Forecasted Earnings per Share and the Cross Section of Expected Stock Returns*

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This version: November 14, 2006

*We appreciate helpful comments from Kalok Chan, Louis Chan, Eric Chang, Xin Chang, Sudipto Dasgupta, Jie Gan, Chu Zhang, and the seminar participants at the Hong Kong University of Science and Technology, National Chiao-Tung University, and Peking University.

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Abstract

In this paper, we document that analysts' forecasted earnings per share (*FEPS*) can predict subsequent stock returns. More specifically, stocks with higher *FEPS* earn substantially higher future returns than do stocks with lower *FEPS*, even after controlling for the market risk, the size, the value and earnings-to-price effects, and the price and earnings momentum. This *FEPS* effect is the strongest for stocks of small firms, those with low prices, those with little analyst coverage, and those that were past losers. Furthermore, the *FEPS* effect is sustained over a long period of time without any subsequent reversal. We also find that trading strategies based on *FEPS* are not fundamentally riskier. The abnormal returns on *FEPS* trading strategies are even countercyclical to the overall market performance. Further analysis indicates that stocks with lower *FEPS* show larger *ex ante* forecast errors as measured by forecasted earnings per share minus actual earnings per share divided by the absolute value of actual earnings per share relative to stocks with higher *FEPS*. In addition, the abnormal returns are largely concentrated during the three-day windows around future earnings announcements. The evidence is consistent with the errors-in-expectations explanation that investors overvalue (undervalue) stocks when their expectations about future earnings per share are low (high). Our results are robust to several risk-adjustment techniques, various measures of earnings, and are not due to outliers or sample selection.

JEL Classification: G11, G12, G14

Keywords: Forecasted earnings per share; Earnings-to-price; Earnings momentum; Forecast errors; Errors-in-expectations

The capital asset-pricing model (CAPM) of Sharpe (1964) and Lintner (1965) predicts that expected stock returns are only related to the market beta or systematic risk. Nevertheless, several empirical studies have found results that contradict the predictions of the CAPM. Such observations are generally referred to as anomalies. For example, it has been well established that the cross section of future stock returns is predictable based on value strategies, such as earnings-to-price (*E/P*) ratios, cash-flow-to-price (*C/P*) ratios, book-to-market (*B/M*) ratios and past sales growth rates, and based on past return strategies, such as long-term contrarian and medium-term momentum.[1] However, Fama and French (1996) find that their three-factor model, as an extension to the Merton's (1973) intertemporal CAPM (ICAPM), can largely explain the abnormal profitability generated by the value and contrarian strategies, which are often referred to as the value and contrarian effects, respectively.[2] In contrast, the three-factor model fails to explain the medium-term momentum profitability. Therefore, unlike the value and contrarian profitability, momentum profitability is not driven by known risk factors and stands out as a perfect example of the existence of anomalies.

In this paper, we find a strong positive relation between the levels of analysts' forecasted earnings per share (*FEPS*) and future stock returns. Stocks with high *FEPS* significantly outperform stocks with low *FEPS*. In particular, the *FEPS* strategy of buying stocks in the highest *FEPS* decile and selling stocks in the lowest *FEPS* decile generates a return of 1.199 percent per month, which has a similar magnitude as that generated by the momentum strategy. This return spread remains as large as 0.878 percent per month even after controlling for the Fama and French three factors and the momentum factor (i.e., a four-factor model). Additionally,

[1] See, for example, Fama and French (1992, 1996) for the detailed discussions of these anomalies. A contrarian (momentum) strategy is called for buying (selling) past losers and selling (buying) past winners.
[2] A popular view held by many economists is that small or value stocks are fundamentally riskier. Hence, the size and value factors in the Fama and French model simply capture the distress risk. This is consistent with the spirit of the ICAPM in the sense that these two factors could be viewed as proxies for special hedging demands by investors.

FEPS predicts future abnormal returns for up to three years, but with diminishing significance over time. The results are robust to several risk-adjustment techniques, various measures of earnings, and not due to outliers or sample selections.[3]

Although earnings-related strategies can be traced back to Graham and Dodd (1934), the isolated role played by the level of earnings itself in predicting future returns has mostly been ignored. Prior empirical studies investigating the information content of earnings focus mainly on *earnings surprises* and not much on earnings per share (*EPS*) or *FEPS*.[4] The implicit assumption is that only earnings surprises reflect new information coming to the market, while *EPS* or *FEPS* does not contain any useful information that has not been priced by the market. Academics and professional investors often treat *EPS* or *FEPS* as a deflator to obtain other normalized measures (e.g., dispersion in analyst forecasts) in order to make meaningful comparisons across stocks. However, since *EPS* or *FEPS* can predict future stock returns as discussed here, the predictability of any accounting or stock variable using *EPS* or *FEPS* as a deflator could be from the predictability of *EPS* or *FEPS* itself rather than from the variable of interest.[5]

It is not easy to reconcile the *FEPS* effect with any existing risk-based interpretation. The four-factor model leaves a large unexplained proportion of superior profits produced by the *FEPS* strategy, although those profits are partially explained by the value and momentum factors. We find little, if any, support for the view that the *FEPS* strategy is fundamentally riskier. In fact, stocks with higher *FEPS* show properties that are associated with lower risk, represented by

[3] In fact, both the levels of forecasted total earnings and the past actual earnings on the per share basis have a similar predictive power on future stock returns, which suggests that the scaling of earnings by the number of shares outstanding does not affect our results. We also examine several measures of consensus analyst forecasts such as the mean, median or time-weighted average of analyst earnings forecasts. Our results remain unchanged.

[4] Earnings surprises can be measured by the unexpected components in earnings, the analysts' revisions of earnings forecasts, or the abnormal returns around earnings announcements (see Chan, Jegadeesh, and Lakonishok (1996)).

[5] For example, Diether, Malloy and Scherbina (2002) use *FEPS* as the denominator of their measure of dispersion in analyst forecasts.

lower market risk (beta), better liquidity (larger firm size and higher price per share), and higher profitability (higher returns on equity). The evidence seems inconsistent with our finding of the positive relation between *FEPS* and future returns. Furthermore, if the *FEPS* strategy is fundamentally riskier, these strategies should underperform the market with some frequency, especially when the marginal utility of wealth is high. However, the time-series pattern of the *FEPS* effect shows that the *FEPS* strategy is countercyclical to the overall market performance. This seems to contradict the traditional argument about risk according to the consumption-based CAPM. In general, the results strongly reject the possibility that *FEPS* serves as a measure of identified risk according to our current knowledge. Of course, at this stage, we cannot rule out the possibility that the *FEPS* effect is actually driven by some unknown risk factors or time-varying risks that coincide with the *FEPS* effect.

An alternative explanation, initially introduced by Lakonishok, Shleifer, and Vishny (1994) and La Porta (1996) in support of a series of value strategies, is that these strategies work because they capture systematic errors in the way that investors form expectations about future returns and because the stock market is not fully efficient.[6] Along this line, the *FEPS* strategy might be just a value strategy. Value strategies produce superior returns because they exploit the suboptimal behavior of typical investors and not because they are fundamentally riskier. Regardless of the reasons, investors or analysts might consistently overestimate the growth rates of future earnings for stocks with low *FEPS* and underestimate future growth rates of earnings for stocks with high *FEPS*. As a result, the former group of stocks becomes overpriced, while the latter group of stocks becomes underpriced. In a nutshell, the essence of this argument is that

[6] These value strategies call for buying stocks that have low prices relative to earnings, dividends, historical prices, book assets, or other measures of fundamental value. Lakonishok, Shleifer, and Vishny (1994) argue that value investments that bet against investors who extrapolate past performance too far into the future have superior performance. La Porta (1996) empirically proves that the superior performance of value strategies can be attributed to investors' errors about future growth in earnings.

investors are excessively optimistic (pessimistic) about stocks with low (high) *FEPS*, because they tie their expectations for future growth in earnings inversely to the levels of their expectations for future *EPS*. Ultimately, the *FEPS* strategy generates abnormal profits as systematic errors-in-expectations are corrected by the market when actual earnings arrive in the future. Consistent with this view, we find that stocks with lower *FEPS* show much larger forecast errors as measured by (*FEPS – Actual EPS*)/|*Actual EPS*| relative to stocks with higher *FEPS*. In addition, the abnormal returns to the *FEPS* strategy are largely concentrated during the three-day windows around future earnings announcements. Finally, the predictive power of *FEPS* diminishes over time. Moreover, we provide evidence that the historical *EPS* strategy predicts similar cross-sectional patterns in returns (although smaller) as the does *FEPS* strategy, suggesting that systematic errors made by investors, if any, are indeed linked to the levels of *EPS*.[7]

Our results inevitably raise the question of how the *FEPS* strategy continues to make profits if this strategy is are not fundamentally riskier but actually captures mispricing in stocks. Although the errors-in-expectations explanation appears to be a good start, we take a step further in this direction by presenting some other possible explanations that rely on recent findings in the behavioral finance literature. First, the natural behavior of investors constitutes the key prerequisite for the existence of any mispricing related to *FEPS*. Barberis, Shleifer, and Vishny (1998) suggest that there is a "conservatism bias," which is widely recognized by cognitive psychologists. They show that this conservatism bias might lead investors to underreact to information. Jegadeesh and Titman (2001) suggest that this conservatism bias potentially explains momentum profits in the way that investors tend to gradually incorporate past

[7] The historical *EPS*, which is public information known by investors, could serve as a less-than-perfect proxy for the level of expectations of investors on future *EPS*, compared with analysts' earnings forecasts.

information into stock prices. Similarly, an extensive body of literature argues that security analysts respond sluggishly to news on past earnings announcements in updating their earnings forecasts and investors also underreact to past news on fundamentals such as earnings announcements. Consequently, the well-known price momentum or earnings momentum (researchers also refer to the latter as the "post earnings announcement drift") arises.[8] We postulate that the *FEPS* effect might share a similar mechanism. More generally, given the bounded rationality of investors and the limited information set of securities, any systematic bias tied to the levels of *FEPS* might result in substantial mispricing in stocks, which, in turn, might provide trading opportunities to explore such mispricing. It is possible that *FEPS* itself conveys some information that is ignored by analysts and investors. It is also possible that investors mistakenly perceive that *FEPS* possesses a "mean-reverting" property, when, in fact, this is not the case.[9] If these conjectures are true, it is plausible that we observe another type of momentum based on the levels of *FEPS*, in addition to the conventional types based on past returns or earnings surprises.

However, it is worth noting that the *FEPS* effect is not attributed to any recognized anomalies in the prior literature. The abnormal returns predicted by *FEPS* last a long period of time and do not show any subsequent reversal, which visually differentiates the *FEPS* effect from price momentum. Further analysis shows that the *FEPS* effect survives several well-known cross-sectional effects, such as the earnings-to-price effect (Basu (1983) and Jaffe, Keim and Westerfield (1989)) and earnings momentum (Chan, Jegadeesh, and Lakonishok (1996)).

[8] See, for example, Bernard and Thomas (1989, 1990), Abarbanell and Bernard (1992), Chan, Jegadeesh, and Lakonishok (1996), Bernard, Thomas, and Wahlen (1997), and Hong, Lim, and Stein (2000).

[9] Given the belief that *EPS* is mean-reverting, investors could naively postulate that stocks with high *EPS* cannot maintain their earnings. Similarly, stocks with low *EPS* cannot be always the losers. If investors act in this way, stocks with extreme *EPS* are mispriced.

On the other hand, the mispricing related to *FEPS* cannot be traded away immediately by arbitrageurs since the limits of arbitrage deter arbitrage activities. In recent years, arbitrage risk has attracted great academic attention. Several authors (see, for example, Shleifer and Vishny (1997), Loewenstein and Willard (2000), and Liu and Longstaff (2004)) provide theoretical models to demonstrate that arbitrage is both costly and risky, and hence mispricing can be sustained in equilibrium for a long period of time when financial markets have frictions or imperfections. As a result, arbitrageurs may not be willing to exploit arbitrage opportunities in the mispricing related to *FEPS*, if the costs and risk of arbitrage exceed its benefits. The situation should be more prevalent in stocks with the greatest arbitrage risk, thereby allowing mispricing to have a larger magnitude in these stocks. As time goes by and earnings news is released, such mispricing will eventually converge. Consistent with this argument, we find that the *FEPS* effect is most pronounced in stocks of small firms, with low prices, low analyst coverage, and past losers, for which the arbitrage risk is obviously the most severe. We also find that the profits of the *FEPS* strategy mainly contribute to the short side of the hedge portfolios that have low *FEPS*. This evidence supports Miller's (1977) prediction that the prices of overvalued stocks tend to reflect optimistic investors' valuations because pessimistic investors are forced to stay out of the market by short-sale constraints. High short-sale costs only affect the correction of overvalued stocks, whereas the correction of undervalued stocks is not affected. Consequently, the upwardly biased prices in stocks with low *FEPS* are more common than the downwardly biased prices in stocks with high *FEPS*.

The remainder of this paper is organized as follows. The next section briefly describes our data and summarizes our sample characteristics. Section II examines the profitability of trading strategies based on *FEPS* and analyzes the risk profile of the *FEPS* strategy. Section III provides some evidence that supports the mispricing explanation related to errors-in-expectations. Various robustness checks are reported in Section IV. Finally, Section V concludes the paper.

I. Data and Sample

Our basic sample consists of all NYSE, AMEX and Nasdaq-listed common stocks in the intersection of (a) the CRSP stock file, (b) the merged Compustat annual industrial file, and (c) the I/B/E/S unadjusted summary historical file for the period from January 1983 to December 2004. To be included in the sample for a given month, *t*, a stock has to satisfy the following criteria. First, its mean of analyst forecasts on the one-year-ahead (*FY*1) earnings per share (*FEPS*) in the previous month, *t*-1, should be available from the I/B/E/S unadjusted summary historical file. Second, its returns in the current month, *t*, and the previous six months, from *t*-6 to *t*-1, should be available from CRSP, and sufficient data should be available to obtain market capitalization and stock price in the previous month, *t*-1. Third, sufficient data from CRSP and Compustat should be available to compute the Fama and French (1993) book-to-market ratio as of December of the previous year. Ultimately, stocks with share prices lower than five dollars at the end of the previous month, *t*-1, are excluded, as are the stocks with negative reported Compustat book value of stockholders' equity (Item #60) as of the previous month, *t*-1.[10] This screening process yields 712,563 stock-month observations or an average of 2,699 stocks per month.[11]

[10] Following previous literature (e.g., Jegadeesh and Titman (2001)), we remove stocks with prices under $5 because these stocks not only have small analyst coverage, but they also incur large transaction costs due to their poor market liquidity (thin trading and large bid-ask spreads), which could distort the feasibility of the trading strategies based on *FEPS*. We remove the stocks with negative book value of stockholders' equity simply to make some measures meaningful (e.g., returns on equity or fundamental value-to-price ratios).

[11] Using the above criteria in sample screening does not overstate the results in this paper. Actually, the *FEPS* anomalies are even stronger if we relax the last three criteria.

For each stock, we construct the following variables for each month.[12] *FEPS* is the mean of forecasted *FY*1 *EPS* in the previous month, *t*-1, from I/B/E/S. *Size* is the market value of equity at the end of the previous month, *t*-1, from CRSP. *B*/*M* is the ratio of book value of equity (*BE*) to market value of equity (*ME*), where *BE* is defined as the Compustat book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credits (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. As in Fama and French (1993), the value of *B*/*M* in predicting returns from July of year τ to June of year τ+1 is computed using *BE* for the fiscal year-end in calendar year τ-1 from Compustat and *ME* at the end of December of year τ-1 from CRSP.

Price is the stock price at the end of the previous month, *t*-1, from CRSP. $Ret_{-6:0}$ is the cumulative return over the past six months as of the previous month, *t*-1, from CRSP. *Analyst* is the number of I/B/E/S analysts who provide *FY*1 *EPS* in the previous month, *t*-1. *FE/P* is the forecasted earnings-to-price ratio in the previous month, *t*-1, and is *FEPS* divided by *Price* on the corresponding date of the I/B/E/S statistical period.[13] *BPS* is the book value of stockholders' equity per share in the previous month, *t*-1, which is simply the book value of equity on the most recent announced fiscal year-end as of the previous month, *t*-1, divided by the number of shares outstanding on the corresponding date of the I/B/E/S statistical period.[14] *FROE* is the forecasted returns on equity in the previous month, *t*-1, and is *FEPS* divided by *BPS*.

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[12] For each of these characteristic variables, values greater than the 0.995 fractile or less than the 0.005 fractile in each month are set equal to the 0.995 and 0.005 fractile values, respectively, in order to avoid the twist of summary statistics induced by outliers.

[13] To obtain the stock price and the number of shares outstanding (used in computing *FROE*) on the corresponding date, we match the I/B/E/S statistical period *STATPERS* with the date in the CRSP daily stock file.

[14] We match the monthly *FEPS* to the recent book value of stockholders' equity according to the fiscal year-end date in the following way. First, we take the variable *FY0EDATS* from the I/B/E/S unadjusted summary historical file for each monthly observation, which shows the exact latest fiscal year-end at which the accounting data have already

All these variables are either lagged by one month or computed based on public information as of the previous month, t-1, in order to guarantee that they are already known by investors at the beginning of each month. Table I provides the summary descriptive statistics of our sample. Panel A reports the time-series averages of the cross-sectional means, medians, standard deviations and other statistics of the above variables, while Panel B reports the correlation coefficients among these variables. As shown in Panel A, all of the variables exhibit substantial variation, suggesting that the portfolio sorting strategies using these characteristics should offer reasonably statistical power for our tests. Since *Size* displays the largest skewness, in the following regression analysis, we employ a logarithmic transformation of this variable. Moreover, its distribution as represented by a relatively large mean (1.929 billion) or median (0.332 billion) compared with the breakpoints for all CRSP stocks (data not shown) indicates that the sample restricted to firms covered by I/B/E/S unavoidably omits many small stocks. Since the return anomalies reported in this paper are stronger in small stocks, the bias of our sample towards relatively large stocks seems not to overstate our results. In Panel B, it is not surprising that *FEPS* is highly correlated with *Price* (correlation=0.729), *FE/P* (0.594), and *BPS* (0.644). *FEPS* is also mildly correlated with *Size*, *Analyst* and *FROE*. Surprisingly, *FEPS* has a very low correlation with *B/M* (correlation=0.061).

[Insert Table I about here]

Though I/B/E/S began in 1976, we restrict our sample period to January 1983 through December 2004 for two reasons. First, by January 1983, the cross section of stocks was large enough and had substantial variation in size and book-to-market ratios, which is helpful for the portfolio tests. Second, the I/B/E/S detailed historical file began in 1983. Hence, we can only

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been released to the public. We then find the corresponding accounting data in Compustat by matching *FY0EDATS* with the Compustat variable *FYENDDT*, which denotes the fiscal year-end for each annual observation.

conduct robustness checks on the results in this paper with the detailed file data since 1983. Extending the sample period to 1976 does not change our results.

Before examining the predictions of the consensus analyst forecasts (proxied by *FEPS*) on stock returns, we would like to emphasize the importance of using the I/B/E/S unadjusted data rather than the I/B/E/S adjusted data. The difference between these two data sets is that the unadjusted *FEPS* is the historical value, while the adjusted *FEPS* has been adjusted for stock splits and reported on the basis of the number of shares outstanding as of the latest data release day. Consequently, when we perform trading strategies based on *FEPS*, the results are only valid when the unadjusted *FEPS* is used because this measure reflects the actual value that investors had historically perceived at that time. The results are not valid based on the adjusted *FEPS* because this measure contains *ex post* information reflecting stock splits which could induce severe selection biases.

II. Trading Strategies Based on *FEPS*

To identify the predictive power of *FEPS* on future returns, we first use portfolio analysis. Specifically, we form portfolios based on the ranking of the updated *FEPS*. To control for other standard cross-sectional effects, we first sort the portfolios based on certain firm characteristics, such as *Size*, *Price*, *B/M*, and $Ret_{-6:0}$. Within each of these sorted portfolios, we further sort the portfolio based on *FEPS*. To control for risk, we also use the four-factor model to adjust portfolio returns.

A. *Portfolio Characteristics and Abnormal Returns*

In this section, we assign our sample into decile portfolios (*P*1 - *P*10) based on *FEPS* in the previous month. Portfolio *P*1 (*P*10) comprises stocks with the lowest (highest) *FEPS*. On monthly average, there are about 270 stocks in each portfolio. Table II presents the averages of the portfolio characteristics for these ten *FEPS*-sorted portfolios over the period 1983 to 2004 and future returns over the period 1983 to 2005.[15] The last row of Table II reports the differences in means between the highest and the lowest *FEPS* portfolios, denoted as *P*10–*P*1.[16] To partially remedy the survival biases in calculating the cumulative portfolio returns, $Ret_{0:n}$, over different holding periods (n = 1, 6, 12, or 36 months), we use all available returns of individual stocks up to the delisting month. That is, if a stock is delisted during the holding period, the proceeds of the stock are invested equally in the remaining stocks from the month it is delisted.

[Insert Table II here]

The patterns of *FEPS*-sorted portfolio characteristics appear to be consistent with the correlation matrix reported in Table I. Firm size, price, analyst coverage, forecasted earnings-to-price ratio, book value of stockholders' equity per share, and forecasted returns on equity monotonically increase as we move from *P*1 (*FEPS* = -0.584) to *P*10 (*FEPS* = 4.825). On the other hand, the book-to-market ratio and past return does not vary much. In a comparison of portfolio *P*10 with *P*1 only, the *P*10 stocks are slightly higher in book-to-market ratios and in the past six-month returns. But the difference in the past returns is not statistically significant, unlike the differences in other characteristics. As a result, we need to control for the effects of these firm characteristics in the following analysis.

[15] As an exception, we restrict the sample period to January 1983 to December 2002 in calculating $Ret_{0:36}$.

[16] Throughout this paper, the statistical significance of such differences is assessed using the time-series means and standard errors of the monthly estimates over the sample period, and the Newey and West (1987) procedure is used to correct for serial correlations.

FEPS shows a strong predictive power on future returns, which is not reported in the prior literature. There is an almost monotonic relation between *FEPS* and future returns, $Ret_{0:n}$. The $P10$–$P1$ strategy produces remarkable positive returns for different holding periods. Specifically, this hedging strategy earns 1.199 percent, 5.792 percent, 11.386 percent, and 26.541 percent returns over one-, six-, twelve-, and thirty-six-month holding horizons, respectively. The returns are both statistically and economically significant.[17] More interestingly, of those $P10$–$P1$ spreads, about two-thirds of the profits come from the short side of the trade ($P1$), and one-third comes from the long side ($P10$). We take as an example, the six-month horizon. The difference in returns between $(P5+P6)/2$ and $P1$ is 3.937 percent, which accounts for 68 percent of the total spread, while the difference in returns between $P10$ and $(P5+P6)/2$ is 1.855 percent, which accounts for the remaining 32 percent of the total spread. In addition, when we plot the portfolio returns against the portfolio ranks from $P1$ to $P10$, it appears that the slope is the steepest from $P1$ to $P2$. This indicates that the contributions to the profits based on the *FEPS* strategy are asymmetrical between high *FEPS* stocks and low *FEPS* stocks. These results appear to support the mispricing explanation for the *FEPS* effect, in the way that stocks are easier to overvalue than to undervalue due to short-sale constraints.

Figure 1 plots the average cumulative returns at monthly intervals to the hedging strategy of buying portfolio $P10$ and selling portfolio $P1$. It reveals that the abnormal returns to the *FEPS* strategy grow stably and smoothly. Although the profits are accumulated at a decreasing speed, they do not show any reversal over thirty-six months. This evidence clearly distinguishes the *FEPS* effect from the momentum profitability, as Jegadeesh and Titman (2001) find a dramatic reversal of returns to the momentum strategies after one year.

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[17] We report *t*-statistics for n-month cumulative returns adjusted for serial correlation using the Newey and West (1987) procedure with n–1 lags.

[Insert Figure 1 here]

The returns to the *FEPS* strategy do not simply capture the earnings-to-price effect, although *FEPS* and earnings-to-price ratios are positively correlated. We replicate the above analysis by using *FE/P* instead (results not shown). The characteristics of *FE/P*-sorted portfolios look largely different from those of *FEPS*-sorted portfolios. In particular, *FE/P*-sorted portfolios do not show any monotonic pattern, especially in firm size, price, and analyst coverage. Unlike the highest *FEPS* portfolio, the highest *FE/P* portfolio consists of stocks that are small in firm size, low in stock prices, and past losers. The returns to the *FEPS* strategy are not due to outliers. We compute the median of stock returns for each of the *FEPS*-sorted portfolios and find that these medians exhibit an even more significant increasing pattern from *P*1 to P10. In addition, we omit those stocks with negative *FEPS* and the results remain similar.[18]

B. Explaining Portfolio Returns: Adjusted for Mutlifactor Risk

It is well known that many asset-pricing anomalies can be explained by the Fama and French three-factor model at the portfolio level, such as the book-to-market equity (*B/M*), earnings-to-price (*E/P*) and cash-flow-to-price (*C/P*) effects (e.g., Fama and French (1996)). In addition, Carhart (1997) adds a momentum factor to this model to capture the medium-term continuation of returns documented by Jegadeesh and Titman (1993). To see whether the *FEPS* profits are attributed to those standard cross-sectional effects, we update the *FEPS* decile portfolios every month, and then control their monthly excess returns for these four factors in the following time-series regression,

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^M (Mkt_t - R_{f,t}) + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^U UMD_t + \varepsilon_{i,t}, \tag{1}$$

[18] The negative *FEPS* observations account for about five percent in our sample.

where *Mkt* – R_f, *SMB* and *HML* constitute the Fama and French model's market, size and value factors, and *UMD* denotes the Carhart (1997) momentum factor.[19]

Table III presents the estimates of intercepts (*Alpha*) from equation (1), as well as factor sensitivities on the above four factors. Similar to the pattern of raw returns in the column $Ret_{0:1}$ of Table II, *Alpha* increases almost monotonically with *FEPS* deciles from negative to positive, resulting in a strongly significant risk-adjusted return of 0.878 percent per month for the *P*10–*P*1 hedge portfolio. *Alpha* is also statistically significantly different from zero for the portfolio *P*1, *P*2, *P*9 and *P*10. These results indicate that the four-factor model cannot account for the return patterns in the *FEPS* strategy. Factor sensitivities reveal a mixed risk profile for the two extreme *FEPS* portfolios. The highest *FEPS* stocks tend to have somewhat lower market risk than the lowest *FEPS* stocks (the *Mkt*–R_f factor loading is 1.030 for *P*10 versus 1.196 for *P*1). Meanwhile, *P*10 has a small loading of 0.093 on *SMB* but a large loading of 0.568 on *HML*, indicating that the highest *FEPS* stocks tend to behave like big, value stocks. In contrast, *P*1 has a large loading of 1.280 on *SMB* but a negative loading of -0.370 on *HML*, indicating that the lowest *FEPS* stocks tend to behave like small, growth stocks. Moreover, the lowest *FEPS* stocks tend to behave like losers, as the *UMD* factor loading is reliably negative (-0.202) for *P*1. Taken together, *P*10 and *P*1 display different or even opposite factor sensitivities. Therefore, it is difficult to tell which one is riskier. Though the value and momentum effects contribute to the raw return on the *P*10–*P*1 portfolio, the four-factor model still leaves a large unexplained proportion of profitability. These results suggest that the *FEPS* effect is consistent with the mispricing explanation rather than with the risk explanation, at least when judged by the well-established four common risk factors.

[Insert Table III here]

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[19] These factors are retrieved from French's website.

In order to see how long *FEPS* can predict future returns after controlling for these four risk factors, we also employ the method suggested by Jegadeesh and Titman (1993 and 2001) in computing monthly returns for the *P*10–*P*1 hedge portfolio. Specifically, we hold stocks for different periods (*T*: from one month to twelve months). At the beginning of each month, stocks are ranked and assigned into the ten *FEPS*-sorted portfolios. The stocks are then held in the *P*10–*P*1 portfolio for *T* months, with 1/*T* of the portfolio reinvested monthly. Finally, we compute the monthly equally weighted returns for the *P*10–*P*1 portfolio and regress them on the four factors to obtain the risk-adjusted returns as before. The time-series of our portfolio returns is restricted from December 1983 through December 2005. Figure 2 illustrates the raw and risk-adjusted monthly returns to the *FEPS* strategy for different holding periods. Consistent with Figure 1, the returns to the *P*10–*P*1 portfolio decrease as the holding horizon increases. When the hedging portfolio is held for longer than six months, both the raw and risk-adjusted returns are no longer significant at the 5 percent level. The evidence seems to imply that the *FEPS* profits come from the correction of mispricing over the short term.

[Figure 2 here]

C. The FEPS Strategy within Five Size Groups

Although the *FEPS* effect is not completely driven by the Fama and French four risk factors, this effect might be contingent on certain firm characteristics. In this section, we examine the interaction between the *FEPS* trading strategy and firm size (*Size*). In each month, we sort all the stocks into quintiles (*G*1-*G*5) based on their *Size* at the end of the previous month. Stocks in each *Size* group are further sorted into quintiles (*E*1-*E*5) based on *FEPS* as of the previous month in ascending order.[20] The procedure results in 25 balanced portfolios in each month, with each portfolio consisting of an average of 108 stocks. These portfolios are held for twelve months following the portfolio formation and we compute the one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) cumulative returns for each portfolio in the same way as before. Similarly, we estimate the risk-adjusted returns (*Alpha* for $Ret_{0:1}$) of the various portfolios by regressing their $Ret_{0:1}$ (minus the risk-free rate except for the zero-cost *E*5–*E*1 portfolio) on the four-factor model described in equation (1).

Table IV reports the *FEPS* strategy within each of the five *Size* groups. The short-term portfolio returns (i.e., $Ret_{0:1}$) exhibit a perfect monotonic pattern from *E*1 to *E*5 in each *Size* group. This pattern is retained even after adjusting for common risk factors (i.e., *Alpha*), and it persists over the future one year (i.e., $Ret_{0:12}$). In particular, the highest *FEPS* stocks strongly outperform the lowest *FEPS* stocks in the smallest *Size* group, *G*1, by an enormous return of 1.531 percent per month that is statistically significant at the one percent level. Of the 1.531 percent in the monthly return differential, a large portion cannot be captured by the four-factor model (the corresponding *Alpha* is 1.461 percent). However, the one-month return spread between the *E*5 and *E*1 portfolios, no matter whether it is raw or risk-adjusted, decreases monotonically as the firm size increases. While the *E*5–*E*1 strategies produce positive returns within all *Size* groups, the statistical significance of these hedge profits disappears in the largest *Size* group, *G*5. Basically the results hold for the medium-term portfolio returns (i.e., $Ret_{0:12}$). The last column of Table IV shows that the overall *FEPS* effect is still highly significant.

[20] As in the correlation matrix of Table I, the partitioning variables used for portfolio sorting, such as *Size* and *FEPS* etc., have high correlations with each other. Thus, for consistency, we use dependent sorting throughout the paper. Using independent sorting instead does not affect the results, but it results in skewed unbalanced portfolios (too few stocks in certain portfolios).

Therefore, in general, our results indicate that the abnormal returns to the *FEPS* strategy are inversely correlated with firm size.

[Insert Table IV here]

It is worth mentioning that we choose the one-month and twelve-month portfolio returns as representatives to illustrate the short-term and medium-term patterns of returns for two reasons. First, our choice is for simplicity since other holding periods follow essentially the same patterns. Second, Figures 1 and 2 show that the cumulative returns to the *FEPS* strategy are concave and the predictive power of *FEPS* decays over time. In addition, we find that historical *EPS* predicts a similar pattern of portfolio returns as *FEPS* does. But after controlling for the risk factors, the return spread becomes less significant. The evidence implies that the abnormal returns to the *FEPS* strategy are concentrated in the first one-year window after the portfolio formation.[21] Thus, in the following analysis, we follow this line and focus on studying the *FEPS* strategy over a one-year horizon.

D. The FEPS Strategy within Five Price Groups

This section examines the interaction between the *FEPS* strategy and stock price (*Price*), as the price level of a stock is highly correlated with its *FEPS*. We repeat the previous analysis by performing two-way dependent sorting on *Price* and *FEPS*. Table V reports the returns on the resulting 25 portfolios. In general, *FEPS* shows strong predictive power on future returns in all *Price* groups (*G*1-*G*5). As the group price increases, the *FEPS* strategy becomes less and less profitable. For example, in the highest *Price* group, *G*5, the *E*5–*E*1 portfolio earns a return of 0.429 percent if it is held for one month. After controlling for the four common factors, the risk-

[21] The actual historical *EPS* is announced at most twelve months after *FEPS* is released by analysts. Here we assume that the analysts' forecast biases are not too big so that the portfolios formed on historical *EPS* consist of similar stocks with those in the corresponding *FEPS* portfolios.

adjusted profit is small (the corresponding *Alpha* is 0.154 percent). If this strategy is held for twelve months, the cumulative hedge return is 5.682 percent, which is still not statistically significant. In contrast, the *E*5–*E*1 portfolios produce strongly significant profits in the low *Price* groups (i.e., *G*1 and *G*2) for the short-term holding horizon. Interestingly, we find that for the medium-term holding horizon, the *FEPS* strategy only works in the medium *Price* group, *G*3, which might suggest that the twelve-month portfolio returns capture other effects as well.

[Insert Table V here]

The above results are very close to those of the two-way sorting on *Size* and *FEPS*, since *Price* and *Size* are highly correlated with each other. In the same way, we test the *FEPS* strategy within five groups ranked by analyst coverage (*Analyst*), and the results are also similar (not shown to save space). Overall, we find that the abnormal returns to the *FEPS* strategy are robust after controlling for firm size, stock price and analyst coverage, and the *FEPS* effect is greatest in stocks with small firm size, low price, and low analyst coverage, where the costs and risk of arbitrage are high.

E. The FEPS Strategy within 3×3 Size and Book-to-Market Groups

The evidence in the previous sections shows that the superior profits on the *FEPS* strategy are slightly driven by the value premium. In this section, we triple-sort the sample by ranking stocks based on firm size (*Size*), book-to-market ratio (*B/M*) and *FEPS* to test whether the *FEPS* effect simply captures the book-to-market effect in cross-sectional returns. As we have already shown that the level of market capitalization affects the *FEPS* profits dramatically, we try to control for this size effect in further analysis by sorting on *Size* first. More specifically, in each month stocks are sorted into three categories based on *Size* at the end of the previous month.

Stocks in each *Size* group are further sorted into three categories based on *B*/*M*. Finally, within each *Size* and *B*/*M* group, we implement the *FEPS* strategy by forming three portfolios based on *FEPS* as of the previous month. The procedure produces 27 balanced portfolios, with each portfolio consisting of an average of 100 stocks. As before, we report the average one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) cumulative returns for each portfolio as well as for the hedge portfolios in Table VI. Since the sorting itself controls for the two most important factors (size and book-to-market) in returns to some extent, we report just the raw portfolio returns for the sake of brevity. In fact, using the same methodology to adjust the risk does not change our results.

[Insert Table VI here]

Again we observe a perfect increasing pattern in returns predicted by *FEPS*. This pattern holds in each column corresponding to a certain combination of *Size* and *B*/*M*. The short-term return differential between high and low *FEPS* stocks is significant in five of the nine *Size* and *B*/*M* groups, indicating that the *FEPS* effect does not merely pick up the book-to-market effect. Similar to the results in Table IV, we find that small stocks exhibit the largest return spread, especially for the short term. Nonetheless, no clear pattern emerges with respect to the book-to-market ratio. In particular, the return spread is larger and more statistically significant for value stocks within the smallest *Size* stocks, whereas the pattern seems to reverse within the medium and big *Size* stocks. The pattern is even more obvious for the medium-term portfolio returns.

F. The FEPS Strategy within 3×3 Size and Momentum Groups

Our final portfolio strategy aims to rule out the possibility that the *FEPS* profits are driven by the momentum effect. We repeat the same analysis as described in the previous section by replacing *B*/*M* with the past six months' returns ($Ret_{-6:0}$). Specifically, we perform three-way dependent sorting on *Size*, $Ret_{-6:0}$, and *FEPS* and present the returns on the resulting portfolios in Table VII. The predictive power of *FEPS* on future returns is still very clear after controlling for size and momentum. For the short-term holding period, the return differential between high and low *FEPS* stocks is significant in seven out of the nine *Size* and $Ret_{-6:0}$ groups, indicating that the *FEPS* effect does not simply pick up the momentum effect. Furthermore, we observe a clear pattern with respect to momentum, as both the magnitude and statistical significance of the return spread decrease with $Ret_{-6:0}$, regardless of the *Size* category. In other words, the *FEPS* effect is strongest among past losers. These results hold fairly well for the medium-term holding period.

[Insert Table VII here]

III. Further Evidence for the Mispricing Explanation

So far, our evidence rejects the existing risk explanation for the *FEPS* effect. An alternative theory is a mispricing explanation derived from the combination of the errors-in-expectations hypothesis and conservatism bias. As developed by Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), Barberis, Shleifer, and Vishny (1998), and others, the idea is as follows. When analysts and investors form expectations for future earnings, they are likely to be conservative so they often understate the impact of good or bad information. If they predict a firm will have high (low) *EPS* in the future, the firm might eventually turn out to perform even better (worse), and the extent to which the firm's earnings are underestimated (overestimated) is conditional on the level of their expectation. More specifically, this errors-in-expectations explanation implies that stocks with higher (lower) *FEPS* exhibit larger systematic undervaluation (overvaluation) in prices. This argument suggests two empirical implications. First, the earnings forecasts for stocks with higher *FEPS* should be relatively smaller than the actual earnings announced after the formation of expectations, compared with the earnings forecasts for stocks with lower *FEPS*. Second, the abnormal returns to the *FEPS* strategy should be concentrated around earnings announcement dates. This is because if the return predictability of *FEPS* is due to over/under-valuation, such mispricing should be significantly corrected during future periods when a relatively large amount of information about earnings reaches the market.

To directly test the above two hypotheses, we examine analysts' forecast errors (*FE*) and subsequent earnings surprises (*ES*). *FE* is defined as the difference between *FEPS* and the corresponding actual earnings per share (*Actual*), deflated by the absolute value of *Actual*. That is, $FE = (FEPS - Actual)/|Actual|$). Therefore, it measures relative forecast biases in the percentage of actual earnings. For consistency in computing *FE*, we retrieve both analyst earnings forecasts and actual *EPS* data from the I/B/E/S adjusted summary historical file.[22] *ES* is defined as the cumulative abnormal return relative to the CRSP value-weighted index in the three-day window (t = -1, 0, +1) around the future quarterly announcement date of earnings. This measure captures the sudden change in the market's views about earnings, which is widely used in previous studies (e.g., La Porta et al. (1997) and others).[23]

Since the profitability of the *FEPS* strategy exhibits a size effect, we repeat the same portfolio formation as in Section II.C to study how forecast errors and earnings surprises vary

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[22] Note that the I/B/E/S unadjusted summary historical file does not contain actual earnings data, so we use the adjusted file. Since *FE* is computed as a relative value that is neutral to the adjustments of stock dividends and stock splits, using the I/B/E/S adjusted file is not a problem.

[23] This idea comes from Bernard and Thomas (1989, 1990), Bernard, Thomas, and Wahlen (1997), Chopra, Lakonishok, and Ritter (1992) and La Porta et al. (1997). They argue that if abnormal returns are due to omitted risk factors, such returns should not be concentrated around earnings announcement periods, because asset-pricing models do not predict significant shifts in expected returns over short windows. For example, La Porta et al. (1997) find that abnormal announcement returns are significantly more positive for value than for growth stocks. They interpret their results as evidence to support the mispricing explanation of the value premium.

across *FEPS* portfolios within *Size* groups. Table VIII reports the time-series averages of medians of *FE* and means of *ES* for each of the 5×5 *Size* and *FEPS* portfolios. Following Doukas, Kim and Pantzalis (2002), we use the medians of *FE* instead of means because mean values are highly influenced by extreme outliers.[24] However, this is less a problem for *ES*.

[Insert Table VIII here]

Consistent with the recent literature (for example, Lim (2001) and Doukas, Kim and Pantzalis (2002)), our evidence shows that *FE* is positive for almost all the *Size* and *FEPS* portfolios with only one exception, suggesting that in general, analysts are excessively optimistic about future earnings on all stocks. More importantly, stocks with different *FEPS* have distinctly different forecast errors, as is evidenced from the highly significant *t*-statistics at the one-percent level for *E*5–*E*1 in each *Size* group. *FE* monotonically decreases as *FEPS* increases, indicating that investors' systematic errors-in-expectations are indeed correlated with the level of their expectations. The lowest *FEPS* portfolio displays the largest median *FE*, while the highest *FEPS* portfolio displays the smallest median *FE*. This evidence strongly supports the hypothesis that investors are relatively more optimistic about stocks with low *FEPS* than about those with high *FEPS*. For example, in the smallest *Size* group, stocks with the lowest expectations are overstated by 35.5 percent relative to the actual value, whereas stocks with the highest expectations are only overstated by 5.0 percent. Again we observe a clear size effect on the patterns of forecast errors. That is, the difference in *FE* between the highest and the lowest *FEPS* portfolio diminishes as the group size increases. Consistent with previous findings that the

[24] For instance, if the absolute value of *Actual* is merely one cent, a small deviation in *FEPS* from *Actual* would yield a value of *FE* as high as several hundred percent. Unfortunately, such cases are very common in all the five *FEPS* groups, because *Actual* from the I/B/E/S adjusted file is subject to the adjustments in stock dividends and stock splits and rounding of the numbers.

FEPS effect is inversely correlated with firm size, this evidence implies that the correction of errors-in-expectations is an important source of the *FEPS* profits.

The results are essentially similar for earnings surprises. The cumulative *ES* around the subsequent announcement date following portfolio formation also shows an increasing pattern from portfolio *E*1 to portfolio *E*5. Particularly in the small and medium size groups (i.e., *G*1, *G*2 and *G*3), the lowest *FEPS* portfolio experiences negative earnings surprises, and conversely the highest *FEPS* portfolio experiences positive earnings surprises. The difference in *ES* between these two portfolios is also statistically significant in the above three groups. These results are consistent with the view that stocks with the lowest expectations are overvalued, while those with the highest expectations are undervalued. Earnings surprises account for a substantial component of the *FEPS* profits. For example, in the smallest *Size* group, the three-day abnormal return around the subsequent announcement is 0.654 percent higher for the highest *FEPS* stocks than for the lowest *FEPS* stocks. Recall that the annual return spread between these two groups of stocks is 9.470 percent (see Table IV). The abnormal return over a window of only three days thus accounts for 6.9 percent of this spread, which is equivalent to 27.6 percent per year.[25] Taken together, the patterns in forecast errors and earnings surprises are consistent with the pattern in portfolio returns for the 5×5 *Size* and *FEPS* portfolios. The results appear to support that the argument that the *FEPS* effect is more likely to be due to market mispricing than to the omitted risk factors.

[25] The corresponding figures on an annual basis are 22.6% and 16% for the G2 group and the whole sample, respectively. For comparison, La Porta et al. (1997) find that a significant portion of the return difference between value and growth stocks is attributable to earnings surprises. More specifically, differences in earnings announcement returns account for 25-30% of the annual return differences between value and growth stocks in the first three years after portfolio formation.

IV. Robustness Checks

By providing compelling evidence at the portfolio level, we document that the level of *FEPS* is cross-sectionally correlated with future stock returns and suggest that errors-in-expectations of investors play a potential role in this predictive power of *FEPS*. To further ascertain that the *FEPS* strategy is not caused by existing asset-pricing anomalies, outliers, or specific measures of earnings and sample selections, we employ the following tests to demonstrate the robustness.

A. Explaining the Cross Section of Individual Stock Returns: Fama-Macbeth Tests

Though we control portfolio returns for risk factors in the previous analysis, it is possible that the measure of *FEPS* captures other asset-pricing anomalies, such as earnings momentum or the earnings-to-price effect. Since we are more interested in identifying the incremental role of *FEPS* in predicting future returns, we perform the following multiple regression tests at the individual stock level:

$$\begin{aligned} \mathrm{Re}t_{0:1} &= a + b_1 \ln(Size) + b_2 \ln(B/M) + b_3 \mathrm{Re}t_{-7:-1} + b_4 \mathrm{Re}t_{-1:0} \\ &+ b_5 ES_{recent} + b_6 E/P + b_7 FEPS + e, \end{aligned} \tag{2}$$

where ES_{recent} denotes the three-day abnormal return around the most recent announcement date of earnings up to the end of the previous month; *E/P* denotes the historical earnings-to-price ratio. We compute *E/P* in two ways. First, following Fama and French (1992), we divide net income before extraordinary items for the fiscal-year-end in calendar year *y*-1 by the market value of equity at the end of December of year *y*-1 to obtain E/P_{y-1}. The second measure, E/P_{t-1}, is a more updated earnings-to-price ratio, which is derived from the latest announced net income before extraordinary items in Compustat and the number of shares outstanding and price in CRSP up to the end of the previous month. *Size*, *B/M*, $Ret_{-7:-1}$ are included as the control variables to capture standard cross-sectional effects, such as the size and value effects documented by Fama and French (1992) and the momentum effect documented by Jegadeesh and Titman (1993). $Ret_{-1:0}$ is used to capture the first-order negative serial correlation in monthly returns because of thin trading or the bid-ask spread effect, which is documented by Jegadeesh (1990). ES_{recent} and *E/P* are used to capture the earnings momentum and the earnings-to-price effect, respectively, following the prior literature (e.g., Chan, Jegadeesh, and Lakonishok (1996) and Lakonishok, Shleifer, and Vishny (1994)).

The standard Fama and Macbeth (1973) method is used to estimate equation (2) each month and the means of the monthly estimates are calculated. We also report the *t*-statistics of the means of the monthly estimated coefficients using the Newey and West (1987) corrected standard errors. Since *Size* and *B/M* are positively skewed, we use the logarithmic transformation to normalize the variables.

Table IX reports the estimates for different versions of the regression derived from equation (2). All the slope coefficients on the control variables show the expected signs with considerably significant levels. Among those variables, the earnings surprise (i.e., ES_{recent}) exhibits the strongest predictive power on returns. The results also indicate the presence of the value, price momentum, short-term reversal, earnings momentum and earnings-to-price effects, and the disappearance of the size effect, which is consistent with abundant prior literature. However, none of these cross-sectional effects in returns captures the *FEPS* effect. The coefficient on the variable *FEPS* is positive for all of the specifications to predict future one-month returns ($Ret_{0:1}$). This coefficient is highly significant at the one-percent level. Notably we observe that the predictive power of *FEPS* on future returns remains essentially unchanged with the inclusion of ES_{recent} and *E/P*. For example, the coefficient on *FEPS* is 0.190 with a *t*-value of 3.27 in Column

(1), while the coefficient on *FEPS* is 0.171 with a *t*-value of 3.23 in Column (4). These results reveal that *FEPS* incrementally predicts the cross-sectional variation in individual stock returns, confirming our previous analysis reported in Tables II to IV and Tables VI-VIII.

[Insert Table IX here]

There might be a concern that the *FEPS* effect is driven by several particular industries. In order to address this issue, we repeat the same regressions as in Column (5) using industry-median-demeaned *FEPS* and E/P_{t-1} instead of the raw values for each individual stock in each month.[26] The 48 industries are defined by Fama and French (1997). Column (6) presents the results of the complete model using demeaned values of *FEPS* and E/P_{t-1}. The coefficient on *FEPS* is even more significant, and so is the coefficient on E/P_{t-1}. The evidence suggests that both the *FEPS* and *E/P* effects are not driven by particular industries, and, further, they are more likely to be associated with mispricing within industries.

B. Seasonality and Subperiod Analysis

This section tests for possible seasonal effects and periodic robustness in the performance of the *FEPS* strategy. In Table X, we replicate the portfolio strategies as in Section II.A in only January and the other non-January calendar months and in certain subperiods. The *P*10–*P*1 portfolio loses 3.003 percent on average in each January, but it achieves significantly positive returns of 1.581 percent per month in the other calendar months. This striking seasonality in *FEPS* profits is quite similar to the seasonality in momentum profits reported by Jegadeesh and Titman (1993). Given the characteristic that the highest *FEPS* portfolio (*P*10) has much larger firm size than the lowest *FEPS* portfolio (*P*1) has, the January effect in the *FEPS* profits might

[26] Up to day, numerous investors advocate trading strategies based on relative evaluation by comparing *E/P* ratios across stocks within the same industry. Therefore, we perform the same transformation on *E/P* as on *FEPS* to test whether or not these effects on returns are stronger within industries.

be due to the strong size effect in January. We also separate the entire sample period into two equal subperiods. The results indicate that the returns on the $P10–P1$ portfolio are significantly high in the earlier period 1983 to 1993. Although the returns on the $P10–P1$ portfolio are economically significant with returns of 1.083% and 8.421% for the holding period of one month and twelve months, respectively, it is not statistically significant in the later period 1994 to 2004. However, during the economic recession after the Internet bubble (i.e., from August 2000 to March 2003), the $P10–P1$ strategy was extremely profitable.[27] The evidence appears to suggest that the abnormal returns on the *FEPS* strategy are countercyclical to the overall market performance.

[Insert Table X here]

C. Various Measurements of Earnings

Finally, we test several other measurements of earnings for robustness (not tabulated). As we mention before, forecasted total earnings behave very closely to *FEPS* in predicting future returns, which suggests that our findings are not driven by stock splits. In fact, the sample of split stock-month observations is quite small compared with our large sample. Historical total earnings or historical *EPS* from Compustat also predicts future returns but the predictive power is much weaker. We also replicate our results using analyst forecasts in the I/B/E/S detailed historical file. We find that the more the recent forecasts are used in computing consensus analyst forecasts, the stronger the predictive power is. For example, when we calculate the average of earnings forecasts weighted by the reciprocal of the age of each forecast, we find that this proxy provides the best predictions among other measures of forecasts.

[27] We define the economic recession period based on the declining window of the S&P 500 index.

V. Conclusions

Earnings-related studies have a long tradition in both the investment community and academia. Earnings-related strategies can be traced back to Graham and Dodd (1934), who advocate buying stocks that sell at low multiples of earnings (i.e., price-to-earnings). The modern finance literature that studies the earnings-related cross-sectional behavior of stock returns emphasizes the second moment of earnings, such as unexpected components in earnings or analyst forecast revisions in earnings. In this paper, we document a novel pattern in stock returns that is simply related to the levels of expectations of investors about earnings, which seems to be neglected by investment professionals and researchers. We provide strong evidence that stocks with higher (lower) forecasted earnings per share (*FEPS*) earn substantially higher (lower) future returns, even after controlling for the market risk, the size, value, and earnings-to-price effects, and price and earnings momentum. This *FEPS* effect is most pronounced in small, low price, and low analyst coverage stocks, and among past losers, and it is sustained over long periods of time without any subsequent reversal. The results are robust to several risk-adjustment techniques, various measures of earnings, and not due to outliers or sample selection.

The interpretation of the cross-sectional predictive power of *FEPS* presents a challenge to our profession. Tests of a potentially new asset-pricing anomaly are inevitably subjected to Fama's (1976) joint hypothesis problem. Although we cannot rule out the possibility that *FEPS* might be subsumed by some omitted risk factors or explained by time-varying risk, we find little evidence that supports the view that strategies based on the levels of *FEPS* are fundamentally riskier. The abnormal returns on the *FEPS* strategy are even countercyclical to the overall market performance, which is inconsistent with the prediction of the consumption-based CAPM. Alternatively, the findings could be interpreted as evidence of market inefficiency. We find that stocks with lower *FEPS* show larger *ex ante* forecast errors (positive biases) of earnings relative to stocks with higher *FEPS*, and the abnormal returns are largely concentrated over the three-day windows around future earnings announcements. This evidence is consistent with the errors-in-expectations explanation that investors overvalue (undervalue) stocks when their expectations about earnings per share (*EPS*) are low (high). Therefore, the *FEPS* strategy produces superior profits because such a strategy captures systematic biases of investors. In sum, our findings open up a new field for scholars to study unknown risk factors and market efficiency.

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Appendix I
Variable Definitions

Variable	Definition and data source
FEPS:	Mean of forecasted one-year-ahead earnings per share in the previous month from I/B/E/S unadjusted summary historical file
Size:	Market value of equity at the end of the previous month computed from CRSP
B/M:	The Fama and French (1993) book-to-market ratio, where the value for July of year *y* to June of year *y*+1 is computed using the book value of equity for the fiscal-year-end in calendar year *y*-1 from Compustat and the market value of equity at the end of December of year *t*-1 from CRSP
Price:	Stock price at the end of the previous month from CRSP
$Ret_{-6:0}$:	Cumulative (buy-and-hold) return over the past six months as of the previous month computed from CRSP
Analyst:	Number of analysts following a stock in the previous month from I/B/E/S
FE/P:	Forecasted earnings-to-price ratio, which is equal to *FEPS* in the previous month divided by the stock price on the corresponding date of I/B/E/S statistical period
BPS:	Book value of stockholders' equity per share in the previous month, which is equal to the Compustat Item #60 at the recent announced fiscal-year-end as of the previous month divided by the number of shares outstanding on the corresponding date of I/B/E/S statistical period
FROE:	Forecasted return-on-equity in the previous month, which is equal to *FEPS* divided by *BPS*

Table I
Summary Statistics

This table reports the descriptive statistics for our final sample during the period from January 1983 to December 2004. The sample includes all stocks listed on the NYSE, AMEX or Nasdaq, excluding stocks with prices less than $5 at the end of the previous month. Additionally, a stock is eligible to be included in the sample if it has sufficient data in CRSP, Compustat and I/B/E/S for the characteristic variables defined in Appendix I. Panel A reports the time-series averages of common statistics for all stocks, while Panel B reports the time-series average of correlations among those variables. All correlations in Panel B are statistically significant at the one percent level.

Panel A: Summary Statistics

Variables	Mean	Median	Standard Deviation	Skewness	Percentile 10%	Percentile 90%
FEPS ($)	1.597	1.331	1.530	1.103	0.161	3.429
Size ($ billion)	1.929	0.332	5.977	5.782	0.056	3.874
B/M	0.697	0.605	0.473	1.734	0.215	1.258
Price ($)	24.599	20.273	17.321	1.756	7.788	46.262
$Ret_{-6:0}$ (%)	10.860	6.964	31.653	1.185	-22.307	46.425
Analyst	7.950	5.288	7.444	1.459	1.000	19.318
FE/P	0.062	0.067	0.055	-1.907	0.014	0.113
BPS	12.843	9.954	10.751	2.246	3.119	25.585
FROE	0.133	0.137	0.187	-0.919	0.017	0.273

Panel B: Correlation Matrix

Variables	*FEPS*	*Size*	*B/M*	*Price*	$Ret_{-6:0}$	*Analyst*	*FE/P*	*BPS*
FEPS	1.000							
Size	0.360	1.000						
B/M	0.061	-0.082	1.000					
Price	0.729	0.480	-0.126	1.000				
$Ret_{-6:0}$	0.046	0.020	0.083	0.192	1.000			
Analyst	0.363	0.625	-0.113	0.492	-0.043	1.000		
FE/P	0.594	0.036	0.168	0.099	-0.060	0.029	1.000	
BPS	0.644	0.221	0.486	0.567	-0.028	0.255	0.239	1.000
FROE	0.383	0.114	-0.257	0.199	0.080	0.102	0.530	-0.105

Table II
Portfolio Characteristics for Equally Weighted Forecasted Earnings per Share Deciles

This table reports the time-series averages of firm characteristics and returns of *FEPS*-sorted decile portfolios. *FEPS* denotes the mean of forecasted one-year-ahead earnings per share from I/B/E/S unadjusted summary historical file. At the beginning of each month, stocks are ranked by their *FEPS* of the previous month and are assigned to one of the ten portfolios. *P*1 (*P*10) is the portfolio consisted of the 10 percent of the stocks with the lowest (highest) *FEPS*. The portfolios are equally weighted and are held for 36 months. The sample includes all stocks listed on the NYSE, AMEX and Nasdaq, excluding stocks with prices less than $5 at the end of the previous month. We also require the stocks to have sufficient data in CRSP, Compustat and I/B/E/S for the characteristic variables in Appendix I. All these characteristics are summarized before the portfolios are constructed based on data as of the previous month. After the portfolio formation, one-month ($Ret_{0:1}$), six-month ($Ret_{0:6}$), twelve-month ($Ret_{0:12}$) and thirty-six-month ($Ret_{0:36}$) cumulative returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. The detailed definitions of the characteristic variables are provided in Appendix I. The sample period is January 1983 to December 2004, except that for $Ret_{0:36}$, the period is January 1983 to December 2002. *P*10–*P*1 is the zero-cost hedge portfolio that longs on *P*10 and short on *P*1. The *t*-statistics (in parentheses) for *P*10–*P*1 are assessed using the Newey and West (1987) procedure to adjust for serial correlations.

	Portfolio Characteristics									Portfolio Returns			
Portfolios	*FEPS*	*Size*	*B/M*	*Price*	$Ret_{-6:0}$	*Analyst*	*FE/P*	*BPS*	*FROE*	$Ret_{0:1}$	$Ret_{0:6}$	$Ret_{0:12}$	$Ret_{0:36}$
*P*1 (low)	-0.584	0.538	0.690	13.024	10.180	5.207	-0.051	7.527	-0.188	0.380	3.603	7.750	35.995
*P*2	0.369	0.573	0.664	12.090	11.468	5.024	0.040	6.229	0.103	0.846	5.452	10.708	44.193
*P*3	0.665	0.747	0.658	14.197	11.105	5.345	0.060	6.925	0.151	1.105	5.956	11.908	44.124
*P*4	0.921	0.850	0.658	16.855	10.495	5.959	0.068	8.112	0.166	1.209	6.739	12.801	44.005
*P*5	1.190	1.014	0.667	19.514	10.737	6.645	0.073	9.530	0.175	1.322	7.181	13.682	46.969
*P*6	1.491	1.370	0.680	22.676	10.974	7.343	0.077	11.206	0.178	1.437	7.900	15.189	50.964
*P*7	1.849	1.838	0.712	26.155	10.739	8.484	0.081	13.301	0.180	1.400	8.062	16.112	55.470
*P*8	2.296	2.332	0.733	30.372	10.635	9.598	0.085	15.934	0.179	1.429	8.630	17.596	60.042
*P*9	2.946	3.449	0.757	36.769	10.766	11.312	0.089	19.833	0.183	1.484	8.787	18.002	59.218
*P*10 (high)	4.825	6.580	0.748	54.338	11.485	14.590	0.097	29.843	0.198	1.579	9.395	19.136	62.536
*P*10 – *P*1	5.409[a]	6.043[a]	0.058[b]	41.315[a]	1.306	9.383[a]	0.149[a]	22.316[a]	0.386[a]	1.199[a]	5.792[b]	11.386[b]	26.541[c]
t-statistic	(37.50)	(9.22)	(2.41)	(32.22)	(0.35)	(14.32)	(26.67)	(21.98)	(8.78)	(2.66)	(2.13)	(2.00)	(1.73)

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table III
Time-Series Tests of the Four-Factor Model on the Equally Weighted *FEPS*-sorted Decile Portfolios

This table reports the estimates of the Carhart (1997) four-factor model, $R_{i,t} - R_{f,t} = a_i + b_{i,m}(R_{m,t} - R_{f,t}) + s_iSMB_t + h_iHML_t + m_iUMD_t + \varepsilon_{i,t}$, for the monthly excess returns on the equally weighted decile portfolios formed on the basis of the mean forecasted one-year-ahead earnings per share (*FEPS*) in the previous month. The four factors are provided by Kenneth French. The market factor ($R_m - R_f$) is the return on the CRSP value-weighted index minus the risk-free rate proxied by the one-month T-bill rate. *SMB* and *HML* are the Fama and French (1993) size and book-to-market factors. *UMD* is the Carhart (1997) momentum factor. *Alpha* is the estimated intercept and the factor sensitivities are the slope coefficients in the four-factor model time-series regressions. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004, and portfolios are held for one month. The adjusted R-squares are also reported and the *t*-statistics (in parentheses) are adjusted using the Newey and West (1987) procedure.

Portfolios	*Alpha* (%)	Factor Sensitivities				
		$R_m - R_f$	*SMB*	*HML*	*UMD*	Adj. R^2
*P*1 (low *FEPS*)	-0.646[a]	1.196[a]	1.280[a]	-0.370[a]	-0.202[a]	0.911
	(-3.79)	(28.19)	(24.43)	(-5.88)	(-5.48)	
*P*2	-0.253[b]	1.177[a]	1.022[a]	-0.155[a]	-0.177[a]	0.940
	(-2.12)	(39.58)	(27.85)	(-3.53)	(-6.87)	
*P*3	-0.044	1.109[a]	0.873[a]	0.085[b]	-0.165[a]	0.941
	(-0.44)	(44.56)	(28.41)	(2.30)	(-7.63)	
*P*4	0.006	1.078[a]	0.720[a]	0.206[a]	-0.117[a]	0.915
	(0.06)	(39.87)	(21.58)	(5.14)	(-4.98)	
*P*5	0.083	1.041[a]	0.625[a]	0.330[a]	-0.093[a]	0.880
	(0.70)	(35.03)	(17.05)	(7.50)	(-3.60)	
*P*6	0.188[c]	1.019[a]	0.500[a]	0.354[a]	-0.061[b]	0.880
	(1.71)	(37.18)	(14.79)	(8.72)	(-2.54)	
*P*7	0.158	0.969[a]	0.374[a]	0.406[a]	-0.041[c]	0.876
	(1.57)	(38.46)	(12.04)	(10.88)	(-1.88)	
*P*8	0.157	0.959[a]	0.307[a]	0.460[a]	-0.014	0.879
	(1.65)	(40.49)	(10.51)	(13.11)	(-0.68)	
*P*9	0.198[b]	0.975[a]	0.200[a]	0.509[a]	-0.026	0.872
	(2.05)	(40.44)	(6.72)	(14.24)	(-1.24)	
*P*10 (high *FEPS*)	0.233[b]	1.030[a]	0.093[a]	0.568[a]	-0.016	0.867
	(2.27)	(40.27)	(2.94)	(14.97)	(-0.71)	
*P*10 – *P*1	0.878[a]	-0.166[a]	-1.187[a]	0.937[a]	0.186[a]	0.743
	(3.60)	(-2.73)	(-15.82)	(10.41)	(3.53)	

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table IV
Mean Returns on Portfolios Sorted by Size and Forecasted Earnings per Share

This table reports returns on *FEPS*-sorted portfolio within each of five *Size* groups. At the beginning of each month, stocks are sorted into five groups based on the level of their market capitalization (*Size*) at the end of the previous month. Stocks in each *Size* group are further sorted into five additional quintiles based on the mean of forecasted earnings per share (*FEPS*) of the previous month from I/B/E/S unadjusted summary historical file. The portfolios are equally weighted and are held for one month and twelve months, respectively. After the portfolio formation, one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) raw returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. We also report the risk-adjusted returns (*Alpha* for $Ret_{0:1}$) estimated as the intercepts in regressions of the monthly excess returns on the Fama and French three factors and the Carhart (1997) momentum factor. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004. The *t*-statistics (in parentheses) for *E*5–*E*1 are assessed using the Newey and West (1987) procedure to adjust for serial correlations.

	Size Quintiles					
FEPS Quintiles	*G*1 (Small)	*G*2	*G*3	*G*4	*G*5 (Large)	All Stocks
Panel A: One-Month Returns ($Ret_{0:1}$)						
*E*1 (Low)	0.325	0.546	0.734	0.712	0.878	0.639
*E*2	0.973	1.066	1.118	1.161	1.140	1.092
*E*3	1.276	1.324	1.279	1.254	1.220	1.271
*E*4	1.508	1.616	1.414	1.255	1.300	1.419
*E*5 (High)	1.856	1.804	1.811	1.542	1.348	1.672
*E*5 – *E*1	1.531[a]	1.259[a]	1.077[b]	0.830[b]	0.471	1.033[a]
t-statistic	(4.82)	(2.90)	(2.42)	(2.02)	(1.41)	(2.82)
Panel B: Monthly Risk-Adjusted Returns (*Alpha* for $Ret_{0:1}$)						
*E*1 (Low)	-0.827	-0.457	-0.358	-0.352	-0.118	-0.422
*E*2	-0.164	-0.108	-0.106	-0.030	0.000	-0.082
*E*3	0.115	0.059	0.001	0.024	0.057	0.051
*E*4	0.292	0.334	0.104	-0.059	0.079	0.150
*E*5 (High)	0.634	0.438	0.460	0.188	-0.016	0.341
*E*5 – *E*1	1.461[a]	0.895[a]	0.818[a]	0.540[b]	0.102	0.763[a]
t-statistic	(6.00)	(3.31)	(3.18)	(2.17)	(0.47)	(3.66)
Panel C: Twelve-Month Cumulative Returns ($Ret_{0:12}$)						
*E*1 (Low)	9.547	9.200	7.612	10.005	11.220	9.517
*E*2	13.285	11.431	11.322	13.129	13.430	12.519
*E*3	13.976	13.347	14.497	14.842	15.243	14.381
*E*4	15.653	15.808	16.593	15.997	16.064	16.023
*E*5 (High)	19.016	20.707	20.843	18.711	17.264	19.308
*E*5 – *E*1	9.470[c]	11.507[c]	13.231[b]	8.706[c]	6.045	9.792[c]
t-statistic	(1.94)	(1.74)	(2.40)	(1.68)	(1.41)	(1.90)

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table V
Mean Returns on Portfolios Sorted by Price and Forecasted Earnings per Share

This table reports returns on *FEPS*-sorted portfolios within each of five *Price* groups. At the beginning of each month, stocks are sorted into five groups based on the level of stock price (*Price*) at the end of the previous month. Stocks in each *Price* group are further sorted into five additional quintiles based on the mean of forecasted earnings per share (*FEPS*) of the previous month from I/B/E/S unadjusted summary historical file. The portfolios are equally weighted and are held for one month and twelve months, respectively. After the portfolio formation, one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) raw returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. We also report the risk-adjusted returns (*Alpha* for $Ret_{0:1}$), estimated as the intercepts in regressions of the monthly excess returns on the Fama and French three factors and the Carhart (1997) momentum factor. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004. The *t*-statistics (in parentheses) for *E*5–*E*1 are assessed using the Newey and West (1987) procedure to adjust for serial correlations.

	Price Quintiles					
FEPS Quintiles	*G*1 (Small)	*G*2	*G*3	*G*4	*G*5 (Large)	All Stocks
Panel A: One-Month Returns ($Ret_{0:1}$)						
*E*1 (Low)	0.211	0.506	0.766	0.806	1.061	0.670
*E*2	0.523	0.991	1.027	1.050	1.086	0.935
*E*3	1.221	1.285	1.320	1.247	1.204	1.256
*E*4	1.413	1.533	1.596	1.399	1.400	1.468
*E*5 (High)	1.599	1.896	2.004	1.823	1.490	1.763
*E*5 – *E*1	1.388[a]	1.390[a]	1.238[a]	1.017[b]	0.429	1.092[a]
t-statistic	(3.84)	(3.87)	(3.46)	(2.56)	(1.08)	(3.12)
Panel B: Monthly Risk-Adjusted Returns (*Alpha* for $Ret_{0:1}$)						
*E*1 (Low)	-0.787	-0.520	-0.314	-0.349	-0.040	-0.402
*E*2	-0.539	-0.135	-0.168	-0.203	-0.142	-0.237
*E*3	0.108	0.060	0.111	-0.006	-0.057	0.043
*E*4	0.234	0.250	0.317	0.110	0.102	0.203
*E*5 (High)	0.299	0.591	0.667	0.498	0.114	0.434
*E*5 – *E*1	1.086[a]	1.110[a]	0.981[a]	0.847[a]	0.154	0.836[a]
t-statistic	(3.85)	(4.46)	(4.74)	(3.95)	(0.68)	(4.25)
Panel C: Twelve-Month Cumulative Returns ($Ret_{0:12}$)						
*E*1 (Low)	8.674	8.144	9.784	10.361	13.174	10.027
*E*2	10.019	12.035	12.286	13.055	14.106	12.300
*E*3	13.034	14.379	15.394	15.939	15.182	14.786
*E*4	14.062	15.431	17.886	17.377	17.230	16.397
*E*5 (High)	13.502	18.133	21.561	20.339	18.856	18.478
*E*5 – *E*1	4.828	9.989[c]	11.777[b]	9.978[b]	5.682	8.451
t-statistic	(0.83)	(1.70)	(2.28)	(2.06)	(1.16)	(1.63)

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table VI
Mean Returns on Portfolio Sorted by Size, Book-to-Market, and Forecasted Earnings per Share

This table reports returns on *FEPS* portfolios within each of 3×3 *Size*- and *B/M*-sorted groups. At the beginning of each month, stocks are sorted into three groups based on the level of market capitalization (*Size*) at the end of the previous month. Stocks in each *Size* group are further sorted into three book-to-market (*B/M*) groups. Stocks in each *Size-B/M* group are further sorted into three additional portfolios based on the mean of forecasted earnings per share (*FEPS*) of the previous month from I/B/E/S unadjusted summary historical file. The portfolios are equally weighted and are held for one month and twelve months, respectively. After the portfolio formation, one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) raw returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004. High–Low is the zero-cost hedge portfolio that longs on high-*FEPS* portfolio and short on low-*FEPS* portfolios. The *t*-statistics (in parentheses) for the High–Low hedge portfolios are adjusted for serial correlation using the Newey and West (1987) procedure.

	Small *Size*			Middle *Size*			Big *Size*		
FEPS	Low *B/M*	Medium *B/M*	High *B/M*	Low *B/M*	Medium *B/M*	High *B/M*	Low *B/M*	Medium *B/M*	High *B/M*
Panel A: One-Month Cumulative Returns ($Ret_{0:1}$)									
Low	0.215	0.945	1.041	0.447	1.100	1.365	0.722	0.975	1.210
Medium	0.802	1.477	1.570	0.983	1.334	1.540	1.071	1.145	1.253
High	1.141	1.877	1.967	1.282	1.580	1.760	1.293	1.346	1.462
High–Low	0.926[a]	0.932[a]	0.926[a]	0.835[b]	0.481[c]	0.395	0.571	0.372	0.253
t-statistic	(2.77)	(3.63)	(4.38)	(2.07)	(1.72)	(1.51)	(1.51)	(1.60)	(1.26)
Panel B: Twelve-Month Cumulative Returns ($Ret_{0:12}$)									
Low	6.546	13.524	14.101	6.782	10.546	15.280	9.062	11.290	15.859
Medium	9.420	15.365	18.370	9.689	14.717	18.167	12.096	14.906	16.104
High	9.526	19.327	21.368	14.068	18.212	21.672	16.275	16.219	18.723
High–Low	2.980	5.803	7.267[b]	7.285	7.667[b]	6.392[c]	7.213[c]	4.928[b]	2.864
t-statistic	(0.62)	(1.45)	(2.11)	(1.43)	(2.44)	(1.93)	(1.77)	(2.13)	(1.24)

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table VII
Mean Portfolio Returns by Size, Momentum, and Forecasted Earnings per Share

This table reports returns on *FEPS* portfolios within each of 3×3 *Size*- and $Ret_{-6:0}$-sorted groups. At the beginning of each month, stocks are sorted into three groups based on the level of market capitalization (*Size*) at the end of the previous month. Stocks in each *Size* group are further sorted into three momentum groups, where momentum is measured by past six months' return ($Ret_{-6:0}$). Stocks in each *Size*- $Ret_{-6:0}$ group are further sorted into three additional portfolios based on the mean of forecasted earnings per share (*FEPS*) of the previous month from I/B/E/S unadjusted summary historical file. The portfolios are equally weighted and are held for one month and twelve months, respectively. After the portfolio formation, one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) raw returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004. High–Low is the zero-cost hedge portfolio that longs on high-*FEPS* portfolio and short on low-*FEPS* portfolios. The *t*-statistics (in parentheses) for the High–Low hedge portfolios are adjusted for serial correlations using the Newey and West (1987) procedure.

FEPS	Small *Size*			Middle *Size*			Big *Size*		
	Losers	Medium	Winners	Losers	Medium	Winners	Losers	Medium	Winners
Panel A: One-Month Cumulative Returns ($Ret_{0:1}$)									
Low	0.028	0.558	1.351	0.374	0.908	1.284	0.640	0.979	1.037
Medium	0.864	1.223	1.741	1.069	1.352	1.554	1.342	1.226	0.999
High	1.406	1.809	2.054	1.555	1.716	1.576	1.554	1.473	1.221
High–Low	1.378[a]	1.251[a]	0.703[b]	1.181[a]	0.808[a]	0.292	0.914[a]	0.494[a]	0.184
t-statistic	(5.16)	(5.80)	(2.28)	(3.61)	(3.40)	(0.77)	(3.25)	(2.83)	(0.65)
Panel B: Twelve-Month Cumulative Returns ($Ret_{0:12}$)									
Low	4.918	12.454	16.079	5.829	11.760	13.400	8.325	11.952	15.415
Medium	8.102	15.297	19.119	10.696	15.685	16.738	13.083	15.114	16.328
High	9.876	19.621	22.260	14.454	19.943	20.676	15.825	17.180	17.561
High–Low	4.958	7.167[b]	6.181	8.625[b]	8.183[a]	7.276	7.500[b]	5.228[a]	2.146
t-statistic	(1.33)	(2.08)	(1.21)	(2.07)	(2.62)	(1.64)	(2.32)	(2.63)	(0.53)

[a,b] indicate statistically significant at the one and five percent levels, respectively.

Table VIII
Forecast Errors and Earnings Surprises for Portfolios Sorted by Size and Forecasted Earnings per Share

This table reports the time-series averages of medians of analysts' forecast errors (*FE*) and means of earnings surprises (*ES*) for 5×5 *Size*- and *FEPS*-sorted portfolios. At the beginning of each month, stocks are sorted into five groups based on the level of market capitalization (*Size*) at the end of the previous month. Stocks in each *Size* group are further sorted into five additional quintiles based on the mean of forecasted earnings per share (*FEPS*) of the previous month from the I/B/E/S unadjusted summary historical file. The portfolios are held for twelve months after formation. The forecast error is defined as the difference between the *FEPS* of the previous month and the corresponding actual earnings per share (*Actual*) deflated by the absolute value of *Actual*, that is, (*FEPS* – *Actual*) / |*Actual*|. The earnings surprise is defined as the cumulative abnormal return relative to the CRSP value-weighted index, cumulated from one day before to one day after the date of the most forthcoming earnings announcement over the future twelve months. The sample selection is the same as in Table II. The sample period is January 1983 to December 2004. The *t*-statistics (in parentheses) for *E*5–*E*1 are assessed using the Newey and West (1987) procedure to adjust for serial correlations.

	Size Quintiles					
FEPS Quintiles	*G*1 (Small)	*G*2	*G*3	*G*4	*G*5 (Large)	All Stocks
Panel A: Forecast Errors of Earnings per Share (*FE*)						
*E*1 (Low)	0.355	0.256	0.172	0.081	0.024	0.177
*E*2	0.272	0.117	0.043	0.016	0.009	0.091
*E*3	0.120	0.055	0.022	0.012	0.008	0.043
*E*4	0.076	0.035	0.016	0.010	0.005	0.028
*E*5 (High)	0.050	0.021	0.005	-0.002	0.001	0.015
*E*5–*E*1	-0.305[a]	-0.236[a]	-0.166[a]	-0.082[a]	-0.023[a]	-0.162[a]
t-statistic	(-8.59)	(-5.96)	(-5.15)	(-4.58)	(-3.23)	(-6.77)
Panel B: Earnings Surprises (*ES*)						
*E*1 (Low)	-0.217	-0.446	-0.152	0.054	0.109	-0.130
*E*2	0.106	-0.071	0.012	0.285	0.175	0.101
*E*3	0.203	0.125	0.098	0.271	0.301	0.200
*E*4	0.359	0.233	0.173	0.218	0.180	0.233
*E*5 (High)	0.437	0.205	0.175	0.250	0.248	0.263
*E*5–*E*1	0.654[a]	0.650[a]	0.327[b]	0.195	0.138	0.393[a]
t-statistic	(4.67)	(4.64)	(2.22)	(1.52)	(1.22)	(3.91)

[a,b] indicate statistically significant at the one and five percent levels, respectively.

Table IX
Fama-MacBeth Regressions: Explaining the Cross Section of Individual Stock Returns

This table reports the regression tests of the incremental role of *FEPS* in explaining the cross section of individual stock returns. The dependent variable is the one-month returns ($Ret_{0:1}$) in current month t. The independent variables include a constant (not reported), log of market capitalization at t–1 (*Size*), log of book-to-market ratio (*B/M*), one-month lag of past six-month return ($Ret_{-7:-1}$), past one-month return ($Ret_{-1:0}$), the three-day abnormal return around the most recent earnings announcement date up to the end of month t (ES_{recent}), two measures of historical earnings-to-price ratios (E/P_{y-1} and E/P_{t-1}), and one-month lag of mean forecasted earnings per share (*FEPS*). The values of *B/M* and E/P_{y-1} for July of year y to June of year y+1 is calculated using the book value of equity and net income before extraordinary items for the fiscal-year-end in calendar year y–1 and the market value of equity at the end of December of year y–1. E/P_{t-1} is calculated as follows. First, net income before extraordinary items (Compustat Item 237) for the recently announced fiscal-year-end (I/B/E/S Item *FY0EDATS*) is divided by the number of shares outstanding on the corresponding date of I/B/E/S statistical period to obtain the historical earnings per share (E) for month t–1. Next, E is divided by the stock price (P) on the same day as E to obtain E/P_{t-1}. *FEPS* is directly retrieved from I/B/E/S unadjusted summary historical file. In Model (6), *FEPS* and E/P_{t-1} are demeaned by subtracting their industry medians in each month, where the 48 industries are defined as in Fama and French (1997). Fama and Macbeth (1973) cross-sectional regressions are estimated each month from February 1983 to December 2004, and the means of the monthly estimates are reported. Stocks with a price less than \$5 are excluded from the sample. For all dependent and independent variables, values greater than the 0.995 fractile or less than the 0.005 fractile are set to equal to the 0.995 and 0.005 fractile values, respectively. The t-statistics (in parentheses) are adjusted for serial correlations using the Newey and West (1987) procedure.

Variables	$Ret_{0:1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(*Size*)	-0.075[c]	-0.072[c]	-0.072[c]	-0.070[c]	-0.069[c]	-0.043
	(-1.84)	(-1.76)	(-1.77)	(-1.70)	(-1.65)	(-0.95)
Ln(*B/M*)	0.227[b]	0.210[b]	0.223[b]	0.206[b]	0.201[c]	0.270[b]
	(2.18)	(2.02)	(2.15)	(1.99)	(1.95)	(2.31)
$Ret_{-7:-1}$	0.010[a]	0.008[a]	0.010[a]	0.008[a]	0.008[a]	0.009[a]
	(3.84)	(3.05)	(3.87)	(3.06)	(3.16)	(3.21)
$Ret_{-1:0}$	-0.032[a]	-0.038[a]	-0.032[a]	-0.038[a]	-0.039[a]	-0.037[a]
	(-5.87)	(-6.92)	(-5.94)	(-7.00)	(-7.06)	(-6.54)
ES_{recent}		0.059[a]		0.059[a]	0.059[a]	0.058[a]
		(15.15)		(15.29)	(15.37)	(15.10)
E/P_{y-1}			0.467[c]	0.465[c]		
			(1.87)	(1.85)		
E/P_{t-1}					0.847[b]	1.143[a]
					(2.01)	(2.93)
FEPS	***0.190[a]***	***0.183[a]***	***0.177[a]***	***0.171[a]***	***0.159[a]***	***0.146[a]***
	(3.27)	***(3.18)***	***(3.32)***	***(3.23)***	***(3.22)***	***(4.23)***
Avg. Adj. R^2	0.052	0.054	0.054	0.055	0.056	0.051
Avg. *N*	2,626	2,573	2,625	2,573	2,573	2,573

[a,b,c] indicate statistically significant at the one, five and ten percent levels, respectively.

Table X
Seasonality and Subperiod Analysis for Equally Weighted Forecasted Earnings per Share Deciles

This table reports the time-series averages of returns on *FEPS*-sorted decile portfolios for different months and different subperiods. At the beginning of each month, stocks are sorted into deciles based on the level of mean forecasted earnings per share (*FEPS*) of the previous month. Equally weighted portfolios are held for one month and twelve months, respectively. After the portfolio formation, one-month ($Ret_{0:1}$) and twelve-month ($Ret_{0:12}$) raw returns are calculated for each portfolio, and the returns are adjusted for the survivorship biases. The sample selection is the same as in Table II. The entire sample period is January 1983 to December 2004. The seasonality analysis reports the portfolio returns for the January-only month (portfolios constructed by the end of December) as well as non-January months. In the subperiod analysis, we separate the entire period into the period 1983-1993 and the subsequent period 1994-2004. We also report the portfolio returns for the bubble burst period (August 2000 to March 2003). The *t*-statistics (in parentheses) for *P*10–*P*1 are assessed using the Newey and West (1987) procedure to adjust for serial correlations.

	Seasonality Analysis		Subperiod Analysis					
	Entire Period 1983–2004		Period 1983–1993		Period 1994–2004		Period Aug 2000–Mar 2003	
Portfolios	$Ret_{0:1}$, Jan	$Ret_{0:1}$, Non-Jan	$Ret_{0:1}$	$Ret_{0:12}$	$Ret_{0:1}$	$Ret_{0:12}$	$Ret_{0:1}$	$Ret_{0:12}$
*P*1 (low *FEPS*)	5.136	-0.052	0.350	4.366	0.411	11.134	-4.006	-7.982
*P*2	4.645	0.501	0.779	7.574	0.913	13.841	-1.914	2.185
*P*3	3.878	0.853	1.107	9.764	1.103	14.051	-0.754	8.523
*P*4	3.301	1.018	1.114	10.587	1.303	15.014	0.170	12.780
*P*5	2.923	1.177	1.347	12.435	1.297	14.929	0.597	13.662
*P*6	2.799	1.313	1.520	14.452	1.354	15.926	0.679	14.928
*P*7	2.215	1.326	1.496	16.044	1.303	16.181	0.749	14.309
*P*8	2.066	1.371	1.537	17.479	1.320	17.713	0.852	16.352
*P*9	1.858	1.450	1.613	18.012	1.354	17.992	0.781	14.035
*P*10 (high *FEPS*)	2.133	1.529	1.675	18.718	1.483	19.555	0.869	13.777
*P*10–*P*1	-3.003[c]	1.581[a]	1.325[a]	14.352[a]	1.073	8.421	4.875[a]	21.759
t-statistic	(-1.91)	(3.40)	(3.89)	(3.65)	(1.28)	(0.79)	(2.74)	(1.25)

[a,b,c] indicates statistically significant at the one, five and ten percent levels, respectively.

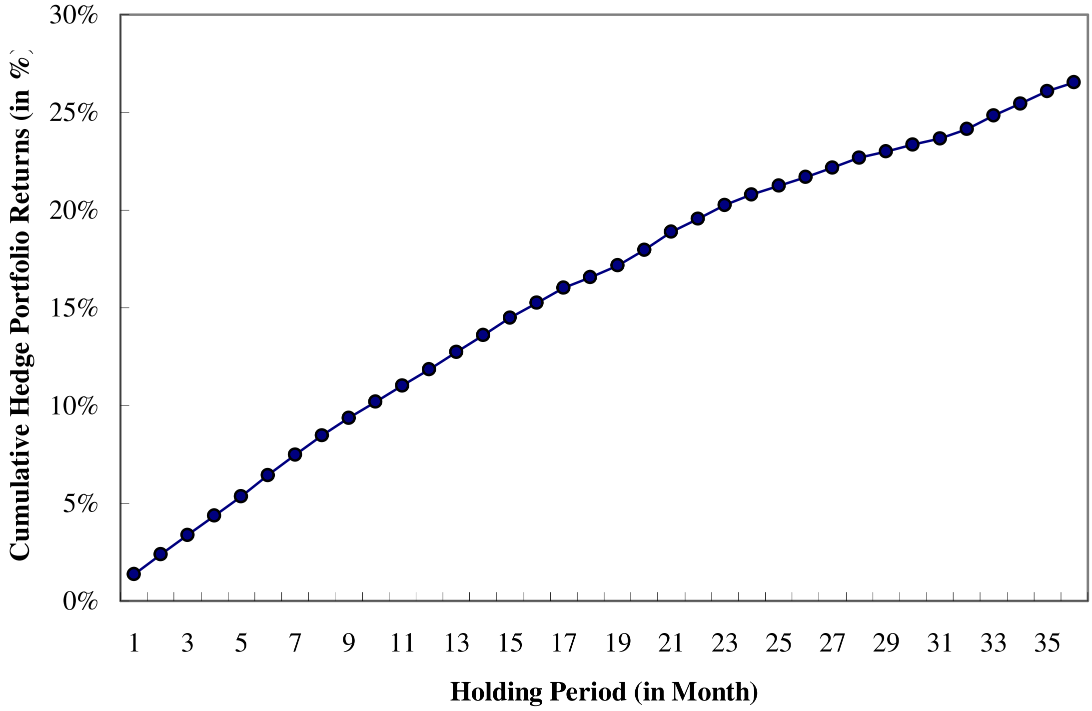

Figure 1. The cumulative (buy-and-hold) returns to a hedge strategy of buying the highest *FEPS* stocks and selling the lowest *FEPS* stocks. At the beginning of each month from January 1983 to December 2002, stocks are ranked into deciles based on the mean of forecasted earnings per share (*FEPS*) of the previous month. Ten *FEPS*-sorted portfolios are formed and held for 36 months and portfolio returns are equally weighted. The figure plots the mean cumulative return differentials between the highest *FEPS* portfolio and the lowest *FEPS* portfolio.

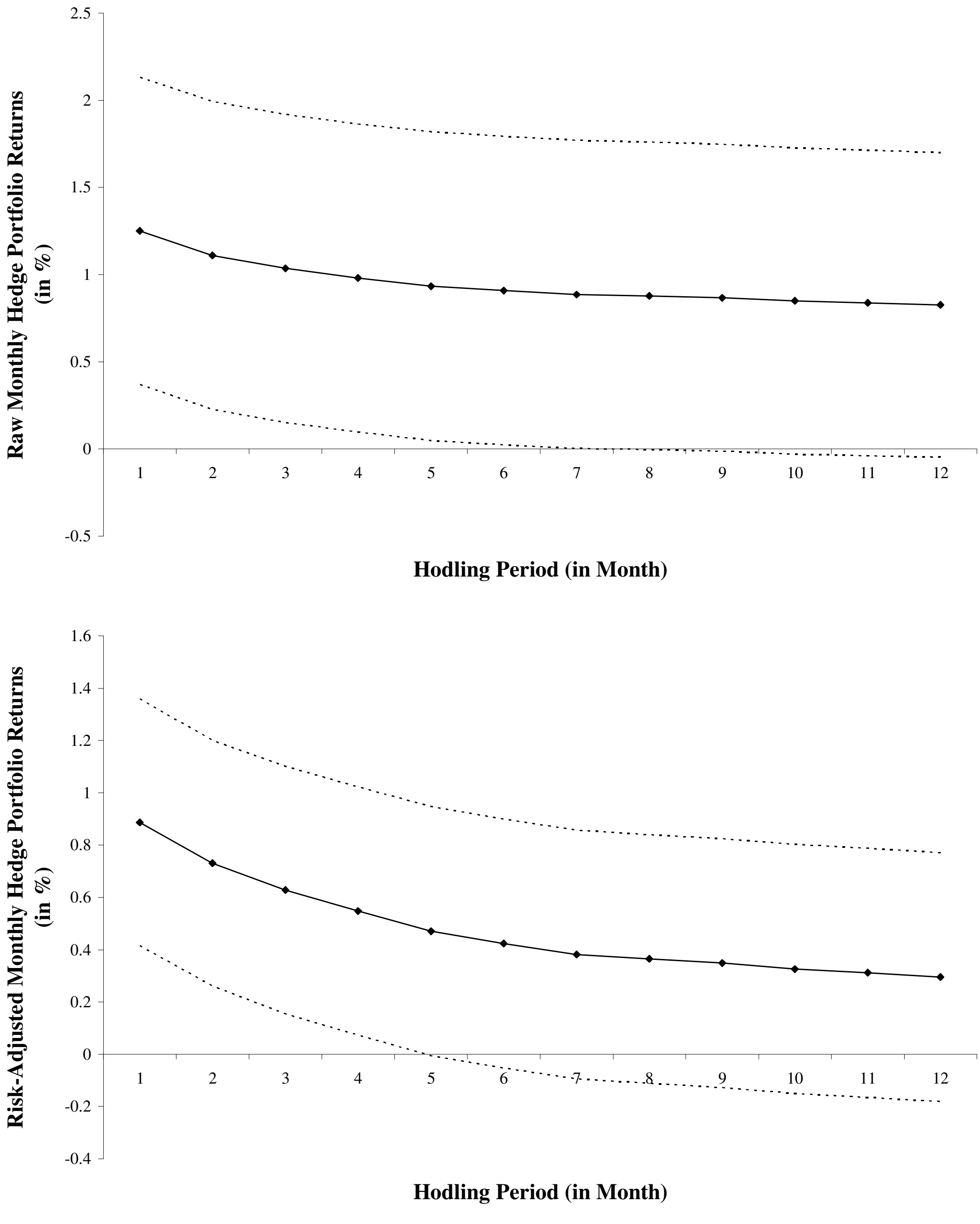

Figure 2. The monthly returns to a hedge strategy of buying the highest *FEPS* stocks and selling the lowest *FEPS* stocks for different holding periods. At the beginning of each month, stocks are ranked into deciles based on the mean of forecasted earnings per share (*FEPS*) of the previous month. Then stocks are held in each *FEPS* portfolio for *T* months (*T*: from 1 month to 12 months), with 1/*T* of the portfolio reinvested monthly. The time-series of portfolio returns from December 1983 to December 2005 are equally weighted and are regressed on the Fama and French three factors and the Carhart (1997) momentum factor to obtain the risk-adjusted return. The figures plot the raw and risk-adjusted monthly return differentials between the highest *FEPS* portfolio and the lowest *FEPS* portfolio for different holding period *T*. The dashed lines denote the 95 percent confidence interval adjusted for serial correlations.