

Methodological Choices In Detecting Divergent Earnings

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Abstract

This paper empirically tests for methodological superiority in detecting divergent earnings (the difference between actual and expected earnings). Divergent earnings are generated using Value Line forecasted and reported earnings data. Two hundred random samples of 100 cases each are drawn. One hundred independent two sample tests are performed with 0%, 1%, 3%, 5%, 7%, and 10 % positive earnings introduced. The two sample tests are performed using both parametric (t test), and nonparametric (Mann Whitney test) statistics. They are performed on the "divergent earnings" data deflated by: 1) forecasted earnings, and 2) the market price of the stock. The results indicate that the superior alternative is nonparametric statistical methods based upon ranks, and the deflator choice under these nonparametric methods is of little consequence.

Introduction

Numerous studies have been conducted that require scrutinization of differences between actual and expected (divergent) earnings. One such area of study tests the relative accuracy of various earnings forecast agents (see for example Brown and Rozeff (1978), Fried and Givoly (1982), Brown et. al., 1987, and Philbrick and Ricks (1991)). Studies of earnings signaling also monitor earnings divergence; specifically, earnings divergence that may be associated with particular events. Such works compare reported earnings with some measure of pre-event earnings expectation. For example, the plausibility that stock splits are signals of favorable earnings has been investigated by Doran and Nachtmann (1988), Asquith, et. al., (1989), and Doran (1994).

Studies investigating divergent earnings generally apply a deflator in order to allow cross sec-

tional analysis at varying earnings levels, and to control for data heteroscedasticity. Two common deflators used are: the firm's stock price, and some measure of earnings¹ (e.g., expected or reported earnings). For example, Williams (1996) uses a stock price deflator, while Doran (1994) uses a forecasted earnings deflator, and Philbrick and Ricks (1991) and Doran (1995) use both. No universally superior deflator choice has been established in the literature.

Christie (1987) argues that when earnings performance is scrutinized in association with market returns (i.e., earnings response coefficients), stock price is the appropriate deflator choice because it provides dimensional consistency of the independent and dependent variables. Although stock price may be the appropriate deflator in studies of earnings response coefficients (it has never been empirically tested), the appropriate deflator in other studies of earnings divergence remains an open issue.

Readers with comments or questions are encouraged to contact the author via e-mail.

The issue of appropriate statistical method is also unresolved. Both parametric and nonparametric statistical methods have been used in previous studies of divergent earnings (see for example Brown and Kim (1991), Bowen et al. (1992), or Doran (1995)). This study empirically tests for methodological superiority in detecting divergent earnings. Both deflator choice (market price of stock vs. expected earnings) and choice of statistical analysis (parametric vs. nonparametric) are scrutinized. Their relative performance in detecting divergent earnings is determined at various levels of introduced error and statistical significance.

Data and Methodology

Two sources of expected earnings data are generally used in studies of divergent earnings: analysts' forecasts and time series models. Analyst forecasts have been found to be superior to time series models in terms of absolute accuracy and market reaction correlation. Value Line has been found to be at least as good as other analysts in forecasting earnings. For a discussion of the superiority of analysts' forecasts relative to time series models and the particular superiority of Value Line, see Fried and Givoly (1982), Brown and Rozeff (1978), Brown et al. (1987 and 1987a), and Philbrick and Ricks (1991).

Value Line analysts' forecasts are used as earnings expectations in this study. Three firms are randomly selected from each week's Value Line Summary and Index publication issued between November 17, 1971 and December 31, 1990. For some weeks, less than three firms are included in the analysis due to lack of requisite information (e.g., forecasted earnings per share (EPS) was "no meaningful figure"). Actual reported earnings were gathered from subsequent issues of Value Line. The earnings forecast period includes four sequential quarters straddling the Value Line publication date. The full sample includes 2,701 cases.

From this full sample, randomly drawn port-

folios of 100 cases each (with replacement) are drawn. This process was repeated 200 times. All analysis is conducted using these 200 randomly selected portfolios of 100 cases each.

Divergent earnings (DE) is deflated by stock price (DE\$), and by the absolute value of the EPS forecast (DE%). The stock price deflator used is the market price of the particular firm's stock on the date of the Value Line forecast. Formally stated:

$$DE\$ = \frac{\text{Reported EPS} - \text{Forecast EPS}}{\text{Stock Price}} \quad (1)$$

$$DE\% = \frac{\text{Reported EPS} - \text{Forecast EPS}}{|\text{Forecast EPS}|} \quad (2)$$

Previous research has documented that analyst forecasts are optimistically biased (see O'Brien (1988), Butler and Lang (1991), Philbrick and Ricks (1991), Abarbanell (1991), and Ali, et al. (1992)). The Value Line forecasts here are consistent with this finding. This results in disproportionately negative observations of DE. For the 2701 full sample cases of DE, 40% are positive, 58% are negative and 2% are zero. Full sample distribution characteristics (e.g., consistently negative full sample means and medians) presented in Table 1 also document the optimism bias. With the Value Line forecasts optimistically biased, the expected value of DE is negative, and one sample tests of significant difference from zero are inappropriate. To accommodate the optimism bias, two sample tests are conducted.

Positive divergent earnings is introduced to all sample cases in the "divergent" group, while the "control" group remains consistently unaltered. Statistical tests of observed differences in average DE\$ and DE% between the divergent group and the control group are conducted. The 200 randomly drawn portfolios accommodate 100 individual two sample tests. One half of the portfolios are designated as "divergent", while the others are designated "control". Each of the divergent portfolios is matched with a control

group portfolio. In order to better isolate the effects of alternative methodologies and minimize differences due to random fluctuation, the 100 matched companion samples are held identical across all analysis.

The t-test is the parametric statistical method applied, while the Mann Whitney (rank) test is the nonparametric statistical method used. Since only positive divergent earnings is introduced, the tests of significance are one tailed and the null hypothesis is:

H₀: DE% (DE\$) of the divergent group is not greater than DE% (DE\$) of the control group. Type I error is observed when the null hypothesis is rejected where zero divergent earnings has been introduced. Observed frequency of Type I error is scrutinized relative to expected using a binomial test. Type II error is observed where the null hypothesis is not rejected, but positive divergent earnings has been introduced. Incidence of type I and type II error is examined at the 1%, 5%, and 10% levels of significance.

In order to scrutinize incidence of type II error, actual EPS is increased for all sample cases in the divergent group. The levels of divergent positive earnings introduced are: 1%, 3%, 5%, 7%, and 10%. Lower levels of type II error (higher incidence of rejection of the null hypothesis) indicate more powerful methodological choices. That is, they demonstrate superiority in detecting divergent earnings performance. Significant differences in the power of methodological alternatives are identified by applying a chi-square test.²

Large measures of DE% and DE\$ can result at low deflator levels (i.e., as the deflator value approaches zero, DE% and DE\$ approach infinity). This outlier problem is particularly acute when using the forecasted earnings deflator. For a discussion of the outlier problem, see Fried and Givoly (1984), and Beaver et al. (1979). Additional analysis is conducted where outliers are controlled for by applying a simple truncation rule. Measures of DE% and DE\$ are truncated to result

in a minimum value of -1, and maximum value of +1 (consistent with Philbrick and Ricks (1991))³. The nonparametric Mann Whitney test applied here uses rank (ordinal) values rather than continuous interval measurements, and outliers are of lesser importance. In order to empirically test the need for controlling outliers, tests of DE\$ and DE% are conducted both with and without truncation.

Results

Sample descriptives are provided in Table 1. As indicated in Panel A, the full sample distributions of DE% and DE\$ without adjustment (truncation) are severely nonnormal (Kolmogorov - Smirnov test statistics of 21.92 and 16.97, respectively). Nonnormality is more severe for the sample distribution of DE%. The kurtosis measure of 1,654 is indicative of a extremely leptokurtic distribution (long fat tails). This is consistent with the outlier problem discussed previously. Outliers result from low deflator levels, which is a particularly severe problem when using the forecasted earnings deflator.

Panel B of Table 1 provides the same sample descriptives with the truncation rule applied. Although the sample distributions remain nonnormal, they are less severely so. There is a more pronounced movement toward normality of DE% with the kurtosis measure declining to 2.22 and the Kolmogorov - Smirnov test statistic dropping to 7.74. Although the sample distribution of DE\$ becomes less nonnormal, the improvement is relatively slight. With truncation, the sample distribution of DE% is less nonnormal than DE\$. This difference is likely attributed to the arbitrary truncation rule (-1, +1) being more appropriate for DE% than DE\$. It is not presumed to indicate a general superiority of forecasted earnings over market price of stock as a deflator when outliers are controlled.

Tables 2, 3, and 4 provide the same results under different presentation formats in order to accommodate analysis of the effects of: trunca-

Table 1
Properties Of Full Sample Distribution (N=2701)

| Panel A - Without Truncation | | |
|------------------------------------|------------|-------------|
| | <u>DE%</u> | <u>DE\$</u> |
| Mean | -.502 | -.020 |
| Median | -.029 | -.003 |
| Standard Deviation | 8.481 | .177 |
| Minimum | -389.000 | -3.780 |
| Maximum | 71.000 | 4.630 |
| Skewness | -37.200 | 2.940 |
| Kurtosis | 1654.280 | 315.983 |
| Kolmogorov - Smirnov Z | 21.915*** | 16.965*** |
| Panel B - With Truncation (-1, +1) | | |
| | <u>DE%</u> | <u>DE\$</u> |
| Mean | -.089 | -.019 |
| Median | -.029 | -.003 |
| Standard Deviation | .353 | .106 |
| Minimum | -1.000 | -1.000 |
| Maximum | 1.000 | 1.000 |
| Skewness | -.479 | -3.963 |
| Kurtosis | 2.221 | 49.361 |
| Kolmogorov - Smirnov Z | 7.740*** | 14.952*** |

Where: DE% = Unexpected earnings deflated by the absolute value of forecasted earnings
 DE\$ = Unexpected earnings deflated by market value of the Stock
 *** = Significant at 1%

tion - Table 2, deflator choice - Table 3, and statistical method - Table 4. The results presented represent the observed frequency of rejection of the null hypothesis. Since N=100 individual two sample tests, the presented numerical frequencies are also percentage incidence of rejection of the null. With divergent earnings introduced, the higher the reported frequency rejection of the null - the lower the type II error (and the more powerful the corresponding methodology).

Incidence of type I error is presented under the "0% error" columns in Tables 2 - 4. With sample size of 100, applying a 95% confidence interval under the binomial distribution results in the following lower and upper limits for observed frequency of type I error: 1% = 0 and 3,

5% = 1 and 10, 10% = 5 and 16. In all cases, the observed frequencies of Type I error fall within these 95% confidence limits.

Type I error will be discussed initially here with reference to the results presented in Table 2. Panel A illustrates the general improvement in t test specification for DE% when the arbitrary truncation rule is applied. This observation is expected given the full sample descriptives presented in Table I. However, the chi-square statistic indicates no significant difference. Panel B of Table 2 indicates that truncation has no notable impact on type I error when applying the market price deflator. Panels C and D indicate identical incidence of type I error regardless of truncation under the Mann Whitney test.

Table 3, Panel A indicates one instance of marginal significance indicating the forecasted earnings deflator is conservative relative to the market price deflator under the t test. The chi-square value of 3.19 is only significant at the 10% level, and loses significance with application of the -1, +1 truncation rule (see Panel B). The apparent relative conservatism of the forecasted earnings deflator is likely attributed to the severe non-normality of the DE% distribution when outliers aren't controlled. Panels C and D of Table 3 indicate identical incidence of type I error regardless of deflator choice under the Mann Whitney test.

Table 4 scrutinizes the effect of statistical method, and indicates a general tendency for the Mann Whitney test to reject the null hypothesis less often than the t test when no divergent earnings is introduced. This general observation may indicate that the Mann Whitney test is relatively conservative; however, the chi-square values indicate the difference between statistical methods is insignificant.

In summary regarding type I error, there is weak evidence indicating that controlling for outliers is needed when using the forecasted earnings deflator under parametric tests, and that the Mann Whitney test is relatively conservative when compared with the t test. However, these findings are not statistically significant.

The relative power of methodological alternatives is scrutinized next. Table 2 empirically analyzes the benefit of the truncation rule while holding constant the choices of deflator and statistical method. Panels A and B provide parametric t test results that are consistent with expectations given the full sample characteristics of DE% and DE\$ described in Table 1. Panel A indicates that when deflating divergent earnings by forecasted earnings, truncation results in significantly lower incidence of type II error (for abnormal earnings of 5%, 7%, or 10%). However, the truncation of DE\$ sample data (Panel

B) does not significantly reduce the incidence of type II error (consistent with the notion that the arbitrary -1, +1 cut-off is more appropriate for the DE% sample data).

Panels C and D of Table 2 provide the results with and without truncation under the Mann Whitney test. As anticipated, using ranks rather than continuous interval values diminishes the outlier problem and therefore the need to use truncation (or some other method) of data refinement. The empirical results are unaffected by truncation across all introduced error levels for both DE% and DE\$. The largest chi-square value under the Mann Whitney test is .03. The conclusion is drawn that controlling for outliers is not important when applying nonparametric statistical methods that are based upon ranks.

In Table 3 the statistical test (t or Mann Whitney) as well as outlier control (with or without truncation) are held constant while choice of deflator is examined. Panels A and B compare incidence of rejection of the null hypothesis when applying the parametric t test, while Panels C and D provide the same analysis under the nonparametric Mann Whitney test.

Panel A of Table 3 (t test without truncation) indicates a general superiority of the market price deflator under parametric statistical methods, particularly at higher levels of introduced divergent earnings (greater than 3%). However, there is only one instance of significant difference (7% divergent earnings at 1% level of significance), and it is only significant at the 10% level. Panel B (t test with truncation) indicates lower incidence of type II error for DE%. Again, this is likely the result of the arbitrary truncation rule applied here, rather than an indication of the general superiority of the forecasted earnings deflator when outliers are controlled for. However, the results do indicate that when parametric statistical methods (e.g., the t test) are applied, the results are deflator sensitive,

particularly when a preconceived method of controlling outliers is applied.

Panels C and D of Table 3 document that incidence type II error is fairly consistent across DE% and DE\$ when the Mann Whitney test is applied. The market price deflator seems to perform somewhat better than the forecasted earnings deflator, but the superiority is not significant in any instance. This finding indicates that when applying nonparametric statistical methods based upon ranks (e.g., the Mann Whitney test), deflator choice is of little (if any) consequence.

Table 4 analyzes the effect of statistical method while holding constant the effects of truncation and the deflator choice. Panels A and B provide analysis without truncation, while Panels C and D depict the results with the -1, +1 truncation rule applied. Without truncation (Panels A and B of Table 4) the nonparametric Mann Whitney test is overwhelmingly superior to the parametric t test. For all levels of induced divergent earnings, at all levels of significance, using either deflator, the Mann Whitney test outperforms the t test. The observed superior performance is consistently significant when divergent earnings of 3% or more is introduced. The conclusion is drawn that when data are unaltered (i.e., no refinement methods are applied in attempts to normalize the data), nonparametric methods based upon ranks are more powerful than parametric statistical methods. Nonparametric methods based upon ranks are superior in detecting divergent earnings.

Panels C and D of Table 4 again indicate the superiority of the Mann Whitney test relative to the t test. Although the superiority is not as overwhelming with the sample data truncated at -1, +1, it is still generally consistent and pronounced. Even in the case of DE% (where truncation resulted in a much less nonnormal sample distribution and made the parametric t test more well specified), the Mann Whitney test outperforms the t test.

Although seemingly convincing, these results only demonstrate the superiority of nonparametric statistical methods under the -1, +1 truncation rule that was applied in this study. The results do not conclusively indicate that nonparametric tests based upon ranks will outperform parametric statistical methods under all possible data refinement techniques. However, the results do indicate that if the researcher chooses to apply parametric statistical methods when scrutinizing divergent earnings, a sophisticated data refinement method that results in a more normal sample distribution is required; otherwise, nonparametric rank based methods are more powerful.

Conclusion

When conducting empirical studies wherein the detection of divergent earnings is critical to the analysis, choosing the superior methods that best distinguish relative earnings performance is essential. The conclusion drawn here is that the choice of statistical method is of primary importance. For unaltered sample data, the superior alternative is nonparametric statistical methods based upon ranks. When these nonparametric methods are applied, deflator choice (forecasted earnings or market price of stock) is of little (if any) consequence. The results also indicate that if parametric statistics are applied, some method of data refinement is required in order to normalize the distribution of sample data. The simple minimum - maximum truncation rule applied here (-1, +1) proved to be deficient. A more sophisticated method is required in order for parametric statistical methods to be comparatively powerful. However, any such sophisticated data refinement techniques will necessarily affect (and taint) the results. Data refinement is found here to be unnecessary if nonparametric statistical methods based upon ranks are applied.

Suggestions for Future Research

The results here using Value Line data are likely to be consistent with results of similar

Table 4
Parametric T Test Vs. Nonparametric Mann Whitney Test
Observed Frequency [%] - Rejection Of The Null Hypothesis

| SIG LEV | 0%ERROR | | | 1%ERROR | | | 3%ERROR | | | 5%ERROR | | | 7%ERROR | | | 10%ERROR | | |
|--|---------|----|----------------|---------|----|----------------|---------|----|----------------|---------|----|----------------|---------|----|----------------|----------|----|----------------|
| | t | MW | X ² | t | MW | X ² | t | MW | X ² | t | MW | X ² | t | MW | X ² | t | MW | X ² |
| Panel A | | | | | | | | | | | | | | | | | | |
| T-Test [T] Vs. Mann Whitney Test [Mw] Of De\$ Without Truncation | | | | | | | | | | | | | | | | | | |
| 1% | 0 | 1 | 1.01 | 0 | 2 | 2.02 | 1 | 8 | 5.70** | 1 | 23 | 22.92*** | 2 | 42 | 46.62*** | 5 | 74 | 99.61*** |
| 5% | 3 | 4 | .15 | 4 | 8 | 1.42 | 7 | 21 | 8.14*** | 9 | 44 | 31.45*** | 11 | 70 | 72.23*** | 14 | 94 | 128.82*** |
| 10% | 13 | 8 | 1.33 | 13 | 13 | .00 | 17 | 34 | 7.61*** | 17 | 62 | 42.37*** | 18 | 86 | 92.63*** | 27 | 98 | 107.54*** |
| Panel B | | | | | | | | | | | | | | | | | | |
| T-Test [T] Vs. Mann Whitney Test [Mw] Of De\$ Without Truncation | | | | | | | | | | | | | | | | | | |
| 1% | 1 | 1 | .00 | 1 | 1 | .00 | 1 | 8 | 5.70** | 4 | 21 | 13.21*** | 7 | 49 | 43.75*** | 11 | 77 | 88.39*** |
| 5% | 9 | 4 | 2.06 | 9 | 8 | .06 | 10 | 20 | 3.92** | 14 | 52 | 32.65*** | 18 | 73 | 60.99*** | 22 | 95 | 109.75*** |
| 10% | 10 | 8 | .24 | 13 | 14 | .04 | 17 | 41 | 13.99*** | 22 | 64 | 35.99*** | 24 | 84 | 72.46*** | 32 | 98 | 95.74*** |
| Panel C | | | | | | | | | | | | | | | | | | |
| T-Test [T] Vs. Mann Whitney Test [Mw] Of De\$ With Truncation | | | | | | | | | | | | | | | | | | |
| 1% | 2 | 1 | .34 | 2 | 1 | .34 | 2 | 8 | 3.79* | 4 | 21 | 13.21*** | 9 | 49 | 38.85*** | 12 | 77 | 85.54*** |
| 5% | 9 | 4 | 2.06 | 9 | 8 | .06 | 11 | 20 | 3.09* | 14 | 51 | 31.20*** | 19 | 73 | 58.70*** | 26 | 95 | 99.61*** |
| 10% | 10 | 8 | .24 | 13 | 14 | .04 | 18 | 41 | 12.72*** | 22 | 64 | 35.99*** | 26 | 84 | 67.96*** | 32 | 98 | 95.74*** |
| Panel D | | | | | | | | | | | | | | | | | | |
| T-Test [T] Vs. Mann Whitney Test [Mw] Of De\$ With Truncation | | | | | | | | | | | | | | | | | | |
| 1% | 1 | 1 | .00 | 3 | 2 | .21 | 4 | 8 | 1.42 | 8 | 23 | 8.59*** | 11 | 42 | 24.67*** | 27 | 74 | 44.18*** |
| 5% | 5 | 4 | .12 | 5 | 8 | .74 | 11 | 21 | 3.72* | 21 | 45 | 13.03*** | 32 | 71 | 30.45*** | 46 | 94 | 54.86*** |
| 10% | 7 | 8 | .07 | 12 | 13 | .05 | 20 | 34 | 4.97** | 34 | 60 | 13.57*** | 45 | 86 | 37.19*** | 65 | 98 | 36.13*** |

Where:
DE% = Unexpected earnings deflated by the absolute value of forecasted earnings
DE\$ = Unexpected earnings deflated by market value of the Stock
X² = Chi-squared distribution value [2-tailed]
*** = Significant at the 1% level
** = Significant at the 5% level
* = Significant at the 10% level

analysis performed on alternative earnings data. However, future studies should be conducted using different sources of analysts' forecasts (e.g., Institutional Brokers Estimate System (IBES)), and/or historical earnings based prediction models in order to ascertain that these results are robust.

Also, this study has implications for previous research efforts involving earning divergence detection. Such studies that found statistically weak or insignificant results should be repeated using nonparametric statistical methods that are based upon ranks. Using these more powerful methods should strengthen the results.

Endnotes

1. Another less commonly used deflator is the standard deviation of the forecasts by various agents that are included in developing a point forecast estimate. For example, the Institutional Brokers Estimate System (IBES) provides an average forecast that is derived from averaging numerous individual analysts forecasts. A problem with IBES data is that the composition of the analysts changes from month to month. Also, the age of these individual forecasts is not uniform. Value Line has been found to be superior to other analysts in forecasting earnings and is the source of forecast earnings data used in this study. Since Value Line provides one point estimate, the standard deviation deflator can not be tested here.
2. For each methodological alternative tested, there are two groups of 100 cases each. The number of instances where null is accepted or rejected therefore sums to 100 for each group. The results can be viewed as a 2 x 2 contingency table where the columns are the alternative methodologies scrutinized (e.g. deflator choice) and the rows are frequency of rejection, vs. frequency of acceptance (100 minus frequency of rejection). This classification scheme accommodates a chi-square test. For a detailed discussion of

the chi-square test applied here, see Conover (1980), p.144.

3. Another method of controlling outliers is exclusion of sample events where the deflator level is small. However, due to the substantial reduction in sample size (see Doran and Nachtmann (1988)), it is not included in this study.

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Notes

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