsilon_3 = a_0 + a_1[a_0(1 + a_1) + a_1^2 y_0 + a_1\varepsilon_1 + \varepsilon_2] + \varepsilon_3 \\ &= a_0(1 + a_1 + a_1^2) + a_1^3 y_0 + a_1^2\varepsilon_1 + a_1\varepsilon_2 + \varepsilon_3 \qquad \cdots\cdots\cdots\cdots (3) \end{aligned}$$

$$\wr$$

$$\begin{aligned} y_t &= a_0 + a_1 y_{t-1} + \varepsilon_t = a_0 + a_1[a_0(1 + a_1) + a_1^2 y_0 + a_1\varepsilon_1 + \varepsilon_2] + \varepsilon_3 \\ &= a_0(1 + a_1 + a_1^2 + \cdots a_1^{t-1}) + a_1^t y_0 + (a_1^{t-1}\varepsilon_1 + a_1^{t-2}\varepsilon_2 + \cdots + a_1\varepsilon_{t-1} + \varepsilon_t) \\ &= a_0 \sum_{i=0}^{t} a_1^i + a_1^t y_0 + \sum_{i=1}^{t} a_1^{i-1}\,\varepsilon_{t+1-i} \qquad \cdots\cdots\cdots\cdots (4) \end{aligned}$$

As t→∞, Equation (4) turns to be:

$$y_t = a_0 \sum_{i=0}^{\infty} a_1^i + a_1^{\infty} y_0 + \sum_{i=1}^{\infty} a_1^{i-1}\,\varepsilon_{t+1-i} \qquad \cdots\cdots\cdots\cdots (5)$$

Meanwhile as $|a_1|<1$ holds, the second term of Equation (5) will converge to zero. Then we get Equation (6):

$$y_t = a_0 \sum_{i=0}^{\infty} a_1^i + \sum_{i=1}^{\infty} a_1^{i-1} \varepsilon_{t+1-i} \qquad \cdots\cdots\cdots\cdots (6)$$

Taking the expected value of Equation (6), we get Equation (7):

$$E(y_t) = E\left(a_0 \sum_{i=0}^{\infty} a_1^i\right) + E\left(\sum_{i=1}^{\infty} a_1^{i-1} \varepsilon_{t+1-i}\right) = E\left(a_0 \sum_{i=0}^{\infty} a_1^i\right) = a_0 \sum_{i=0}^{\infty} a_1^i$$
$$= \frac{a_0}{1-a_1} \qquad \cdots\cdots\cdots\cdots (7)$$

The second equal sign in Equation (7) holds, since the $\{\varepsilon_t\}$ sequence is a white noise residual sequence with zero means. The third equal sign in Equation (7) holds, because a_0 and a_1 are constants. As a result, $\{y_t\}$ sequence turns to be a geometric sequence with a common ratio a_1, and $\frac{a_0}{1-a_1}$ is the long-run equilibrium mean value of y_t. In the above derivation, the most important condition for Equation (7) to hold is the stationary condition, $|a_1|<1$. In time series analysis terms, the stationary condition requires that all characteristic roots lie within the unit circle. In addition, because the residual terms are all white noise processes with zero means, moving average (MA) terms have no influence on a stationary condition.

Taking expected value of Equation (6) implies to estimate an unconditional mean of y_t. The essential meaning behind Equation (7) is that through a sufficiently long-time period, if y_t series is stationary, the value of y_t will *converge* to a long-run equilibrium mean value, $\frac{a_0}{1-a_1}$. For generalized ARMA(p,q) models, the stationary conditions and long-run means are $1-\sum_{k=1}^{p} a_k < 0$ and $\frac{a_0}{1-\sum_{k=1}^{p} a_k}$, respectively; p represents the lagged order of autoregressive terms, and q represents the lagged order of moving average terms. a_k is an autoregressive coefficient.

Based on the above introduction to the properties of ARMA models, we believe that we could take advantage of ARMA models to capture the mean reverting processes of E/P ratios for individual stocks.

2.2 Data and Sample

Firm specific E/P time series are adopted as the sample in the current study to provide a better understanding of the behavior of individual stock E/P ratios. To avoid the in-sample flaw in prediction, argued by Goyal and Welch (2006), we adopt out-of-sample forecasts in our following examinations. Accordingly, we define the period from the first observation in a firm-specific E/P time series to December 31, 2006, as an information period and the period from January 1, 2007, to December 31, 2009, as an experiment period. By defining such an experiment period which covers the subprime crisis period in 2008, we are given an opportunity to check the investment performance of our strategy during a severe recession period.

The sample in the current study consists of 1,156 non-finance firms listed on the Taiwan Stock Exchange (TSE) and Over the Counter (OTC) in Taiwan in 2006. If a firm was delisted during 2007 to 2009, then the experiment period is defined as the period from January 1, 2007, until the day when the firm was delisted.

E/P ratio, the pivot of this study, is defined as lagged annual earnings before extraordinary items to daily market value of common stocks. Stock prices and earnings before extraordinary items data are retrieved from the Taiwan Economics Journal (TEJ) database. However, annual earnings before extraordinary items data date back to 1981 in the TEJ; hence, E/P time series are truncated in 1982 for the firms listed before 1982. In 2006, there are 53 firms listed before 1982.

2.3 ADF Unit Roots Tests

If a time series follows a unit root process, then the series rambles without any tendency to revert to a long-run equilibrium level. To test each E/P time series for unit roots, we conduct augmented Dickey and Fuller tests (ADF tests) on each firm specific E/P time series. All available observations from 1982 to 2006 (the information period) in a firm specific E/P time series are used to conduct the ADF tests. However, according to Dickey and Fuller (1979), there are three possible testing models that could be used to diagnose unit roots. There is no general consensus as which model is more exact. Accordingly, we adopt a weak criterion, if the null hypothesis: a series contains a unit root, is rejected in any one of the three forms, the series in this study is viewed as a series without unit roots. To adopt such a weak criterion could avoid excluding too many sample firms.

In order to improve estimation efficiency, we follow the suggestion from Hayashi (2000) to select an upper boundary by $12((N/100)^{1/4})$ in determining lagged orders; where N is the number of observations in an E/P series. Then, under the upper boundary, we adopt the Schwartz Bayesian information criterion (SBC) to select an optimal number of lagged difference terms. The optimal number of lagged difference terms, denoted as m, is chosen to minimize $-2(m/\mathrm{T})+k \cdot \ln(\mathrm{T})/\mathrm{T}$; where k is the upper boundary. In addition, we set 10% as the significance level when conducting ADF tests. The ADF testing processes are performed with the software EViews 5.0.

2.4 Fit ARMA Models

In the ADF testing processes, the series with unit roots are excluded. The next step is to fit ARMA models for each stationary firm-specific E/P time series. In the ARMA models fitting processes, we employ the smallest canonical (SCAN) correlation technique, proposed by Tsay and Tiao (1985), to determine lagged autoregressive orders, as well as lagged moving average orders. The SCAN technique can tentatively identify lagged orders for a stationary ARMA model. The lagged orders are tentatively identified by finding a pattern in which the smallest eigenvalue are insignificant for all testing orders. In order to improve estimation efficiency in the SCAN processes, we set an upper boundary of the lagged orders for autoregressive and moving average terms as five. In other words, we fit 25 (5x5) tentative ARMA models for each stationary E/P time series, and determine an adequate model exhibiting the specific pattern described above. If there are several models presenting the wanted pattern, SBC is utilized to select a most parsimonious model. The SCAN processes are performed by the software SAS 9.0, with the “proc arima” code.

A stationary ARMA model suggests the tested variable will converge to a long-run equilibrium mean value through a sufficiently long-time period. Accordingly, the result of each determined ARMA model is used to calculate an expected long-run E/P ratio, $\frac{a_0}{1-\sum_{k=1}^{P} a_k}$, for each corresponding stationary E/P time series. Of course, each determined ARMA model must satisfy the stationary condition, $1-\sum_{k=1}^{p} a_k < 0$, where p is the lagged order of AR (autoregressive) terms, and a_k is a fitted autoregressive coefficient.

2.5 Mean Reverting Speed

As argued by Campbell and Shiller (1998, 2001), two factors would cause a change in E/P ratios. The first, which we are most interested in, is the correction strength due to the price adjusting mechanism. Stock prices of the firms with high E/P ratios are expected to rise to bring the E/P ratios down to long-run average levels. The same adjusting mechanism in stock prices is expected to apply to firms with low E/P ratios. The second cause is due to the changes in earnings from year to year. There would exhibit a *jump* process in an E/P time series when a change in annual earnings occurs.

To illustrate, we choose a stationary E/P time series as an example. Figure 1 exhibits the E/P time series of Formosa Plastics Corporations (code=1301) from January 2, 1982, to December 29, 2006. There are 6,892 observations in the time series. An

ARMA(2,1) model is determined by the SCAN technique, to capture the mean reverting behavior of E/P ratios for the Formosa Plastics Corporation (hereafter Formosa). The long-run E/P ratio is estimated to be 0.0672 and symbolized as the dash line in Figure 1. Label 1 presents a jump-up process occurred on January 6, 1987. It is the first trading day in 1987, and we updated lagged earnings before extraordinary items from 1,557,932 thousand NT dollars to 2,814,549 thousand NT dollars to calculate the E/P ratios in 1987. As a result, the E/P ratio jumps up on that day to respond to the change in earnings. By contrast, Label 4 highlights a jump-down process which is due to a decline in earnings.

Regarding the price adjustment processes, Label 2 and Label 3 in Figure 1 present an upward and a downward price adjustment processes, respectively. Label 2 illustrates that the rose in price from 22.8 on August 30, 1985, to 37.5 on December 29, 1986, to bring the E/P ratio back to the long-run mean. Meanwhile, Label 3 presents a price downward adjustment process. Formosa's stock price on January 19, 1990, was 98.5 (E/P was 0.0299). From then on, the stock price declined to 30.1 until August 24, 1990 (E/P was 0.0883). In summary, both changes in earnings and price adjustments would cause E/P ratios to revert to long-run average levels.

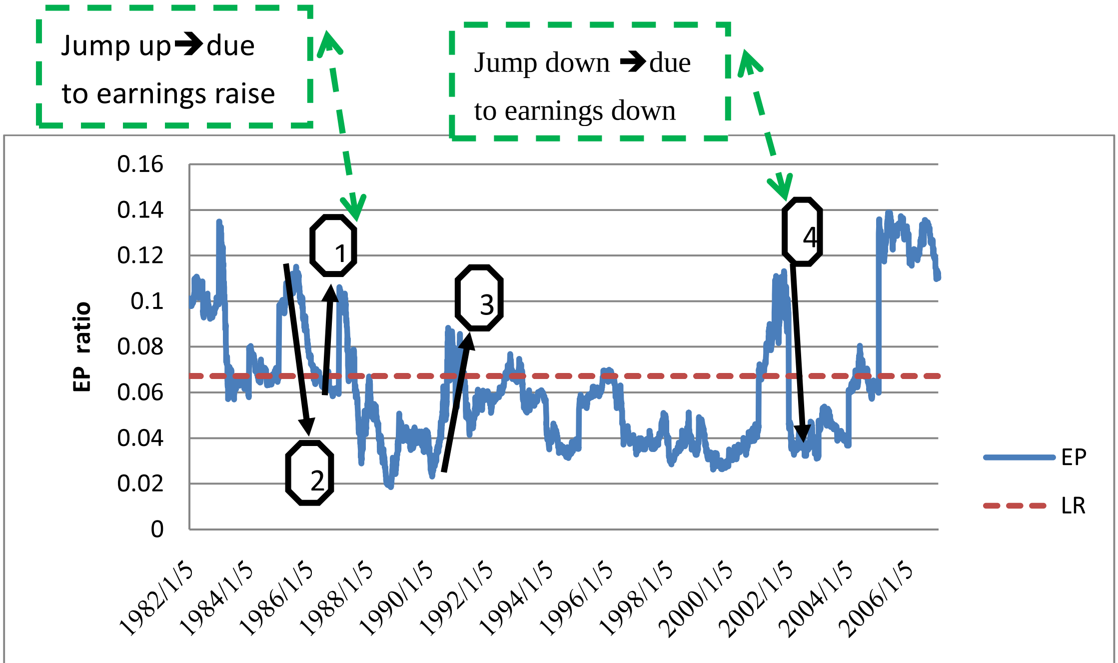

Figure 1 Formosa Plastics Corporation (code=1301) E/P Time Series 1982/1/5~2006/12/29

To understand the mean reverting behavior of firm specific E/P ratios, we employ the inverse of an adjustment coefficient as a proxy of mean reverting speed. As illustrated by Figure 1, both price adjustments and changes in earnings affect the mean reverting processes of E/P ratios, and we are more interested in the price adjustment processes than in changes of earnings. Taking advantage of the regression technique, we could easily distinguish the two different causes from each other. The following regression is used to measure the mean reverting adjustment process:

$$\Delta EP_{i,t} = b_0 + b_1\left(LR_i - EP_{i,t-1}\right) + b_2 CY_{i,t} + b_3 PTN_{i,t} + \epsilon_{i,t} \qquad \cdots\cdots\cdots (8)$$

$EP_{i,t}$ is the E/P ratio of Firm i on Day t; $EP_{i,t-1}$ is the E/P ratio of Firm i on Day t-1. $\triangle EP_{i,t}$ is the difference in E/P ratios between Day t and Day t-1. LR_i is the expected long-run E/P ratio of Firm i. $CY_{i,t}$ is a dummy variable; when a fiscal year changes to the next year on Day t, then $CY_{i,t}$ is set to be 1, and it is 0 otherwise. $PTN_{i,t}$ is a dummy variable used to control a downturn in earnings before extraordinary items. If a firm's earnings before extraordinary items deteriorate from positive to negative on Day t, then the PTN is set to be 1; otherwise it is 0.

The price adjusting mechanism is captured by the (LR_i – $EP_{i,t-1}$) term in Equation (8). If a firm's E/P ratio on Day t-1 deviates from its long-run mean, the E/P ratio would, on average, revise b_1 unit on Day t. In other words, b_1 is the average movement size of E/P from Day t-1 to Day t, which responds to the magnitude of the disequilibrium on Day t-1. More specifically, if positive deviation of a firm's E/P ratio occurred on Day t-1 (so that LR_i-$EP_{i,t-1}$<0), it means the E/P on Day t-1 is higher than a normal level; hence, we could expect the E/P to fall subsequently (so that $\triangle$EP<0). As a result, the b_1 coefficient is expected to be positive. Furthermore, the deviation would take, on average, $1/b_1$ trading days to restore equilibrium. We call the b_1 coefficient an adjustment coefficient, and $1/b_1$ the expected mean reverting speed. The larger b_1 is, the greater the response to the previous period's deviation from long-run equilibrium. The meanings of b_1 coefficient and expected mean reverting speed are the same for negative deviation.

The effect of changes in earnings on the E/P mean reverting process is measured by the CY and PTN dummy variables in Equation (8). When positive earnings turn to negative, or negative earnings turn to positive, the jump size will be extended. The enlarged jump size is captured by the PTN dummy variable in Equation (8). Yet, we prefer to treat changes in earnings as an exogenous source since investors are unable to manipulate reported earnings.

3. The Deviation Size-Based Investment Strategy

In addition to the mean reversion feature, the time-independent second-order moments are the alternative characteristic of a (weakly) stationary time series. Refer to Enders (2004, p.56~60) for more detailed derivation. In other words, the mean, variance and covariance of a distribution are identical at any observing time, if a time series is stationary. Moreover, the mean and variance of a stationary variable could be well approximated through sufficiently long time averages. In time series analysis terms, a stationary time series must satisfy the following three conditions for all t and t-s:

$$\begin{cases} E(y_t) = E(y_{t-s}) = LR & \cdots\cdots\cdots (9) \\ var(y_t) = var(y_{t-s}) = \sigma_y^2 & \cdots\cdots\cdots (10) \\ cov(y_t, y_{t-s}) = cov\left(y_{t-j}, y_{t-j-s}\right) = \theta & \cdots\cdots\cdots (11) \end{cases}$$

where LR, σ_y^2, and θ are all constants.

Equation (9) represents the mean reversion feature. Equation (10) and Equation (11) represent the time-independent second-order moments. According to the two properties of a stationary time series (i.e., the mean reversion feature and time-independently identical distributions), we design our investment strategy as a strategy triggered by the deviation size of a firm's E/P ratio (hereafter, the deviation size-based strategy). The principle of the deviation size-based strategy is to buy (short sell) the stocks whose E/P ratios exhibit a mean reversion feature but deviate sufficiently from its long-run mean. The stocks will not be sold (covered) until the day when the E/P ratios revert to the long-run means. Meanwhile, if a firm's E/P ratio does not sufficiently deviate from its long-run mean, significant abnormal returns could not be realized due to high transaction costs. However, how to identify the extreme values of a firm's E/P ratio? The two properties of a stationary variable introduced above are invoked to deal with this task.

First of all, we construct an E/P ratio empirical distribution for each stationary E/P time series with all available observations in a firm specific E/P time series during the information period (from the listing day to December 31, 2006). Then, the 99th, 95th, 90th, 10th, 5th, and 1st percentiles of a constructed E/P distribution are selected as proxies of high degree deviation. The 99th, 95th, and 90th percentiles of an empirical distribution are used to identify extremely high E/P levels, and are used as triggers for buying stocks. The 10th, 5th, and 1st percentiles, in contrast, are proxies for extremely low E/P levels and the triggers for short selling stocks. We determine the six triggers for each firm of having a stationary E/P time series.

Because the mean and variance of a distribution are identical in any observing time for a stationary time series, we assume the distribution of a firm's E/P ratios in the experiment period is the same as the distribution in the information period. As a result, if a company's E/P ratio on a certain day, during the experiment period, falls above the 99th, 95th or 90th percentile of a constructed E/P distribution, a buy-in strategy is triggered, and the stock is held until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio during the experiment period falls below the 1st, 5th, or 10th percentile of a constructed E/P distribution, a short position for the company's stock is established. This short position is covered only after the E/P ratio regresses to its long-run mean. Then, the holding period returns are calculated and compared with the TSE market performance over a corresponding period. If a triggered strategy is not ended before December 31, 2009, the holding period return is calculated until December 31, 2009.

The inspiration for identifying the two tails of an E/P distribution as extreme levels comes from that a distribution represents the probability of an event happening, and the two tails suggest the lesser probability for an E/P ratio to deviate further. Moreover, the distributions are identical at any observing time for a stationary E/P time series, and a stationary E/P will eventually regress to mean when deviating. Accordingly, we design our deviation size-based strategy through combining the concept of event-happening probability with the two properties of a stationary time series, which are the mean reversion feature and time-independently identical distributions.

Let us again take the Formosa as an example. The 6,892 E/P observations from January 5, 1982, to December 29, 2006, are used to construct an E/P ratio empirical distribution, as illustrated by Figure 2. Then the 1st, 5th, 10th, 90th, 95th and 99th percentiles are determined, which are 0.0244, 0.0310, 0.0339, 0.1060, 0.1254 and 0.1334, respectively. From 2007 to 2009, if Formosa's E/P ratio on a certain day falls above 0.1060, 0.1254, or 0.1334, our strategy is triggered to purchase Formosa's stock and hold it until the E/P reverts to 0.0672 (the long-run E/P). On the contrary, if Formosa's E/P ratio on a certain day between 2007 and 2009 falls below 0.0244, 0.0310, or 0.0339, then we short sell Formosa's stock. The short position is covered only after the E/P ratio reverts to its long-run average level. Subsequently, holding period returns are calculated as investment performance.

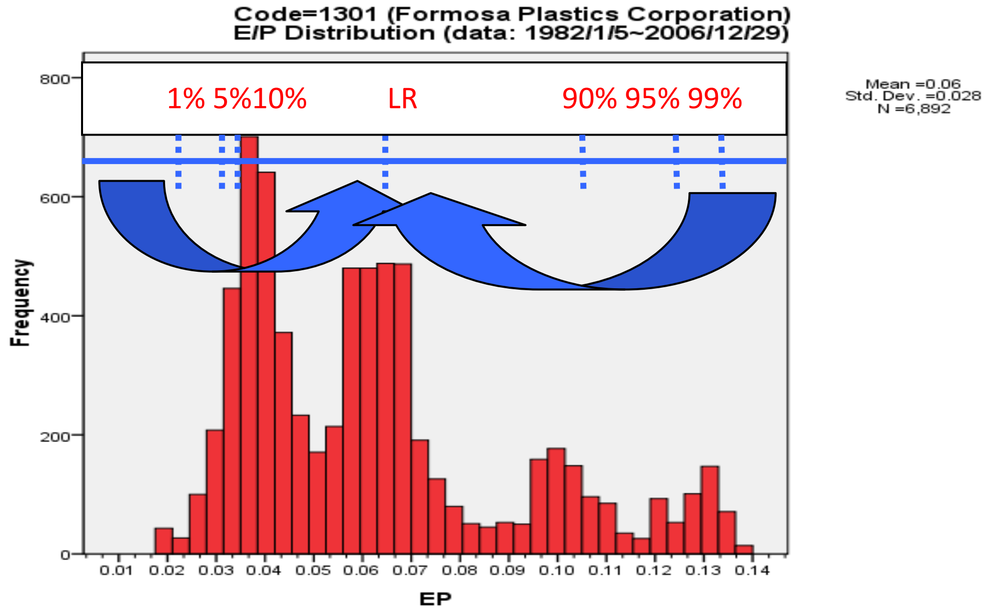

Figure 2 E/P Distribution of Formosa Plastics Corporation (code=1301)

3.1 The Influence of Long-Run E/P Levels on the Investment Performance

The influence of long-run E/P levels on the investment performance is introduced in this section. We propose four propositions to describe the relationship. The derivation is available from the corresponding author upon request. The empirical results of the four propositions are presented in the next section.

Proposition 1: In a buy-in strategy, the probability of realizing positive returns for the firms with negative long-run E/P ratios is lower than the probability for the firms with positive long-run E/P ratios.

Proposition 2: In a short-sale strategy, the probability of realizing negative returns for the firms with negative long-run E/P ratios is higher than the probability for the firms with positive long-run E/P ratios.

Proposition 3: In a buy-in strategy, if the long-run E/P ratio of a firm is positive, everything else being equal, the probability of realizing positive returns is increasing with the long-run E/P ratio.

Proposition 4: In a short-sale strategy, if the long-run E/P ratio of a firm is positive, everything else being equal, the probability of realizing negative returns is decreasing with the long-run E/P ratio.

Simply put, the implications of Proposition 1 and Proposition 2 for investing practice are that the firms with negative long-run E/P ratios are neither good targets to buy nor good targets to short sell. Meanwhile, the implications of Proposition 3 and Proposition 4 for investing practice are that the stocks with high long-run E/P ratios are better investment targets, even for short-selling, than the stocks with low long-run E/P ratios.

4. Empirical Results

4.1 Results of ADF Tests

The sample in the current study consists of 1,156 non-finance firms listed on the TSE and OTC in Taiwan in 2006. Table 1 presents the stability of the E/P time series for the 1,156 firms. Not all firm specific E/P time series are stationary. Among the 1,156 firms, 516 firms (about 45%) have stationary E/P time series. More specifically, the 1,156 firms are grouped into two categories by the exchanges on which their stocks are listed. 676 are classified as TSE-listed firms, and 480 are OTC-listed firms. TSE-listed firms tend to have higher percentages of having a stationary E/P time series (approximately 55%, compared to the percentage of 29% for the OTC-listed firms). Table 1 further reports the stability percentage in 20 industries. The specifics of which firms belong to each industry are judged by TSE and OTC. Most listed firms in Taiwan cluster in the electronic industry; 57% (=656÷1,156) of our sample firms are classified as electronic firms, while most electronic listed firms are so nascent that only 34% of them have a stationary E/P time series. Not only are the stability percentage in electronic firms lower than in any other industries, but also the stability percentages in the tourism and chemical industries. The percentages in tourism and chemical industries are 36% and 34%, respectively.

Table 1 Stability percentage of firm specific E/P time series

Industry [b]	n	No. of stationary E/P time series [a]	% of stationary	No. of non-stationary E/P time series	% of non-stationary
Construction	8	7	87.50%	1	12.50%
Foods	22	16	72.73%	6	27.27%
Plastic	28	18	64.29%	10	35.71%
Textile	57	35	61.40%	22	38.60%
Electric Machinery	57	21	36.84%	36	63.16%
Electric Wire and Cable	15	12	80.00%	3	20.00%
Ceramics	6	6	100.00%	0	0.00%
Paper	6	6	100.00%	0	0.00%
Steel	38	25	65.79%	13	34.21%
Rubber	11	8	72.73%	3	27.27%
Vehicle	5	4	80.00%	1	20.00%
Electronic	656	220	33.54%	436	66.46%
Building	53	37	69.81%	16	30.19%
Transportation	23	17	73.91%	6	26.09%
Tourism	11	4	36.36%	7	63.64%
Service and Retail	18	11	61.11%	7	38.89%
General Merchandise	60	33	55.00%	27	45.00%
Other	35	17	48.57%	18	51.43%
Chemical	35	12	34.29%	23	65.71%
Biotech	12	7	58.33%	5	41.67%
Firms listed on TSE and OTC	1156	516	44.64%	640	55.36%
TSE listed firms	676	375	55.47%	301	44.53%
OTC listed firms	480	141	29.38%	339	70.63%

a. E/P ratio is defined as lagged annual earnings before extraordinary items to daily market value of common stocks. Whether an E/P time series is stationary or not is judged by the results of the ADF tests. There are three possible testing models that could be used to diagnose unit roots. We adopt a weak criterion, if the null hypothesis: a series contains a unit root, is rejected in any one of the three forms, the series in this study is viewed as a series without unit roots.

All available observations between 1982 and 2006 in a firm specific E/P time series are used to conduct ADF tests. An E/P time series is truncated in 1982 since the earnings data provided by the TEJ database are no earlier than 1982. In the unit roots testing processes, we follow the suggestion from Hayashi (2000) to select an upper boundary for lagged difference terms by $12((N/100)^{1/4})$ to improve estimation efficiency; where N is the number of observations in a series. Under the upper boundary, we adopt Schwartz Bayesian information criterion (SBC) to select the optimal number of lagged difference terms. The optimal number of lagged difference terms, denoted as *m*, is chosen to minimize $-2(m/T)+k \cdot \ln(T)/T$; where k is the upper boundary. In addition, we set 10% as the significance level when conducting ADF tests.

b. The specifics of which firms belong to each industry are judged by TSE and OTC.

Table 2 presents the relationship between the duration of a firm and the probability of its E/P time series to become stationary. The fifth column in Table 2 shows clearly that the probability of being a stationary E/P time series is increasing with the duration of a firm. The increasing pattern is consistent with the theory of time series analysis. Among the firms listed for less than 10 years (with less than 2,500 observations in an E/P time series during the information period), the percentage of being stationary is less than 50%. There are 179 firms listed over 15 years (over 3,750 observations in an E/P time series during the information period), and 161 of them (about 90%) have a stationary E/P time series. In Table 2, the 1,156 listed firms are further categorized into TSE-listed firms and OTC-listed firms. It is obvious that TSE-listed firms tend to have longer duration than OTC-listed firms. For example, 75 of the 77 firms which have listed over 21 years (observations more than 5,250) are TSE-listed firms. Among the 75 firms listed on TSE over 21 years, 70 firms have a stationary E/P time series. There are in total 480 OTC-listed firms in 2006, and only 141 of them (about 29%) have a stationary E/P time series. The stability percentage for OTC-listed firms is lower than the percentage of TSE-listed firms. This result is attributable to the short duration of OTC-listed firms.

Table 2 The relationship between stability percentage and the duration of a firm

	TSE+OTC				TSE				OTC			
Duration [a] (trading days)	n	ST[b]	NS[b]	% of ST	n	ST[b]	NS[b]	% of ST	n	ST[b]	NS[b]	% of ST
less than 250	44	14	30	32%	11	2	9	18%	33	12	21	36%
250 to 500	66	30	36	45%	16	11	5	69%	50	19	31	38%
500 to 750	93	18	75	20%	17	6	11	35%	76	12	64	16%
750 to 1,000	102	8	94	9%	36	3	33	8%	66	5	61	8%
1,000 to 1,250	124	21	103	16%	60	12	48	20%	64	9	55	14%
1,250 to 1,500	99	32	67	32%	47	18	29	38%	52	14	38	27%
1,500 to 1,750	91	28	63	30%	52	17	35	33%	39	11	28	28%
1,750 to 2,000	83	29	54	35%	55	18	37	33%	28	11	17	39%
2,000 to 2,250	79	39	40	49%	52	24	28	46%	27	15	12	56%
2,250 to 2,500	43	24	19	57%	29	14	15	48%	14	10	4	71%
2,500 to 2,750	43	32	11	74%	33	24	9	73%	10	8	2	80%
2,750 to 3,000	44	35	9	80%	34	28	6	82%	10	7	3	70%
3,000 to 3,250	33	24	9	73%	30	21	9	70%	3	3	0	100%
3,250 to 3,500	14	7	7	50%	14	7	7	50%	0	0	0	-
3,500 to 3,750	19	14	5	74%	19	14	5	74%	0	0	0	-
3,750 to 4,000	23	21	2	92%	20	18	2	90%	3	3	0	100%
4,000 to 4,250	18	14	4	76%	17	14	3	82%	1	0	1	0%
4,250 to 4,500	18	17	1	94%	18	17	1	94%	0	0	0	-
4,500 to 4,750	19	16	3	84%	18	16	2	89%	1	0	1	0%
4,750 to 5,000	15	14	1	93%	15	14	1	93%	0	0	0	-
5,000 to 5,250	9	8	1	89%	8	7	1	88%	1	1	0	100%
5,250 to 5,500	2	2	0	100%	2	2	0	100%	0	0	0	-
5,500 to 5,750	6	6	0	100%	6	6	0	100%	0	0	0	-
5,750 to 6,000	3	3	0	100%	3	3	0	100%	0	0	0	-
6,000 to 6,250	2	2	0	100%	2	2	0	100%	0	0	0	-
6,250 to 6,500	2	2	0	100%	2	2	0	100%	0	0	0	-
6,500 to 6,750	7	7	0	100%	7	7	0	100%	0	0	0	-
6,750 to 6,892	55	49	6	89%	53	48	5	91%	2	1	1	50%
total	1,156	516	640	45%	676	375	301	55%	480	141	339	29%

a. Duration is defined as the number of observations in a firm specific E/P time series from 1982 to 2006. An E/P time series is truncated in 1982 since the earnings data provided by the TEJ database are no earlier than 1982.

b. ST is the number of firms which have a stationary E/P time series. NS is the number of firms which have a non-stationary E/P time series.

4.2 Results of Fitted ARMA Models

After excluding non-stationary E/P time series, we fit stationary ARMA models to capture the mean reverting behavior of firm specific E/P ratios. In the ARMA models fitting processes, we employ the smallest canonical (SCAN) correlation technique, proposed by Tsay and Tiao (1985), to determine lagged autoregressive orders, as well as lagged moving average orders. Table 3 presents a summary for the fitted ARMA models of the 516 stationary E/P time series. As shown in Table 3, the E/P time series of 201 firms (about 39%) are dominated by ARMA(1,0) which is the most common model to capture the mean reverting behavior of E/P ratios. For another 85 firms (about 16%), the mean reverting behavior of E/P ratios are determined by ARMA (2,0). There are an additional 57 (about 11%) and 23 firms (about 4%) whose E/P time series are dominated by ARMA(2,1) and ARMA(1,1), respectively.

Table 3 Results of fitted ARMA models

ARMA(p,q)[a]	(1,0)	(1,1)	(1,2)	(1,3)	(1,4)	(1,5)
n	201	23	8	2	2	15
n to 516 (%)	38.95%	4.46%	1.55%	0.39%	0.39%	2.91%
ARMA(p,q)[a]	(2,0)	(2,1)	(2,2)	(2,3)	(2,4)	(2,5)
n	85	57	2	0	1	0
n to 516 (%)	16.47%	11.05%	0.39%	0.00%	0.19%	0.00%
ARMA(p,q)[a]	(3,0)	(3,1)	(3,2)	(3,3)	(3,4)	(3,5)
n	29	7	7	2	2	1
n to 516 (%)	5.62%	1.36%	1.36%	0.39%	0.39%	0.19%
ARMA(p,q)[a]	(4,0)	(4,1)	(4,2)	(4,3)	(4,4)	(4,5)
n	19	5	0	2	0	3
n to 516 (%)	3.68%	0.97%	0.00%	0.39%	0.00%	0.58%
ARMA(p,q)[a]	(5,0)	(5,1)	(5,2)	(5,3)	(5,4)	(5,5)
n	27	4	3	1	3	5
n to 516 (%)	5.23%	0.78%	0.58%	0.19%	0.58%	0.97%

a. We utilize the smallest canonical (SCAN) correlation technique proposed by Tsay and Tiao (1985) to determine the lagged orders of autoregressive and moving-average terms. In order to improve estimation efficiency, in the SCAN processes, we set an upper boundary of lagged orders for autoregressive and moving average terms as five. In other words, we fit 25 (5x5) tentative ARMA models for each stationary E/P time series, and determine an adequate model exhibiting the specific pattern in which the smallest eigenvalue are insignificant for all testing orders. If there are several models exhibiting the pattern described above, SBC is employed to select a most parsimonious model.

4.3 Long-Run E/P Ratios

After identifying ARMA models for the stationary E/P time series, the long-run E/P ratios could easily be estimated as $a_0/(1-a_1-a_2-\cdots a_p)$; a_p is a fitted autoregressive coefficient, and p is the lagged order of autoregressive terms. Descriptive statistics for the long-run E/P ratios of the 516 firms with stationary E/P time series are given in Table 4. The mean and median of the 516 long-run E/P ratios are -0.02 and 0.03, respectively. The 516 long-run E/P ratios spread from the minimum of -1.68 to the maximum of 0.14. The standard deviation equals to 0.22. The 25% quartile and the 75% quartile are -0.0006 and 0.062, respectively. Table 4, additionally, presents descriptive statistics for long-run E/P ratios in different industries. The average long-run E/P level in electronic industry is 0.003. The average long-run E/P ratio in the vehicle industry and the biotech industry are relatively higher than that of any other industries, which are 0.073 and 0.063, respectively. Among all 20 industries, the lowest long-run E/P level, on average, is -0.211 of the building industry.

Figure 3 exhibits the distribution of long-run E/P ratios. About 75% of the long-run means are positive, and 25% are negative. The long-run E/P ratios for 70 stationary E/P time series (about 14%) are between 0.07 and 0.1. About 20% of the long-run E/P ratios locate between 0.05 and 0.07. Another 16% of the long-run E/P ratios range from 0.03 to 0.05. In addition, 21% of the long-run means range from 0 to 0.03. As illustrated in Figure 3, obviously, the distribution of the long-run E/P ratios is skewed toward negative.

Table 4 Descriptive statistics for long-run E/P ratios[a]

	Mean	Median	Standard Deviation	25% quartile	75% quartile	Max	Min
Total stationary sample (n=516)	-0.022	0.035	0.223	-0.0006	0.062	0.14	-1.68
Construction (n=7)	-0.080	0.051	0.340	0.022	0.056	0.07	-0.85
Foods (n=16)	0.033	0.026	0.031	0.009	0.057	0.09	-0.02
Plastic (n=18)	0.034	0.044	0.046	0.024	0.058	0.11	-0.11
Textile (n=35)	-0.065	-0.013	0.189	-0.070	0.026	0.09	-0.89
Electric Machinery (n=21)	0.024	0.030	0.053	0.008	0.061	0.09	-0.14
Electric Wire and Cable (n=12)	-0.071	0.039	0.352	-0.005	0.053	0.07	-1.18
Ceramics (n=6)	-0.144	-0.012	0.253	-0.443	0.037	0.07	-0.51
Paper (n=6)	0.018	0.041	0.059	-0.013	0.052	0.06	-0.10
Steel (n=25)	-0.086	0.029	0.296	-0.115	0.071	0.11	-1.32
Rubber (n=8)	0.042	0.050	0.024	0.014	0.057	0.07	0.01
Vehicle (n=4)	0.073	0.064	0.039	0.040	0.113	0.12	0.04
Electronic (n=220)	0.003	0.041	0.182	0.011	0.066	0.14	-1.59
Building (n=37)	-0.211	-0.014	0.439	-0.295	0.027	0.13	-1.68
Transportation (n=17)	0.025	0.039	0.083	0.015	0.082	0.14	-0.18
Tourism (n=4)	0.000	0.019	0.058	-0.060	0.042	0.05	-0.08
Service and Retail (n=11)	0.039	0.042	0.046	0.006	0.064	0.12	-0.06
General Merchandise (n=33)	-0.060	0.038	0.309	-0.009	0.072	0.11	-1.29
Other (n=17)	0.016	0.043	0.074	-0.045	0.059	0.12	-0.14
Chemical (n=12)	0.042	0.051	0.040	0.021	0.064	0.11	-0.05
Biotech (n=7)	0.063	0.069	0.031	0.034	0.09	0.11	0.03

a. Each ARMA model determined by the SCAN technique is used to calculate an expected long-run E/P ratio for each corresponding stationary E/P time series. The fitted ARMA models must satisfy the stationary condition, $1-\sum_{k=1}^{p} a_k < 0$, where p is the lagged order of AR (autoregressive) terms, and a_k is a fitted autoregressive coefficient. The long-run E/P ratios of stationary ARMA(p,q) models are referred to as $a_0/(1-a_1-a_2-\cdots a_p)$.

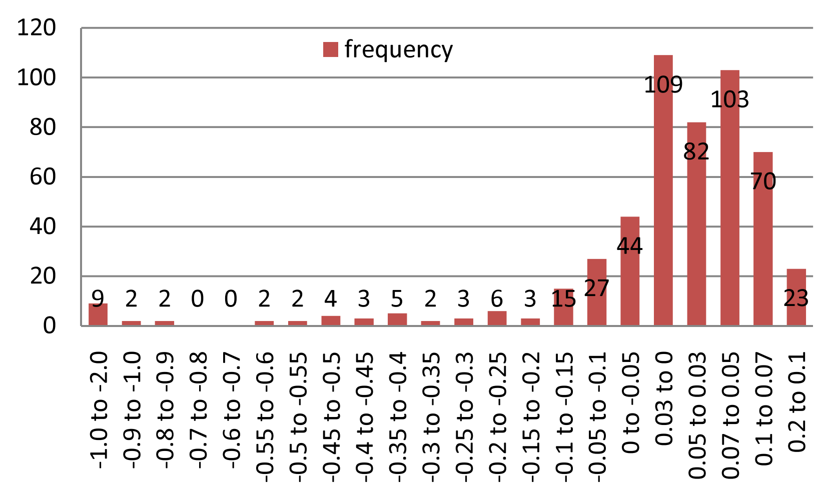

Figure 3
Distribution of long-run E/P ratios

4.4 Expected Mean Reverting Speed

We employ the regression technique to estimate the adjustment coefficients, b_1, which are used to define an expected mean reverting speed. Table 5 presents descriptive statistics for the adjustment coefficient. For the 516 firms with stationary E/P time series, the average of b_1 coefficients is 0.008. This result implies that E/P ratios of the 516 firms, on average, take 125 trading days to regress to mean when deviating away. The median and standard deviation of b_1 coefficients are 0.004 and 0.022, respectively.

In industry levels, an average of the mean reverting period estimated by b_1 coefficients for electronic firms is about 110 trading days ($1/0.009 \fallingdotseq 110$), somewhat shorter than the average period of the total sample. Among all industries, the shortest mean reverting period, on average, is 28 trading days ($1/0.036 \fallingdotseq 28$) of the rubber industry. In addition to the rubber industry, the vehicle and chemical industries tend to have shorter adjusting period than any other industries. E/P ratios in the vehicle and chemical industries, on average, take 56 and 63 trading days to restore equilibrium, respectively. The averages of b_1 coefficients for several traditional industries, such as the construction, textile, paper, and building industries, are 0.003. This result implies the price adjusting speed of these traditional industries, on average, takes about 333 trading days. The mean reverting speed of the traditional industries is slower than that of any other industries. The slower adjusting speed is likely attributable to less attention from investors.

Table 5 Descriptive statistics for adjustment coefficient-b_1[a]

	Mean	Median	Standard Deviation	25% quartile	75% quartile	Max	Min
Total stationary sample (n=516)	0.008	0.004	0.022	0.002	0.006	0.294	-0.002
Construction (n=7)	0.003	0.003	0.001	0.003	0.004	0.005	0.002
Foods (n=16)	0.004	0.003	0.002	0.002	0.005	0.009	0.001
Plastic (n=18)	0.004	0.003	0.002	0.003	0.005	0.010	0.002
Textile (n=35)	0.003	0.002	0.002	0.001	0.004	0.008	0.001
Electric Machinery (n=21)	0.009	0.004	0.016	0.002	0.006	0.057	0.001
Electric Wire and Cable (n=12)	0.003	0.003	0.002	0.001	0.005	0.006	0.001
Ceramics (n=6)	0.004	0.004	0.002	0.002	0.006	0.006	0.002
Paper (n=6)	0.003	0.003	0.001	0.002	0.004	0.006	0.002
Steel (n=25)	0.005	0.002	0.004	0.002	0.006	0.017	-0.002
Rubber (n=8)	0.036	0.004	0.092	0.003	0.005	0.265	0.002
Vehicle (n=4)	0.018	0.003	0.031	0.002	0.050	0.066	0.002
Electronic (n=220)	0.009	0.004	0.023	0.003	0.008	0.294	-0.002
Building (n=37)	0.003	0.003	0.002	0.002	0.004	0.009	0.001
Transportation (n=17)	0.003	0.003	0.001	0.003	0.004	0.007	0.002
Tourism (n=4)	0.004	0.003	0.003	0.002	0.006	0.007	0.002
Service and Retail (n=11)	0.004	0.004	0.002	0.003	0.006	0.007	0.002
General Merchandise (n=33)	0.013	0.004	0.038	0.003	0.007	0.210	0.001
Other (n=17)	0.007	0.004	0.010	0.003	0.006	0.045	0.001
Chemical (n=12)	0.016	0.004	0.020	0.002	0.039	0.050	0.001
Biotech (n=7)	0.007	0.008	0.004	0.002	0.011	0.011	0.002

a. Adjustment coefficient, b_1, is the regression coefficient of the (LP_i-$EP_{i,t-1}$) term in the following regression equation: $\Delta EP_{i,t} = b_0 + b_1(LR_i - EP_{i,t-1}) + b_2 CY_{i,t} + b_3 PTN_{i,t} + \epsilon_{i,t}$.

$EP_{i,t}$ is the E/P ratio of Firm i on Day t; $EP_{i,t-1}$ is the E/P ratio of Firm i on Day t-1. $\Delta EP_{i,t}$ is the difference in E/P ratios between Day t and Day t-1. LR_i is the expected long-run E/P ratio of Firm i, and defined as $a_0/(1 - a_1 - a_2 - \cdots a_p)$; p is the lagged order of AR (autoregressive) terms, and a_p is a fitted autoregressive coefficient. When a fiscal year changes to the next year on Day t, then $CY_{i,t}$ is set to be 1; otherwise it is 0. $PTN_{i,t}$ is a dummy variable used to control a downturn in earnings before extraordinary items. If a firm's earnings before extraordinary items deteriorate from positive to negative on Day t, then the PTN is set to be 1; otherwise it is 0.

Figure 4 shows the distribution of b_1 adjustment coefficients. Obviously, the distribution of b_1 coefficients is skewed. With a mean of 0.008 and a median of 0.004, the distribution of b_1 spreads from 0 to 0.294. 72% of the adjustment coefficients distribute from 0.002 to 0.005. The E/P ratios of 42 firms (about 8%), whose adjustment coefficients range from 0.005 to 0.006, take approximately 167 to 200 trading days to restore equilibrium. The E/P ratios of another 64 firms (about 12%), whose adjustment coefficients range from 0.004 to 0.005, take 200 to 250 trading days to converge. In addition, there are 86 firms (about 17%) with adjustment coefficients ranging from 0.003 to 0.004, and their mean reverting period is about 250 to 333 trading days. 21% of the adjustment coefficients range from 0.002 to 0.003. There are further 126 firms (about 24%), whose adjustment coefficients are greater than 0.006, and the mean reverting speed of their E/P ratios is less than 167 trading days.

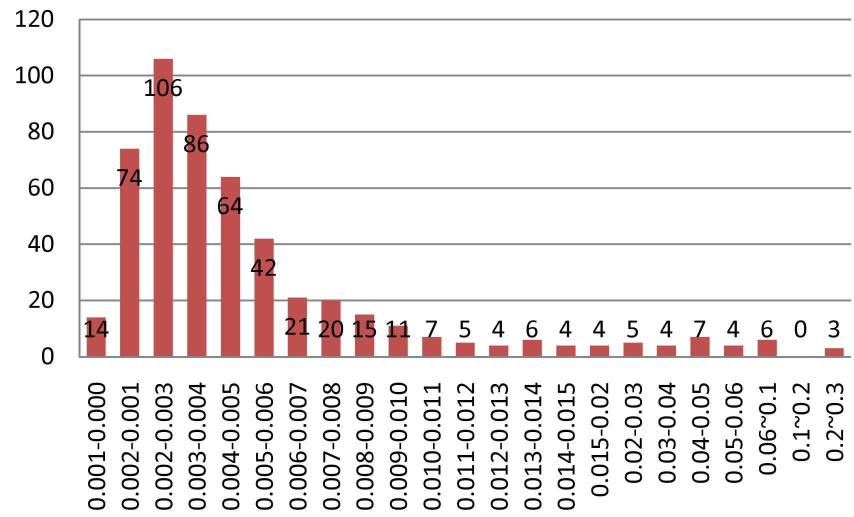

Figure 4 Distribution of b1 coefficients

4.5 Investment Performance of the Deviation Size-Based Investment Strategy

Table 6 presents the investment performance of the deviation size-based investment strategy. If a company's E/P ratio on a certain day, from 2007 to 2009 (the experiment period), falls above the 99^{th}, 95^{th} or 90^{th} percentile of an E/P empirical distribution constructed with all the E/P observations during the information period, the deviation size-based strategy is triggered to buy the company's stock and hold it until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio during the experiment period falls below the 1^{st}, 5^{th}, or 10^{th} percentile of a constructed E/P distribution, the deviation size-based strategy is triggered to short sell the company's stock. The short position is covered only after the E/P ratio regresses to its long-run mean.

The buy-in strategy is triggered 304, 380, and 452 times with respect to the 99th, 95th and 90th percentile triggers. The market adjusted return is, on average, 13% under the 99th percentile criterion, which is the best realized performance under the three buy-in criteria. The performances under the 95th and 90th percentile criteria are 11% and 8%, respectively. Those returns are significantly different from zero at a 1% level. The declining pattern in realized returns is attributable to the relatively lower uncertainty when a firm's E/P is at the 99th percentile. It is less likely for a stationary E/P ratio to deviate further when the E/P ratio is at its historically extreme level.

As to the performance of the short-sale strategy, the average market adjusted return is 12%, 15%, and 14% under the 10th, 5th, and 1st percentile criteria, respectively. The short-sale strategy is triggered 322, 247, and 197 times with respect to the 10th, 5th, and 1st percentile triggers. Those returns are all significantly different from zero, at least at a 5% level. There is also a similar pattern of decline in performance for the short-sale investments triggered by different criteria.

In addition to market adjusted returns, investors concern about raw returns. The average raw returns of buy-in investments are 24%, 16%, and 9% with respect to the 99th, 95th, and 90th percentiles triggers, respectively. The raw returns of buy-in investments are somewhat higher than the market adjusted returns and are significantly different from zero at a 1% level. The average raw returns of short-sale investments range from 5% to 8%, but are insignificantly different from zero.

Interestingly, it seems to be a fifty-fifty chance that positive returns will be realized through the buy-in strategies. For example, 149 of the 304 investments (about 49%) triggered by the 99th percentile criterion realize positive market adjusted returns, and 160 of the 304 investments (about 53%) realized positive raw returns. The percentages of the investments triggered by the 95th and 90th percentiles criteria are also about 50%. However, the buy-in strategy could still realize significantly positive returns. The results imply that the magnitudes of profits are large enough to dominate the losses.

Additionally, Table 6 reports the average holding period for the investments triggered by the deviation size-based strategy. It is obvious that the deviation size-based strategy is a long-term investment strategy. The average holding period is about 300 trading days for the buy-in investments and is about 250 trading days for short-sale investments. The holding period for the short-sale strategy is somewhat shorter than the holding period for the buy-in strategy. The shorter holding period for short-sale investments suggests the downward speed of price adjustments is faster than the price upward speed. Such an asymmetric adjusting speed might be of interest for further studies.

Table 6 Performance of the deviation size-based investment strategy[b]

Triggers[a]	99th		95th		90th		10th		5th		1st	
Average market adj. returns[c]	13.02%		11.16%		8.38%		12.17%		15.20%		13.81%	
(t value)	(3.61)	***	(3.68)	***	(3.28)	***	(3.01)	***	(3.14)	***	(2.59)	**
Raw returns[d]	23.80%		15.59%		8.58%		6.01%		7.84%		4.69%	
(t value)	(5.23)	***	(4.10)	***	(2.84)	***	(1.29)		(1.39)		(0.74)	
Number of times to invest stocks	304		380		452		322		247		197	
Average holding period (trading days)	282		300		308		236		244		256	
No. of positive market adj. returns	149		185		231		162		129		91	
% of positive market adj. returns	49%		49%		51%		50%		52%		46%	
No. of positive raw returns	169		192		225		151		110		84	
% of positive raw returns	56%		51%		50%		47%		45%		43%	

a. We construct an E/P ratio empirical distribution for each stationary E/P time series with all available observations during the information period (from the beginning of an E/P series to December 31, 2006). Then, the 99^{th}, 95^{th}, 90^{th}, 10^{th}, 5^{th}, and 1^{st} percentiles of each E/P ratio distribution are selected as proxies of high degree deviation. The 99^{th}, 95^{th}, and 90^{th} percentiles of an empirical distribution are used to define extremely high E/P levels and the triggers for purchasing stocks. The 10^{th}, 5^{th}, and 1^{st} percentiles, in contrast, are used to define extremely low E/P level and the triggers for short selling stocks.

b. The period from January 1, 2007, to December 31, 2009, is defined as the experiment period in this study. If a company's E/P ratio on a certain day, during the experiment period, falls above the 99^{th}, 95^{th}, or 90^{th} percentile of an E/P empirical distribution, we purchase the company's stock and hold it until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio in the experiment period falls below the 1^{st}, 5^{th}, or 10^{th} percentile of a constructed E/P distribution, a short position for the company's stock is constructed. The short position is covered only after the E/P ratio regresses to its long-run mean.

c. Market adjusted returns are defined as the holding period returns subtracted by the market performance over a corresponding time period.

d. Raw returns are defined as the buy-and-hold returns without subtracting the market performance over a corresponding time period.

4.6 Empirical Results for the Influence of Long-Run E/P Levels on Investment Performance

Proposition 1 and Proposition 2 predict that the firms with negative long-run E/P ratios are neither good targets to buy nor good targets to short sell. In order to test the two propositions, all investments are grouped into two categories; the investments in the stocks with negative long-run E/P ratios and in the stocks with positive long-run E/P ratios. Then, we compare the percentages of realizing positive (negative) returns in two categories for buy-in (short-sale) investments. Since the experiment period is end in 2009, the investments which are forced to end on December 31, 2009, are excluded in the testing processes of Proposition 1 and Proposition2[2]. The result is presented in Table 7. As predicted by Proposition 1, the percentage of realizing positive raw returns for buying the stocks with positive long-run E/P ratios is higher than the percentage for buying the stocks with negative long-run E/P ratios. Evidence in support of Proposition 2 is also reported in Table 7. The percentage of realizing negative raw returns for short selling the stocks with negative long-run E/P ratios is higher than the percentage for short selling the stocks with positive long-run E/P ratios.

Table 7 The effects of positive and negative long-run E/P ratios on investment performances [a]

	99th percentile [b]			95th percentile [b]			90th percentile [b]		
	n	no. positive raw return	% positive raw returns	n	no. positive raw return	% positive raw returns	n	no. positive raw return	% positive raw returns
positive LR	160	71	44%	215	97	45%	274	134	49%
negative LR	18	2	11%	19	1	5%	23	1	4%

	10th percentile [b]			5th percentile [b]			1st percentile [b]		
	n	no. negative raw return	% negative raw returns	n	no. negative raw return	% negative raw returns	n	no. negative raw return	% negative raw returns
positive LR	141	18	13%	99	9	9%	72	6	8%
negativeLR	12	5	42%	7	2	29%	5	2	40%

a. The sample analyzed in Table 7 excludes the investments which are forced to end on December 31, 2009.

[2] The analyzing processes are not reported. The investments which are forced to end on December 31, 2009, do not satisfy the analyzing conditions. As a result, the investments are excluded. The analyzing processes are available from the corresponding author by request.

b. If a company's E/P ratio on a certain day, from 2007 to 2009, falls above the 99th, 95th, or 90th percentile of an E/P empirical distribution constructed with all the E/P observations during the information period, a buy-in strategy is triggered to purchase the company's stock and hold it until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio, from 2007 to 2009, falls below the 1st, 5th, or 10th percentile of a constructed E/P distribution, a short-sale strategy is triggered to short sell the company's stock. The short position is covered only after the E/P ratio regress to its long-run mean. Raw returns are defined as the holding period returns without subtracting the market performance over a corresponding time period.

c. LR is a firm's long-run E/P ratio.

Proposition 3 and Proposition 4 predict the effect of the magnitudes of long-run E/P ratios on the investment performance. Panel A of Table 8 provides evidence to support the prediction of Proposition 3. Although the relationship between the magnitudes of long-run E/P ratios and the percentage of realizing positive raw returns is not monotonously increasing, there still exhibits an increasing pattern in Panel A of Table 8. Panel B of Table 8 presents the relationship between the levels of long-run E/P ratios and short-sale performances. As predicted by Proposition 4, for the firms with positive long-run E/P ratios, the percentage of realizing negative raw returns in short-sale investments decreases with the levels of long-run E/P ratios. The implication behind Table 8 for investing practice is that the stocks with high long-run E/P ratios are better investment targets, even for short-selling, than the stocks with low long-run E/P ratios.

Table 8

Panel A. The relationship between the levels of long-run E/P ratios and the investment performances－buy in strategies [a]

Range of LR [c]	99th percentile [b]			95th percentile [b]			90th percentile [b]		
	n	no. positive raw returns	% of positive raw returns	n	no. positive raw returns	% of positive raw returns	n	no. positive raw returns	% of positive raw returns
0~0.02	12	3	25%	14	2	14%	17	4	24%
0.02~0.03	10	2	20%	14	4	29%	15	5	33%
0.03~0.04	22	10	45%	23	9	39%	30	14	47%
0.04~0.05	8	5	63%	13	5	38%	22	9	41%
0.05~0.06	17	10	59%	29	17	59%	45	24	53%
0.06~0.07	26	14	54%	38	21	55%	41	21	51%
0.07~0.08	20	10	50%	28	16	57%	39	27	69%
0.08~0.09	25	7	28%	30	9	30%	33	11	33%
0.09~0.10	7	5	71%	8	5	63%	9	6	67%
more than 0.10	13	5	38%	18	9	50%	23	13	57%

a. The sample analyzed in Table 8 excludes the investments which are forced to end on December 31, 2009.

b. If a company's E/P ratio on a certain day, during 2007 to 2009, falls above the 99th, 95th, or 90th percentile of an E/P empirical distribution constructed with all the E/P observations during the information period, a buy-in strategy is triggered to purchase the company's stock and hold it until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio, during 2007 to 2009, falls below the 1st, 5th, or 10th percentile of a constructed E/P distribution, a short-sale strategy is triggered to short sell the company's stock. The short position is covered only after the E/P ratio regress to its long-run mean. Raw returns are defined as the holding period returns without subtracting the market performance over a corresponding time period.

c. LR is a firm's long-run E/P ratios.

Table 8

Panel B. The relationship between the levels of long-run E/P ratios and the investment performances－short sale strategies [a]

Range of LR [c]	10th percentile [b]			5th percentile [b]			1st percentile [b]		
	n	no. raw negative returns	% of raw negative returns	n	no. raw negative returns	% of raw negative returns	n	no. raw negative returns	% of raw negative returns
0~0.02	8	3	38%	4	1	25%	3	1	33%
0.02~0.03	10	0	0%	10	1	10%	8	1	13%
0.03~0.04	8	2	25%	5	0	0%	5	0	0%
0.04~0.05	5	0	0%	3	0	0%	2	0	0%
0.05~0.06	10	2	20%	7	2	29%	5	0	0%
0.06~0.07	21	2	10%	14	1	7%	7	1	14%
0.07~0.08	22	3	14%	17	1	6%	12	0	0%
0.08~0.09	28	4	14%	14	3	21%	11	2	18%
0.09~0.10	11	0	0%	8	0	0%	5	0	0%
more than 0.10	18	2	11%	17	1	6%	14	1	7%

a. The sample analyzed in Table 8 excludes the investments which are forced to end on December 31, 2009.

b. If a company's E/P ratio on a certain day, from 2007 to 2009, falls above the 99th, 95th, or 90th percentile of an E/P empirical distribution constructed with all the E/P observations during the information period, a buy-in strategy is triggered to purchase the company's stock and hold it until the firm's E/P ratio reverts to its long-run mean. On the contrary, if a company's E/P ratio, from 2007 to 2009, falls below the 1st, 5th, or 10th percentile of a constructed E/P distribution, a short-sale strategy is triggered to short sell the company's stock. The short position is covered only after the E/P ratio regress to its long-run mean. Raw returns are defined as the holding period returns without subtracting the market performance over a corresponding time period.

c. LR is a firm's long-run E/P ratios.

5. Conclusion

The purpose of this study is to investigate the mean reversion characteristic in firm-specific P/E ratios and employ it for investment practice. However, negative P/E ratio is meaningless, and P/E ratio will diverge when the denominator (EPS) is close to zero. We adopt E/P ratio in our tests. The sample in this study consists of 1,156 non-finance firms listed on TSE and OTC in Taiwan in 2006. Not all E/P time series of individual stocks exhibit a mean reversion feature. Among the 1,156 firms, the E/P ratios of 516 firms (about 45%) exhibit the tendency of mean reversion. For the firms which have listed over 10 years, their E/P time series have a higher probability to become stationary. Furthermore, ARMA models are utilized to capture the mean reverting behavior of firm specific E/P ratios. According to the results of our investigation, ARMA(1,0), ARMA(2,0) and ARMA(2,1) are the most common models to dominate the mean reverting behavior of firm specific E/P ratios. The mean reversion feature of the E/P ratio implies a firm's E/P ratios would revert to a long-run average level when deviating away. Using the fitted ARMA models, we estimate firm-specific long-run E/P ratios for the 516 firms of having stationary E/P time series. The mean and median of the 516 long-run E/P ratios are -0.022 and 0.035, respectively. In addition, we analyze the mean reverting speed for the 516 firms whose E/P ratios exhibit a mean reversion feature. The average mean reverting speed for the 516 firms is about 125 trading days.

The current study also makes an effort to combine the mean reversion theory with investment practice. An investment strategy based on the detected mean reversion feature of E/P ratio is argued. The strategy is a strategy triggered by the deviation size of E/P ratios, and it could realize significantly positive raw returns and market adjusted returns in Taiwan stock market. More specifically, we argue that the firms with negative long-run E/P ratios are neither good targets to buy nor good targets to short sell. In addition, firms with higher long-run E/P ratios are better investment targets, even for short selling. An area of future research that should be considered is the factors which would affect the investment performances of the strategy. Furthermore, the adjusting speed of upward and downward mean reverting processes might differ from each other. Such asymmetric mean reverting speed might be helpful to improve the investment performances. It might be of interest for further studies.

Finally, there are three more recommendations for future research. First, whether firm-specific E/P ratios in other stock markets exhibit the mean reversion feature needs further exploration. Second, the factors accounting for long-run E/P ratios and the mean reverting speed remain for future studies. Third, perhaps future research could replace the E/P ratio by the price-to-equity book value ratio (P/B) as a valuation indicator to overcome the influence of changes in earnings on the E/P mean reverting process.

Reference

Ahmed, P., K. Beck, and E. Goldreyer. 2000. "Can Moving Average Technical Trading Strategies Help in Volatile and Declining Markets? A Study of Some Emerging Asian Markets." *Managerial Finance* 26, no. 6: 49-53.

Aksoy, H. and I. Saglam. 2006. "Patience Extracts Sugar from a Lemon-Buy and Hold with a Classifier System in the Istanbul Stock Exchange." *Emerging Markets Finance and Trade* 42, no. 1 (Jan/Feb): 50-61.

Bhargava, V. and D. Malhotra. 2006. "Do Price-Earnings Ratios Drive Stock Values?" *Journal of Portfolio Management* 33, no. 1 (Fall): 86-92.

Campbell, J. and R. Shiller. 1988. "Stock Prices, Earnings, and Expected Dividends." *Journal of Finance* 43, no. 3 (July): 661-676.

Campbell, J. and R. Shiller. 1998. "Valuation Ratios and the Long-Run Stock Market Outlook." *Journal of Portfolio Management* 24, no. 2 (Winter): 11-26.

Campbell, J. and R. Shiller. 2001. "Valuation Ratios and the Long-Run Stock Market Outlook: An Update." Working Paper. Yale University.

Campbell, J. and M. Yogo. 2006. "Efficient Tests of Stock Return Predictability." *Journal of Financial Economics* 81, no. 1 (July): 27-60.

Campbell, J. and S. Thompson. 2008. "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?" *Review of Financial Studies* 21, no. 4 (July): 1509-1531.

Carlson, J., E. Pelz, and M. Wohar. 2002. "Will Valuation Ratios Revert to Historical Means?" *Journal of Portfolio Management* 28, no. 4 (Summer): 23-35.

Dickey, D. and W. Fuller. 1979. "Distribution of the Estimates for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74, no. 366 (June): 427-431.

Granger, C. and P. Newbold. 1974. "Spurious Regressions in Econometrics." *Journal of Econometrics* 2 (July): 111-120.

Enders, W. *Applied Econometric Time Series*. 2nd ed. NJ: John Wiley & Sons. 2004.

Goyal, A. and I. Welch. 2006. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies* 21, no. 4 (July): 1455-1508.

Hayashi, F. *Econometrics*. 1st ed. Princeton, NJ: Princeton University Press. 2000.

"Hybrid Vigour-Taiwan's tech firms are conquering the world-and turning Chinese." (2010, May 27) *The Economist*.

Ito, A. 1999. "Profits on Technical Trading Rules and Time-Varying Expected Returns: Evidence from Pacific-Basin Equity Markets." *Pacific-Basin Finance Journal* 7, no. 3 (August): 283-330.

Kang, J., M. Liu, and S. Ni. 2002. "Contrarian and Momentum Strategies in the China Stock Market: 1993-2000." *Pacific-Basin Finance Journal* 10, no. 3 (June): 243-265.

Krausz, J., S. Lee, and K. Nam. 2009. "Profitability of Nonlinear Dynamics under Technical Trading Rules: Evidence from Pacific Basin Stock Markets." *Emerging Markets Finance and Trade* 45, no. 4 (Jul/Aug): 13-35.

McKenzie, M. 2007. "Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises." *Emerging Markets Finance and Trade* 43, no. 4 (July): 46-73.

Muga, L. and R. Santamaria. 2007. "The Momentum Effect in Latin American Emerging Markets." *Emerging Markets Finance and Trade* 43, no. 4 (July): 24-45.

Rouwenhorst, K. 1999. "Local Return Factors and Turnover in Emerging Stock Markets." *Journal of Finance* 54, no. 4(August): 1439-1464.

Tsay, R. S. and Tiao, G. C. 1985. "Use of canonical analysis in time series model identification." *Biometrika* 72, no. 2: 299-315.

Weigand, R. and R. Irons. 2007. "The Market P/E Ratio, Earnings Trends, and Stock Return Forecasts." *Journal of Portfolio Management* 33, no. 4 (Summer): 87-101.

Zhou, H., J. Geppert, and D. Kong. 2010. "An Anatomy of Trading Strategies: Evidence from China." *Emerging Markets Finance and Trade* 46, no. 2 (Mar/Apr): 66-79.