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CONSERVATISM AND CROSS-SECTIONAL VARIATION IN THE POST-EARNINGS-ANNOUNCEMENT-DRAFT

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Conservatism and cross-sectional variation in the post-earnings-announcement-drift[1]

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Abstract

Accounting conservatism allows me to identify a previously undocumented source of *predictable* cross-sectional variation in Standardized Unexpected Earnings' autocorrelations viz. the sign of the most recent earnings realization and present evidence that the market ignores this variation ("loss effect"). It is possible to earn returns higher than from the Bernard and Thomas (1990) strategy by incorporating this feature. Additionally, the paper shows that the "loss effect" is different from the "cross quarter" effect shown by Rangan and Sloan (1998) and it is possible to combine the two effects to earn returns higher than either strategy alone. Thus, the paper corroborates the Bernard and Thomas finding that stock prices fail to reflect the extent to which quarterly earnings series differ from a seasonal random walk and extends it by showing that the market systematically underestimates time-series properties resulting from accounting conservatism.

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Key words: *Anomalies, time series forecasts, conservatism, Post-earnings-announcement-drift, Market Efficiency*

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1. Introduction

Following Bernard and Thomas (1990), the debate around explanations for the Post-earnings-announcement-drift (PEAD) anomaly has centered around the market's ignorance of the serial correlation in Standardized Unexpected Earnings (SUEs). While BT themselves are vague about the extent to which the market ignores the serial correlation, Ball and Bartov (1996) show that the market does not totally ignore SUE autocorrelations. In a recent paper, Jacob et al. (2000) show that BT's tests of the naïve seasonal random walk hypothesis are necessary but not sufficient to conclude that markets naively follow a seasonal random walk model for quarterly earnings expectations. Given these results, further testing of the BT hypothesis is important. One avenue for testing is cross-sectional analysis. An increased ability to predict and earn higher abnormal returns using *predictable cross-sectional variation* in SUE autocorrelations[2] provides stronger evidence that a SUE-based trading rule can generate abnormal returns. I use *accounting conservatism* to

(a) demonstrate predictable cross-sectional variation in the SUE autocorrelation pattern
(b) show the predictable cross-sectional variation in the autocorrelation pattern can be exploited to earn abnormal returns higher than from the BT strategy

My results thus corroborate the BT finding that the market ignores serial correlation in SUEs **and extend it by showing that the market systematically underestimates time-series properties resulting from accounting conservatism.**

Predictable cross-sectional variation in the SUE autocorrelation pattern

Using a simple IMA (1,1) characterization, I first show that the *SUE autocorrelations vary cross-sectionally with the extent of mean reversion in the earnings process.* The higher the mean reversion, the lower are the SUE autocorrelations. One important source of mean reversion in the earnings process that has been empirically documented is accounting conservatism. For example, using conservatism arguments, Basu (1997) argues and finds strong empirical support for *losses and earnings decreases having a greater tendency to mean revert than profits and earnings increases.*[3]

The evidence of a positive relation between losses and mean reversion along with variation in SUE autocorrelations due to mean reversion implies that *firm quarters with losses and decreases will lead to lower SUE autocorrelations than quarters with profits and increases respectively.* I show that using losses and decreases, one can get significant cross-sectional variation in SUE autocorrelations. For instance, the mean first order SUE autoregressive coefficient for profit firms (0.43) is significantly higher (by 42.5%) than the mean first order coefficient for loss firms (0.30). I then investigate the incremental effect of losses over decreases on the autocorrelation pattern. I find that the effect of decreases, though still significant, is quite small in magnitude relative to the effect of losses.

The magnitude of variation in SUE autocorrelations due to losses is comparable to the only other significant *ex-ante* variation in the SUE autocorrelation pattern in the literature viz. the "cross-quarter effect" first documented by BT and further explained by Rangan and Sloan (1998). Hayn et al. (2001) find that there is a higher incidence of losses in the fourth quarter than in other quarters indicating that Rangan and Sloan's "cross-quarter effect" could essentially be the "loss effect" that I document in this paper. However, I find that the "loss effect" and the "cross-quarter effect" lead to significant variation in SUE autoregressive coefficients that are incremental to each other. In fact, the coefficients for the "loss effect" remain essentially the same even after controlling for the "cross-quarter effect".

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[2] I use autocorrelations and autoregressive coefficients interchangeably.

[3] Brooks and Buckmaster (1976) and Elgers and Lo (1994) also find a significant relation between losses and mean reversion.

Cross-sectional variation in abnormal returns

I primarily consider two return windows for my stock return tests: a quarter-long window between the current and first subsequent earnings announcement and a three-day window around the first subsequent quarter's earnings announcement. SUE-based portfolios are formed using information from the current earnings announcement.

As predicted by the SUE-based PEAD strategy, use of loss firms only generates significantly lower abnormal returns than using profit firms only. Average one-quarter ahead three-day announcement return for the profit firms is 1.34% while for loss firms it is only 0.68% (range of 0.66%). The 1.34% return is larger than the average return from following a trading strategy without considering the implications of losses which yields 1.09%. Average quarter-long return for profit firms is 5.39% while for loss firms it is only 3.04%. This is larger than the return from a strategy without considering losses that yields 5.11%. The three-day return for decreases is 0.79% compared to a return of 1.15% (range of 0.36%) for earnings non-decreases. Incremental to losses, however earnings decreases are only marginally significant in explaining abnormal returns.

Similar to the variation in the autocorrelation pattern, there is significant incremental variation in the abnormal returns generated using the "loss effect" even after controlling for the "cross-quarter effect". For example, loss firms in the first fiscal quarter earn –0.11% from the BT strategy while profit firms in other quarters earn 1.70% over a three-day window (range of 1.81%). This variation is significantly higher than the variation due to the "cross-quarter effect" alone at 0.48% for the first fiscal quarter vs. 1.22% for the other quarters (range of 0.74%). For the quarter-long window, the results are similar.

Collins and Hribar (2000) look at the interaction between PEAD and Sloan's accrual anomaly and find that PEAD is virtually non-existent when large negative SUE's are associated with large negative accruals. It is possible that firms with losses have large negative accruals [Hayn et al. (2001)]. Therefore, the same underlying economic attribute could be driving both sets of results. However, Collins and Hribar do not look at whether SUE autocorrelations are also lower. Thus, their study while documenting cross-sectional variation in the PEAD is not a cross-sectional test of the Bernard and Thomas explanation for the Drift. The concern that losses proxy for large negative accruals is mitigated to some extent since the trading strategy using loss firms involves going *both* long and short in loss firms. In any case, I find that even after controlling for large negative accruals, the "loss effect" dominates in both autocorrelations and abnormal returns.

Finally, I present formal statistical tests of whether stock prices reflect, in sign and magnitude, accounting conservatism's implications for the time-series properties of earnings. Recent market efficiency tests[4] adopt the Mishkin (1983) procedure over the two-stage OLS procedure adopted by Ball and Bartov. The Mishkin Test result reinforces the finding that the market fails to fully appreciate the implications of conservatism.

While other papers document cross-sectional variation in abnormal returns, few link it to *predictable* variation in SUE autocorrelations. Rangan and Sloan (1998) is the only paper I know that documents predictable cross-quarter variation in autocorrelations and links it to cross-quarter variation in returns. This paper can thus be viewed as the cross-sectional complement to Rangan and Sloan's cross-quarter result.

The remainder of the paper is as follows: In section 2, I derive testable implications for cross-sectional variation in SUE autocorrelations. Section 3 covers the empirical results for cross-sectional variation in SUE autocorrelations and PEAD. Section 4 concludes and lists future research ideas.

2. Cross-sectional variations in SUE autocorrelations

Since BT explain the post-earnings-announcement-drift using past time-series properties of the quarterly earnings series, logically one should be able to exploit cross-sectional differences in past time-series properties to earn higher abnormal returns. Bernard and Thomas say they attempted cross-sectional tests based on past time-series properties, but were unable to predict variation in the SUE autocorrelations. They state that a possible reason their cross-sectional tests don't yield adequate separation in autocorrelations, out of sample, may be that parameters are estimated with considerable error in small time-series. The considerable error may be due to the use of Brown-Rozeff (1979) and Foster (1977) models to characterize the quarterly earnings process. Both these models use seasonal differencing. Narayanamoorthy (2001) provides justifications for considering IMA (1,1) as a reasonable parsimonious process for quarterly earnings.

Using a parsimonious model means fewer coefficients are estimated leading to more stable estimates. Also, the problem of over-fitting within the sample is mitigated, potentially improving out of sample predictability. While it is difficult to represent different accounting processes using simple time-series models, I show in Section 2.1 that this simple model [IMA (1,1)] can parsimoniously represent the SUE autocorrelation pattern. However, this or any other simple model does not adjust for structural changes that may have taken place during the eight-year estimation period. One cannot also take advantage of the richness of the accounting processes since pooling different accounting processes under one umbrella model can result in poor net cross-sectional variation. In Section 2.2, I overcome this problem by exploiting accounting

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[4] Sloan (1996), Rangan and Sloan (1998), Collins and Hribar (2000) etc.

conservatism to derive implications for cross-sectional variation in the SUE autocorrelations. I empirically test these implications in Section 3.

2.1 Representing SUE autocorrelations using IMA (1,1)

In this sub-section, I show that seasonally differencing an IMA (1,1) process generates the (+ + + -) autocorrelation structure observed[5]. Then I derive implications for cross-sectional variation in the autocorrelations with the IMA (1,1) parameter.

Let earnings follow a simple IMA (1,1) process with parameter $\theta \neq 0$. θ is a measure of the extent of mean reversion in earnings changes. The higher the θ, the higher the extent of mean reversion. If X_t is the earnings at time t, then the IMA (1,1) process characterizing X_t is:

$$X_t = X_{t-1} + \varepsilon_t - \theta\, \varepsilon_{t-1}$$

If we seasonally difference this series,

$$\Delta_4 X_t = X_t - X_{t-4} = (X_t - X_{t-1}) + (X_{t-1} - X_{t-2}) + (X_{t-2} - X_{t-3}) + (X_{t-3} - X_{t-4})$$

$$= \varepsilon_t - \theta\, \varepsilon_{t-1} + \varepsilon_{t-1} - \theta\, \varepsilon_{t-2} + \varepsilon_{t-2} - \theta\, \varepsilon_{t-3} + \varepsilon_{t-3} - \theta\, \varepsilon_{t-4}$$

$$\Delta_4 X_{t-1} = \varepsilon_{t-1} - \theta\, \varepsilon_{t-2} + \varepsilon_{t-2} - \theta\, \varepsilon_{t-3} + \varepsilon_{t-3} - \theta\, \varepsilon_{t-4} + \varepsilon_{t-4} - \theta\, \varepsilon_{t-5}$$

$$\Delta_4 X_{t-2} = \varepsilon_{t-2} - \theta\, \varepsilon_{t-3} + \varepsilon_{t-3} - \theta\, \varepsilon_{t-4} + \varepsilon_{t-4} - \theta\, \varepsilon_{t-5} + \varepsilon_{t-5} - \theta\, \varepsilon_{t-6}$$

$$\Delta_4 X_{t-3} = \varepsilon_{t-3} - \theta\, \varepsilon_{t-4} + \varepsilon_{t-4} - \theta\, \varepsilon_{t-5} + \varepsilon_{t-5} - \theta\, \varepsilon_{t-6} + \varepsilon_{t-6} - \theta\, \varepsilon_{t-7}$$

$$\Delta_4 X_{t-4} = \varepsilon_{t-4} - \theta\, \varepsilon_{t-5} + \varepsilon_{t-5} - \theta\, \varepsilon_{t-6} + \varepsilon_{t-6} - \theta\, \varepsilon_{t-7} + \varepsilon_{t-7} - \theta\, \varepsilon_{t-8}$$

Thus,

$$\delta_{t-1} = \text{Corr}\,(\Delta_4 X_t, \Delta_4 X_{t-1}) = \frac{3(1-\theta)^2}{3(1-\theta)^2 + 1 + \theta^2}$$

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[5] I am grateful to Ross Watts for making this point

$$\delta_{t-2} = \text{Corr}\,(\Delta_4 X_t, \Delta_4 X_{t-2}) = \frac{2(1-\theta)^2}{3(1-\theta)^2 + 1 + \theta^2}$$

$$\delta_{t-3} = \text{Corr}\,(\Delta_4 X_t, \Delta_4 X_{t-3}) = \frac{(1-\theta)^2}{3(1-\theta)^2 + 1 + \theta^2}$$

$$\delta_{t-4} = \text{Corr}\,(\Delta_4 X_t, \Delta_4 X_{t-4}) = \frac{-\theta}{3(1-\theta)^2 + 1 + \theta^2}$$

A simple first-order process thus generates the (+ + + -) pattern observed in autocorrelations of a seasonally differenced series. The economic intuition behind deriving the (+ + + -) pattern is slightly involved. Let $\Delta_{4,t}$ represent the seasonal difference in earnings X_t-X_{t-4} and Δt the difference in adjacent quarters X_t-X_{t-1}. $\Delta_{4,t}$ can be thought of as the sum of four adjacent differences, i.e. $\Delta_{4,t} = \Delta_t + \Delta_{t-1} + \Delta_{t-2} + \Delta_{t-3}$. The lagged seasonal difference term $\Delta_{4,\, t-1}$ will then be $\Delta_{t-1} + \Delta_{t-2} + \Delta_{t-3} + \Delta_{t-4}$. It is seen that there are three common adjacent difference terms between $\Delta_{4,t}$ and $\Delta_{4,t-1}$. These common differences lead to a positive autocorrelation between $\Delta_{4,t}$ and $\Delta_{4,t-1}$. Similarly at lags two and three, there are two common adjacent difference terms and one common term respectively. These lead to the progressively smaller autocorrelations seen for lags 1-3. Comparing $\Delta_{4,t}$ and $\Delta_{4,t-4}$ there are no common difference terms. However, existence of errors in one period that get corrected in the next [IMA (1,1)] implies that adjacent differences are negatively autocorrelated. Since $\Delta_{4,t}$ includes the Δ_{t-3} term and $\Delta_{4,t-4}$ includes the Δ_{t-4} term and Δ_{t-3} and Δ_{t-4} are negatively autocorrelated, we see a negative autocorrelation between $\Delta_{4,t}$ and $\Delta_{4,t-4}$. Thus, the (+ + + -) pattern seen in SUE autocorrelations is consistent with seasonally differencing an IMA (1,1) process.

From the expressions for the δ_j, the lag j autocorrelation in the seasonally differenced series, one can derive their sensitivity to θ.

$$\frac{d\delta_{\text{t-1}}}{d\theta} = \frac{-6\left(1-\theta^2\right)}{\left(3(1-\theta)^2+1+\theta^2\right)^2} < 0 \qquad \forall \qquad \theta < 1$$

Similarly derivatives of δ_{t-2} and δ_{t-3} are negative.

$$\frac{d\delta_{\text{t-4}}}{d\theta} = \frac{-4\left(1-\theta^2\right)}{\left(3(1-\theta)^2+1+\theta^2\right)^2} < 0 \qquad \forall \qquad \theta < 1$$

The intuition behind the negative sign on the derivatives follows from the intuition given earlier for the (+ + + -) autocorrelation pattern. Positive autocorrelations at lags 1-3 are a manifestation of common adjacent quarter difference terms in the seasonally differenced series. The larger the error correction (or mean reversion) in accounting data across adjacent periods (i.e. the larger the θ), the lesser is the sum of adjacent differences, and hence the lesser the autocorrelations in the seasonally differenced series. This implies that the autocorrelations decrease in θ. The negative autocorrelation at the fourth lag of the seasonally differenced series was shown to be a result of the autocorrelation between Δ_{t-3} and Δ_{t-4}. The higher the θ, more negative is this autocorrelation and hence more negative is the 4^{th} lag autocorrelation in the seasonally differenced series.

All correlations algebraically decrease in θ i.e. the positive correlations for the first three lags are decreasing in θ and the (absolute) magnitude of the negative correlation for lag 4 is increasing in θ. First order autocorrelation in earnings changes for the above process is $\rho = \frac{-\theta}{1+\theta^2}$. Since this is monotonically decreasing in θ, I use it as a proxy for mean reversion. Hence, if my characterization of the earnings process is representative, I expect that all the SUE autocorrelations will increase in ρ.

Use of simple models like IMA (1,1) treats all firms as having identical time series properties, which, in practice, is not likely. For instance, Bathke and Lorek (1984) and Brown and Han (2000) show that AR (1) is a good representation for the quarterly earnings process for about 20% of the firms. However, the simple characterization demonstrates the relation between mean reversion and SUE autocorrelations, and hence, guides the search for variables that can have implications for cross-sectional variation in the PEAD. In the next sub-section, I take advantage of the implications of accounting conservatism for mean reversion to draw inferences for cross-sectional variation in SUE autocorrelations. In a sense, this paper is very similar to Rangan and Sloan's paper. While Rangan and Sloan take advantage of the richness of the quarterly accounting process (integral method of accounting) to get cross-quarter variation, I exploit accounting conservatism to get cross-sectional variation.

2.2 *Accounting Conservatism and cross-sectional variation in SUEs*

Basu (1997) defines conservatism in accounting as capturing accountants' tendency to require a higher degree of verification for recognizing good news than bad news in financial statements. Thus earnings reflects bad news more quickly than good news. For example unrealized losses are typically recognized earlier than unrealized gains. He shows that this asymmetry in recognition leads to systematic differences between bad news and good news periods in the persistence of earnings.

In his empirical tests, consistent with the above argument, Basu finds strong support for losses[6] and earnings decreases having a greater tendency to mean revert than profits and earnings

[6] There is another reason for losses to be linked with increased mean reversion. Firms incurring losses have the option to liquidate the firm if the management does not anticipate recovery [Hayn (1995), Collins, Maydew and Weiss (1997)]. That means surviving firms are expected to reverse their poor performance. Thus, the abandonment option and survivor bias imply that losses will revert more.

increases. He shows that the autoregressive coefficient on earnings changes is significantly more negative for loss (and earnings decrease) firms than profit (and earnings increase) firms.[7,8]

Based on the discussion in section 2.1 linking mean reversion with SUE autocorrelations, this implies that firm quarters with losses and decreases will lead to lower SUE autocorrelations than profits and increases respectively i.e. losses and decreases are two factors that drive mean reversion in the time-series process. [9]

In other words, since losses (and earnings decreases) mean revert more (above discussion), and higher mean reversion leads to lower future SUE autocorrelations, I predict that *loss (and earnings decrease) firms have lower first, second and third order SUE autocorrelations and higher fourth order negative autocorrelations in SUE deciles than profit (and earnings increase) firms. In other words, all four autocorrelations will be algebraically lower for loss (and earnings decrease) firms.*

3. Empirical Results

3.1 Data

Quarterly earnings data for years 1978-98 are obtained from COMPUSTAT. I compute earnings as COMPUSTAT Data Item 8 – earnings before extraordinary items. Return data are taken from the CRSP daily file.

The variable used as a measure of scaled earnings surprise is Standardized Unexpected Earnings (SUE). The numerator of SUE is current earnings minus earnings from the corresponding quarter

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[7] Basu (1997 p.21) Table 3 panels B and C

[8] Brooks and Buckmaster (1976) and Elgers and Lo (1994) also find that there is more mean reversion in losses than profits

a year ago ($\Delta_4 X$). The scaling factor is the previous fiscal quarter's closing market value (product of Compustat Data Item 14 – end of quarter price of common share and Data Item 61 – number of common shares outstanding). This definition is similar to Rangan and Sloan, who scale by current market value. Bernard and Thomas scale by the standard deviation of past seasonally differenced earnings. Since SUE is a measure of seasonally differenced earnings and I need up to four lags of SUEs for the autocorrelation pattern, similar to BT and Rangan and Sloan, I have a requirement of minimum 9 quarters of consecutive earnings data. This leaves 169,727 firm quarters from 1978-1998 with valid COMPUSTAT and CRSP data.

BT and Rangan and Sloan use decile ranks of SUEs instead of SUEs themselves. This is to mitigate the impact of outliers. In Table 1, similar to Rangan and Sloan, I provide the autoregressive coefficients pattern for decile ranks of SUE for my full sample. These are computed as coefficients from the following regression:

$$SUE_t = a_k + b_k SUE_{t-k} + e_t, \quad k = 1,2,3,4 \qquad (1)$$

where SUE_t is the scaled SUE decile rank at time t. SUE decile ranks are originally numbered from 0 to 9. I convert them to scaled ranks by the following transformation: divide by 9 and subtract 0.5. Now the scaled ranks vary from –0.5 to +0.5. The main advantage of the scaling is that, because the mean is zero, if autocorrelations are stable, I expect to see a near zero intercept when I regress current SUE on past SUE. The range of one implies that the coefficient on SUE in a return regression represents the abnormal return from a zero investment strategy of going long on the highest SUE decile and short on the lowest SUE decile.

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[9] Narayanamoorthy (2001) discusses that asymmetry in reporting good and bad news, while sufficient, is not a necessary condition to have an association between losses and mean reversion.

All intercept terms are economically close to zero and are omitted for brevity. The (+ + + -) pattern is clearly there in the autoregressive coefficient pattern. The positive autocorrelations decrease from 0.40 at first lag to 0.07 at lag three. I present these in the same panel along with the coefficients from Rangan and Sloan's sample. The coefficients are nearly indistinguishable.

While Bernard and Thomas document abnormal returns around announcement days for the four quarters subsequent to an earnings announcement, these returns are highest around first subsequent quarter's announcement. Soffer and Lys (1999) show that, even though information about the implications of current SUE for future SUE are not anticipated by the market immediately following the current earnings announcement, nearly 50% of this information is anticipated prior to the next quarter's earnings announcement.[10] Hence I primarily consider two return windows for my stock return tests: a quarter-long window that starts two days after the earnings announcement date and ends with the next quarter's earnings announcement date and a three-day window around the first subsequent earnings announcement.

Returns are with-dividend, buy and hold compounded over the return windows. Bernard and Thomas (1989) show that the predictable stock returns are robust to a battery of risk adjustments. Hence, like Rangan and Sloan, I restrict my analysis to market adjusted returns. They are adjusted by the market return on the CRSP value-weighted index over the corresponding window. I also include dummies for losses and decreases in my return regressions, where applicable, to proxy for any additional risk.

Table 2 presents the results of the SUE-based PEAD strategy. The following regression has been estimated:

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[10] Ball and Bartov (1996) show that the other 50% manifests as abnormal returns around the first subsequent earnings announcement.

$$AR_t = a_k + b_k\, SUE_{t-k} + e_t \qquad k=1,2,3,4 \qquad (2)$$

where AR_t is the market adjusted return measured over the two windows – three-day and quarter-long – described earlier.

As outlined earlier in this sub-section, the scaling of the SUE decile rank (from –0.5 to 0.5 – i.e. range of one) enables interpretation of the coefficient on SUE in the return regression (2) as the average abnormal return from a zero investment portfolio formed by going long in the top SUE decile and short in the bottom SUE decile. Thus, at lag one, the coefficient of 1.09 (5.11) can be interpreted as a 1.09% (5.11%) abnormal return over a three-day (quarter-long) window from a zero investment portfolio long in the top SUE decile and short in the bottom SUE decile. A three-day return of 1.09% translates to an annualized abnormal return of 107% (assuming 200 trading days in a year). The quarter long abnormal return of 5.11% is comfortably in excess of transaction costs.[11]

Besides the first subsequent quarter, both the short and long window abnormal returns for subsequent quarters two and four are also significantly different from zero. The abnormal return three quarters hence is negative, but insignificantly different from zero. The total return from the four subsequent quarters' short window is 2.11% ($r_{t+1} + r_{t+2} + r_{t+3} – r_{t+4}$). The total return from the four announcement periods for Bernard and Thomas is 2.72%[12]. The total return from the four subsequent quarters' quarter-long windows is 6.91%. Consistent with Soffer and Lys (1999),

[11] To appreciate further the economic significance of the long and short window abnormal returns, see Bernard and Thomas (1989) and Ball (1992 p. 332)

[12] Johnson and Schwarz (2001) show that the drift has become smaller in recent years. Also my return of 2.11% represents includes all observations while BT's return of 2.72 % is only from the top and bottom SUE deciles where the effect is strongest. For my analysis, the regressions are better than hedge portfolios

most of the return (5.11% out of 6.91%) comes before and immediately after the next quarter's earnings announcement.

3.2 Cross-sectional variation in SUE autocorrelations

Empirically I test, whether, as hypothesized, future SUE autocorrelations are predictable using past ρ, the first order autocorrelations in earnings changes. The requirement of having 16 past observations and 16 future observations of earnings reduces the sample to 41,428 observations. For every firm quarter, I compute ρ using the previous 16 observations.

I then run the following regression:

$$scorr_k = \alpha + b_k \rho_t + \varepsilon_t \qquad k=1,2,3,4 \qquad (3)$$

where $scorr_k$ is the k^{th} order autocorrelation computed at t using future 16 observations and ρ_t is the first order autocorrelation in earnings changes computed using the past 16 observations.

From the results in Table 3, exactly as predicted, the coefficient of ρ is positive and significant at the 1 % level for first, second and fourth order future autocorrelations in seasonally differenced SUE deciles. The coefficient is also significant at the 5% level for the third order autocorrelations. Bernard and Thomas themselves attempted to find cross-sectional variation in SUE autocorrelations using past time series properties. However, they report that they were unsuccessful due to errors in estimation. My parsimonious representation of the earnings process as IMA (1,1) enables me to get statistically significant variation as predicted. However, the magnitude of the variation is not large. The largest coefficient b_1 in equation (3) is 0.07. This

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since they allows me to include a direct loss dummy to control for potential correlated omitted variable bias means a large 0.5 (more than half its range) change in ρ generates only a 0.035 change in the first order autocorrelation.

To get larger variation in the SUE autocorrelations, I investigate variation with accounting conservatism. I argue in section 2.2 that SUE autocorrelations should be lower for losses (and earnings decreases) than profits (and earnings increases). I estimate the effect of losses (or earnings change) on SUE autocorrelations by running the following pooled time series regression:

$$SUE_t = a_k + b_k\, SUE_{t-k} + c_k\, DUM_k + d_k\, (DUM_k \times SUE_{t-k}) + e_t \qquad k=1,2,3,4 \qquad (4)$$

where SUE_t is the scaled SUE decile rank at time t and the indicator variable DUM_k is one when earnings at t-k (or earnings change at t-k) is negative and zero when it is not.

In section 3, I demonstrated that SUE autocorrelations at all four lags decrease in the extent of mean reversion. I also argued why losses are more mean reverting than profits. Thus, I hypothesize that SUE autocorrelations at all four lags decrease in losses, which means that I expect d to be negative for all k. I include DUM_k as a separate variable in the regression. The inclusion of this direct effect addresses the possibility that the SUE decile for losses is different from the SUE decile for profits. If the DUM_k term is not included, it is possible the correlated omitted variable problem will lead to a spurious relation between SUE_t and the interactive dummy variable ($DUM_k \times SUE_{t-k}$) i.e. it will lead to a spurious coefficient d.

Table 4 panels A and B list the results of the above regression. In panel A, d is strongly significant and in the predicted direction for every k. The variation in profit and loss SUE autoregressive coefficients is large. In panel A, while profit firms have a SUE first order

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problems.

autoregressive coefficient of 0.43, loss firms have a coefficient of 0.30 (= 0.43-0.13). A similar difference for the first order autoregressive coefficient is observed by Rangan and Sloan in their study of cross-quarter variation in the BT effect. Panel C replicates their result (running the above regression with DUM_k equal to one when quarters t and t-k are in the same fiscal year and zero otherwise - note that this regression is not estimated for k = 4 since any quarter at lag four is always in a different fiscal year). From panel C, the maximum difference in SUE autoregressive coefficient is 0.17 at lag one, which is comparable to 0.13 at lag one for loss firms in panel A. Thus, I succeed in getting significant cross-sectional variation in the autocorrelation pattern. In panel B, there is significant difference in the first order autocorrelation for earnings increase and decrease firms for lags one, two and four. However the difference at lag one (-0.05) is much smaller than the difference for loss firms.

To quantify the incremental effect of losses and decreases on SUE autoregressive coefficients, I run the following regression:

$$SUE_t = a_k + b_k\, SUE_{t-k} + c_k\, DUM_k + d_k\, (DUM_k \times SUE_{t-k}) + g_k\, DEC_k + h_k\, (DEC_k \times SUE_{t-k}) + e_t \qquad k=1,2,3,4 \quad (5)$$

where DUM_k is one when the earnings realization at quarter t-k is less than zero and zero otherwise and DEC_k is one when earnings at quarter t-k is less than earnings at quarter t-k-1 and zero otherwise.

Table 5 panel A presents the results of this regression. Loss firm SUE autoregressive coefficients continue to be much smaller than profit firms even after adjusting for decreases. For example, at lag 1 (k=1), loss firm autoregressive coefficients are still 0.12 lower than profit firm coefficients. At lags one, two and four, loss firm dummies have a larger incremental effect than decrease firm dummies. At lag one, decrease firm autoregressive coefficients are only 0.03 lower than increase firm coefficents after controlling for losses. It is interesting, however, that at lag three, the interactive decrease dummy dominates and the coefficient on the interactive loss dummy is in the opposite direction. I do not have a reason for this effect. This result does not have any major implications for the PEAD since three quarter ahead abnormal returns are very small.

The other significant variation in the SUE autocorrelation pattern in the literature is the "cross-quarter effect" first documented by BT and further explained by Rangan and Sloan (1998) as occurring because of the integral method of reporting. APB opinion 28 states that each quarter should be viewed as an integral part of the fiscal year and not a stand-alone period. Thus, certain provisions or estimates are made for the entire fiscal year and apportioned to each quarter. Rangan and Sloan argue that the use of integral method of reporting leads to variation in SUE autoregressive coefficients across quarters. They find that autoregressive coefficients and the PEAD are larger for quarters within the same fiscal year than for quarters in different fiscal years. In other words, portfolios formed following fourth quarter earnings are shown to have lower PEAD than other quarters. Hayn et al. (2001) find that there is a higher incidence of losses in the fourth quarter than in the other quarters. It is thus possible that the "loss effect" documented in this paper and the "cross-quarter effect" investigated by Rangan and Sloan are the same. To see if the "loss effect" and the "cross-quarter effect" are two different effects or the same, I run the following regression:

$$SUE_t = a_k + b_k\, SUE_{t-k} + c_k\, DUM_{t-k} + d_k\, (DUM_{t-k} \times SUE_{t-k}) + g_k\, Q_{t-k} + h_k\, (Q_{t-k} \times SUE_{t-k}) + \varepsilon_t \qquad k=1,2,3 \qquad (6)$$

where the indicator variable Q_{t-k} is 1 when Q_{t-k} and Q_t are in the same fiscal year and is zero otherwise and the indicator variable DUM_k is one when earnings at t-k is negative and zero when it is not. Again note that this regression is not run for k = 4 since any quarter at lag four is always in a different fiscal year.

From the results in Table 5 panel B, coefficients on both interactive dummies are significant indicating losses have significant incremental predictive power for the SUE autoregressive coefficients even after adjusting for the fourth quarter effect. Loss firm coefficients remain essentially the same before and after controlling for the "cross-quarter effect" (compare Table 4 panel A and Table 5 panel B). Loss firm coefficients remain 0.12 lower than profit firm coefficients even after controlling for the effects of the Integral Method of Reporting. The highest autoregression coefficient at lag one is for non-fourth quarter profit firms (0.47% = 0.31% + 0.16%) and the lowest coefficient if for fourth quarter loss firms (0.19% = 0.31% - 0.12%). Thus, the "loss effect" reported in this paper, is different from the "cross-quarter effect" reported by BT and Rangan and Sloan and is of comparable magnitude.

Collins and Hribar (2000) look at the interaction between PEAD and Sloan's accrual anomaly and find that PEAD is virtually non-existent when large negative SUE's are associated with large negative accruals. It is possible that firms with losses have large negative accruals (Hayn et al. (2001); therefore, the same underlying economic attribute could be driving both sets of results. However, Collins and Hribar do not look at whether SUE autocorrelations are also lower. To see if large negative accruals are driving the "loss effect" autocorrelations, I run a regression similar to (5). The results are presented in Panel C. The "loss effect" autoregressive coefficient dominates the negative accrual autoregressive coefficient for all four lags. For example, at lag one, the loss firm coefficients are 0.12 lower than profit firms while the coefficient for large negative accrual firms are only 0.04 lower.

3.3 Cross-sectional variation in abnormal returns

When I investigate cross-sectional variation in future abnormal returns with the mean reversion proxy, past ρ (first order autocorrelation in earnings changes), I find that the one-quarter ahead and three-day abnormal returns have signs consistent with the seasonal random walk fixation story i.e. the abnormal returns are lower for lower for lower ρ (not reported). They are, however, economically and statistically insignificant. Since Bernard and Thomas show that abnormal returns decrease in size, I included size as a potential explanatory variable in the abnormal return regressions. Even in these regressions, while signs of the coefficients are consistent with the fixation story, they are not significant. This is understandable since the variation in SUE autocorrelations using ρ (documented in section 3.2 and reported in Table 3) is not large.

Since losses and decreases lead to much greater variation in the SUE autocorrelations, they have greater promise in the ability to detect variation in abnormal returns. Table 6 panel A presents the results of the SUE-based PEAD strategy incorporating the effect of losses. The regression estimated is:

$$AR_t = a_1 + b_1 \, SUE_{t-1} + c_1 \, DUM_1 + d_1 \, (DUM_1 \times SUE_{t-1}) + e_t \qquad (7)$$

Where $DUM_1 = 1$ if a loss was reported in quarter t-k

The coefficient on lagged SUE, $b_1 = 1.34$ implies that the return using profit firms only is 1.34%. Using loss firms only, the return is 0.68% (= 1.34% - 0.66%). This is as predicted by the lower autocorrelation for loss firms outlined in section 3.2 and reported in Table 3. Recall that the first lag autoregressive coefficients in Table 4 panel A were 0.43 for profit firms and 0.30 (=0.43 – 0.13) for loss firms. An abnormal return of 0.66% over a three-day window translates to an annualized return of in excess of 55% indicating the economic significance of the effect of losses for PEAD. It is pertinent to point out that there are minimal additional transaction costs in earning incremental returns by employing the SUE-based PEAD strategy for profit firms only over employing the strategy for all firms since similar transaction costs would be incurred in both strategies.[13]

To control for possible cross-correlation, I estimated equation (7) for each year from 1980 to 1998 separately. The coefficient d_1 is negative for 17 out of the 19 years. The average coefficient d_1 was -0.62% (compared to a coefficient of –0.66% without controlling for cross –correlation) and the t-statistic across the years was -3.78. Thus, even after controlling for cross correlation, the "loss effect" is statistically and economically significant.

Panel B presents the results using decreases instead of losses (DUM_1 = 1 if earnings decreased from quarter t-2 to quarter t-1). The returns following decreases are 0.79% (1.15% - 0.36%), and for earnings increases, the returns are 1.15%. From Table 4 panel B the first lag autoregressive coefficients are 0.36 (0.41 – 0.05) for earnings decreases and 0.41 for earnings increases. Again the abnormal return pattern is similar to the autoregressive coefficient pattern.

Since the variations in abnormal returns mirror the variations in SUE autoregressive coefficients, the results are consistent with the market failing to understand implications of losses / decreases for the SUE autocorrelation pattern.

For comparison, panel C presents the returns on the PEAD strategy incorporating the cross-quarter variation documented by Rangan and Sloan. The regression estimated is:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + e_t \qquad (8)$$

Where DUM_1 = 1 if t and t-1 are in the same fiscal year and zero otherwise

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[13] An argument can also be made for lower transaction costs for a strategy involving profit firms only since profit firms, on average, are larger than loss firms and transaction costs are lower for larger firms.

The coefficient on lagged SUE, $b_1 = 0.23$ implies that the returns following the fourth quarter are 0.23% while the average for the other quarters is 1.38% (= 0.23% + 1.15%). The corresponding long window abnormal returns are 2.25% and 6.03% (= 2.25% + 3.78%). Table 4 panel C shows that the autoregressive coefficients at lag one are 0.17 following the fourth quarter and 0.44 (= 0.17 + 0.27) following other quarters.[14] Thus, similar to the autoregressive coefficient pattern in Table 4, abnormal returns are significantly lower following the fourth quarter, which is consistent with the market ignoring the implications of the integral method of reporting for the autoregressive coefficient pattern. This is the Rangan and Sloan result.

Table 7 panel A presents the results for a PEAD strategy including both losses and decreases. The regression used is

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + g_1\, DEC_1 + h_1\, (DEC_1 \times SUE_{t-1}) + e_t \tag{9}$$

where $DUM_1 = 1$ if a loss was reported in quarter t-1 and $DEC_1 = 1$ if a earnings decreased from quarter t-2 to quarter t-1.

SUE autoregressive coefficients outlined in the previous sub-section and reported in Table 5 panel A show that, by and large, the “loss effect” dominates the effect of decreases in terms of cross-sectional variation. For example, at lag one (k = 1), loss autoregressive coefficient is 0.12 lower while the decrease autoregressive coefficient is only 0.03 lower. The coefficient on the interactive loss dummy in Table 7 is –0.58% and on the interactive decrease dummy is only –

[14] $DUM_1 = 1$ means quarters t and $t\text{-}1$ are in different fiscal years which is only possible for the fourth quarter

0.19%. Thus, similar to the autoregressive coefficient pattern, incremental to losses, decreases have an economically small effect, though still statistically significant.

Table 7 Panel B presents the results for the SUE-based PEAD strategy incorporating both cross-sectional variation due to losses and cross-quarter variation due to the Integral Method of Reporting. The following regression is estimated:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + g_1\, Q_1 + h_1\, (Q_1 \times SUE_{t-1}) + e_t \quad (10)$$

Where $DUM_1 = 1$ if a loss was reported in quarter t-1 and $Q_1 = 1$ if t and t-1 are in the same fiscal year and zero otherwise

Coefficients on both the interactive loss dummy and the interactive quarter dummy are significant and economically large. The highest short window abnormal return is for non-fourth quarter profit firms (1.70% = 0.48% + 1.22%) and the lowest abnormal return is for fourth quarter loss firms (–0.11% = 0.48% - 0.59%). Again, this pattern is similar to the SUE autoregressive coefficient pattern discussed in section 3.2 and reported in Table 5 panel B. The highest autoregressive coefficient at lag one is for non-fourth quarter profit firms (0.47 = 0.31 + 0.16) and the lowest coefficient at lag one is for fourth quarter loss firms (0.19 = 0.31 – 0.12). Thus, using losses and the integral method of reporting together, I am able to achieve a range of variation of 1.81% compared to a range of 0.66% for losses alone (Table 6 panel B) and 1.15% for integral method of reporting alone (Table 6 panel A).

To see if the abnormal return due to loss firms is distinct from the effect of large negative accruals [documented by Sloan (1996) and Collins and Hribar (2000)], I run a regression similar to (9). The results are presented in Panel C. The short window loss firm interactive coefficient is still significant at -0.50% while the negative accrual interactive coefficient is very close to zero, showing that the “loss effect” documented in the paper remains even after controlling for the effect of large negative accruals. For the long window, the loss firm interactive coefficient is -1.81%, while the negative accrual interactive coefficient is actually positive and marginally significant at the 10% level. The coefficient on the negative accrual dummy, g_1, is 0.86% with a t-statistic of 10.89, which is the Sloan (1996) result of positive returns following large negative accruals. The results for the long window are similar.

Hayn et al. (2001) document a negative relation between losses and size. Cross-sectional variation in PEAD due to size has been documented by BT. It is possible that size is a significant correlated omitted variable in the prior analyses of cross-sectional variation in PEAD with losses. However, BT find that smaller firms show higher abnormal returns. Thus, due to the effect of size, loss firm returns are likely to be higher, which is opposite to the prediction I make in the paper using the autocorrelation pattern. As such, controlling for size should only make the “loss effect” stronger. Indeed, I find in Table 8 that loss firm short window returns after adjusting for size are 0.91 % lower (compared to 0.66% lower without controlling for size under k = 1 in Table 6 Panel A). However, the long window return after controlling for size is only lower by 1.52% (compared to 2.35% without considering losses).

Table 8 also presents the results incorporating all three effects (losses, cross-quarter and size). The regression estimated is

$$AR_t = a_1 + b_1 SUE_{t-1} + c_1 DUM_1 + d_1 (DUM_1 \times SUE_{t-1}) + g_1 S_1 + s_1 (S_1 \times SUE_{t-1}) + + r_1 Q_1 + h_1 (Q_1 \times SUE_{t-1}) + e_t \quad (11)$$

where $DUM_1 = 1$ if a loss was reported in quarter t-1 and S_1 is the size decile based on previous quarter’s results scaled to –0.5 to 0.5 and $Q_1 = 1$ if t and t-1 are in the same fiscal year and zero otherwise.

The estimated coefficient on the interactive loss dummy, d_1 continues to be significant for the short-window return at –0.85%. The highest short window return is for non-fourth quarter profit firms in the lowest size decile (1.53% = 0.48 + 1.05) and the lowest return is for fourth quarter loss firms in the highest size decile (-1.97% = 0.48 – 0.85 – 1.60). In order to address possible cross-correlation effects, I ran yearly regressions of equation (11) from 1980-1998. d_1 was negative in 17 out of 19 years. Average d_1 was –0.78 and the t-statistic was –3.93 (compared with –0.85 and –6.13 for the pooled regression), indicating the economic and statistical significance of the interactive loss dummy even after controlling for cross-correlation.

One final note is in order. I have focused on cross-sectional variation in the one-quarter ahead announcement period and quarter-long abnormal returns. The naïve seasonal random walk fixation hypothesis implies abnormal returns two, three and four quarters ahead also. From table 4, there is cross-sectional variation in the autoregressive coefficients at lags two, three and four also. However, I do not find significant variation in abnormal returns in subsequent quarters two, three and four. This is consistent with the Soffer and Lys (1999) argument that even though information about the implications of current SUE for future SUE are not anticipated immediately following the current earnings announcement, a large part of this information is anticipated prior to the next quarter's earnings announcement. It is also consistent with the Ball and Bartov finding that the market appreciates a part of the implications of the autocorrelation pattern and is not totally naively fixated.

3.4 Test of Market Efficiency

In this sub-section, I conduct formal statistical tests of whether the signs and magnitudes of abnormal stock returns reflect the implications of conservatism for the SUE autocorrelation structure. Two types of tests have been employed in the literature. Ball and Bartov (1996) investigate the earnings expectation model implicit in the price reaction to current earnings by including current SUE in a regression of abnormal returns on past SUE. They estimate the actual relation between current SUE and past SUE and test whether the actual relation is the same as the relation implicit in abnormal returns. While Ball and Bartov use a two-stage least squares estimation approach, Mishkin (1983) advocates the estimation of a simultaneous equation system in preference to the two-stage least squares approach. The Mishkin test has become the industry standard for market efficiency tests. However, recent evidence in Kothari et al. (2000) suggests that the test is very sensitive to survivor biases and truncation errors. Here I report only the results of the Mishkin Test. Narayanamoorthy (2001) reports the results of the Ball–Bartov Tests , which are similar to the results from the MIshkin Test.

The methodology for the Mishkin Test is similar to that adopted by Rangan and Sloan in their study of the "cross-quarter effect". As in the previous sub-section, assuming the price response to unexpected SUE is linear, abnormal returns are related to unexpected SUE as:

$$AR_t = \alpha + \beta e_t^* + f_t \qquad (12)$$

where e_t^* represents the market's assessment of unexpected SUE.

In section 3.2, the realized autoregressive coefficients of SUE are categorized by:

$$SUE_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_{t-1} + d_1\, (DUM_{t-1} \times SUE_{t-1}) + g_1\, Q_{t-1} + h_1\, (Q_{t-1} \times SUE_{t-1}) + e_t \qquad (6)$$

Substituting unexpected SUE implied by equation (6) in equation (12) yields:

$$\begin{aligned} AR_t = {} & (\alpha - \beta\, a_1^*) + \beta\, SUE_t - \beta\, b_1^*\, SUE_{t-1} - \beta\, c_1^*\, DUM_1 - \beta\, d_1^*\, (DUM_1 \times SUE_{t-1}) \\ & - \beta\, g_1^*\, Q_1 - \beta\, h_1^*\, (Q_1 \times SUE_{t-1}) + f_t \qquad (13) \end{aligned}$$

The coefficients with * represent the market's estimate of the coefficients in equation (6).

If the market is fully aware of implications of past SUE for the current SUE and the implications of the "cross-quarter" and "loss" effects for the SUE autoregressive coefficients, then the market's estimate of various coefficients (coefficients with *) in equation (13) should be the same as the realized coefficients in equation (6). That is $b_1 = b_1^*$, $d_1 = d_1^*$, $h_1 = h_1^*$. If the market is using a naïve seasonal random walk model for quarterly earnings expectations, b_1^*, d_1^* and h_1^* will be zero since the market is ignoring the relation between SUE_t and SUE_{t-1} and the implications of past losses and the integral method of reporting for the relation between SUE_t and SUE_{t-1}. Mishkin (1983) argues that estimating the two equations - (6) and (13) - simultaneously is superior to the two-stage ordinary least squares estimation done by Ball and Bartov. A clear advantage of the Mishkin approach over the two-stage OLS approach is that point estimates of the autoregressive coefficients implicit in stock returns are directly available. The cross-equation restrictions ($b_1 = b_1^*$, $d_1 = d_1^*$, $h_1 = h_1^*$) are tested using a likelihood ratio test. Mishkin shows that the likelihood ratio statistic $2 \times n \times \ln(SSR^c/SSR^u)$ is distributed asymptotically as χ^2 (q) where

q is the number of restrictions imposed by market efficiency,
n is the number of observations in the sample,
SSR^c is the sum of squared residuals from the constrained weighted system, and
SSR^u is the sum of squared residuals from the unconstrained weighted system.

Market efficiency is rejected if the likelihood ratio statistic is large enough, i.e. SSR^c is substantially larger than SSR^u.

Table 9 presents the results of the Mishkin test. Since $b_1 = b_1^*$ (likelihood ratio 137 for short window and 93 for the long window) is rejected at the one percent level and since $b_1 > b_1^*$, the market is underestimating the implications of past SUE for current SUE. Since b_1^* is still significant and of the same sign as b_1, the result is consistent with the Ball and Bartov finding that the market appreciates a part of the serial correlation in SUEs. The long window b_1^* (= 0.15) is less than the short window b_1^*(= 0.24). Again recall that the short window begins two days before the quarter t earnings announcement and the long window begins earlier at two days after the quarter t-1 earnings announcement. This means that the market's underestimation of the magnitude of b_1 is reduced by the time the short window commences. This result is consistent with Soffer and Lys' (1999) argument of the market using sources of information other than past earnings to form earnings expectations. Since $h_1 = h_1^*$ (LR = 148 and 46) is rejected at the one percent level, the market is ignoring the implications of the integral method of reporting for the autocorrelation pattern, which is consistent with Rangan and Sloan's findings.

Finally since $d_1 = d_1^*$ (LR = 96 and 118) is rejected at the one percent level and since $d_1 < d_1^*$, the market is ignoring the implications of conservatism for the autocorrelation pattern. Since d_1^* is insignificantly different from zero, I conclude that the market is ignoring almost all the implications of losses for the SUE autocorrelation pattern and I cannot reject the hypothesis that the market is using a naïve seasonal random walk model when forming quarterly earnings expectations. Additionally, since the short-horizon d_1^* and h_1^* are also zero, it implies that the market has not learnt about the implications of losses and the integral method of reporting for the SUE autoregressive coefficient pattern from other sources by the time of the current earnings announcement.

Overall the evidence is consistent with investors failing to incorporate the implications of conservatism for the SUE autoregressive coefficient pattern. The principle of conservatism has been rooted in accounting for several years and the finding in this paper begs the question why investors' earnings expectations embedded in stock prices do not reflect the implications of conservatism. The straightforward explanation is that investors do not understand time series properties of quarterly earnings. While evidence from behavioral and experimental research [Maines and Hand (1996)] is consistent with this argument, I would like to stress that the principal contribution of this paper is to extend BT's hypothesis to a cross-sectional level.

Additional research is needed to better understand why investors' earnings expectations are systematically biased and why mispricing is not instantaneously eliminated.

4. Conclusion and ideas for future research

PEAD is a major anomaly facing the efficient markets paradigm. Since Rendleman et al. (1987) and Bernard and Thomas (1990) hypothesized that the anomaly is consistent with the market ignoring predictable autocorrelation, there have been attempts to find predictable cross-sectional variation in the autocorrelation pattern, but they have not been successful. I use a parsimonious representation of quarterly earnings to demonstrate cross-sectional variation in SUE autocorrelations. Though the magnitude of variation is not large, the representation guides the search for variables that can lead to greater variation. I show that knowledge of accounting processes can be used to generate significant cross-sectional variation in SUE autocorrelations. The autocorrelations decrease in losses, which, due to accounting conservatism, have time series properties different from profits. Incorporating this feature in a PEAD strategy generates higher abnormal returns than one not considering this feature. Since the variation in the abnormal return pattern mirrors the variation in the autocorrelation pattern, there is support that the market is ignoring predictable implications of conservatism for the autoregressive coefficient pattern. Additional formal tests of market efficiency fail to reject the hypothesis that the market uses a naïve seasonal random walk model to form quarterly earnings expectations.

The analysis presented in the paper suggests a number of interesting research possibilities:

1. A potentially fertile area of research can focus on combining this anomaly with other accounting-based anomalies to earn higher abnormal returns. It would be interesting to see if cross-sectional variation in PEAD can be combined with the Sloan (1996) anomaly to earn abnormal returns higher than that shown by Collins and Hribar (2000).

2. Johnson and Schwarz (2001) report that the magnitude of drift has decreased in recent years and attribute it to market learning from academic research. Several papers[15] have documented a higher incidence of losses in recent years. It would be interesting to see how much of the decrease can be attributed to losses and whether there is any market learning after adjusting for the higher incidence of losses.

3. Future research can focus on implications of other accounting features for the autocorrelation pattern. Consider for example the Dechow et al. (1998) model that shows that the first order autocorrelation, ρ, in earnings changes is decreasing in a firm's profit margin and increasing in m, the variability of a firm's fixed costs in relation to its variability in sales. Thus cross-sectional variation in m should have implications for cross-sectional variation in the SUE autocorrelations. A potential test of cross-sectional variation in the BT effect could involve estimating this factor and showing that ρ and SUE autocorrelations vary with this factor as predicted.

4. The current analysis focuses on the earnings realization sign only. It is possible that the magnitude of losses can have implications for cross-sectional variation in mean reversion, and hence PEAD. For example, in an early paper, Brooks and Buckmaster (1976) found that mean reversion exists for only the most extreme earnings changes. It would be interesting to explore the variation in PEAD due to variation in the magnitude of losses.

5. A related line of literature in PEAD studies shows that analysts also anchor on a seasonal random walk while forming earnings expectations.[16] I plan to investigate whether they systematically overlook the autocorrelation variation due to the loss dummy.

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[15] For e.g., see Collins, Maydew and Weiss (1997)

[16] For e.g., see Wu (1998), Abarbanell and Bernard (1992) etc.

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Table 1

Autoregressive coefficients of SUEs

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998 *(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$SUE_t = a_k + b_k SUE_{t-k} + e_t$ $k=1,2,3,4$

where SUE_t is the scaled SUE decile rank at time t. SUE is defined as (current earnings – earnings from corresponding quarter a year ago) divided by the market capitalization at the end of the last quarter. Decile ranks are scaled from –0.5 to 0.5.

	k = 1	k = 2	k = 3	k = 4
my sample	0.40***	0.22***	0.07***	-0.16***
	(180.4)	(94.3)	(29.7)	(-69.8)
Rangan and Sloan	*0.40****	*0.23****	*0.09****	*-0.17****

Table 2

Abnormal returns from the SUE strategy

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_k + b_k \, SUE_{t-k} + e_t \qquad k=1,2,3,4$$

Where AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return. SUE_t is the scaled SUE decile rank at time t. SUE is defined as (current earnings – earnings from corresponding quarter a year ago) divided by the market capitalization at the end of the last quarter. Decile ranks are scaled from –0.5 to 0.5.

	k = 1	*k = 2*	*k = 3*	*k = 4*
3-day	1.09***	0.44***	-0.00	-0.58***
	(20.6)	(8.28)	(-0.47)	(-11.0)
Quarter-long	5.11***	0.76***	-0.03	-1.07***
	(34.1)	(5.1)	(-0.20)	(-7.19)

Table 3

Cross-sectional variation in SUE autocorrelations with mean reversion proxy, ρ

SUE is defined as (current earnings – earnings from corresponding quarter a year ago) divided by the market capitalization at the end of the previous quarter. Decile ranks are scaled from –0.5 to 0.5. SUE deciles are SUEs converted to decile ranks. Scorr1-4 are the first to fourth order SUE decile autocorrelations computed for every firm quarter using the next 16 observations. ρ is the first order autocorrelation in earnings changes computed using the past 16 observations. Sample has 41,428 firm quarters from 1978-1998. t-statistics are in parentheses. (*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)

Future SUE autocorrelations and ρ

$Scorr_k = a + b_k*\rho + err \quad k = 1,2,3,4 \qquad n=41428$

	$scorr_1$	$scorr_2$	$scorr_3$	$scorr_4$
Intercept	*0.399**** *(273.8)*	*0.194**** *(160.3)*	*0.031**** *(22.2)*	*-0.250**** *(-174.0)*
Coefficient of ρ	*0.073**** *(20.7)*	*0.024**** *(8.26)*	*0.008**** *(2.42)*	*0.014**** *(4.19)*
R^2	*0.64*	*0.10*	*0.01*	*0.02*

Table 4

Autoregressive coefficients of SUEs incorporating separately the implications of *Losses, Decreases* and *Integral Method of Reporting*

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$SUE_t = a_k + b_k\, SUE_{t-k} + c_k\, DUM_k + d_k\, (DUM_k \times SUE_{t-k}) + e_t$ $\qquad k=1,2,3,4$

SUE_t is the scaled SUE decile rank at time t. SUE is defined as (current earnings – earnings from corresponding quarter a year ago) divided by the market capitalization at the end of the last quarter. Decile ranks are scaled from –0.5 to 0.5.

Panel A: Losses

DUM_k = 1 if a loss was reported in *quarter t-k*

	k = 1	k = 2	k = 3	k = 4
b_k	0.43***	0.26***	0.11***	-0.07***
	(159.3)	(89.8)	(39.0)	(-23.8)
d_k	-0.13***	-0.09***	-0.07***	-0.12***
	(-24.6)	(-16.3)	(-12.1)	(-20.5)

Panel B: Decreases

DUM_k = 1 if a earnings decreased from *quarter t-k-1* to *quarter t-k*

	k = 1	k = 2	k = 3	k = 4
b_k	0.41***	0.22***	0.01***	-0.09***
	(129.4)	(64.22)	(3.12)	(-26.3)
d_k	-0.05***	-0.04***	0.00	-0.12***
	(-11.8)	(-7.62)	(0.23)	(-24.9)

Panel C: Integral Method of Reporting

DUM_k = 1 if *t* and *t-k* are in the same fiscal year and zero otherwise

	k = 1	k = 2	k = 3
b_k	0.27***	0.17***	.05***
	(62.7)	(52.5)	(19.1)
d_k	0.17***	0.10***	0.08***
	(33.3)	(21.4)	(14.0)

Table 5

Autoregressive coefficients of SUEs jointly incorporating the implications of *Losses* and *Decreases*; *Losses* and *Integral Method of Reporting* and *Losses* and *Large Negative Accruals*

Panel A: Losses and Decreases

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$SUE_t = a_k + b_k SUE_{t-k} + c_k DUM_k + d_k (DUM_k \times SUE_{t-k}) + g_k DEC_k + h_k (DEC_k \times SUE_{t-k}) + e_t$

$k=1,2,3,4$

Where DUM_k = 1 if a loss was reported in *quarter t-k and* DEC_k = 1 if a earnings decreased from *quarter t-k-1* to *quarter t-k*

	k = 1	k = 2	k = 3	k = 4
b_k	0.43*** (129.9)	0.24*** (68.0)	0.04*** (11.64)	-0.04*** (-11.7)
d_k	-0.12*** (-21.7)	-0.08*** (-14.2)	0.08*** (38.0)	-0.10*** (-17.5)
h_k	-0.03*** (-5.66)	-0.01 (-1.36)	-0.15*** (-94.1)	-0.05*** (-10.6)

Panel B: Losses and Integral Method of Reporting

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$SUE_t = a_k + b_k SUE_{t-k} + c_k DUM_k + d_k (DUM_k \times SUE_{t-k}) + g_k Q_k + h_k (Q_k \times SUE_{t-k}) + e_t$

$k=1,2,3$

Where DUM_k = 1 if a loss was reported in *quarter t-k and* Q_k = 1 if *t* and *t-k* are in the same fiscal year and zero otherwise

	k = 1	k = 2	k = 3
b_k	0.31*** (65.7)	0.21*** (56.5)	0.10*** (29.7)
d_k	-0.12*** (-23.1)	-0.09*** (-15.9)	-0.07*** (-12.1)
h_k	0.16*** (32.2)	0.10*** (20.6)	0.08*** (13.7)

Panel C: Losses and Large Negative Accruals

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 162, 560 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$SUE_t = a_k + b_k\, SUE_{t\text{-}k} + c_k\, DUM_k + d_k\, (DUM_k \times SUE_{t\text{-}k}) + g_k\, DAC_k + h_k\, (DAC_k \times SUE_{t\text{-}k}) + e_t$$

k=1,2,3,4

Where DUM_k = 1 if a loss was reported in *quarter t-k and* DAC_k = 1 if scaled accruals for quarter *t-k* are in the lowest accrual decile for that quarter. Accruals are measured as Earnings before extraordinary items (COMPUSTAT Data Item #8) less Cash Flow from Operations (COMPUSTAT Data Item #108). They are scaled by market value at the beginning of the quarter *t-k*.

	k = 1	*k = 2*	*k = 3*	*k=4*
b_k	*0.43****	*0.25****	*0.10****	*-0.08****
	(151.4)	*(84.3)*	*(34.9)*	*(-28.2)*
d_k	*-0.12****	*-0.08****	*-0.06****	*-0.11****
	(-21.1)	*(-13.9)*	*(-10.0)*	*(-17.8)*
h_k	*-0.04****	*-0.02***	*-0.02***	*-0.05****
	(-5.3)	*(-2.1)*	*(-2.1)*	*(-5.5)*

Table 6

Abnormal returns from the SUE strategy incorporating separately the implications of *Losses, Decreases* and *Integral Method of Reporting*

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\,(DUM_1 \times SUE_{t-1}) + e_t$$

AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return

Panel A: Losses

DUM_1 = 1 if a loss was reported in *quarter t-1*

	3-day	Quarter-long
a_1	0.24***	-2.18***
	(12.5)	(-41.5)
b_1	1.34***	5.39***
	(20.5)	(29.25)
c_1	0.09**	-1.11***
	(1.67)	(-7.72)
d_1	-0.66[a]***	-2.35***
	(-5.06)[a]	(-6.40)

[a] *When I run yearly regressions to control for possible cross correlation, average d_1 is -0.62 with a t-statistic of –3.78.*

Panel B: Decreases

Where DUM_1 = 1 if a earnings decreased from quarter *t-2* to quarter *t-1*

	3-day	Quarter-long
a_1	0.34***	-2.00***
	(13.7)	(-30.4)
b_1	1.15***	5.56***
	(18.7)	(25.7)
c_1	-0.06	-0.77***
	(-0.92)	(-7.87)
d_1	-0.36***	-1.67***
	(-3.04)	(-5.30)

Panel C: Integral Method of Reporting

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + e_t$$

where $DUM_1 = 1$ if *t* and *t-1* are in the same fiscal year and zero otherwise. AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return

	3-day	*Quarter-long*
a_1	*0.39****	*-0.28****
	(11.5)	*(-3.02)*
b_1	*0.23***	*2.25****
	(2.22)	*(7.73)*
c_1	*-0.14****	*-2.65****
	(-3.61)	*(-24.5)*
d_1	*1.15****	*3.78****
	(9.45)	*(11.13)*

Table 7

Abnormal returns from the SUE strategy jointly incorporating the implications of *Losses* and *Decreases*; *Losses and Integral Method of Reporting* and *Losses* and *Large Negative Accruals*

Panel A: Losses and Decreases

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + g_1\, DEC_1 + h_1\, (DEC_1 \times SUE_{t-1}) + e_t$$

where $DUM_1 = 1$ if a loss was reported in *quarter t-1 and* $DEC_1 = 1$ if a earnings decreased from *quarter t-2* to *quarter t-1,* AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return

	3-day	*Quarter-long*
b_1	*1.34****	5.69***
	(16.7)	*(25.16)*
d_1	*-0.58****	*-0.96****
	(-4.30)	*(-6.59)*
h_1	*-0.19**	*-0.67****
	(-1.64)	*(-4.56)*

Panel B: Losses and Integral Method of Reporting

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + g_1\, Q_1 + h_1\, (Q_1 \times SUE_{t-1}) + e_t$$

where $DUM_1 = 1$ if a loss was reported in *quarter t-1 and* $Q_1 = 1$ if *t* and *t-1* are in the same fiscal year and zero otherwise. AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return.

	3-day	*Quarter-long*
b_1	*0.48****	*2.34****
	(4.26)	*(7.41)*
d_1	*-0.59****	*-1.29****
	(-4.56)	*(-5.40)*
h_1	*1.22****	*3.77****
	(9.09)	*(11.10)*

Panel C: Losses and Large Negative Accruals

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 162,560 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$AR_t = a_1 + b_1\, SUE_{t-1} + c_1\, DUM_1 + d_1\, (DUM_1 \times SUE_{t-1}) + g_1\, DAC_1 + h_1\, (DAC_1 \times SUE_{t-1}) + e_t$

where $DUM_1 = 1$ if a loss was reported in *quarter t-1 and* $DAC_1 = 1$ if scaled accruals for quarter *t-k* are in the lowest accrual decile for that quarter. Accruals are measured as Earnings before extraordinary items (COMPUSTAT Data Item #8) less Cash Flow from Operations (COMPUSTAT Data Item #108). They are scaled by market value at the beginning of the quarter *t-k*. AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return.

	3-day	Quarter-long
b_1	1.25***	4.27***
	(18.50)	(23.36)
d_1	-0.50***	-1.81***
	(-3.76)	(-5.00)
g1	0.86***	1.15***
	(10.89)	(5.40)
h_1	0.08	0.89*
	(0.41)	(-1.66)

Table 8

Abnormal returns from the SUE strategy incorporating the implications of S*ize* along with *Losses* and *Integral Method of Reporting*

Coefficient estimates (t – values in parentheses) from the following pooled regressions for my sample of 169,727 firm quarters from 1978-1998*(*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level)*:

$$AR_t = a_1 + b_1 SUE_{t-1} + c_1 DUM_1 + d_1 (DUM_1 \times SUE_{t-1}) + g_1 S_1 + s_1 (S_1 \times SUE_{t-1}) + + r_1 Q_1 + h_1 (Q_1 \times SUE_{t-1}) + e_t$$

where DUM_1 = 1 if a loss was reported in *quarter t-1* ; S_1 is the size decile based on previous quarter's results scaled to –0.5 to 0.5 ; and Q_1 = 1 if *t* and *t-1* are in the same fiscal year and zero otherwise, AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return.

	3-day	*Quarter-long*	*3-day*	*Quarter-long*
b_1	*1.30****	*5.45****	*0.48****	*2.47****
	(18.9)	*(29.38)*	*(3.97)*	*(7.28)*
d_1	*-0.91****	*-1.52****	*-0.85[a]****	*-3.07****
	(-6.63)	*(-10.3)*	*(-6.13)[a]*	*(-7.55)*
h_1			*1.05****	*3.93****
			(8.15)	*(10.8)*
s1	*-1.60****	*-6.96****	*-1.60****	*-7.10****
	(-8.90)	*(-14.2)*	*(-8.81)*	*(-13.4)*

[a] *When I run yearly regressions to control for possible cross correlation, average d_1 is -0.78 with a t-statistic of –3.93.*

Table 9

Test of Stock Market Efficiency with respect to the Implications of Conservatism (*Losses)* for the prediction of future quarterly earnings (Mishkin Test)

Coefficient estimates (t – values in parentheses) from the simultaneous estimation of the following two equations using the simultaneous non-linear procedure proposed by Mishkin (1983):

$$SUE_t = a_1 + b_1 SUE_{t-1} + c_1 DUM_1 + d_1 (DUM_1 \times SUE_{t-1}) + g_1 Q_1 + h_1 (Q_1 \times SUE_{t-1}) + e_t$$

$$AR_t = (\alpha\text{-}\beta a_1^*) + \beta SUE_t - \beta b_1^* SUE_{t-1} - \beta c_1^* DUM_1 - \beta d_1^* (DUM_1 \times SUE_{t-1}) - \beta g_1^* Q_1 - \beta h_1^* (Q_1 \times SUE_{t-1}) + f_t$$

Sample has 169,727 firm quarters from 1978-1998. *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. DUM_1 = 1 if a loss was reported in *quarter t-1*. Q_1 = 1 if quarter t and quarter t-1 are in the same fiscal year. AR_t is the abnormal return in % from a 3-day window around quarter t's earnings announcement or the quarter-long window starting two days after the quarter t-1 earnings announcement and ending on the next announcement date. It is computed as the raw return adjusted for the CRSP Value Weighted Index return. * on coefficients indicates those are the market's estimate of the coefficients implicit in stock returns.

	3-day	*Quarter-long*
b_1	*0.34****	*0.34****
b_1^*	*0.24****	*0.15****
d_1	*-0.13***	*-0.13****
d_1^*	*0.00*	*-0.02*
h_1	*0.19****	*0.19****
h_1^*	*-0.01*	*-0.04*
β	*4.60****	*13.4****

Likelihood Ratio Statistics to test Market Efficiency Constraints[17]

Constraint	*Likelihood-ratio statistic*	
	3-day	*Quarter-long*
$b_1 = b_1^*$	*137****	*93****
$d_1 = d_1^*$	*96****	*118****
$h_1 = h_1^*$	148***	46***

[17] The likelihood-ratio statistic is distributed asymptotically as χ^2 with one degree of freedom