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Post-Earnings Announcement Drift?

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ABSTRACT

The predictability of abnormal returns based on information contained in past earnings announcements is an anomaly that is statistically and economically significant. Neither is it illusory, nor is it an artefact of the experimental design. It may be a result of market inefficiency. Our results cannot rule out this explanation. However, we find that earnings change numbers are associated with the probability that firms leave the sample through acquisition, bankruptcy or for other reasons, or are not included in the sample in the first place. Moreover, we find that the magnitude of the post-earnings announcement effect is correlated with factors that proxy for the *ex ante* probability of the firm surviving to be part of the earnings surprise sample. It also appears to be related to determinants of the bid-ask spread.

[JEL Classification: G14, M41; Keywords: post-announcement drift, survival, anomalies]

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Post-Earnings Announcement Drift?

1. Introduction

The predictability of abnormal returns based on information contained in past earnings announcements appears to be a statistically and economically significant equity market anomaly. The exhaustive analysis of Bernard and Thomas (1989, 1990) confirms the findings of Ball and Brown (1968), Foster, Olsen and Shevlin (1984), Freeman and Tse (1989) and Rendleman, Jones and Latané (1987) that stock prices do not instantaneously adjust to information in earnings announcements. Estimated post-announcement abnormal returns are positively correlated with estimated unexpected earnings for a period of up to four years. Additionally, a substantial proportion of the post-announcement drift in the first year is "delayed" until earnings announcements in subsequent quarters, with future event-period abnormal returns being positively correlated with current unexpected earnings for three quarters and negatively correlated four quartead (Bernard and Thomas, 1990).

In this paper we extend previous attempts to examine whether the research design contributes to the observed post-announcement drift phenomenon. Ball (1992) notes that there are several, possibly related, explanations of the post-announcement drift that may be consistent with the evidence: inefficient information processing by the market; efficient information processing in the presence of significant transactions costs; and misspecification in the measurement of abnormal returns. In reviewing and interpreting the available evidence, he concludes that the drift phenomenon is most likely to be due to information processing costs or to market inefficiency. On balance he does not favour possible explanations discussed in Bernard and Thomas (1989,

1990) associating unexpected earnings with expected returns, risk, transaction costs, liquidity or trading-mechanism effects. However, Ball notes that existing tests have low power to discriminate between hypotheses. He also suggests that some combination of alternative effects could provide an explanation and concludes by suggesting that future research can further clarify the issues.

The investor irrationality (i.e., market inefficiency) and information processing cost explanations imply that the market's earnings expectations differ from the true process generating earnings, thus creating a direct link between estimated unexpected earnings and future abnormal returns. Relative to the market's earnings expectation, there should be no post-earnings drift phenomenon if the market is otherwise rational. This view finds support in the Foster, Olsen and Shevlin (1984) result that the drift phenomenon disappears when a measure of abnormal returns over days -1 and zero is used as an alternative proxy for unexpected earnings. However, upon a re-examination of the evidence, we find that post-earnings drift is indeed associated with this alternative proxy. We conclude that market inefficiency and information processing cost explanations do not explain the entire phenomenon. However, the magnitude of the drift is smaller using the abnormal return proxy for unexpected earnings. This suggests that misspecification of the time-series process for earnings might have a role to play explaining at least part of the drift.

In the empirical analysis we focus on two issues: first whether there are risk characteristics of stocks that are correlated with unexpected earnings and may not be fully controlled for by the standard benchmarks used in event studies; and second whether proxy variables for market microstructure-related returns measurement errors are associated with unexpected earnings and abnormal returns. Both types of effect represent alternatives to the investor-irrationality explanation of the post-announcement drift. We suggest that the negative fourth-order serial correlation in SUE is important in establishing SUE as a proxy for risk. It is consistent with components in earnings that *ex post* analysis suggests are transitory: *if they survive*, firms that reported relatively bad news four quarters earlier are more likely to report high SUE (good news) this quarter. However, the observed transitivity in earnings may be due in part to a subtle form of survival effect inherent in the research design. At least some of the transitivity in earnings may not be predictable *ex ante*. Our analysis indicates that SUE is, in fact, correlated with *ex ante* measures of risk associated with non-survival. Since this risk is at least in part security-specific, and idiosyncratic risk is higher around earnings announcements, the clustering of post-announcement drift in abnormal returns around subsequent earnings announcements could be at least partially explained by a non-survival risk premium. Finally, we show that SUE are associated with determinants of market microstructure-related measurement errors that are themselves associated either directly or indirectly with risk.

Our results indicate that extreme caution should be exercised in interpreting the post-announcement drift as evidence of market inefficiency. Although our analysis is not able to entirely eliminate the possibility of forms of market irrationality, it does suggest for the first time that the drift phenomenon is at least partially related to risk and measurement error differences across unexpected earnings portfolios. This suggests that there are some subtle issues in research design that future analysis should take into consideration.

The remainder of the paper is organized as follows. In Section 2 we discuss the empirical evidence on post-announcement drift and discuss the possible research design-related explanations of the stylized facts; in Section 3 we present our empirical analysis; and Section 4 contains our conclusions.

2. Analysis

2.1 The Post-Announcement Drift Phenomenon

The results of Bernard and Thomas (1989, 1990) represent the most comprehensive analysis available. Bernard and Thomas (1989) report that the return to an equally weighted hedge portfolio consisting of long positions in extreme good news announcers and short positions in extreme bad news announcers earns +4.19% average estimated abnormal return over the 60-day post-announcement period. Although one sixth of the overall abnormal return accrues in the first five days, Bernard and Thomas find that the abnormal return continues to increase as the holding period is extended beyond 60 days. After 180 days the abnormal return to the hedge portfolio is 7.74%. Underlying the extended drift are abnormal returns of 1.32%, 0.70%, 0.04% and -0.66% occurring at subsequent earnings announcements (Bernard and Thomas, 1990).

Bernard and Thomas (1989, 1990) and Foster, Olsen and Shevlin (1984) also estimated abnormal returns relative to size-decile control portfolios, with similar results. Rendleman, Jones and Latané (1987) used the return on the CRSP equally weighted market portfolio as a benchmark and also found a significant spread between extreme good news and extreme bad news portfolio abnormal returns. Thus, the significance of the post-announcement drift does not appear to be sensitive to the method of estimating abnormal returns.[1]

[1]Rendleman, Jones and Latané (1987) find that the pattern of abnormal returns across earnings surprise portfolios varies across different size groups.

2.2 *The Serial Correlation Structure of SUE*

Research on the time-series behavior of quarterly earnings shows that seasonal differences are positively correlated over the first three lags and negatively correlated for the fourth lag [e.g., Watts (1975), Foster (1977), Griffen (1977), Brown and Rozeff (1979), Bathke and Lorek (1984) and Brown, Griffen, Hagerman and Zmijewski (1987)]. The apparent predictability of forecast errors has been interpreted by some researchers as evidence that the true time series process followed by earnings cannot be a seasonal random walk and that earnings must follow a seasonally differenced autoregressive process. The association between forecast errors based on the "naïve" seasonal random walk model and abnormal returns in future event periods has consequently been attributed by Bernard and Thomas (1990) to a failure of the market to fully understand the implications of current earnings for future earnings outcomes. In other words, the market is not efficient.

This argument implies that the market's earnings expectations differ from the true process generating earnings. This creates a direct link between estimated unexpected earnings and future abnormal returns. This explanation is consistent with the empirical findings reported in Bernard and Thomas (1989) and those of others who have studied this phenomenon. This view finds support in the Foster, Olsen and Shevlin (1984) result that the drift phenomenon disappears when a measure of abnormal returns over days -1 and 0 is used as an alternative proxy for unexpected earnings. This is an important empirical finding. If the abnormal return proxy also explains post-earnings drift, we would be forced to look elsewhere for a complete explanation of the post-earnings drift phenomenon[2].

Bernard and Thomas (1990) demonstrate that the positive signs of the first three autocorrelations in unexpected earnings do suggest that earnings subsequent to quarter t-4 contain information useful for predicting earnings in quarter t. However, the positive autocorrelations do not necessarily imply that the seasonal random walk model produces biased forecasts, or that the true earnings process is an autoregression in seasonally differenced earnings. Positive autocorrelation can result from a "statistical illusion" caused by sampling data at a higher frequency than the order of differencing (Appendix). When earnings are sampled quarterly and unexpected earnings are based on the seasonal random walk model, positive autocorrelations that decline with the lag order will be expected if quarterly earnings changes are stationary. We also suggest that the negative fourth-order autocorrelation in seasonally differenced earnings may reflect transitory earnings, but that this component is not necessarily identifiable *ex ante* in an efficient market.

2.3 Transitory Earnings and Survivorship

Previous research into the time series of earnings together with the negative autocorrelation in seasonally-differenced earnings at lag four reported by Bernard and Thomas (1990) seems to point to the seasonal random walk being an imperfect description of the true earnings process because of transitory earnings components. Several sources of transitory earnings components

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[2]We replicate the Bernard and Thomas (1989) findings in Table 1. The 60-day post-announcement period cumulative abnormal return increases monotonically with SUE and the magnitude of the difference in abnormal returns between extreme SUE portfolios declines with size. However, we do not replicate the Foster Olson and Shevlin (1984) result. We find that a drift effect is still present using a standardized CAR proxy for unexpected earnings (Table 3). It is weaker than the drift based on SUE, but still statistically significant. We conclude that misspecifications of the SUE measure cannot be a complete explanation of the post-earnings drift phenomenon.

have been discussed, including the effects of accounting accruals procedures, accounting policy choices and economic events having temporary consequences for earnings. Some of these sources will be value-relevant and some will be value-irrelevant (Ramakrishnan and Thomas, 1992). In a rational market containing investors who do not face significant information processing costs, the implications of these sources of transitory earnings for earnings expectations should be understood. The "naïve investor" hypothesis suggests that the market fails to develop this understanding and that a seasonal random walk expectation is adopted when it is not appropriate. However, the impediments to understanding the true nature of earnings would have to be implausibly high and long-lived in order for this hypothesis to be capable of explaining fully the magnitude, duration and serial correlation pattern of the post-announcement drift effect.

We conjecture that the transitory earnings components observed in the data *ex post* may not be capable of being detected *ex ante*, even if information processing costs and other impediments to rational expectations are absent. The *ex ante* identification of transitory components is necessary if the seasonal random walk model is to be rejected on the grounds of being an inefficient expectations mechanism. It is extremely important to remember that in studies of post-announcement drift the reversal of transitory components *is only observed ex post for firms that survive for at least one year.* If the probability of a firm not surviving in the sample for a year depends on the level of earnings at the start of the year, it is *inevitable* that when we examine the sample of firms that survive we will find negative serial correlation in earnings. For example, if a firm reports a loss of $0.50 per share in quarter t-4 and has a 50% chance of a further $1 decrease in earnings per share in quarter t, in which case it will enter bankruptcy (and disappear from the sample), and a 50% chance of a $1 increase in earnings in quarter t, in which case it will survive, then *conditional on observing that the firm survives to report earnings for quarter t*, we will observe the loss of $0.50 in quarter t-4 change to a gain of $0.50 in quarter t. However, the *ex ante* unbiased forecast of earnings is -$0.50 (i.e., a random walk forecast). *Ex post*, estimated unexpected earnings are +$1 and it appears that a transitory earnings component in quarter t-4 has been reversed. Earnings changes at lag 4 are negatively serially correlated *ex post*.

The *ex ante* probability that a firm will fail to survive in a sample need not be large in order to cause an observable *ex post* effect.[3] Even a very low probability of an extreme event (such as bankruptcy) associated with earnings outcomes could significantly affect expected returns and thereby influence estimated *ex post* abnormal returns based on a returns benchmark that ignores the risk of non-survival. There are good reasons for believing that this subtle form of survival effect may be present in the case of earnings announcements. For example, unprofitable firms are more likely to become bankrupt or subject to takeovers than are more profitable firms (Altman, 1968). Therefore, if they survive, last year's low earnings firms are likely to have achieved better earnings numbers this year. Similarly, it is possible that non-survival due to a takeover and delisting as a result of buy-outs may be positively related to growth in profitability. Palepu (1986) finds that firms with a mismatch between their growth and their available financial resources have a higher probability of being takeover targets. Palepu's results suggest that high (low) growth firms having low (high) liquidity will have a higher probability of being subject to a takeover.[4] If high profitability is related to the probability of non-survival, high earnings firms

[3]The well-known peso problem identified as a possible explanation of forward exchange rate bias reflects similar ideas to those outlined here.

[4]Although Palepu (1986) uses sales growth in his empirical tests, this will be highly correlated with earnings growth, and hence with SUE.

that are seen *ex post* to have survived in a sample are likely to be less profitable on average than in the past. In the present context, the empirical SUE measure contains information about last year's earnings. If SUE is correlated with the probability of non-survival and if the market's required rate of return depends on the probability of non-survival, SUE will be correlated with expected returns and with abnormal returns estimated in *ex post* analysis.

Brown, Goetzmann and Ross (1995) provide a formal model linking the conditional path of prices to earnings announcements. If firms that face a given level of financial distress are more likely to survive on favorable earnings surprises than on an unfavorable earnings surprises, firms that successfully overcome financial distress are more likely to have announced favorable earnings surprises than less distressed firms. Viewing equity as a call option on a firm's assets, the exercise price being the value of the firm's debt, firms in financial distress are effectively at-the-money call options and financially secure firms are effectively deep in-the-money call options. The expected return and returns volatility of a call option increase as the underlying asset value falls relative to the exercise price (Cox and Rubinstein, 1985). Therefore we would expect the equity of distressed firms to have higher returns and higher returns volatility than the equity of financially secure firms (Stapleton, 1982).

To the extent that there is cross-sectional variation in the degree of financial distress, this will show up in an induced cross-sectional relation between measures of announcement period earnings surprise, such as SUE and event period abnormal returns, and post-announcement returns. A further anticipated consequence is skewness in the cross-sectional distribution of returns.[5] Furthermore, if portfolios are formed on the basis of a firm characteristic that is correlated with financial distress, such as SUE, far from diversifying away unsystematic risk the portfolio formation procedure may have a magnifying effect (Lo and MacKinlay, 1990).

The possibility that SUE may be correlated with bankruptcy risk (and the probability of takeovers) raises the question of whether traditional event study research designs adequately control for risk. Abnormal returns analyses based on the hedge portfolio approach, and market- or size-adjusted abnormal returns metrics, implicitly assume no risk differences across treatment portfolios sorted on SUE. If there are differences in non-diversifiable risk across portfolios, estimated abnormal returns might simply reflect risk premia. If the normal return distribution assumption underlying the abnormal performance metrics is violated to differing degrees across different treatment portfolios, total risk becomes relevant because idiosyncratic risk will not be completely diversifiable. Indeed, it is not even likely that standard deviation (or variance) will be a sufficiently complete measure of risk in such circumstances.[6]

2.4 *Market Microstructure-Related Measurement Error*

Although there are strong grounds for suspecting that risk variation across SUE portfolios has a direct effect on expected returns and hence on estimated abnormal returns, it is also possible that risk can have an indirect impact on estimated abnormal returns through market

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[5] Interestingly Ball, Kothari and Shanken (1995) find evidence of returns skewness in loser portfolios associated with contrarian investment strategies.

[6] Duffee (1995) reports that the contemporaneous association between volatility and returns is strongest for non-survivors on the CRSP database, and a large proportion of the strong correlation can be traced to the last six months of a firm's CRSP history. Non-survivorship is due primarily to merger/acquisition. It is quite plausible that the probability of takeover is related to past earnings news and that firms, particularly small firms, are "put into play" when they report good earnings news. This in turn may lead to higher volatility, as discussed by Duffee (1995).

microstructure-related measurement errors. Again, to be capable of explaining post-announcement drift without appealing to notions of irrationality, risk would have to vary systematically and predictably across SUE portfolios. The effect of possible measurement error in returns related to bid-ask bounce effects has recently been considered as a possible explanation of stock price overreaction. Conrad and Kaul (1993) conclude that bid-ask spread explains part of the observed market overreaction. The question here is whether similar arguments can help in explaining the apparent market underreaction implied by post-announcement drift.

Observed closing transaction prices measure the "true" equilibrium stock price with error for two reasons: first, transactions occur at either the bid-price or the ask-price due to the demands of market makers for a spread as compensation for the cost and risks involved in the provision of market making services; and second, non-synchronous trading implies that the last transaction price on a given day is stale. Blume and Stambaugh (1983) show that both sources of measurement error lead to an increase in returns based on closing transaction prices, but their analysis suggests that the non-synchronous trading effect is likely to be small in relation to the bid-ask bounce effect. Under certain simplifying assumptions the expected magnitude of the bid-ask effect is proportional to the square of the bid-ask spread. A stock having a bid-ask spread equal to 5%, consistent with estimates for small stocks reported in Keim (1989), would experience a return of 0.066% per day attributable to bid-ask bounce. An arithmetic cumulation of daily returns over 60 days would therefore be expected to have a measurement error effect of nearly 4%. This is the same order of magnitude as the post-announcement drift itself, and therefore the possibility that the drift is a manifestation of measurement error is worth considering.

Theoretical models and empirical evidence suggest that several factors determine bid-ask spreads. First, spreads are inversely related to the expected level of trading activity in a stock - more liquid stocks are expected to have lower spreads because of economies of scale in market making (Cohen et al., 1979; Schwartz, 1988). Second, bid-ask spreads are positively associated with the price risk to which market maker inventory positions are exposed. Glosten and Harris (1987) report evidence that spreads are positively correlated with the standard deviation of returns. Third, the adverse selection models of Kyle (1985), Easley and O'Hara (1987) and Glosten (1987) suggest that the bid-ask spread will include a component associated with the probability that market makers will be transacting with better informed investors. Glosten and Harris (1987) report results consistent with this hypothesis.

The impact of bid-ask spread on measured returns is dependent on returns being based on transactions prices. As Blume and Stambaugh (1983) note, if bid-ask quotes are not stale, the prices and returns recorded in CRSP will be less a function of bid-ask spread on days when there is *no* trading because of the convention of using mid-market quotes in place of transaction prices when no transaction occurs on a particular day. For this reason we would also expect that the cumulative measurement error effect will be negatively associated with the frequency of days on which no trading occurs (Keim, 1989).[7]

On the basis of prior research we may therefore consider the bid-ask spread to be determined by "normal" trading volume, volatility and information asymmetry and the frequency of non-trading days. If these factors are correlated with SUE, thereby inducing correlation between the bid-ask spread and SUE, return measurement error could have a role to play in

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[7]Keim's model also shows that the degree of measurement error will be related to the probability that closing transaction prices on consecutive days will be bid (or ask) prices.

explaining the post-announcement drift.

3. Empirical Evidence

3.1 Data

The evidence in this paper is based on the data described in Bernard and Thomas (1989, 1990).[8] The original data for which announcement dates are available comprise 82,067 quarterly earnings announcements by NYSE and AMEX firms over the years 1974-1986. For each announcement, trading volume data was collected from the 1991 *CRSP* daily file. Our analysis includes all data points for which the following criteria were satisfied:

(a) the number of shares outstanding over the pre- and post-announcement periods are available in the *CRSP* shares structure; and

(b) trading volume data is available for at least thirty days in each of the pre and post announcement periods.

For these purposes the pre-announcement period was defined as the period spanning day -52 to day -3, and the post-announcement period was defined as day +1 to day +60, where day zero is the announcement date, as defined in Bernard and Thomas (1989). The post-announcement period corresponds to the period over which cumulative abnormal returns are measured and for which the drift is observed. Trading volume is defined as the average proportion of total outstanding shares traded on days within a period for which volume data are available on *CRSP*.

The possible impact of survivorship risk is examined, in part, by estimating the failure

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[8]We are extremely grateful to Vic Bernard and Jake Thomas for allowing us access to the data and for explaining its structure. We are also indebted to Ravi Bhushan for his help in transferring the data and for spending time in helping us to understand its organization.

probability given by Ohlson's (1980) bankruptcy prediction model. Failure probability estimates are obtained from this model on an annual basis, allowing a one-quarter lag for the disclosure of the financial statement information required by the model. All data for this model are obtained from *Compustat*.

3.2 Empirical Results

3.2.1 Preliminary evidence on earnings changes and non-survival

Table 1 contains evidence, based on the 1993 *Compustat* files, that annual earnings changes scaled by beginning-of-year market value are associated with non-survival in important and interesting ways. Panel A is based on all firms listed on *Compustat,* including both survivors and non-survivors, over the period 1975-87. This period corresponds as closely as possible to the period analysed by Bernard and Thomas (1990).[9] There is clear evidence that firms excluded from the Bernard and Thomas sample have more extreme earnings changes. Their sampling criteria require that the excluded firms have fewer than 10 consecutive quarterly announcements, corresponding to a *Compustat* "life" of less than 2.5 years. The sampling constraints imposed by the estimation of SUE appear to cause some censoring of the earnings change distribution compared to the full *Compustat* population. The likelihood of a firm surviving more than 2.5 years appears to be inversely related to the volatility of earnings.

Panel B of table 1 contains evidence that certain non-survival events are associated with earnings outcomes. We report the distribution of the last available scaled earnings change for firms

[9] We thank Dan Givoly for suggesting that we exaamine the association between survival and annual earnings changes. The use of the 1993 *Compustat* files precluded the identification of earnings changes for 1974, the first year in the Bernard and Thomas analysis.

in the acquisitions and bankruptcy categories of deleted firms in the *Computstat* research file. All other deletion codes, including liquidations and buyouts are classified as "other". A large majority of firms are deleted from *Compustat* because they are acquisition targets. For these firms the last available earnings change has a mean value of -0.004. This is lower than the full sample mean in panel A, but the medians are the same. The percentage of positive earnings changes is 64.6%, again similar to the overall population. Therefore, there is some evidence that aquisition targets have more negatively skewed earnings changes immediately prior to acquisition. In contrast, the median bankrupt firm has an earnings decrease of -0.125 in its final year on *Compustat,* but the distribution of earnings changes for bankrupt firms is positively skewed leading to a mean earnings change of 0.029. Only 39.5% of firms report positive earnings changes in the year prior to bankruptcy. The very high standard deviation of 1.822 is consistent with the positive skewness. Firms that are deleted for other reasons, including liquidation and buyouts, on average report significantly higher earnings changes compared with all firms and other deleted firms in their final year. However, the higher mean earnings change again reflects positive skewness in earnings changes for these firms. Analysis of the non-survivors according to whether they make the Bernard and Thomas sample leads to similar conclusions, although sample sizes, particularly for bankrupt firms, become small. In summary, panel B contains preliminary evidence that non-survival is associated with unusual earnings changes in the year prior to deletion, and confirm that the pattern of earnings changes differs systematically between the Bernard and Thomas sample and the sample of firms they exclude.

In panel C of table 1 we show how sorting firms on the basis of annual earnings changes can induce differential survival rates across earnings change portfolios. There is clear evidence that extreme negative and extreme positive earnings changes are associated with higher non-survival rates. Some 6.24% (6.64%) of firms in the lowest (highest) earnings decile in year t-1 fail to survive to report another annual earnings number. In contrast, approximately 3% of firms with intermediate earnings changes fail to survive to the next annual earnings announcement. The J-shaped pattern of non-survival frequency based on earnings performance is consistent with the analysis presented in Hendricks, Patell and Zeckhauser (1996).

Figure 1 contains new evidence for the Bernard and Thomas sample on association between SUE, firm size and sample censoring. The figure plots the sample frequencies of firms in different SUE portfolios analyzed by size deciles. The overall number of earnings announcements for smaller firms is substantially lower than for larger firms. If the probabilities of inclusion and non-survival in the sample are uncorrelated with size, we would expect all size deciles to be approximately equally represented in the sample, given that the annual *CRSP* size partitioning is based on the full population of firms traded on the NYSE and AMEX. The pattern that we observe in Figure 1 is consistent with small firms having higher probabilities of (i) failing to be included in the sample, possibly because they do not have sufficient time series observations for the estimation of SUE; (ii) failing to survive in the sample due to takeover or bankruptcy; and (iii) failing to survive as small firms because growth leads to a transition to larger size categories. These potential sampling effects could be important because survival (by which we mean the *ex ante* probability of inclusion/exclusion in the *ex post* surviving sample) may be directly related to SUE. They may also have an indirect influence because excluded firms will still be influential in the *CRSP* control portfolios used as expected returns benchmarks.

It is also interesting to note from Figure 1 that the cell frequency counts across SUE categories generally follow an inverted U-shape for smaller firms and a regular U-shape for larger firms. *Ex post*, surviving large firms are more likely to be observed reporting extreme good news and extreme bad news than are surviving small firms. This is consistent with probability of non-survival being associated with extreme earnings outcomes, particularly for smaller firms. In view of the much lower economic significance of the estimated abnormal returns for large firms (Bernard and Thomas, 1990) these results provide a further preliminary indication that survival effects may be influential.

3.2.2 The Serial Correlation Structure of SUE

Figure 2 shows how the negative serial correlation in SUE at the fourth quarter lag documented by Bernard and Thomas (1990) is reflected in the probabilities of SUE decile membership at t conditional on SUE decile membership four quarters previously.[10] Each block of ten bars depicts the probabilty of SUE at t being in the lowest decile 1 (extreme left hand side) through the highest decile 10 (extreme right hand side), conditional on the SUE decile membership at t-4. If SUE displays no fourth order serial correlation, the probability of observing SUE_t in decile k conditional on SUE_{t-4} should be equal to the unconditional probability 0.10.[11] Figure 2 shows that this is far from the case. Of particular interest are the conditional probabilities in the

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[10]Table 2 is based on those firms for which SUE_t is observed. It does not include those firms for which SUE_{t-4} existed but which failed to survive for four quarters. However, it should also be remembered that the calculation of SUE_t requires that earnings be available for at least 20 quarters prior to quarter t. This constraint is likely to be the most influential in ensuring survival effects in the sample.

[11]The unconditional probabilities are very close to but not exactly 0.10 due to a small number of returns being unavailable and due to the procedure used to identify SUE_{t-4}. This involved sorting the original dataset by firm and taking the fourth lag, if that record had the same firm identifier (CUSIP). Records in the early part of a firm's effective history were therefore excluded.

extreme SUE_{t-4} portfolios. These show that firms with very low (very high) SUE_{t-4} have a high probability of belonging to very high (very low) SUE_t portfolios. For example, in this sample 22.47% of firms in the lowest SUE decile at t-4 appear in the *highest* SUE decile at t. This indicates that good news firms have a high probability of having been bad news firms in the recent past. Similarly, 17.86% of firms in the highest SUE decile at t-4 appear in the lowest SUE decile at t, indicating that bad news firms at t are more likely to have been good news firms in the recent past. Generally, the conditional probabilities follow a U-shaped pattern for the four extreme SUE_{t-4} portfolios. It should also be noted that based on table 1, panel C, these portfolios can be expected to have suffered the highest levels of non-survival.

Figure 2 suggests that the *ex post* time series behavior of SUE is extremely complex and nonlinear. There is *positive* association between SUE_{t-4} and SUE_t for intermediate levels of SUE_{t-4}, reflected in the inverted U-shape patterns for the middle portfolios. Underlying the weak overall negative serial correlation is strong negative serial correlation in the extreme SUE deciles and strong positive serial correlation in the intermediate deciles. The observed negative serial correlation does not appear to reflect mean reversion towards a "normal" rate of earnings growth due to elimination of transitory earnings components, but rather extreme and opposite consecutive changes for a subset of observations. We are unaware of an extant model of the time series evolution of earnings that predicts these phenomena. However, the extreme decile behavior is consistent with the potential survival effects discussed earlier.

3.2.3 SUE, Announcement-Period Returns and Post-Announcement Drift

In the first panel of table 2 we replicate the main result in Bernard and Thomas (1989) for the 60-day post-announcement period cumulative abnormal return. The post-announcement drift increases monotonically with SUE. Subsequent analysis also confirmed prior findings that the difference in abnormal returns between extreme SUE portfolios declines with size.[12]

The second panel of table 2 analyzes the post-announcement abnormal return for portfolios formed on the basis of the standardized 3-day announcement period abnormal return[13]. The standardized abnormal return over days -2 to 0 is used as an alternative proxy for unexpected earnings. Foster, Olsen and Shevlin (1984) report that the drift phenomenon disappears when the abnormal return measured over days -1 and zero is used as an alternative proxy for unexpected earnings. In contrast, we find that the drift is weaker than the drift based on SUE, but it is still statistically significant. Foster, Olsen and Shevlin (1984) did not standardize their measure of abnormal performance. This factor alone accounts for the difference in results.

Further analysis shows that the magnitude of the announcement-return-based measure of drift is inversely related to firm size.[14] Overall the difference between the abnormal returns for the extreme event-period abnormal return deciles is approximately 2.6%, compared with 5.4% when SUE is the basis for partitioning. However, the finding that post-announcement drift is still present when unexpected earnings are proxied by the standardized announcement-period stock

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[12] Not reported. Details avaliable from the authors on request.

[13] Announcement period return standardized by the standard deviation of this quantity estimated on the basis of abnormal returns up to 60 days prior to the announcement period.

[14] Not reported. Details avaliable from the authors on request.

price reaction is important. It suggests that we must look beyond naive market expectations of earnings based on the seasonal random walk model for an explanation of the drift.

Ball and Bartov (1995) show that the lagged SUE are incrementally important beyond current SUE in explaining three-day earnings announcement period abnormal returns. They find that the signs on lagged SUE follow (-,-,-,+) pattern, the reverse of the SUE serial correlation pattern. This result is interpreted by Ball and Bartov (1995) as evidence that the market does not use a naive seasonal random walk expectations model. In table 3 we report similar regressions of 60-day post-announcement period abnormal returns on contemporaneous and lagged unexpected earnings proxies. Similar to Ball and Bartov's results for announcement period returns, post-announcement returns are seen to be significantly related to both contemporaneous and lagged SUE and the signs of the coefficients on lagged SUE follow the (-,-,-,+) pattern. Sequential SUE realizations clearly interact in explaining longer period post-announcement abnormal returns.

Table 3 also reports the result of regressing post-announcement abnormal returns on contemporaneous and lagged three-day quarterly announcement period returns. In this case lagged event-period returns are associated with post-event returns, but only at the first two lags. Further, the pattern of signs is different and specifically it does not appear to be related to the pattern of signs of the autocorrelation coefficients of SUE. Since post-announcement returns are more highly related to SUE than to return-based measures of unexpected earnings, and since the time series of SUE measures have significance for post-announcement returns lacking in the return-based measures, we conclude that the process of measuring earnings has a significant impact on the magnitude of measured post-announcement drift. On the other hand return-based measures do explain at least part of the post-announcement effect. We therefore conclude that the earnings measurement process does not fully explain the post-announcement drift phenomenon.

3.2.4 Regressions of post-announcement abnormal returns on proxies for financial distress and returns measurement error

In table 4 we report the results of regression analysis of the relation between post-announcement abnormal returns, SUE_t, size, trading volume, the standard deviation of returns, stock price at the beginning of the period, the number of non-trading days, a proxy for post-announcement returns skewness and the *a priori* probability of bankruptcy estimated using the model in Ohlson (1980). These variables are predicted to be potential correlates with post-announcement abnormal returns either by the survival argument and/or by the bid-ask spread hypothesis. Abnormal returns are measured in two ways. First we use the size-adjusted CAR as in tables 1 and 2. We also report comparable regressions based on buy-and-hold excess returns relative to the buy-and-hold return on the comparable value-weighted *CRSP* size-decile portfolio. Conrad and Kaul (1993) suggest that buy-and-hold excess returns are less likely to be subject to return measurement effects. To allow for possible nonlinearity in the relationships we include multiplicative interaction terms in the regressions.

Whether survival arguments or the bid-ask spread can explain post-announcement drift depends on whether the proxy variables are correlated with SUE. To allow for the possible endogeneity of the regressors relating to the post-announcement period (trading volume, standard deviation, non-trading days and skewness) we employ instrumental variables regression where the regressors are represented by the fitted values from first stage instrument regressions in which the regressors reflect the information set prior to the SUE announcement date, including the SUE category itself.[15]

To provide a benchmark for subsequent model specifications, the first column of table 4 reports the regression framework counterpart to table 2. It shows that SUE and size interact in explaining CAR. The results of previous research and those in Table 2 suggest that the spread between abnormal returns for low-SUE and high-SUE portfolios is economically and statistically significant. However, the regression result shows that despite the statistical significance of SUE in explaining abnormal returns, the overall explanatory power in terms of the regression adjusted R^2 is very low at 1.7%. Even when the regression is performed on the subset of extreme decile portfolios corresponding to the hedge strategy examined in Bernard and Thomas (1990) the explanatory power only increases to 3.3%.[16]

The second column in table 4 shows that the predictability of abnormal returns by SUE does not depend on the choice of abnormal performance metric. Buy-and-hold excess returns are also predictable on the basis of SUE and size, although the explanatory power is even lower than in the case of CAR's. To the extent that buy-and-hold returns are purged of measurement errors, bid-ask spread cannot completely explain the drift phenomenon.

In columns (3) and (4) in table 4 we examine the ability of the regressors other than SUE to explain abnormal returns. Overall, the introduction of the additional correlates and allowance for interaction effects leads to only slightly higher explanatory power than reported for the SUE regressions. Size remains significant, and in addition all other correlates have significant effects

[15]For all except the skewness variable, the instrument variable regressions have high explanatory power (in excess of 80%). SUE is highly significant in each case.

[16]Not reported. Details avaliable from the authors on request.

either directly or as interactions with size. The F-tests in table 5 confirm that each set of coefficients relating to the effects of interest is different from zero. However, while the set of all coefficients relating to SUE and SUE-interactions contains significant explanatory power, the significance of SUE now evidently arises through the interactions with variables other than size. Interestingly, the main SUE effect and the interaction between SUE and size are now insignificant at the 5% level.[17]

When the innovations in the regressors are also included as regressors in columns (5) and (6), it can be seen that a substantial proportion of the variation in CAR can be explained. Some 23% of the variation in CAR is explained by regression (5) and 13% of the varaition in buy-and-hold excess returns by regression (6). Particularly noteworthy are the high t-values associated with unexpected trading volume and unexpected non-trading days. Note that the innovation terms are orthogonal to SUE and all other information included in the instrument set. Therefore, these results do not reflect market inefficiency.

The test statistics reported in table 5 are derived from the regressions in table 4 and summarize the significance tests of joint hypotheses that various sets of coefficients relating to the main effects of interest are zero. All F-tests are significant, indicating that SUE, size, financial distress and microstructure-related effects are all significant effects across all models. The log-

[17]Note that this model corresponds to the predictor-generated regressor model II of Pagan[1984]. In general, standard errors on the instruments will be biased. However, the t-values will be appropriate if, as in this application, the value of the coefficients of the instruments are zero under the null hypothesis, and where the variables that are not predicted values are used in the regressions that define the instrument. The regressions reported in Columns [5] through [6] of Table 4 correspond to the residual-generated regressor model described by Pagan. In this instance, the standard errors (and associated t-values) on the residuals are appropriately specified, regardless of the values of coefficients under the null hypothesis. Pagan's analysis applies to the case where both the instrumental variable regression and the regression used to define the instruments are based on the same time series data. In the present application, time series data are used to form the instruments, which are then regressed against the subsequent cross-section of performance measures.

odds ratios provide a means of comparing the non-nested models obtained by restricting one set of coefficients at a time to be zero. The results show that the set of variables capturing financial distress is marginally "more significant" than the set of variables involving SUE.

In summary, the regression results show that SUE and the SUE-size interaction on their own have low explanatory power for abnormal returns. When we control for financial distress and micro-structure differences, SUE and its interaction with size fail to contribute expanatory power, although SUE interacts with other variables to a significant degree and financial distress contributes more to expalnatory power. Finally, innovations in the instruments considerably enhance the explanatory power for abnormal returns.

3.2.5 Bankruptcy risk model sub-sample results

In table 6 we provide evidence that the SUE effect is associated with return distribution differences and risk differences across portfolios. We classify firms by independent SUE and bankruptcy probability measures, basing the bankruptcy probability measure on the one year model in Ohlson (1980). The results show first that the magnitude of the drift, measured by the difference between high-SUE and low-SUE abnormal returns, increases with the *ex ante* bankruptcy risk. The mean abnormal return difference for high bankruptcy risk firms is 5.78% compared with 3.56% for the relatively low risk firms.

Although the results in table 6 are consistent with the survival explanation, their main importance is not in establishing a link between drift and bankruptcy probability but in demonstrating clear differences in the sample distributions of abnormal returns across SUE portfolios, and in showing how distributional differences are associated with bankruptcy risk. The skewness of portfolio abnormal return is particularly noteworthy. The results show that independent of bankruptcy risk, the skewness of abnormal returns increases with SUE. There is also a very strong positive association between bankruptcy risk and both the skewness and the kurtosis of post-announcement abnormal returns. In all cases the skewness of abnormal returns is positive.

The results in table 6 suggest that the correlation between SUE and mean abnormal returns may be consistent with a survival effect in the data of the kind described by Brown, Goetzmann and Ross (1995). Unfavorable earnings in the past are indeed associated with a lower probability of survival. On the other hand, firms that survive a period of financial distress will be more likely to report high SUE and to display greater positive skewness in returns. Table 6 also shows that skewness induces positive correlation between the standard deviation of returns in the post-announcement period and the mean of the abnormal returns distribution in the same period.[18] In the absence of information on cross-sectional differences in skewness, one might conclude that this correlation is evidence that the drift contains a risk premium component. However, we note that the correlation is *also* consistent with positive skewness in the distribution of returns.

In table 7 we conduct a similar analysis to that in table 6, but this time with respect to abnormal returns in the *next* subsequent three-day earnings announcement period, approximately three months after the announcement of SUE_t. Previous research has found strong positive correlation between the abnormal return over this subsequent three-day period and SUE, measured at time t. Table 7 indicates that in our sample the difference in the three-day abnormal return

[18]For a discussion of the spurious cross-sectional relation between mean and standard deviation induced by higher order moments, see Roll and Ross (1980).

between low-SUE and high-SUE portfolios is 1.05%. It also shows that when the sample is partitioned on the basis of the bankruptcy probability prior to the *previous* earnings announcement, firms having relatively high bankruptcy risk have average abnormal returns, measured by the difference between high- and low-SUE portfolio abnormal returns, that are more than twice the magnitude of abnormal returns for firms with relatively low bankruptcy risk (1.43% compared to 0.62%). Much of the difference is explained by high-SUE, high-bankruptcy risk firms. This portfolio separately displays abnormal returns of 1.07% over the three-day period.

Table 7 also reveals dramatic differences in returns skewness across different partitions. Although the statistics are not directly comparable across tables 6 and 7 because of the length of the returns accumulation (sixty days versus three days), the two tables contain qualitatively similar results. They both demonstrate that high positive skewness and high kurtosis are associated with abnormal returns for firms with high bankruptcy probabilities.

Finally, table 8 provides further evidence that the survival related path-dependency in returns predicted by Brown Goetzmann and Ross (1995) is present in the data. The table reports descriptive statistics for the three-day announcement period abnormal return, standardized by the prior period standard deviation of returns, for the extreme high and low bankruptcy probability observations. The results show that the in the high probability of bankruptcy categories, mean return, skewness and kurtosis of announcement period returns and correlation between the event period return and the post-announcement period return is a decreasing function of the pre-event period decline in price. This is consistent with high bankruptcy risk firms *that survive* reporting both positive earnings announcements and positive post-event performance. However, the table also shows that the correlation between event period return and post-announcement return is positive for the low bankruptcy probability firms, suggesting that bankruptcy-related survival risk can only provide a partial explanation of post-announcement abnormal returns.

4. Conclusions

In this paper we confirm earlier findings that post-earnings drift is an important feature of observed equity returns. It is neither illusory, nor an artefact of the experimental design. It may be a result of market inefficiency. Our results cannot rule out this explanation. However, we find that the magnitude of the post-earnings announcement effect is correlated with factors that proxy for the *ex ante* probability of the firm surviving to be part of the earnings surprise sample, and with determinants of the bid-ask spread. Furthermore, it appears that there are complex nonlinear interactions between these factors and unexpected earnings. The results suggest that future event studies or alternative research designs should attempt to control for these factors.

Appendix:
Induced time series properties in standardized unexpected earnings

Bernard and Thomas (1990), assume that the "true" time series process followed by quarterly earnings, Q_t is given by the Brown and Rozeff (1979) model:

$$Q_t = \delta + Q_{t-4} + \phi\,(Q_{t-1} - Q_{t-5}) + \theta\epsilon_{t-4} + \epsilon_t \tag{A1}$$

where ϵ_t is a serially uncorrelated, zero mean innovation in earnings in quarter t, and $\phi > 0$, $\theta < 0$. This model is designed to account for the positive and decaying autocorrelations observed in seasonally differenced earnings at lags 1 through 3 and the negative autocorrelation observed at lag 4. The "naïve expectations" seasonal random walk with drift model that underlies standardized unexpected earnings (SUE) in Bernard and Thomas (1990) is a special case of (A1) with $\phi = \theta = 0$, i.e.

$$Q_t = \delta + Q_{t-4} + \epsilon_t \tag{A2}$$

Equation (A2) is the basis of the earnings expectation model in most previous research on the post-announcement drift.[19] Standardized unexpected earnings are defined as

$$SUE_t = \frac{Q_t - Q_{t-4}}{\sigma_\epsilon} \tag{A3}$$

where σ_ϵ is the standard deviation of seasonally differenced earnings.

From equation (A1) estimated unexpected earnings from the seasonal random walk model, conditional on information at time t-1 are equal to

$$Q_t - \delta - Q_{t-4} = \phi\,(Q_{t-1} - Q_{t-5}) + \theta\epsilon_{t-4} + \epsilon_t \tag{A4}$$

Q_{t-1}-Q_{t-5} can be rewritten in terms of prior period shocks to give

$$Q_t - \delta - Q_{t-4} = \phi\epsilon_{t-1} + \phi^2\epsilon_{t-2} + \phi^3\epsilon_{t-3} + (\theta + \phi^4)\epsilon_{t-4} + v_t + \epsilon_t \tag{A5}$$

where v_t is a linear function of earnings shocks prior to period t-4.

The positive autocorrelation in SUE at lags 1 through 3 has been explained in previous research by the moving average error terms on the right hand side of equation (A5). The first three MA terms are positive if $\phi>0$ and the fourth term is negative if $-\theta>\phi^4$. However, it can be shown that if quarterly earnings changes are stationary, the positive autocorrelation structure in seasonally differenced earnings can be accounted for by less complex processes.

Suppose that the true earnings process is actually a stationary ARMA process in quarterly

[19]Most previous work includes a drift term. This can be ignored for the purposes of the present analysis.

earnings. The sign of the autocorrelations in seasonally differenced earnings will be determined by the autocovariances between earnings changes at lags 1 through 4. For example, if earnings are assumed to follow a *quarterly* random walk, i.e. $Q_t = Q_{t-1} + \epsilon_t$, then if we denote $UE_t = Q_t - \delta - Q_{t-}$ we can write

$$\begin{aligned}
Cov(UE_t, UE_{t-1}) &= E[(Q_t - Q_{t-4})(Q_{t-1} - Q_{t-3})] \\
&= E[\{(Q_t - Q_{t-1}) + (Q_{t-1} - Q_{t-2}) + (Q_{t-2} - Q_{t-3}) + (Q_{t-3} - Q_{t-4})\} \\
&\qquad \{(Q_{t+1} - Q_t) + (Q_t - Q_{t-1}) + (Q_{t-1} - Q_{t-2}) + (Q_{t-2} - Q_{t-3})\}] \\
&= 3\sigma_Q^2
\end{aligned}$$

where σ_Q is the standard deviation of quarterly earnings changes. In other words, unless quarterly earnings changes are constant, the autocovariance of unexpected earnings will be positive. This result holds irrespective of the values of ϕ and θ. Similarly, it is straightforward to show that

$$Cov(UE_t, UE_{t-2}) = 2\sigma_Q^2$$

$$Cov(UE_t, UE_{t-3}) = \sigma_Q^2$$

$$Cov(UE_t, UE_{t-4}) = 0$$

and

$$Var(UE_t) = 4\sigma_Q^2$$

It is clear that positive autocorrelation at the first three lags could be a simple statistical artefact. Any stationary series differenced at lag k and sampled at a higher frequency will display positive autocorrelation for lags 1 to (k-1) because of the moving average error induced from the use of overlapping data. Therefore the observed autocorrelation structure for SUE over the first three lags does not represent evidence that the seasonal random walk expectation model is biased. The only firm conclusion that can be drawn is that it is an inefficient expectations model and that there is information in quarterly earnings subsequent to t-4 relevant for predicting Q_t. One would have to examine the *magnitudes* of the autocorrelations in SUE in order to draw inferences about time series structure of quarterly earnings series.

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Figure 1

Joint Frequency of SUE and Size Classifications in BT Sample

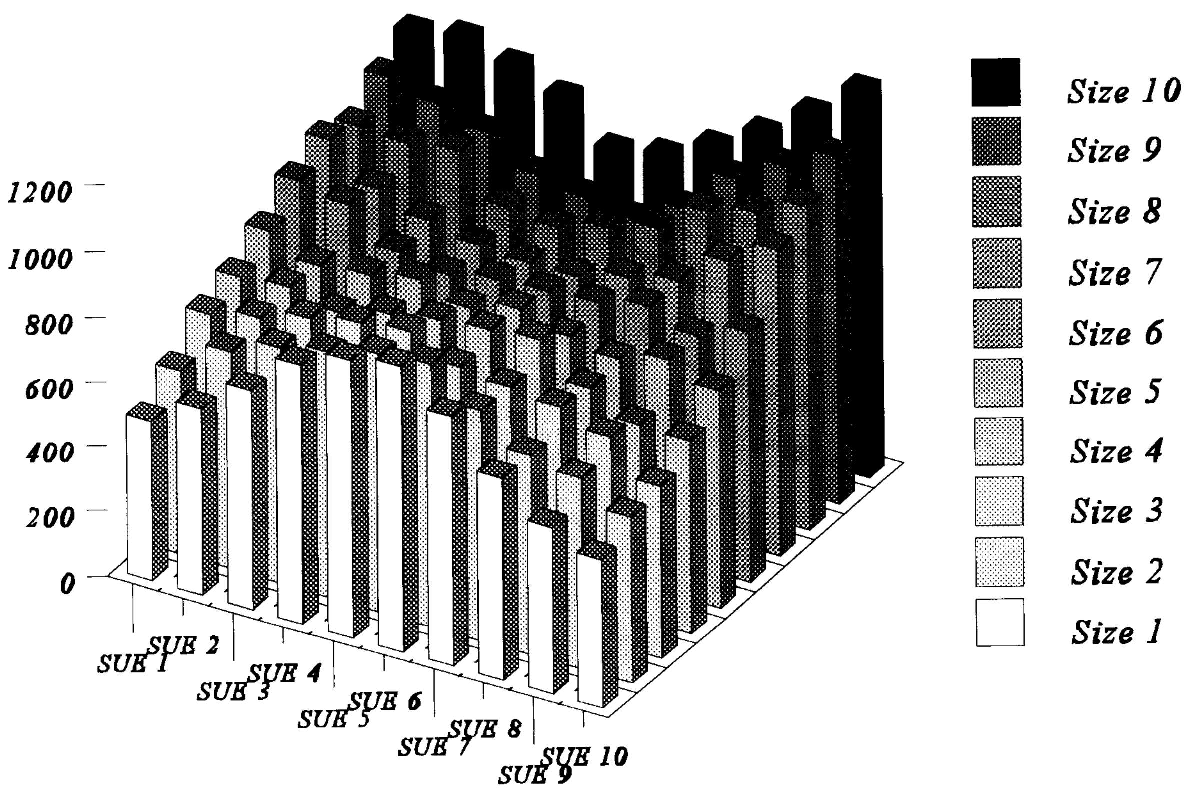

Figure 2

Conditional Probability of SUE[t] Given SUE[t-4]

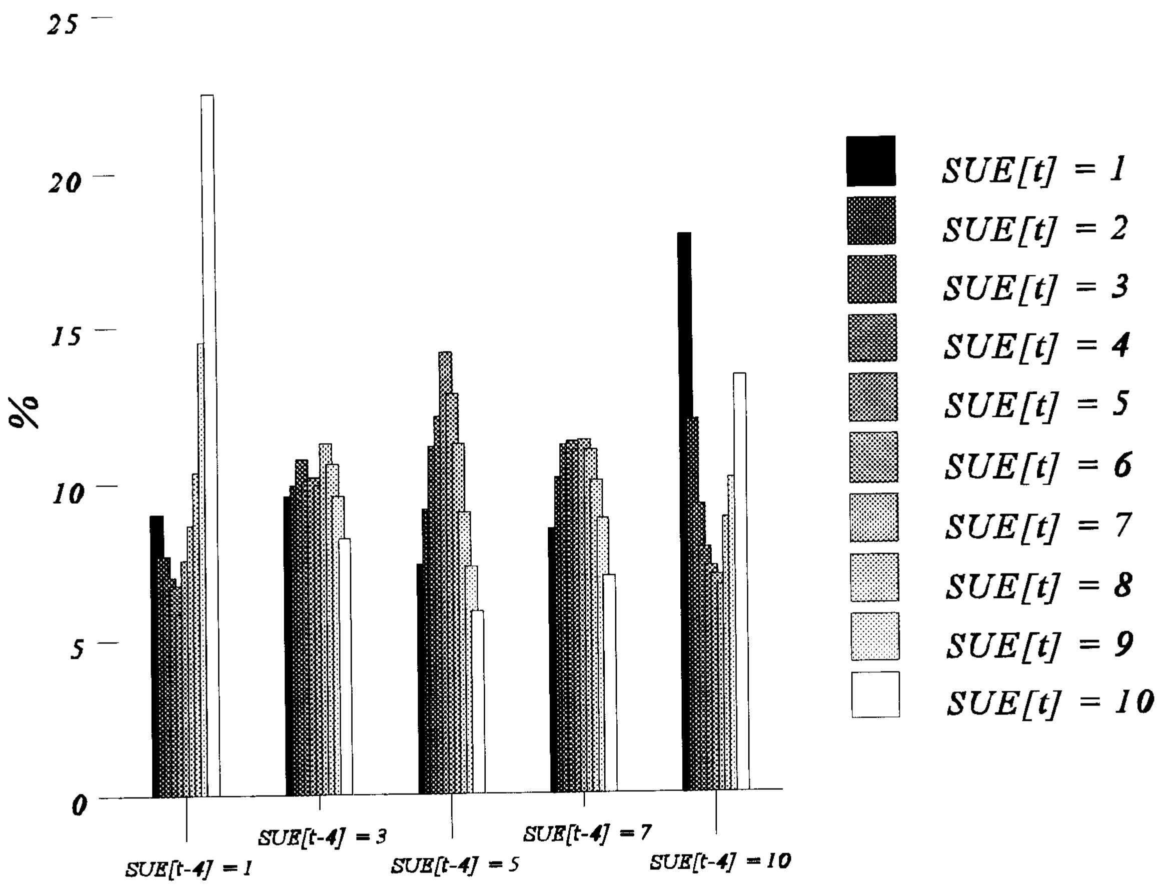

Table 1: Annual earnings changes and non-survival: NYSE/AMEX-listed firms, 1975-87

		Earnings Change							
	# firm-years	*Mean*	S.D.	Min	Q1	*Median*	Q3	Max	*% positive*
Panel A: All Years									
All NYSE/ AMEX firms, 1975-87	26,614	0.030	0.487	-12.944	-0.017	0.013	0.045	24.740	65.2
Bernard and Thomas sample, 1975-87	18,317	0.026	0.372	-6.034	-0.016	0.013	0.043	21.840	65.7
Firms not included in Bernard and Thomas sample, 1975-87	8,297	0.041	0.674	-12.944	-0.021	0.014	0.049	24.74	64.0
Panel B: Non-Survivors' Final Year									
All Non-Survivors:									
Acquisition targets	836	-0.004	0.499	-12.944	-0.017	0.013	0.050	2.070	64.6
Bankruptcies	32	0.029	1.822	-1.807	-0.643	-0.125	0.055	9.300	37.5
Other	199	0.124	1.499	-1.480	-0.038	0.011	0.092	20.267	60.8
Bernard and Thomas sample non-survivors:									
Acquisition targets	447	0.003	0.216	-1.420	-0.023	0.009	0.035	1.803	60.4
Bankruptcies	12	-0.179	0.955	-1.807	-0.576	-0.115	0.054	1.537	16.7
Other	126	0.190	1.847	-1.149	-0.033	0.011	0.086	20.267	61.9

Table 1, Panel B
cont....

Non-Bernard and Thomas sample non-survivors:									
Acquisition targets	389	-0.011	0.645	-12.944	-0.010	0.021	0.071	2.070	69.9
Bankruptcies	20	0.153	2.202	-1.177	-0.643	-0.313	0.072	9.300	35.0
Other	73	0.010	0.483	-1.480	-0.047	0.008	0.093	2.535	58.9

Panel C: Non-Survivorship Rates by Earnings Change Decile

	Earnings change decile									
	1	2	3	4	5	6	7	8	9	10
Mean scaled earnings change in year t-1	-0.187	-0.052	-0.017	0.001	0.010	0.018	0.028	0.046	0.083	0.241
% with missing earnings in year t	6.24	4.03	4.40	4.73	3.11	3.45	3.45	4.28	4.98	6.64

Notes:
E_t is primary earnings per share in year t; P_{t-1} is the stock price at the beginning of year t. Earnings change is defined as $(E_t-E_{t-1})/P_{t-1}$. Non-survivors are identified from the Research File of the 1993 version of Compustat. Acquired firms have deletion code equal to 1 and bankrupt firms have deletion code equal to 2.

Table 2: Post-Announcement Drift for Alternative Unexpected Earnings Proxies

	Unexpected Earnings Proxy			
	SUE		*Announcement Period CAR*	
Earnings surprise decile	Post-event CAR	t-value	Post-event CAR	t-value
1	-.030	-16.10	-.011	-5.98
2	-.026	-14.93	-.009	4.93
3	-.021	-12.14	-.005	-2.57
4	-.012	-6.77	-.006	-3.59
5	.001	0.77	-.004	-2.03
6	.008	4.29	-.003	-1.62
7	.010	5.64	.000	0.28
8	.012	6.96	.001	0.45
9	.022	12.78	.007	4.12
10	.024	14.28	.017	9.28
All	.001	0.00	-.001	0.00

Notes: Portfolios are formed on the basis of two proxies for unexpected earnings: standardized unexpected earnings (SUE), as defined in Bernard and Thomas (1990); and three-day announcement period cumulative abnormal returns standardized by pre-announcement period returns standard deviation (CAR). Post-event cumulative abnormal returns are measured over the sixty day post announcement period.

Table 3: Regressions of Post-Announcement Abnormal Returns on Current and Lagged Unexpected Earnings Proxies

	Unexpected Earnings Proxy	
	SUE	*Announcement-Period Standardized CAR*
Constant	-.0307 [13.396]	-0.0287 [10.552]
Size	-0.0000 [.005]	0.0002 [0.856]
UE_t	0.0073 [31.007]	0.0025 [11.974]
UE_{t-1}	-0.0009 [3.708]	0.0016 [7.561]
UE_{t-2}	-0.0006 [2.203]	0.0008 [3.893]
UE_{t-2}	-0.0002 [8.373]	-0.0003 [1.298]
UE_{t-4}	0.0018 [7.669]	0.0003 [1.222]
Adj. R^2(%)	1.6	0.3
# obs.	66,620	66,620

Note: UE_t is inexpected earnings in quarter t. Unexpected earnings are proxied by standardized unexpected earnings (SUE) as defined in Bernard and Thomas (1989) or standardized abnormal returns measured over the three-day announcement period for quater t earnings commencing on day -2. SIZE is the CRSP size decile to which a firm belongs at the beginning of the relevant calendar year.

Table 4: Regressions of abnormal post-announcement period abnormal returns on SUE, size and instruments and innovations

	Dependent Variable					
Regressors	[1] CAR	[2] BHRET	[3] CAR	[4] BHRET	[5] CAR	[6] BHRET
Constant	-0.0718	-0.0849	0.1514	0.1834	0.1643	0.2497
	[-21.44]	[-24.26]	[4.37]	[5.37]	[5.29]	[7.62]
SUE	0.0129	0.0095	-0.0004	-0.0015	0.0000	-0.0034
	[23.31]	[16.29]	[-0.14]	[-0.57]	[0.01]	[-1.35]
Size	0.0058	0.006	-0.0072	-0.0103	-0.0135	-0.018
	[12.74]	[12.72]	[-2.90]	[-4.29]	[-5.83]	[-7.67]
Volume			0.146	0.3373	0.1193	0.3809
			[2.53]	[6.01]	[2.26]	[6.81]
S.D.			-5.8763	-7.5169	-6.3526	-9.232
			[-5.92]	[-7.74]	[-7.02]	[-9.82]
Price			-0.0030	-0.0039	-0.0026	-0.0047
			[-4.46]	[-5.99]	[-4.30]	[-7.42]
Nzero			-0.0011	-0.0006	0.0000	0.0001
			[-2.54]	[-1.46]	[0.06]	[0.31]
Skewness			6.7423	5.4874	6.6021	6.6421
			[8.27]	[6.86]	[8.77]	[8.38]
Ohlson Prob			-0.3008	-0.2449	-0.2840	-0.3530
			[-3.39]	[-2.92]	[-4.11]	[-4.63]
SUE × Size	-0.0011	-0.0007	-0.0003	0.0001	-0.0002	0.0003
	[-14.16]	[-8.85]	[-1.93]	[0.49]	[-1.36]	[2.03]
SUE × Volume			-0.0072	-0.0121	-0.0096	-0.0168
			[-2.72]	[-4.74]	[-3.95]	[-6.67]
SUE × S.D.			0.2508	0.1658	0.2162	0.1529
			[3.46]	[2.34]	[3.30]	[2.26]
SUE × Price			0.0001	0.0001	0.0001	0.0001
			[3.43]	[3.25]	[3.05]	[3.85]
SUE × Nzero			0.0000	0.0000	0.0000	0.0000
			[0.11]	[0.05]	[-0.57]	[-0.45]
SUE × Skewness			-0.0779	0.0188	-0.0208	0.0982
			[-0.91]	[0.23]	[-0.26]	[1.23]
SUE × Ohlson Pr.			0.0003	-0.0006	0.0026	0.0056
			[0.04]	[-0.09]	[0.42]	[0.85]
Size × Volume			-0.011	-0.029	0.0024	-0.0184
			[-2.12]	[-5.73]	[0.50]	[-3.68]
Size × S.D.			0.1284	0.1764	0.3173	0.2712
			[1.75]	[2.52]	[4.51]	[3.84]
Size × Price			0.0002	0.0004	0.0002	0.0004
			[4.11]	[6.18]	[4.15]	[7.69]
Size × Nzero			0.0001	-0.0000	-0.0002	-0.0002
			[1.01]	[-0.67]	[-4.78]	[-3.94]
Size × Skewness			-0.3121	-0.0247	-0.2300	0.0065
			[-3.15]	[-0.26]	[-2.19]	[0.07]
Size × Ohlson Pr.			0.0572	0.0513	0.0402	0.0624
			[3.59]	[3.32]	[3.15]	[4.37]
U(Volume)					0.2511	0.3156
					[17.83]	[18.84]
U(S.D)					1.1685	-0.2231
					[3.45]	[-0.71]
U(Nzero)					-0.0029	-0.002
					[-13.43]	[-7.99]
U(Skewness)					0.7459	0.425
					[2.96]	[2.11]
Adj. R^2(%)	1.7	1.3	2.7	2	23.2	13
# obs.	75743	75723	52478	52474	52478	52474

Notes to Table 4: Dependent variables are size adjusted cumulative abnormal return (CAR) as computed in Bernard and Thomas (1990) and buy and hold returns relative to the CRSP value-weighted size-decile portfolio buy and hold return (BHRET). The regressors are SUE, CRSP size category (Size), trading volume (Volume), returns standard deviation (S.D.), stock price (Price), the number of days with zero trading volume in the post-announcement period (Nzero), estimated skewness(Skewness) and Ohlson probability of bankruptcy measure (Ohlson Prob). All regressors not in the information set at the beginning of the post-announcement period are in the form of the fitted values from instrumental variables regressions based on the information set available at the beginning of the post-announcement period. Unexpected values are denoted U(.) and are the residuals from the respective instrument regressions. All t-values are heteroscedasticity consistent estimated using the method in White (1980).

Table 5: Summary Test Statistics of Regressions of post-announcement period abnormal returns on SUE, size, instruments and innovations

	Dependent Variable					
Summary Statistics	[1] CAR	[2] BHRET	[3] CAR	[4] BHRET	[5] CAR	[6] BHRET
Adj. R^2(%)	1.7	1.3	2.7	2.0	23.2	13.0
# obs.	75743	75723	52456	52474	52456	52474
F (all coefficients zero)	435.38	321.13	70.85	52.87	635.32	315.95
d.f.	[3,75739]	[3,75719]	[21,52456]	[21,52452]	[25,52452]	[25,52448]
Log odds ratio	*630.69*	*461.83*	*619.77*	*435.54*	*6805.01*	*3544.84*
F (SUE coefficients zero)	652.03	404.64	40.60	23.06	47.34	25.13
d.f.	[2,75739]	[2,75719]	[8,52456]	[8,52452]	[8,52452]	[8,52448]
Log odds ratio	*635.28*	*391.28*	*118.49*	*48.63*	*145.29*	*56.92*
F (Size coefficients zero)	114.99	113.49	27.82	13.88	28.23	28.62
d.f.	[2,75739]	[2,75719]	[8,52456]	[8,52452]	[8,52452]	[8,52448]
Log odds ratio	*103.58*	*102.09*	*67.62*	*12.00*	*69.25*	*70.82*
F (distress coefficients zero)			43.87	26.56	65.31	28.51
d.f.			[9,52456]	[9,52452]	[9,52452]	[9,52448]
Log odds ratio			*147.83*	*70.41*	*243.49*	*79.16*
F (microstructure coefficients zero)			9.39	15.04	38.51	65.73
d.f.			[9,52456]	[9,52452]	[9,52452]	[9,52448]
Log odds ratio			*-6.67*	*18.72*	*123.92*	*245.39*

Notes to Table 5: Regression results correspond to results reported in Table 4. The first F statistic corresponds to the hypothesis that all coefficients are zero (with appropriate degrees of freedom below). The second F statistic corresponds to the hypothesis that all coefficients associated with SUE are zero (including interaction terms). The third F statistic to the hypothesis that all coefficients associated with the *ex ante* probability of financial distress (predicted standard deviation, skewness and Ohlson probability of bankruptcy, and interactions with SUE and size) are zero. The fourth F statistic corresponds to the hypothesis that all coefficients associated with microstructure effects (price level, predicted volume and number of days with zero trading volume in the post-announcement period together with interactions with SUE and size) are zero. Below each F statistic and degrees of freedom is the associated log odds ratio (see Klein and Brown [1984]). To make the non-nested comparison of, say, the no SUE model with the no financial distress model, simply subtract the log odds ratio associated with SUE coefficients zero from the log odds ratio associated with distress coefficients zero.

Table 6: 60 Day Post Event CAR organized by independent SUE and Ohlson probability of bankruptcy classifications: Measures of skewness, kurtosis and correlation with post-event period standard deviation

		Low SUE (Deciles 1 - 3)	Intermediate SUE (Deciles 4 - 7)	High SUE (Deciles 8 -10)	Total	High SUE - Low SUE
Low Probability of Bankruptcy (Ohlson measure deciles 1 through 3)	Average CAR	-0.0232	-0.0049	0.0124	-0.0058	0.0356
	t-value	(-13.30)	(-3.07)	(6.54)	(-5.71)	(13.83)
	Skewness	0.1002	0.0916	0.4050	0.1973	
	Kurtosis	5.7107	4.9827	8.0968	6.1989	
	Correlation with post-event standard deviation	0.0360	0.0972	0.1560	0.0902	
Intermediate Probability of Bankruptcy (Ohlson measure deciles 4 through 7)	Average CAR	-0.0264	-0.0009	0.0211	-0.0026	0.0475
	t-value	(-14.98)	(-0.57)	(11.60)	(-2.68)	(18.76)
	Skewness	0.0025	0.2585	0.1732	0.1428	
	Kurtosis	4.8554	5.1427	4.2216	4.7755	
	Correlation with post-event standard deviation	0.0130	0.1347	0.1290	0.0863	
High Probability of Bankruptcy (Ohlson measure deciles 8 through 10)	Average CAR	-0.0380	0.0035	0.0198	-0.0037	0.0578
	t-value	(-13.03)	(1.45)	(6.90)	(-2.37)	(14.13)
	Skewness	0.6775	0.6002	0.6517	0.6219	
	Kurtosis	8.4318	6.2574	8.9652	7.5478	
	Correlation with post-event standard deviation	0.2069	0.2200	0.1968	0.2014	
Total	Average CAR	-0.0287	-0.0007	0.0180	-0.0039	0.0467
	t-value	(-23.53)	(-0.61)	(14.26)	(0.00)	(26.60)
	Skewness	0.3610	0.4818	0.5193	0.4476	
	Kurtosis	8.2251	6.8111	8.9255	7.7554	
	Correlation with post-event standard deviation	0.0912	0.1668	0.1604	0.1357	

Table 7: CAR on next quarterly announcement classified by independent SUE and Ohlson probability of bankruptcy classifications: Measures of skewness, kurtosis and correlation with post-event period standard deviation

		Low SUE (Deciles 1 - 3)	Intermediate SUE (Deciles 4--7)	High SUE (Deciles 8 - 10)	Total	High SUE - Low SUE
Low Probability of Bankruptcy (Ohlson measure deciles 1 through 3)	Average CAR	-0.0034	0.0008	0.0027	0.0000	0.0062
	t-value	(-5.94)	(1.51)	(4.43)	(0.07)	(7.29)
	Skewness	0.3483	0.3778	0.0945	0.2903	
	Kurtosis	7.4672	10.7894	6.5366	8.5598	
	Correlation with post-event standard deviation	-0.0539	-0.0169	-0.0022	-0.0266	
Intermediate Probability of Bankruptcy (Ohlson measure deciles 4 through 7)	Average CAR	-0.0049	0.0019	0.0059	0.0009	0.0109
	t-value	(-8.13)	(3.66)	(9.76)	(2.80)	(12.65)
	Skewness	0.3949	0.5160	0.2676	0.3998	
	Kurtosis	8.9720	7.2428	7.1640	7.7091	
	Correlation with post-event standard deviation	-0.0281	-0.0075	0.0085	-0.0143	
High Probability of Bankruptcy (Ohlson measure deciles 8 through 10)	Average CAR	-0.0036	0.0059	0.0107	0.0045	0.0143
	t-value	(-3.45)	(6.50)	(10.30)	(7.91)	(9.69)
	Skewness	1.7920	1.2628	1.1319	1.3631	
	Kurtosis	24.6224	10.6756	12.5797	14.8599	
	Correlation with post-event standard deviation	0.0730	0.0597	0.0509	0.0567	
Total	Average CAR	-0.0041	0.0029	0.0064	0.0017	0.0105
	t-value	(-9.62)	(7.35)	(14.61)	(0.00)	(17.20)
	Skewness	1.3164	1.1007	0.9228	1.1079	
	Kurtosis	23.9592	12.4160	13.6455	15.9112	
	Correlation with post-event standard deviation	0.0204	0.0417	0.0490	0.0343	

Table 8: Conditional distributions of standardized event period abnormal return and correlation with 60 day post event standardized performance. Results organized by probability of bankruptcy, and within each category of probability of bankruptcy, by deciles of standardized abnormal excess return for the 60 days prior to event.

Low probability of bankruptcy decile

Prior return	N	Mean	Variance	Skewness	Kurtosis	Correlation
Most negative	525	-0.0095	2.09	0.18	3.82	0.106
2	526	0.0873	1.95	0.19	5.96	0.147
3	526	-0.0045	1.84	0.25	4.68	0.012
4	525	-0.1063	1.46	-0.21	4.13	0.018
5	526	-0.0391	1.86	-0.88	15.32	0.021
6	526	0.1200	1.64	-0.37	8.80	0.110
7	525	-0.1718	1.98	-1.58	17.81	0.201
8	527	0.0862	1.87	0.41	7.03	0.041
9	525	-0.0257	1.52	-0.15	4.77	0.113
Most positive	526	-0.0962	1.88	-0.07	4.00	0.032
All Cases	5257	-0.0159	1.81	-0.22	8.01	0.083

High probability of bankruptcy decile

Prior return	N	Mean	Variance	Skewness	Kurtosis	Correlation
Most negative	525	0.1811	3.44	3.09	33.60	0.123
2	525	0.1314	2.36	1.50	13.54	0.063
3	525	0.2065	1.99	0.18	9.68	0.037
4	525	0.1790	2.19	0.94	7.38	-0.022
5	526	0.1248	1.86	1.45	11.72	0.044
6	525	0.1464	1.99	1.45	9.62	0.079
7	526	0.0674	1.38	0.51	8.05	0.131
8	524	0.1246	1.66	0.94	6.82	0.088
9	525	0.1001	1.55	1.12	8.02	0.035
Most positive	526	0.0425	1.71	0.65	5.97	0.085
All Cases	5252	0.1304	2.02	1.52	17.24	0.068
Entire sample	75745	0.0553	1.81	0.49	10.30	0.059