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Gillian Yeo Hian Heng

*Senior Lecturer, School of Accountancy and Business
Nanyang Technological University, Singapore*

David A. Ziebart

*Department of Accountancy
University of Illinois*

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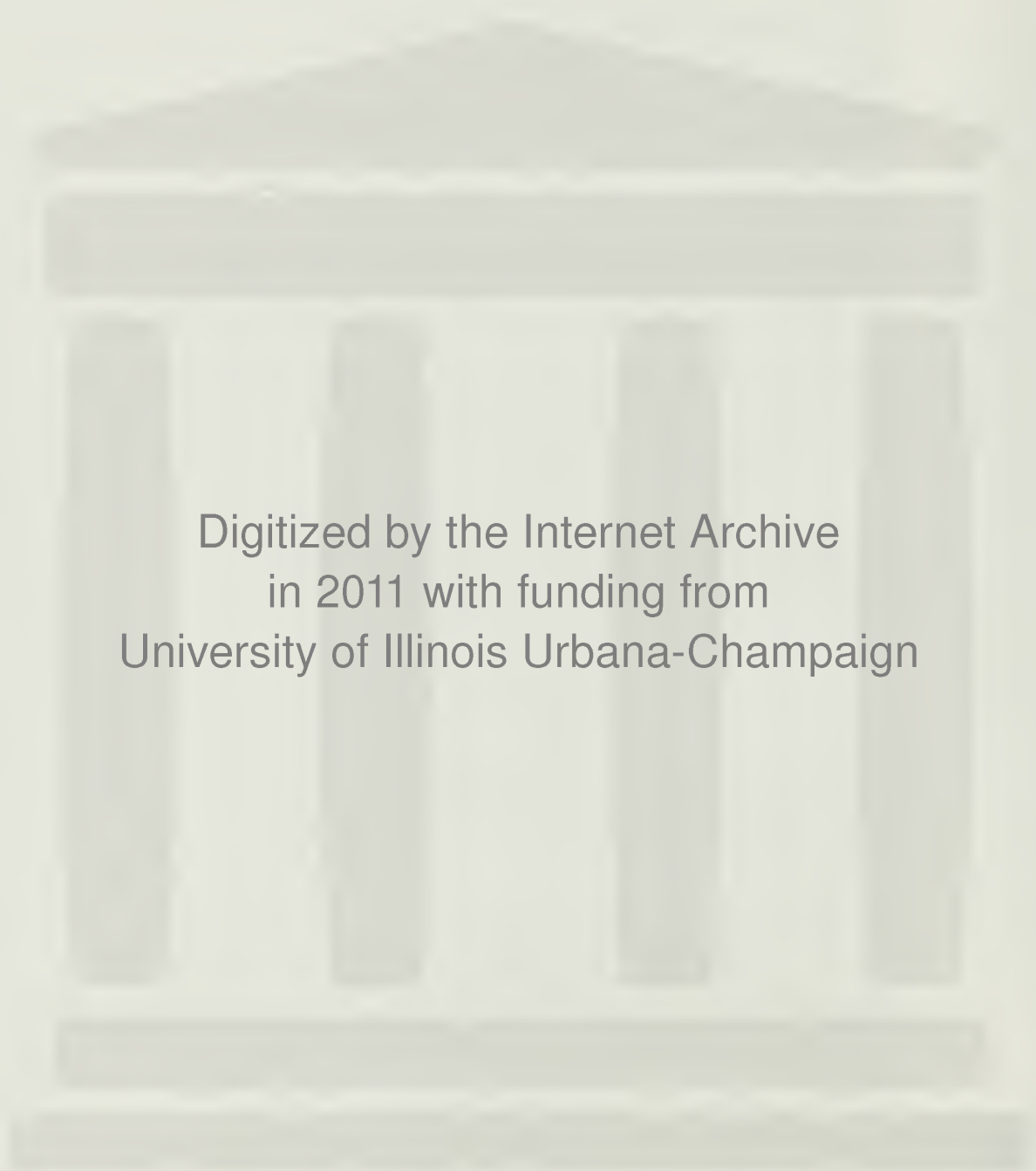
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Gillian Yeo Hian Heng

Senior Lecturer, School of Accountancy and Business
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David A Ziebart

Associate Professor of Accountancy
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**THE EFFECT OF SELF-SELECTION BIAS
ON THE TESTING OF A STOCK PRICE REACTION
TO MANAGEMENT'S EARNINGS FORECASTS**

Gillian Yeo Hian Heng
Senior Lecturer, School of Accountancy and Business
Nanyang Technological University, Singapore

David A. Ziebart
Associate Professor of Accountancy
University of Illinois at Urbana-Champaign

July 1992

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Abstract

This study examines the extent to which self-selection bias affects inferences about the stock market's reaction to management earnings forecasts. Our motivation for this study is that the extent to which inferences in previous studies of the market reaction to management earnings forecasts have been affected by self-selection bias has not been investigated.

To address the self-selection problem, the methodology employed in this study consists of a system of equations comprised of a stock return equation and an independent probit-type selection criterion equation. This approach is based on the Heckman-Lee two stage estimation method to correct for self-selection bias. We compare the results obtained when self-selection is controlled to those obtained when self-selection is ignored.

Our results suggest that inferences regarding the market's reaction to the issuance of a management forecast may be slightly overstated. Significance levels decline when management's decision to issue a forecast is included in the analysis. However, inferences remain essentially the same regardless of whether self-selection bias is controlled or not. This evidence suggests that, although correction for self-selection is theoretically correct, it may have no practical impact on inferences in studies such as this.



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I. Introduction

This study examines the extent to which self-selection bias affects inferences about the stock market's reaction to management earnings forecasts. Our motivation for this study is that the issuance of a management forecast is a natural self-selection event and previous studies of the stock market's reaction to management forecasts have ignored this potential problem. The extent to which inferences in previous studies of the stock market's reaction to management forecasts have been affected by self-selection bias has not been investigated.

Self-selection bias causes the following statistical estimation problem: the estimated effect of the management forecast disclosure may not converge to the true effect. Maddala [1983] notes that this results in biased and inconsistent estimates and incorrect inferences may be drawn. Factors with no real impact seem influential and important variables may have estimated coefficients that appear to be statistically insignificant (Achen [1986]). In addition, ignoring the self-selection problem can lead to inefficiency in estimation of the coefficients (Nakurama and Nakurama [1989]).

To address the self-selection problem, the methodology employed in this study consists of a system of equations comprised of a stock return equation and an independent probit-type selection criterion equation. This approach is based on the Heckman-Lee two stage estimation method to correct for self-selection bias.¹ We compare the results obtained when self-selection is considered to those obtained when self-selection is not addressed. Our results suggest that

¹ The basic Heckman-Lee two-step method, which corrects for selectivity has been used in other accounting applications (Shehata [1988] and Abdel-Khalik [1989a, 1989b]). Also an application in the finance literature is Acharya [1988].

inferences regarding the market's reaction to the issuance of a management forecast may be slightly overstated. Significance levels decline when self-selection is controlled. When self-selection is ignored, the regression coefficients estimated in this analysis, linking the stock price to a zero/one dummy variable representing a good news forecast issuance, are statistically significant at the .025 level using a one-tailed test. The coefficients associated with the issuance of a bad news forecast are also significant at the .025 level. However, after controlling for self-selection, the coefficients for the good news group are significant at the .0591 level while the coefficients for the bad news group are statistically significant at the .0479 level. This suggests that the failure to control for the self-selection bias results in the statistical inferences being somewhat overstated. However, overall inferences remain the same. Therefore, our evidence suggests that, although correction for self-selection is theoretically correct, it may have no practical impact on inferences in research settings such as this.

The rest of this paper is organized as follows. Section II provides a discussion on the limitations of previous standard event-type studies. Section III provides a brief literature review on capital markets and management earnings forecasts. We discuss the sample and data sources in Section IV. The research methodology is developed in Section V and the results are analyzed and discussed in Section VI. Section VII provides the limitations and conclusions for this study.

II. Limitation of Previous Standard Event-Type Studies

The potential problem found in previous studies of the stock market's reaction to management forecasts is that the standard event-type studies do not characterize the forecast event as an outcome of the decision process of the firm's managers. The analysis is conducted as if the treatment (forecast issuance) is random across firms. The problem of self-selection bias, one of a class of statistical problems in which cases (observations) are not randomly assigned to the control and experimental groups, results since management forecasts are not issued randomly across firms. Instead, the observations have self-selected into the control and

experimental groups. Achen [1986, inside cover] notes that self-selection is a common problem in contemporary social science research:

...the quantitative techniques most commonly used - cross-tabulation, correlation, regression, analysis of variance - were originally developed for natural science applications, and they make strong assumptions, most notably the assumption that the subjects of the experiment have been randomly assigned to treatment and control groups.....The outcome is a series of inferential mistakes....

In discussing how researchers try to deal with this problem Achen [1986, p. 2 and p. 4] further explains:

Experimentalists have elaborated their techniques to meet these threats to validity.....but the fundamental principle remains unaltered: randomization guarantees comparability of experimental and control groups, so that a treatment effect may be estimated by simply comparing the outcomes in the two groups (p. 2).....[However, in quasi experiments] The resulting experimental and control groups may be very different indeed, and nothing like the comparable groups that randomization would have produced. Even if control variables are used to fill the inferential gap, the statistical logic is quite different from classical randomization methodology (p. 4).

Similarly, Boruch [1976] and Campbell and Erlebacher [1975] are skeptical that the addition of control variables will adequately resolve the problems associated with nonrandom designs. They claim that the special circumstances inherent in many nonrandomized studies predicate failure of the specification postulate (Achen [1986 p. 14]).

The type of research commonly conducted in market-based empirical studies in finance and accounting is by necessity quasi-experimental. Randomization among experimental and control groups does not occur in many market reaction studies because the characteristic of research interest usually has been pre-selected by the two groups. A common approach to alleviate the self-selection problem is to include additional control variables in the analysis. However, as pointed out by Campbell and Erlebacher [1976, p. 167], "The more one needs the 'controls' and 'adjustments' which these statistics seem to offer, the more biased are their outcomes."

Achen [1986] explains the weaknesses of quasi-experiments and uses econometric theory to explain why classical regression techniques fail. In its simplest form, the self-selection

problem can be construed as a two equation system with a single selection equation and a single outcome equation. Let S represent the selection variable (such as forecast issuance) and O the outcome variable (such as security return). The two system equation is then:

$$S = f(\text{variables}_s) + e_1 \quad (\text{forecast issuance equation}) \quad (1)$$

$$O = f[(\text{variables}_o) + S] + e_2 \quad (\text{security return equation}). \quad (2)$$

where:

S = selection variable (issuance or non-issuance of a management forecast);

variables_s = independent variables of the selection equation;

O = outcome variable (security return);

variables_o = independent variables of the outcome equation;

e₁ and e₂ = regression error terms.

The bias inherent in employing only the single outcome equation (as done in most previous studies) rather than the two equation system can be expressed as the covariance between the error terms of the two equations in the system divided by the error variance which results from regressing the selection variable on the independent variables in the outcome equation (Achen [1986, p. 22]).

$$\text{bias} = \sigma_{e_1 e_2} / [1 - (r_s^2 | \text{variables}_o)]; \quad (3)$$

where:

$\sigma_{e_1 e_2}$ = covariance among the error terms of the selection (1) and outcome (2) equations;

$[1 - (r_s^2 | \text{variables}_o)]$ = error variance from regressing the selection variable

(S from equation (1)) on the independent variables of the outcome equation.

The covariance among the error terms may be large if there is a significant omitted variables problem across the two equations. Including control variables, when using a single outcome equation approach, to alleviate the self-selection problem will actually exacerbate the bias. This occurs because the denominator in the bias expression, the error variance from

regressing the selection variable on the variables in the outcome equation, shrinks as variables that should be in the selection equation are added to the outcome equation. This shrinkage in the denominator increases the bias.

OLS or GLS estimators are inconsistent when applied to simultaneous equations. This problem does not occur if the disturbances in the OLS/GLS regression (stock return equation) are uncorrelated with the disturbances in management's selection function (forecast issuance equation). However, the assumption of uncorrelated error terms is difficult to accept for a study of the price reaction to management earnings forecasts. The complete set of factors that influence management's selection can never be measured, nor can all the variables that explain stock returns. These omitted variables may be common to both equations and affect both the selection and stock price reaction. This causes a correlation between the disturbances. Nakamura and Nakamura [1989] note that the existence and size of any selection biases will depend on the properties of the omitted factors left in the disturbance terms for the selection rule and outcome equation.²

One can represent the previous (single equation) event-type models as a longitudinal regression for the outcome equation in which the dependent variable is the daily stock return. The independent variables are the return on the market index and a zero/one dummy variable for the forecast issuance. The dummy variable is coded zero for the days on which there is not a forecast issued and one for the days of the forecast event window.

In this study, we first estimate the outcome equation without considering the self-selection effect. This is equivalent to the approach employed in previous studies of the price reaction to management forecasts of earnings. We then estimate the outcome equation giving explicit consideration to the self-selection. We estimate the selection equation using variables previously linked with management forecast issuance. A proxy for the probability of a

² Nakamura and Nakamura identify the self-selection bias problem as an omitted variables problem across equations.

management forecast is substituted in the outcome equation for the value of one during the management forecast event period. This approach explicitly models the firm-specific and intertemporal variation in the market's expectations about the forecast event.

III. Literature Review - Capital Markets and Management Earnings Forecasts

Patell [1976] and Penman [1980] examined in detail the security return behavior in the period immediately surrounding an annual earnings forecast announcement. Their results indicate that significant price adjustments accompany forecast disclosures. From these results, one can draw the inference that either the content of the forecast, the act of voluntary disclosure, or both convey information to investors. Ajinkya and Gift [1984] used a more timely expectations model to determine the surprise content of management's earnings forecasts and got results to support the following hypotheses:

- (1) "forecasts are issued by management to move prevailing market expectations toward management beliefs about future earnings," and
- (2) "the capital market revises its expectations (and the equilibrium value of firms' common shares) in an unbiased fashion - a good news forecast is associated with an upward price revision and a bad news forecast with a downward revision."

Waymire [1984] also provided additional evidence on the extent to which price reactions are associated with management earnings forecasts. His evidence showed that (1) good news (bad news) management forecasts are associated with significant positive (negative) abnormal returns in the days immediately surrounding the date of management forecast publication in *The Wall Street Journal*, and (2) a significant positive association exists between the size of forecast deviation and the size of abnormal returns in the period immediately surrounding the forecast disclosure date.

McNichols [1989] documented that stock return prediction errors in the forecast and pre-forecast announcement periods are significantly associated with both forecast deviations and forecast errors. This association indicates that management forecasts contain information not

previously reflected in stock prices and that stock prices reflect information about earnings beyond that in management forecasts.

In Lev and Penman [1989], management earnings forecasts are interpreted within a signaling or screening framework where earnings forecasts are used by managers of good news firms to screen themselves from other firms. Their empirical findings are consistent with the screening motive for disclosing earnings forecasts - on average, firms with good news voluntarily disclose forecasts to distinguish themselves from firms with bad news.

Pownall and Waymire [1989] provide evidence on the extent to which investors view voluntary management forecasts of earnings as less credible than other more highly regulated forms of disclosure. Their results suggest that management forecasts are not discounted relative to earnings announcements.

In general, the results of these studies show that management forecasts convey new information to the market. Good news (bad news) management forecasts are associated with significant positive (negative) abnormal returns in the days immediately surrounding the forecast disclosure date. As previously discussed, the methodology used in these studies is subject to self-selection bias. Supporting this contention is the evidence obtained by McNichols [1989]. She shows there are characteristics that differentiate forecast firms from non-forecast firms. In fact, she finds that returns are positive in the pre-announcement period (about three to four months before the management forecast announcement) for firms whose managers release good news forecasts and are negative for firms issuing bad news forecasts.

The evidence obtained by Lev and Penman [1989] also suggests that a self-selection problem exists since the stock return residuals of forecast firms are significantly different from those of non-forecast firms for 15 months around the forecast. This evidence suggests there are other firm attributes, associated with the forecast announcement decision, linked to stock prices.

IV. Sample and Data

To compare the results obtained when self-selection is ignored to those obtained when self-selection is modeled, we first replicate results similar to those in previous studies that have not considered self-selection. This is accomplished by dividing our sample firms into good news and bad news issuances. For each of these groups, we estimate a traditional returns model in which daily returns are regressed on (1) the market index, and (2) a zero/one dummy indicator for the issuance of the forecast. To control for self-selection, we estimate similar regressions for the good news and bad news groups except that we substitute the probability of forecast issuance for the zero/one dummy variable indicator. These probabilities are estimated using probit-type regressions in which factors identified in previous research as incentives for forecast issuance are the independent variables. We compare the results in which self-selection is ignored with those obtained when we model the self-selection of firms to issue a management forecast.

We collect the management forecasts using the Dow Jones News Retrieval Service (DJNRS). The DJNRS accesses a database of selected articles published in the Wall Street Journal and Barrons as well as unpublished announcements appearing on the Broad Tape. We retrieve forecasts published between January 1981 and December 1987 from the database using key words that would indicate that the article is reporting a management forecast.³ To be included in the sample, the following selection criteria are satisfied:

- (1) the firms must be included on the Compustat Annual Industrial file and CRSP Daily Return files. Compustat industry codes are between 0100 and 3999 or between 5000 and 5999.
- (2) the firms must be listed in the IBES Database, prepared by Lynch, Jones and Ryan (to obtain financial analysts' forecast data).
- (3) the management forecast must be a point forecast of EPS for the current fiscal year, or a range or growth forecast such that a point forecast can be estimated.

³ Although the key words selected provide an extensive coverage of potential management forecast releases, the coverage is not exhaustive. For this study, only a sample of management forecasts that were released during the period are used. The main key words used are "expects" and "earnings".

(4) the management forecast must be attributed to a company official.

(5) the management forecast must be disclosed at least one month before the actual earnings announcement date (to avoid confounding effects of actual earnings announcements).

For comparisons to non-forecasting firms, a random sample of non-forecast firms from the same industry codes is used.⁴ Since analysts' forecast errors are sensitive to the length of the forecast horizon, we match forecast and non-forecast firms by fiscal year-end to ensure that any observed differences are not driven by differing forecast horizons.

We obtain a final sample of 168 forecasts, 104 good news forecasts and 64 bad news forecasts.⁵ For each firm, the daily returns for the four-year period ending in the year of forecast disclosure are used. Firms are dropped from the sample if a significant confounding event occurs in the ten-day period on either side of the forecast release date.

V. Methodology

In general, the results found in previous studies (e.g., Patell [1976], Penman [1980], and Waymire [1984]) indicate that (1) management forecast disclosures are associated with significant abnormal returns on the days immediately surrounding the date of the forecast publication in the Wall Street Journal; and (2) a significant positive association exists between the magnitude of the unexpected component in the management forecast and the magnitude of abnormal returns immediately surrounding the forecast disclosure date. However, these studies that make comparisons, either directly or indirectly, between a group of firms issuing forecasts and a group of firms not issuing forecasts are susceptible to self-selection bias.

⁴ To achieve the best possible difference in voluntary disclosure practice between forecast and non-forecast firms, the DJNRS is searched to ensure that these non-forecast firms did not publish any other form of news which conveyed similar information about earnings (eg. a forecast of quarterly earnings or sales) in the relevant disclosure year.

⁵ An initial sample of 200 forecasts, 125 good news forecasts and 75 bad news forecasts were used for the voluntary disclosure incentives study in Yeo's [1990] dissertation. The final sample is obtained after deleting firms with no data on CRSP tapes, firms with confounding events, and firms with problematic values for the exogenous variables (such as unusually high forecast deviations).

In the previous studies, the self-selection problem may be hidden since there may be no direct comparison between the control group (no forecast) and the treatment group (forecast). For example, most studies assume there is no market reaction to be observed for the firms that do not issue a management forecast (the control group). However, the self-selection problem still exists in this situation since one compares the treatment group to the theoretical non-existence of a reaction for the control group.⁶

Since the price reaction to a good news forecast should be positive, the price reaction to a bad news forecast negative, and the incentives to issue a forecast may differ across the type of news, we conduct separate analyses for the good news and bad news groups. An approach for testing for information content in management forecasts using a traditional information content methodology is as follows for the group of good news firms:

$$R_F = \alpha + \beta R_M + \gamma_{GF} I_{GF} + v_F \quad (4)$$

where:

R_F = return for security F;

R_M = return on the market index;

I_{GF} = 1 if and only if firm issues a good news forecast
= 0 otherwise;

v_F = regression error term; and

α, β, γ = regression coefficients.

⁶ One may contend that there is no self-selection bias if there is no direct comparison made between the control and experimental groups. However, the existence of the problem can be readily demonstrated even in the absence of a direct comparison. In the traditional situation, the treatment group self-selects to receive the treatment while the control group does not. A comparison is then made of the differences in the outcomes to determine the effect. Even if the outcome for the control group is zero, the difference between the outcome of zero for the control group and the outcome for the experimental group is subject to self-selection bias. In a research design in which the control group's outcome is assumed to be zero, the bias still exists even though no direct comparison is made. This is the situation found quite often in stock price reaction research. It is assumed that there is no stock price reaction for the control group since, by definition, it does not have the treatment. However, the self-selection bias is still apparent since the experimental group's outcome is compared to the assumed observation of no price reaction for the control group when other factors which may impact stock prices are linked to the self-selection of the firms to issue a forecast.

A similar model is used for the group of firms with bad news forecasts:

$$R_F = \alpha + \beta R_M + \gamma_{BF} I_{BF} + v_F \quad (5)$$

where:

R_F = return for security F;

R_M = return on the market index;

I_{BF} = 1 if and only if firm issues a bad news forecast
= 0 otherwise

v_F = regression error term; and

α, β, γ = regression coefficients.

The estimate of γ_{GF} or γ_{BF} measures the price reaction effect of forecast disclosure for each firm in the good news and bad news groups, respectively. These estimates are aggregated for each of the two groups and tested cross-sectionally to determine if they are statistically different than zero.

To correct for self-selection in the good news forecast group, the following system of equations can be used to represent the process modeled:

$$R_F = \alpha + \beta R_M + \gamma_{GF} Y_{GF} + \epsilon_F \quad (6)$$

$$Y_{GF} = v_{GF} X + u_{GF} \quad (7)$$

Y_{GF} represents the market's expectation of the manager's decision function to issue a good news forecast and varies across firms. For an individual firm, Y_{GF} varies across time in instances in which multiple forecast events occur during the period of analysis. To be comparable with previous analyses, we use a single Y_{GF} for the forecast event in the longitudinal rate of return equation (equation 6). Theoretically, Y_{GF} varies over time and should be included for each observation in the time series used in equation 6. We chose only to include Y_{GF} for the forecast event since it represents the surprise occurring in the forecast issuance and our model for the issuance of a forecast is determined cross-sectionally.

A similar model is employed for the bad news forecast firms:

$$R_F = \alpha + \beta R_M + \gamma_{BF} Y_{BF} + \epsilon_F \quad (8)$$

$$Y_{BF} = v_{BF} X + u_{BF} \quad (9)$$

Y_{BF} represents the market's expectation of the manager's decision function to issue a bad news forecast and varies across firms.

X denotes the list of factors or variables associated with the manager's incentives to issue a forecast and they are assumed to be in the investor's prior information set. The set of coefficients linking the forecast issue incentive variables to the forecast issue outcome is v .

Assume that u_{GF} and u_{BF} in equations (7) and (9) have unit variance and each are correlated with ϵ_F in either equation (6) or equation (8), as applicable. Also assume that u_{GF} , u_{BF} , and ϵ_F have multivariate (standard) normal distributions. In realized form, equations (6) and (8) have $\epsilon_F | Y_{GF} > 0$ and $\epsilon_F | Y_{BF} > 0$ as conditional error terms (the expected value of these conditional error terms is nonzero).

This approach is based on the two-stage method proposed by Heckman [1976] and Lee [1983] to correct for self-selection bias. The Heckman-Lee method begins by estimating a probit model for selection equations (7) and (9). The two equations (7) and (9) are independent since the decision to issue a good news forecast is not dependent on the decision to issue a bad news forecast.⁷

⁷ For equation (7),

$$\begin{aligned} \text{Prob}(Y_{GF} > 0) &= \text{Prob}(u_{GF} > -v_{GF}X) \\ &= 1 - \Phi(-v_{GF}X) \\ &= \Phi(v_{GF}X) \end{aligned}$$

where $\Phi(\cdot)$ is the standard normal distribution function.

Similarly, for equation (9),

$$\begin{aligned} \text{Prob}(Y_{BF} > 0) &= \text{Prob}(u_{BF} > -v_{BF}X) \\ &= 1 - \Phi(-v_{BF}X) \\ &= \Phi(v_{BF}X) \end{aligned}$$

Since equations (7) and (9) are independent, the error terms should also be independent. Fische, et al., [1981] and Maddala [1983] summarize the expectations of the conditional error terms in the realized form (for the good news forecasts) as follows:

$$\begin{aligned} E(\epsilon_F | Y_{GF} > 0) &= E(\epsilon_F | u_{GF} > -v_{GF}X) \\ &= \pi_{GF} \frac{\phi(v_{GF}X)}{\Phi(v_{GF}X)} \end{aligned} \quad (10)$$

$\phi(\cdot)$ denotes the standard normal probability density function;

$$\pi_{GF} = \text{Cov}(\epsilon_F, u_{GF}).$$

A similar model can be constructed for the bad news forecasts:

$$\begin{aligned} E(Y_{BF} > 0) &= E(u_{BF} > -v_{BF}X) \\ &= \pi_{BF} \frac{\phi(v_{BF}X)}{\Phi(v_{BF}X)} \end{aligned} \quad (11)$$

$\phi(\cdot)$ denotes the standard normal probability density function;

$$\pi_{BF} = \text{Cov}(\epsilon_F, u_{BF}).$$

The Heckman-Lee method first estimates equation (7) and equation (9) to generate the density function ϕ and the distribution function Φ . The estimates of ϕ are then normalized for the relevant cumulative normal distribution, yielding:

$$\begin{aligned} d_{GF} &= \frac{\phi(v_{GF}X)}{\Phi(v_{GF}X)} ; \\ d_{BF} &= \frac{\phi(v_{BF}X)}{\Phi(v_{BF}X)} . \end{aligned}$$

The quantities d_{GF} and d_{BF} are labeled the inverse mills ratios (IMR) and are used as regressors in equations (6) and (8), the outcome equations for the good news and bad news forecasts, respectively. By substituting the inverse mills ratios for the indicator of one in the zero/one indicator variables in the traditional approach, the market's a priori expectation of a

forecast issuance is considered in the analysis. In full form, equations (6) and (8) are estimated in the second stage as:

$$R_F = \alpha + \beta R_M + \pi_{GF} [d_{GF} I_{GF}] + v_F \quad (\text{for the good news firms}) \quad (12)$$

$$R_F = \alpha + \beta R_M + \pi_{BF} [d_{BF} I_{BF}] + v_F \quad (\text{for the bad news firms}) \quad (13)$$

In realized form, the error term v is the unconditional error term with $E(v) = 0$.

Based on previous studies, we employ the following forecast issuance incentive variables. They represent the market's source of information about the manager's incentives/motivations to issue an earnings forecast.

(1) X_{1i} is the absolute percentage change in analysts' forecast of earnings over prior year's earnings. The voluntary forecast disclosure acts as a self-screening device to distinguish firms with good news from those with bad news. The market knows that firms may issue forecasts during a period in which their expected earnings (represented by analysts' forecasts) in the forecast year are higher than their prior year's earnings.

(2) X_{2i} is the ability to change production levels in response to new information. Capital intensity is the chosen proxy and it is defined as the ratio of gross fixed assets to net sales. Where firms have a greater ability to adjust production levels in response to new information to optimize production and improve cashflows, it is more likely that they would want to signal this favorable information to the market through a voluntary forecast disclosure.⁸ If the manager cannot adjust production levels to increase cashflow/earnings when he receives new information, then he will have no favorable information to signal to the market and there will be no forecast release. Lower capital intensity is a characteristic of this greater ability to adjust production levels.⁹

(3) X_{3i} is the variance in security analysts' forecasts of the firm's future earnings. Firms listed in the IBES Database with at least 5 analysts' forecasts for each month during the three months before the management forecast disclosure date are used.¹⁰ The measure of cross-sectional dispersion of

⁸ This is a slight variation from Trueman's (1986) model. In Trueman (1986), the forecast release is a signal of the manager's ability to anticipate future changes in the firm's economic environment and thereafter to adjust production plans accordingly so as to optimize production and cashflows to the end of the period. Due to empirical difficulties of directly modeling the manager's ability to receive new information, the present study models the manager's ability to adjust production levels in response to new information.

⁹ Using capital intensity as the proxy for measuring management's ability to adjust production levels may be problematic. Where the firm has unused capacity, production levels may be more easily adjusted. However, due to empirical difficulties of measuring excess capacity and the unavailability of information, capital intensity appears to be a reasonable substitute.

¹⁰ The requirement that firms have at least 5 analysts' forecasts for each month during the three months prior to the management forecast disclosure date is an attempt to control for the effects on the dispersion measure of changing the number of analysts.

analysts' forecasts used is the mean coefficient of variation (standard deviation of the distribution of the analysts' forecasts divided by the mean of the distribution) for the three months before the management forecast disclosure date. The variance of analysts' forecasts of earnings (i.e., disagreement among analysts) is a potential source of information about the market's aggregate belief/uncertainty about the distribution of the future earnings signal. A high variance in the security analysts' forecasts of earnings indicates that significant information asymmetries exist across investors. Lev (1988) noted that the presence of significant information asymmetries could lead to adverse private and social consequences for investors such as high transaction costs, thin volumes of trade and in general decreased gains from trade. Assuming that the pre-disclosure security prices reflect these adverse consequences and managers act to maximize stockholder wealth and utilities since their future compensation is conditional upon the expected utilities of current stockholders, managers would have incentives to reduce this large information asymmetry by publicly disclosing their inside information through a forecast issue.

(4) X_{4i} is the amount of information available about the firm. The number of financial analysts following the firm in the IBES Database during the year of the forecast is used. Prior research and the results of Jung and Kwon's (1988) analysis show that larger firms have a greater amount of information available through external information sources and are more likely to issue forecasts.

(5) X_{5i} is earnings variability and it is measured by the coefficient of variation of net income before extraordinary items estimated over the previous eight years ending with the year before the forecast disclosure year. When firms have significantly less variability in earnings, executives have more confidence in predicting future trends and events. The smaller probability of forecast errors and smaller size of errors leads to higher likelihood of forecast disclosure. The previous literature has shown that disclosing firms are typically larger and have significantly less variability in their earnings series (Ruland [1979], Waymire [1985]).

(6) X_{6i} is the percentage of outstanding company common shares held by senior management. This data is obtained from the company's proxy statements. Manager's self-interest/personal welfare affects the disclosure decisions they make. Senior managers with large personal stockholdings in their firms have more to gain from a forecast release than managers with small personal stockholdings in their firms. The gain comes from the favorable stock price reaction when good news is released. Though a negative stock price reaction may occur when a bad news forecast is released, managers may still prefer to disclose the bad news to avoid dramatic swings in stock price at the end of the period when actual earnings are announced (Ajinkya and Gift (1984)).¹¹

(7) X_{7ij} is a dummy industry classification indicator. It is based on the SIC two-digit industry code. Foster (1986) discusses the interactive effects of accounting methods choice/disclosure policy on production, investment or

¹¹ A form of price smoothing is implied here where managers prefer a more gradual decline in prices than dramatic swings in stock prices.

financing decisions. Differences in the production-investment opportunity sets provide firms with different comparative advantages in adopting different disclosure policies. Management's underlying motivations for voluntary disclosure could be attributed to these differences in production-investment opportunity sets across industries.

(8) X_{8i} is the frequency of disclosure of earnings forecasts in the past. Forecast disclosure firms are more likely to have adopted a policy of voluntarily disclosing additional information to the market. Previous forecast frequency is measured by the number of earnings forecast announcements, including both annual and quarterly forecasts, during the five-year period before the year of disclosure. Only quantifiable forecasts are included.

The manager's decision function to issue a forecast (modeled by equations (7) for good news firms and equation (9) for bad news firms) is then estimated using probit analysis. The sample of firms issuing management forecasts and a random sample of non-forecast firms are used for this estimation. The model used is as follows:

$$Y_i = a_i + b_1X_{1i} + b_2X_{2i} + b_3X_{3i} + b_4X_{4i} + b_5X_{5i} + b_6X_{6i} + \Sigma b_{7j}X_{7ij} + b_8X_{8i} + u_i \quad (14)$$

where:

Y_i is the indicator for forecast, and

X_{1i} to X_{8i} are the variables as previously discussed.

We define a good (bad) news forecast by the sign of the following measure:

$$(\text{Management EPS Forecast} - \text{Analyst EPS Forecast})$$

The most recent observation of the consensus analysts' forecasts, from the IBES Database, before the management forecast is employed.

Due to the possibility of information leaks, it is desirable to use a multiple day return window surrounding the day of the management forecast release (Teets [1991]). Accordingly, a 5 day return covering days -3 to +1 about the day of the forecast announcement is employed. For the actual regression estimations, a firm return vector and a market return vector are generated to reflect the daily observations during the non-event period and a single observation reflecting the five days of the event window. Vector R_i has elements equal to the firm's daily

returns outside the five day event window and one element equal to the sum of the five daily returns for the event period. Similarly, the market return series, R_{Mi} has elements that correspond to the elements of R_i .¹² The following empirical model of the firm's return-generated process is used for the firms that announced a good news forecast:

$$R_{it} = \alpha_i + \beta_i R_{Mit} + \pi_{iGF} [d_{iGFt} I_{iGFt}] + \omega_{it} \quad (15)$$

where:

t = observation number in new return series;

I_{iGFt} = 1 on the day of the management forecast announcement for a good news forecast firm;
= 0 otherwise;

d_{iGFt} = Inverse Mills Ratio (IMR) representing the probability of a good news forecast issuance;

A similar regression is estimated for firms issuing a bad news forecast:

$$R_{it} = \alpha_i + \beta_i R_{Mit} + \pi_{iBF} [d_{iBFt} I_{iBFt}] + \omega_{it} \quad (16)$$

where:

t = observation number in new return series;

I_{iBFt} = 1 on the day of the management forecast announcement for a bad news forecast firm;
= 0 otherwise;

d_{iBFt} = Inverse Mills Ratio (IMR) representing the probability of a bad news forecast issuance.

¹² Although each R_{M} series is generated from the same market index series, the placement of the event window (the summation of the five daily returns around the forecast announcement) varies across firms. Hence, each R_{M} series has a firm subscript i .

Recall that d_{iGF_t} and d_{iBF_t} are estimated for each firm and each forecast issuance in the first stage by using maximum likelihood estimates to model the decision/incentives for the firms to issue a forecast.¹³

We estimate π for the outcome equations (numbers (15) and (16)) using weighted least squares.¹⁴ The sum of the error terms for each of the outcome equations, ω_{it} , has the following variance:

$$\text{Var}(\omega_{it}) = \sigma_i n_{it}$$

where σ_i is the variance of the daily errors v_i from either equation (12) or (13) and n_{it} is the number of daily returns cumulated in observation t (either 1 for the days in which a forecast is not issued or 5 for the five day event window surrounding the day of the forecast issuance).

Because of the heteroscedasticity in the ω_i series, weighted least squares should be used to estimate the parameters for equations (15) and (16). The observations are weighted by

¹³ A matched sample of forecast and non-forecast firms is used in the probit analysis. The probit model used by Heckman-Lee assumes an unweighted log-likelihood function. As noted by Maddala (1988), the use of a weighted probit model is inappropriate in a situation of unequal sampling proportion. Weighting the observations is the correct procedure if there is a heteroscedasticity problem. A priori, we know of no reason why unequal sampling rates should cause a heteroscedasticity problem. Intuitively, the likelihood of forecast disclosure is more likely determined by the management incentive variables than by the unequal sampling proportion.

¹⁴ As noted in Teets (1988) the cumulation of daily returns around each forecast announcement results in a return series for all firms that do not line up in calendar time. This is a situation of non-synchronous time series observations and it is not possible to use SUR since SUR uses synchronous time series observations to estimate the cross-sectional covariance matrix of the disturbances. Cross-sectional correlation of returns in hypothesis tests on the estimated coefficients of the stock return model can be incorporated through a technique developed by Marais (1986). However, on an ex-ante basis, the cost of using the Marais technique in the present study does not seem to be justified based on the following reasons:

(i) In Teets (1988), all the sample firms used were concentrated in one industry and ex-ante one would expect the potential problem of cross-sectional correlation in returns to be particularly severe. However, the results showed that there is only a very small improvement in the t-statistic after applying the Marais technique. The t-statistic was 4.47 using the full covariance matrix and 4.54 using the diagonal matrix. This shows that the extent of cross-sectional correlation in returns is insignificant even where all the firms are in one industry.

(ii) Even where all firms are in one industry, they may not be in direct competition with each other. Hence, no significant dependencies exist due to, for example, economic conditions affecting firms in the same industry.

(iii) In the present study, the sample forecast firms are scattered in different industries though there are some that are concentrated in certain industries. Hence, on an ex-ante basis, the potential problem of cross-sectional correlation in returns does not appear to be severe.

$1/(n^{1/2})$. For the hypothesis of a market reaction to hold:

$$\frac{1}{j} \sum_{i=1}^j \Pi_{iGF} > 0 \quad (\text{for the good news forecasts}), \text{ and}$$

$$\frac{1}{k} \sum_{i=1}^k \Pi_{iBF} < 0 \quad (\text{for the bad news forecasts});$$

where:

j and k are the number of forecasts in the good news and bad news groups,

respectively.

For each forecast issuance, daily stock returns for the four-year period ending in the year of the forecast disclosure are used for the estimation. In instances in which a firm has multiple forecasts during the period, a separate inverse mills ratio (IMR) is estimated for each forecast event (selection equation), and the outcome regression is estimated separately for each forecast event.

To determine the effect of controlling for self-selection, we estimate equations (4) and (5), the traditional approach using a zero/one dummy variable, and equations (15) and (16), which adjust for the self-selection. Cross-sectional distributions of the estimated coefficients and standard errors are compiled across the two approaches for the good news and bad news forecast groups.

VI. Results and Analysis

As previously discussed, probit analysis is used in the first stage of the approach to estimate the market's expectation of the manager's decision to issue a forecast. Table 1 provides the coefficient estimates and their t-statistics in the estimation of the market's expectation of a good news and bad news forecast issue. The high percentage of correct predictions and high likelihood ratio test statistic indicates that the coefficient vector (X_{ji}) is

significantly different from zero.¹⁵ Differences between the magnitudes of the estimated coefficients across the two groups suggest that the parameters vary between the good news and bad news groups.

INSERT TABLE 1

The probit results indicate that, compared to a matched group of firms not issuing forecasts, good news forecast firms (1) have significantly higher absolute percentage change in analysts' forecasts of earnings over prior year's earnings, (2) have significantly higher capital intensity, (3) have significantly higher percentage of outstanding common shares held by senior management, (4) are significantly larger, and (5) tend to disclose more frequent forecast announcements in the past than non-disclosure firms. Compared to a matched sample of non-forecast firms, the results indicate bad news forecast firms (1) have significantly higher capital intensity, (2) have significantly greater dispersion in the analysts' forecasts, (3) are significantly larger, (4) have significantly less earnings variability, (5) have a higher percentage of outstanding common shares held by senior management, and (6) disclosed more earnings forecasts in the past.¹⁶ The significant coefficients (with correct signs) for the selection equations imply that the probability of a forecast issuance is non-degenerate (neither zero nor one). This implies that the market has partial anticipation of the forecast issuance.¹⁷

¹⁵ If the probit model in the first stage of the analysis does not distinguish well between forecast and non-forecast firms, use of the inverse mills ratios in the stock return model in the second stage of the analysis may introduce confounding errors in the estimates.

¹⁶ In general, the signs of the coefficients of these independent variables, with the exception of the capital intensity variable, are as predicted. The sign for the capital intensity coefficient may be opposite to that predicted due for the following reasons:

- (i) Capital intensity is a poor measure of management's ability to adjust production levels in response to new information.
- (ii) The size factor is driving the results since forecast firms have significantly greater total assets and gross fixed assets than non-forecast firms.

¹⁷ This suggests that the observed market reaction to a management forecast announcement is composed of both a reaction to the surprise of a forecast being issued and a reaction to the surprise in the earnings information. Given that the probability of forecast issuance varies across firms and time periods, this strongly suggests that assuming the probability of forecast issuance to be constant across firms, as done in most previous research, masks the reaction to the surprise in the forecast issuance itself.

The distributions of the estimated coefficients for the forecast firms using the traditional dummy variable approach and the multiple equation approach to control for self-selection are used to test whether the means of the distributions are significantly different from zero. Recall that the difference between the two approaches is that the traditional approach uses a zero/one dummy variable to indicate the presence of a forecast issuance while the self-selection control approach uses the inverse mills ratio (IMR) to represent the expectation that a forecast be issued. These results are reported in Table 2.

INSERT TABLE 2

The results of the dummy variable model, the traditional approach, are compared with the results of the model conditional on management's disclosure incentives (IMR model, hereafter). For both the good news and bad news samples, the results show that the t-ratios and the levels of significance for rejection of the null hypothesis of no significant stock price reaction, are reduced when self-selection is controlled. For both the good and bad news firms, the dummy variable model shows that the stock price reaction to management forecast disclosure is significant at the .025 level for a one-tailed test (.0248 for good news forecasts and .0191 for bad news forecasts). However, considering the probability of forecast issuance (to control for the self-selection problem) the statistical significance of the stock price reaction is reduced to .0591 for good news forecasts and .0479 for bad news forecasts.

Table 3 and Table 4 provide descriptive summaries of the distributions of the coefficient estimates underlying the results reported in Table 2. These tables report the coefficient estimates for both analyses at the stated percentile level (based on the distribution of coefficient estimates for the dummy variable model). The estimate of the regression coefficient using the IMR approach is larger in absolute value with a larger standard error. The t-statistic on the estimated coefficient is usually less by a small amount. However, note that the coefficient of determination, R^2 , is slightly larger. For all of the regressions reported in Tables 3 and 4, there would be no difference in inferences (at the individual firm level) regarding the explanatory

power of the forecast issuance in explaining the variability in returns at the individual firm level. The significance level is usually lower for the IMR model but it is usually at the third or fourth decimal place.

INSERT TABLES 3 AND 4

The results in Tables 3 and 4 are based, primarily, on the observations in which firms have only one forecast during the four-year period. Firms having multiple forecasts during the four years are treated as if each of the forecasts is unique. The analysis is run for each of the forecast events separately. Hence, the coefficients and standard errors obtained using the IMR approach are linear transformations of the coefficients and standard errors obtained using the dummy approach. An additional analysis is conducted for the cases where the firms have multiple forecast events (more than two) during the four-year period by estimating one outcome equation across all the forecast events. Table 5 provides the results of this analysis. The coefficients and standard errors obtained with the IMR approach consider the intertemporal variation in the market's expectation of the forecast issuance within the firm. The results reveal that the t-ratios and levels of significance for the estimated coefficients shrink when self-selection is controlled. Inferences change for three out of the twelve observations with more than two forecasts during the four year period.

INSERT TABLE 5

The results of this study illustrate how inferences are affected regarding the observation of a statistically significant stock price reaction to the issuance of a management forecast if we use the traditional dummy variable approach.. After considering the market's expectations about the issuance of a forecast, a less statistically significant positive (negative) abnormal stock return results for a good (bad) news forecast when the analysis is conducted on individual forecasts.

VII. Conclusions and Limitations

In this study, the methodology controls for self-selection in an analysis of the stock market's reaction to the issuance of management earnings forecasts. The results illustrate that the previous research on the information content of management forecasts may have slightly overstated the significance of the security price reaction to the forecast disclosure although the overall inferences are proper. By using an improved model specification that overcomes the weaknesses of previous event-type methods, this study shows that a less positive (negative) abnormal return is associated with a good (bad) news management forecast. In instances in which only one forecast is issued during the four year analysis period, there is no significant difference in the inferences obtained when one controls for self-selection. However, when multiple forecasts exist during the analysis period, the use of a zero/one dummy indicator variable approach results in three out of twelve questionable inferences.

To summarize, the methodology used in this study to correct for self-selection bias contributes to our understanding of some of the limitations inherent in capital market research. Theoretically, more dependable inferences can be made about the statistical significance of the stock market reaction to the information disclosure when the self-selection problem is controlled. However, we are reluctant to advocate the wholesale use of this methodology since in our application, the inferences remain essentially the same.

Other areas of research in accounting and finance also may have self-selection problems. Some examples include:

- (i) In general, firms that make voluntary accounting changes, firms that elect to disclose line of business data, or firms that elect to make significant structural and organizational changes such as management buyouts or other similar events. Managers of these firms self-select into the change and no-change groups based on various incentives/decision rules.
- (ii) The security price response to financing announcements or dividend announcements. Managers of firms have different incentives/decision rules to use different forms of financing (eg. debt or equity) or different forms of dividend distributions (eg. cash or stocks) depending on several factors.

In conclusion, since our results show that the self-selection bias problem may impact inferences, we suggest that researchers evaluate the extent to which a self-selection problem may exist.¹⁸ Where possible, we advocate using a research design that will mitigate the problem. In instances in which design issues prevent a solution and the problem is potentially severe, we suggest that the researchers conduct a pilot analysis to determine the extent to which a bias in the inferences may occur. We do not suggest the employment of control variables since they may exacerbate the problem. Instead, we suggest that the researchers employ techniques such as those illustrated in this study to control for the self-selection problem.

¹⁸ It should be noted that a priori one would expect the issuance of a management forecast to be a very strong instance of self-selection in the accounting and finance research area. Accordingly, our failure to find a significant effect on inferences is surprising. However, based on our results we can not condone ignoring this potential problem. Although we do not document a significant difference in inferences when self-selection is controlled, we believe that the researcher should at least consider the potential problem and avoid it if possible.

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Table 1

Results of Probit Analysis -
 Issuance/Non-issuance of Forecast Regressed on Explanatory Variables

Variable	Good News	Bad News
Constant	4.079 (.01)	-4.321 (-1.17)
X ₁ (Signaling Incentive)	.006 (1.61) [*]	.003 (.54)
X ₂ (Ability to Change Production Levels)	.007 (1.80) ^{**}	.007 (1.71) ^{**}
X ₃ (Variability of Analysts' Forecasts)	.031 (1.17)	.068 (2.31) ^{**}
X ₄ (Amount of Information - Size)	.059 (3.68) ^{***}	.047 (1.88) ^{**}
X ₅ (Earnings Variability)	-.001 (-.56)	-.004 (-2.05) ^{**}
X ₆ (Executive Stock Ownership)	.037 (3.72) ^{***}	.022 (2.16) ^{***}
X _{7,13} (Industry Classification)	-6.071 (-.01)	-1.923 (-1.33)
X _{7,20} (Industry Classification)	-6.277 (-.01)	-.327 (-.27)
X _{7,23} (Industry Classification)	-6.441 (-.01)	5.910 (.00)
X _{7,25} (Industry Classification)	-6.641 (-.01)	-6.348 (-.01)
X _{7,26} (Industry Classification)	-6.836 (-.01)	-.968 (-.73)
X _{7,27} (Industry Classification)	-6.405 (-.01)	-.636 (-.50)
X _{7,28} (Industry Classification)	-6.404 (-.01)	-.928 (-.75)
X _{7,29} (Industry Classification)		-.393 (-.28)
X _{7,30} (Industry Classification)	-6.686 (-.01)	-.052 (-.04)
X _{7,32} (Industry Classification)	-5.939 (-.01)	-.919 (-.67)
X _{7,34} (Industry Classification)	-7.663 (-.01)	-1.431 (-1.12)
X _{7,35} (Industry Classification)	-5.534 (-.01)	-.043 (-.03)
X _{7,36} (Industry Classification)	-6.258 (-.01)	-.273 (-.22)
X _{7,37} (Industry Classification)	-5.917 (-.01)	-.124 (-.09)
X _{7,38} (Industry Classification)	-6.632 (-.01)	-1.490 (-1.10)
X _{7,50} (Industry Classification)	-6.168 (-.01)	4.577 (.00)
X _{7,51} (Industry Classification)	-5.881 (-.01)	5.423 (.01)
X _{7,54} (Industry Classification)	-6.796 (-.01)	
X _{7,56} (Industry Classification)	-6.389 (-.01)	-.476 (-.36)
X _{7,58} (Industry Classification)		-.371 (-.25)

Variable	Good News	Bad News
X _{7,59} (Industry Classification)	-6.771 (-.01)	-1.604 (-1.07)
X ₈ (Reporting Frequency)	.466 (4.94) ^{***}	.416 (3.810) ^{***}
Likelihood Ratio Test (degrees of freedom) ^(a)	119.316 (26)	61.116 (27)
Percentage of Correct Predictions	79%	75%

(a) Statistic has an asymptotic distribution which is a chi-square with degrees of freedom equal to the number of parameters in the model. The model is significant at less than the .001 level for both good news and bad news samples.

Numbers in parentheses are t-values.
^{***}, ^{**}, ^{*} denote significance at the .01, .05, and .10 levels for a one-tailed test.

Table 2

Test of Significant Price Reaction to Management Earnings Announcement
with and without Controlling for Self-selection

	Dummy Variable Approach (traditional approach)	IMR Approach (control for self-selection)
GOOD NEWS		
Average Coefficient - $\frac{1}{j} \sum_{i=1}^j \Pi_{iGF}^*$.0493	.3504
Standard Error	.0248	.2224
t-statistic	1.987	1.575
p-level	.0248	.0591
BAD NEWS		
Average Coefficient - $\frac{1}{k} \sum_{i=1}^k \Pi_{iBF}^*$	-.0637	-.2523
Standard Error	.0301	.1484
t-statistic	-2.116	-1.690
p-level	.0191	.0479

For the traditional analyses, the regression is $R_k = \alpha + \beta R_M + \pi_{GF} [I_{GF}] + v$ for the good news firms and $R_k = \alpha + \beta R_M + \pi_{BF} [I_{BF}] + v$ for the bad news firms. R_M is the return on the market, π_{GF} and π_{BF} are regression coefficients for the forecast issuance, and I_{GF} is a zero/one indicator for the forecast event.

For the IMR approach, similar regressions are employed -

$R_k = \alpha + \beta R_M + \pi_{GF} [d_{GF} I_{GF}] + v$; and $R_k = \alpha + \beta R_M + \pi_{BF} [d_{BF} I_{BF}] + v$.
 d_{GF} and d_{BF} are the Inverse Mills Ratios that represent the probability of a forecast being issued. They are estimated via probit in the first stage of the analysis.

* j and k are the numbers of good news and bad news management earnings forecasts, respectively.

Table 3.

Coefficient Estimates for Good News Forecasts at Various Percentiles

	Dummy Variable Approach				IMR Approach to Control for Self-Selection				
	π_{GF}	SE(π_{GF})	t-statistic	R ²	π_{GF}	SE(π_{GF})	t-statistic	R ²	IMR
Max.	0.1596	0.0297	5.37	.08	0.2989	0.0566	5.30	.08	0.5339
95%	0.0996	0.0559	1.78	.05	2.1672	1.2170	1.78	.06	0.0459
90%	0.0904	0.0433	2.09	.11	0.2656	0.1282	2.07	.11	0.3404
75%	0.0659	0.0189	3.47	.46	0.1621	0.0477	3.40	.47	0.4067
Med.	0.0510	0.0275	1.86	.15	0.3703	0.1994	1.86	.16	0.1379
25%	0.0374	0.0200	1.87	.19	0.0365	0.0195	1.87	.19	1.0243
10%	0.0322	0.0222	1.45	.41	0.0806	0.0565	1.43	.41	0.3999
5%	0.0292	0.0205	1.43	.30	0.0478	0.0346	1.38	.30	0.6112
Min.	0.0235	0.0166	1.42	.35	0.1449	0.1034	1.40	.35	0.1623

The above estimates are for each forecast at the stated percentile level based on the distribution of the regression coefficient estimates for the Dummy Variable Approach.

Table 4

Coefficient Estimates for Bad News Forecasts at Various Percentiles

	Dummy Variable Approach				IMR Approach to Control for Self-Selection				
	π_{BF}	SE(π_{BF})	t-statistic	R ²	π_{BF}	SE(π_{BF})	t-statistic	R ²	IMR
Max.	-0.0232	0.0167	-1.38	.03	-0.0328	0.0247	-1.33	.03	0.7067
95%	-0.0274	0.0169	-1.62	.55	-0.1270	0.0793	-1.60	.55	0.2155
90%	-0.0312	0.0263	-1.19	.34	-0.8456	0.7115	-1.19	.34	0.0369
75%	-0.0427	0.0287	-1.49	.08	-0.0327	0.0230	-1.42	.08	1.3059
Med.	-0.0587	0.0387	-1.52	.18	-0.0884	0.0594	-1.49	.18	0.6635
25%	-0.0984	0.0210	-4.69	.25	-0.0680	0.0146	-4.65	.25	1.4477
10%	-0.1943	0.0269	-7.23	.20	-0.5449	0.0754	-7.23	.20	0.3566
5%	-0.2119	0.0477	-4.45	.19	-0.6629	0.1490	-4.45	.20	0.3197
Min.	-0.3597	0.0510	-7.05	.17	-0.5030	0.0723	-6.96	.17	0.7150

The above estimates are for each forecast at the stated percentile level based on the distribution of the regression coefficient estimates for the Dummy Variable Approach.

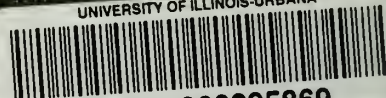
Table 5

Parameter Estimates of Firms with Multiple Forecasts (two or more)
when the Events are Combined in a Single Regression Analysis

Number of Forecasts	Dummy Variable Approach				IMR Approach to Control for Self-selection			
	π_i	SE(π_i)	t-statistic	R ²	π_i	SE(π_i)	t-statistic	R ²
3	0.1159	0.0282	4.105	.12	1.5860	0.3914	4.052	.12
	-0.1026	0.0199	-5.135		-0.0432	0.0218	-1.981	
3	0.0685	0.0158	4.331	.25	0.1163	0.0317	3.665	.25
3	-0.0348	0.0206	-1.691*	.25	-0.1942	0.1670	-1.162	.25
3	0.0157	0.0137	1.142	.43	0.0273	0.0314	0.870	.43
3	-0.0950	0.0222	-4.270	.22	-0.1588	0.0372	-4.265	.22
3	0.0336	0.0155	2.166*	.48	0.0213	0.0208	1.023	.49
3	0.0157	0.0114	1.382	.11	0.0189	0.0137	1.379	.11
4	-0.0087	0.0167	0.522	.46	-0.0143	0.0565	0.254	.46
4	-0.0344	0.0133	-2.586	.18	-1.0918	0.4782	-2.283	.18
4	0.0055	0.0232	2.366	.20	0.1118	0.0487	2.297	.20
5	0.0455	0.0128	3.550	.37	0.7521	0.2215	3.400	.37

* denotes a difference in inference of a market reaction between the two approaches.

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