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*Journal of Accounting Research*
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Time-Varying Stock Price Response to Earnings Induced by Uncertainty About the Time-Series Process of Earnings

MARK LANG*

1. Introduction

In this paper, I examine how changes in the level of uncertainty about the time-series process of earnings affect the magnitude of the stock price response to earnings announcements. The basic premise is that when there is more uncertainty about the time-series parameters of earnings, a given level of unexpected earnings can have a larger effect on stock price because it is weighted more heavily by investors in determining the value of the firm.

Tests are based on a simple model in which price is a function of expected future earnings which follow a random walk with drift time-

* Stanford University. This paper is based on my Ph.D. dissertation of the University of Chicago. I wish to thank the members of my dissertation committee, M. L. Marais, M. Zmijewski, D. Diamond, K. French, and J. Hand, for their helpful suggestions, and especially K. Schipper (chairman) for her guidance and assistance. I have also benefited from the comments of A. Alford, R. Beatty, W. Beaver, S. Chamberlain, P. Cheng, W. Christie, P. Easton, W. Ferson, R. Holthausen, R. Lundholm, M. McNichols, M. Morgan, A. Zellner, participants in workshops at the University of Chicago, University of California at Berkeley, Columbia University, Cornell University, Duke University, University of Iowa, University of Michigan, Northwestern University, University of Pennsylvania, University of Rochester, Stanford University, University of Texas at Austin, Washington University, Yale University, and two anonymous referees. Dissertation funding was provided by the Arthur Andersen and Co. Foundation.

1 Uncertainty in this context refers to the variance of investors' prior distribution on the time-series parameters of earnings preceding the earnings release.
series process. I assume that the drift parameter, which is essentially the
growth rate of earnings, is unknown and is estimated by investors from
the observed time series of earnings. As a result, the stock price response
to earnings will vary across firms and over time depending on how heavily
investors weight current-period earnings in estimating the time-series
parameter of earnings. Investors' weightings depend on how much prior
earnings information is available, so earnings are relatively more inform-
ative (as measured by the magnitude of the associated stock price
response conditional on unexpected earnings) when there is a relatively
short series of past earnings from which to estimate the time-series
parameter, such as early in the firm's life.

I compare the magnitude of the stock price response per dollar of
unexpected earnings (the earnings response coefficient) for a sample of
200 firms over 12 quarterly earnings announcements following the date
they began trading publicly. Consistent with the implications of the
model, the magnitude of the stock price response to earnings declines
over time for the sample of firms.

This research is related to recent studies which examine determinants
find size-related differences in the variance of returns, which they attrib-
ute to differences in the amount of predisclosure information across
firms. Kormendi and Lipe [1987], Easton and Zmijewski [1989], Collins
and Kothari [1989], and Lipe [1990] provide evidence that response
coefficients vary cross-sectionally with differences in the persistence and
predictability of earnings and the systematic risk of the firm, and over
time with the risk-free rate of interest.

This paper suggests that another factor potentially affecting earnings
response coefficients is market agents' uncertainty about the future
prospects of the firm. Unlike most prior research, the primary focus is
on firm-specific time-series variation in earnings response coefficients
rather than cross-sectional or time-series variation resulting from mac-
roeconomic factors like interest rates. The analysis is similar to that of
Rao [1990], which also considers time-series variation in earnings re-
response coefficients following IPOs, but uses annual earnings announce-
ments and a different sample. The result in Rao [1990] differ somewhat
from those presented here, perhaps because the pattern in earnings
response coefficients documented in this paper is most pronounced over
the first 18 months following the IPO and would therefore be difficult to
detect with annual data. Related research is also presented in Affleck-
Graves, Fehrs, and Miller [1990], which compares stock return variance
and volume reactions at quarterly earnings announcements following
IPOs. They present evidence that the stock price response to earnings
tends to dampen over time for their sample, consistent with the results
of this study.

The implications of the model could be studied in other settings. The
same predictions apply, for example, to announcements of nonearnings
information which is correlated with firm value (e.g., dividends) and to earnings announcements following any event which substantially increases investor uncertainty about the future prospects for the firm (e.g., industry deregulation or firm reorganization). In a related manner, Collins and Kothari [1989] suggest a current earnings surprise may be informative about growth opportunities, resulting in a larger earnings response coefficient for high expected growth firms. However, the link between earnings, expected growth rates, and earnings response coefficients is never explicitly modeled. This paper provides a theoretical framework in which to consider the effects of current earnings on expected growth and the implications for earnings response coefficients.

Finally, the model may also have implications for accounting standard setting. Consistent with the argument presented in Atias, Bamber, and Freeman [1988], the model suggests earnings are more informative when there is greater uncertainty about the process governing them. It has been argued that small public firms should be subjected to less stringent disclosure requirements because compliance is most costly for them relative to the benefits to investors. The intuition underlying the model in this paper suggests, however, that to the extent that there is more uncertainty about future earnings for small firms (for example, because they tend to be younger), it may be the small firms for which the incremental disclosure is the most informative. If so, the added cost of incremental disclosure for small firms may be offset by additional benefit to investors.

In section 2, I present a simple model of the stock price response to earnings which motivates the empirical analysis that follows. Section 3 contains the primary empirical analysis, and section 4 considers potential alternative explanations for the empirical results. Section 5 provides a summary and conclusions.

2. Model of Earnings Response Coefficients

Assume that the price of a firm can be expressed as follows:  

$$ P_t = \sum_{\tau=t}^{\infty} \frac{E_t(a_\tau)}{R_t^{F-t}} , $$

(1)

where $a_\tau$ denotes earnings in period $\tau$, $E_t(\cdot)$ denotes the expectation conditioned on the information set available at time $t$, and $R_t$ denotes one plus the risk-free interest rate, assumed to be constant over time.

Equation (1) is expressed in terms of future earnings; but if investors value only consumption, stock price is determined by future dividends and not earnings. Therefore, the role of earnings to predict dividends and the link between earnings and dividends is crucial. Under certain

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2 Similar assumptions about the relation between earnings and price have been made implicitly or explicitly in, for example, Beaver, Lambert, and Morse [1980], Beaver, Lambert, and Ryan [1987], Kormendi and Lipe [1987], and Collins and Kothari [1989].
assumptions, equation (1) is a valid characterization of the relation between price and earnings. In addition, while discounting earnings at the risk-free rate suggests that investors are risk neutral, a similar expression can be derived under more general assumptions about risk preferences.

Assume that earnings follow a random walk with drift process:

\[ a_{t+1} = a_t + \lambda + \epsilon_{t+1}, \]

where \( a_t \) is earnings in period \( t \), \( \lambda \) is the (unknown) drift parameter, and the \( \epsilon_t \)'s are serially uncorrelated normally distributed error terms with \( E(\epsilon_t) = 0 \) and \( \text{var}(\epsilon_t) = \sigma_t^2 \). Investors are assumed to have homogeneous beliefs about firm value, and the general form of the time-series process (random walk with drift) and \( \sigma_t^2 \) are assumed to be known. Investors are assumed to learn about \( \lambda \) over time, with a resulting decrease in uncertainty about firm value. While the parameter itself is assumed to be constant, \( \lambda_t^* \), the market's estimate of \( \lambda \) at time \( t \), is indexed by \( t \) because investors' estimates of \( \lambda \) will change over time as more data are accumulated.

Given these assumptions:

\[ E_t(a_t) = a_t + (\tau + t)\lambda_t^* \quad \tau > t, \]

and unexpected earnings can be expressed as follows:

\[ a_{t+1} - E_t(a_{t+1}) = a_{t+1} - a_t - \lambda_t^* = \epsilon_{t+1} + (\lambda - \lambda_t^*). \]

The resulting expression for price is:

\[ P_t = \frac{R_F a_t}{R_F - 1} + \frac{R_F \lambda_t^*}{(R_F - 1)^2}. \]

\(^3\) While the model assumes that earnings are equal to dividends, Lang [1990] discusses other joint stochastic processes for earnings and dividends (e.g., dividends are related to earnings by a constant payout ratio perturbed by a noise term) for which similar results hold; see also Ohlson [1989] for additional discussion. For notational simplicity, expression (1) assumes that \( P_t \) is the price immediately preceding period \( t \)'s dividend.

\(^4\) See Lang [1990] for an analysis based on the framework in Ohlson [1990] which yields the same basic implications as those which obtain under risk neutrality. The adjustment for risk takes the form of a constant added to earnings, so it does not appear in an expression for the change in price.

\(^5\) Previous empirical studies find that the random walk with drift time-series process is a reasonably good approximation for annual earnings (e.g., Ball and Watts [1972] and Ball, Lev, and Watts [1976]) and for quarterly earnings (e.g., Foster [1977]). The time-series process of earnings is treated as exogenously determined, so issues of strategic behavior on the part of management in reporting earnings are not considered.

\(^6\) The assumption that \( \sigma_t^2 \) is known is not critical; if the joint distribution on the time-series parameter and \( \sigma_t^2 \) is assumed to be normal/gamma, distributions would be in the form of Student's \( t \) rather than the normal distribution (see Zellner [1971]) and the implications of the model would not change.

\(^7\) Given that the error term is assumed normal, \( a_t \) and \( \lambda_t^* \) could be negative, yielding a negative price. This possibility is not unique to the case considered here. One way to avoid the problem is to place restrictions on feasible values of the error term from the time-series process of earnings. As a practical matter, the assumption that the error term is normally distributed should be viewed as an approximation.
TIME-VARYING STOCK PRICE RESPONSE TO EARNINGS

It is useful for the derivations which follow to divide the individual periods into subperiods. Let \( t - s \) denote the date immediately preceding period \( t \)'s earnings announcement, with \( s \) being arbitrarily small so that the risk-free rate of interest between dates \( t - s \) and \( t \) can be ignored. Assume there are no sources of information about future earnings other than current earnings, so that:

\[
E_{t-s}(a_t) = E_{t-1}(a_t) = a_{t-1} + \lambda_{t-1}^*,
\]

and, since price at time \( t - s \) is simply equal to expected price at time \( t \):

\[
P_{t-s} = \frac{R_F(a_{t-1} + \lambda_{t-1}^*)}{R_F - 1} + \frac{R_F \lambda_{t-1}^*}{(R_F - 1)^2}.
\]

The stock price response to the period-\( t \) earnings announcements can be expressed as follows:

\[
P_t - P_{t-s} = \frac{R_F(a_t - a_{t-1} - \lambda_{t-1}^*)}{R_F - 1} + \frac{R_F(\lambda_t^* - \lambda_{t-1}^*)}{(R_F - 1)^2}.
\]

That result can be compared with the result when \( \lambda \) is assumed known by replacing \( \lambda_t^* \) and \( \lambda_{t-1}^* \) by \( \lambda \). If \( \lambda \) is known, the stock price response to announced earnings is \( R_F(a_t - a_{t-1} - \lambda)/(R_F - 1) \), which is the first term in equation (3). With \( \lambda \) unknown, unexpected earnings affect price both through the effect on the first term, as in the case where \( \lambda \) is known, and through the revision to the estimate of \( \lambda \) in the second term.

To proceed, it is useful to decompose \( \lambda_t^* \). Assume that in period 0, the market has a prior distribution on \( \lambda \) which is normal with mean \( \lambda_0 \) and precision \( kh \) where \( h = 1/\sigma^2 \).\(^8\) Let \( \hat{\lambda}_t \) denote the estimate of \( \lambda \) inherent in period \( t \)'s earnings; i.e., \( \hat{\lambda}_t = (a_t - a_{t-1}) \). Because the prior on \( \lambda \) is normal, as is \( \epsilon_t \), the market's distribution on \( \lambda \) at time \( t \) is normal with mean \( \lambda_t^* \) and precision \( h_t \) where:\(^9\)

\[
\lambda_t^* = \frac{\sum_{i=1}^t \hat{\lambda}_i + k \lambda_0}{t + k} = \frac{(a_t - a_1) + k \lambda_0}{t + k}
\]

\[
h_t = (t + k)h.
\]

Investors' estimate of \( \lambda \) in period \( t \) is a weighted average of \( \lambda_0 \) and the observed series of \( \hat{\lambda}_i \)'s, with the weights based on the relative precisions of \( \lambda_0 \) and the \( \hat{\lambda}_i \)s.

The preceding expression can be reexpressed in terms of \( \hat{\lambda}_t \) and \( \lambda_{t-1}^* \):

\[
\lambda_t^* = \frac{1}{t + k} \hat{\lambda}_t + \frac{t + k - 1}{t + k} \lambda_{t-1}^*.
\]

\(^8\) Conceptually, the prior precision would be the posterior precision following \( k \) earnings observations if one assumes a diffuse prior in the first period.

\(^9\) For a derivation of the posterior distribution for a normal prior and likelihood function, see, for example, Zellner [1971].
Therefore:

$$\lambda_t^* = \lambda_{t-1}^* = \frac{\hat{\lambda}_t - \lambda_{t-1}^*}{t + k}. \quad (4)$$

If $\hat{\lambda}_t$ exceeds $\lambda_{t-1}^*$, the value of $\lambda$ implied by $a_t$ is larger than the previous estimate. Therefore, the market revises its estimate of $\lambda$ upward, which in turn increases $P_t$. As time passes, the second term in (3) tends to zero because the denominator in (4) tends to infinity. In the limit, this case comes arbitrarily close to the certainty case.

Absent any changes in the time-series parameter, $\lambda$, the preceding derivation implies investors will revise their estimates of future earnings in response to announced earnings by decreasing amounts as the firm’s earnings history lengthens. To see this, note that the second term in (3) is larger in absolute value as $\lambda_t^*$ deviates more from $\lambda_{t-1}^*$, as, for example, early in the firm’s existence when each of a small number of observations is weighted more heavily.

Substituting (4) into (3) and collecting $(a_t - a_{t-1} - \lambda_{t-1}^*)$ terms yields an explicit expression for the earnings response coefficient:

$$P_t - P_{t-s} = \left[ \frac{R_F}{R_F - 1} + \frac{R_F}{(t + k)(R_F - 1)^2} \right] (a_t - a_{t-1} - \lambda_{t-1}^*). \quad (5)$$

Equation (5) is in the form of a regression of the price change on unexpected earnings. Two points about (5) should be noted. First, because the earnings response coefficient is a decreasing function of the number of earnings realizations, it will decrease over time as more is learned about the firm, and it will be larger for firms for which there is more uncertainty about $\lambda$. Second, the earnings response coefficient for a given firm will decline at a decreasing rate toward a constant; in the limit, only the first term in the earnings response coefficient will remain.

The analysis underlying (5) can be expected to hold more generally. The earnings response coefficient in (5) has two terms, reflecting two effects of current-period earnings surprises on future unexpected earnings and, hence, price. The first term reflects the mapping of current earnings into future earnings (the persistence) inherent in the earnings process; e.g., for the random walk with drift, a current earnings surprise increases expected earnings in each future period dollar for dollar. The second term reflects the fact that a current-period earnings surprise changes the market’s estimate of the drift parameter, which increases expected future earnings. The second term is decreasing in $t$ because, as more data are gathered, the sensitivity of the parameter estimate to another earnings observation tends to decrease. The implication that earnings response coefficients are positive and tend to decrease over time follows from the
fact that both terms in the earnings response coefficient are positive and the second term is decreasing in t.

As long as these two effects of a current earnings increase on price are positive and the second effect dampens with additional data, the resulting earnings response coefficients will be positive and will tend to decrease over time. For most time-series processes likely to describe earnings, the first effect is positive (i.e., a positive current earnings surprise causes expected future earnings to increase, resulting in a positive earnings response coefficient in the absence of parameter uncertainty). In addition, the second effect will typically dampen over time since additional data will have less impact as the parameter estimates become more precise. The requirement that the second effect be positive (i.e., that the change in parameter estimates resulting from an increase in current-period earnings implies higher expected future earnings) is more restrictive. It is met for many of the simple time-series processes typically associated with earnings (e.g., random walk with drift, autoregressive of order one, or trend processes), but the effect will generally be indeterminate for more complex processes.10

3. Empirical Analysis

3.1 Sample

The sample is taken from Beatty and Ritter [1986] and includes 1,076 firms which began trading publicly between 1977 and 1982. To estimate earnings response coefficients, it is necessary to have earnings announcement dates, returns data, and a proxy for unexpected earnings (in this case, the difference between earnings of the current quarter and of the same quarter in the previous year). Earnings announcement dates are taken from the Wall Street Journal Index, where available, and in a few cases from the Compustat tapes. The returns data are from the CRSP NYSE/AMEX and NASDAQ files. Most earnings data are from the 1985 quarterly Compustat tape. When the necessary data are not available from Compustat (either because the data are for periods prior to the IPO or because there is a lag between the IPO data and the date that Compustat coverage begins), I use data from annual reports.

To summarize, I require that sample firms (1) have at least four years of CRSP returns data (which eliminates 429 of 1,076 firms), (2) are included on the 1985 Compustat quarterly tape (which eliminates 154

10 Autoregressive processes also yield the implication that earnings response coefficients vary cross-sectionally based on earning persistence, consistent with existing empirical evidence (e.g., Kormendi and Lipe [1987], Collins and Kothari [1989], Easton and Zmijewski [1989], and Lipe [1990]). Appendix A develops the preceding model for an autoregressive process of order one. Differences in risk can also be incorporated, yielding the prediction that earnings response coefficients are a function of a firm's systematic risk. For further development, see Lang [1990].
firms), (3) have at least 12 usable quarterly earnings announcements in the five years following the IPO year (which eliminates 236 firms),\footnote{Including firms with any valid observations would reduce potential survivorship bias at the cost of changing the composition of the sample over time. Any decrease in the estimated earnings response coefficients over time could reflect a change in sample, rather than a change in the coefficients for individual firms, or the effects of whatever event caused the firm to cease to exist as a separate entity (e.g., bankruptcy or acquisition).} and (4) have the necessary quarterly earnings data available from either Compustat or their annual reports (which eliminates 57 firms). The final sample contains 200 firms, all of which began trading on the NASDAQ system; 47 switched to the NYSE or AMEX by the end of the sample period. The median lag between the IPO and the first earnings announcement in the sample is 138 days.\footnote{Because the event window for some tests is based on time between the current and previous earnings announcements, the first sample observation is never the first earnings announcement for any firm. Also, there is sometimes a lag between when the firm begins trading publicly and the first quarterly earnings announcements reported in the Wall Street Journal. Under the assumptions of the model, excluding some early observations will tend to bias against finding the predicted pattern in earnings response coefficients, since the stock price response to earnings is predicted to be the largest for those observations.}

Because the sample selection criteria exclude about 80\% of the original IPO sample, the firms chosen for this study might differ systematically from the larger population of IPO firms. Table 1 provides a comparison of the 200 sample firms with the 876 firms which were eliminated. Four of the variables (annual revenues for the year preceding the IPO, book value of equity at the end of the year preceding the IPO, the age of the firm [since incorporation] and the number of risk factors reported by the firm) are taken from the firms’ prospectus. The remaining variables (gross proceeds from the IPO, standard deviation of returns over the 20 days following the IPO and the initial return for the first day of public trading) are obtained from stock price data. These data indicate that the median sample firm is significantly larger, older, and less risky (at least in terms of number of risk factors mentioned in the prospectus and standard deviation of returns) than the median nonsample firm.

Given these differences, it is instructive to consider the likely effect on the empirical results. The model predicts the decrease in earnings response coefficients will be most pronounced for firms about which less is initially known and which have less certain prospects. However, the sample criteria appear to select firms about which more is likely to be known at the IPO and which are most established; thus, the sample selection criteria may bias against finding the predicted results.

A second consideration is that the sample covers only eight years. Existing empirical evidence (e.g., Beaver, Lambert, and Morse [1980], Rayburn [1986], Collins and Kothari [1989], and Freeman and Tse [1990]) suggests that earnings response coefficients vary across calendar years. Initial observations for the sample firms are spread over 1977 to


<table>
<thead>
<tr>
<th></th>
<th>Sample Firms</th>
<th>Other Firms</th>
<th>Rank-Sums Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenues ($000)</td>
<td>33,840</td>
<td>17,057</td>
<td>7,956</td>
</tr>
<tr>
<td>Book value of equity ($000)</td>
<td>8,007</td>
<td>4,465</td>
<td>1,708</td>
</tr>
<tr>
<td>Gross proceeds ($000)</td>
<td>13,528</td>
<td>9,020</td>
<td>4,978</td>
</tr>
<tr>
<td>Age</td>
<td>13.71</td>
<td>9.50</td>
<td>6.16</td>
</tr>
<tr>
<td>Risk factors</td>
<td>2.88</td>
<td>0.00</td>
<td>14.31</td>
</tr>
<tr>
<td>Standard deviation of returns</td>
<td>0.036</td>
<td>0.033</td>
<td>0.057</td>
</tr>
<tr>
<td>Initial return</td>
<td>0.119</td>
<td>0.043</td>
<td>0.295</td>
</tr>
</tbody>
</table>

The sample comprises 200 firms which undertook IPOs between 1977 and 1982. Revenues, book value of equity, age, and risk factors are all based on information from the prospectus. Revenues are those reported for the firm over the year preceding the initial public offering. Book value of equity is the book value of tangible equity as of the end of the year preceding the IPO. Age is the number of years since the firm incorporated as reported in the prospectus. Gross proceeds is the offering price in the IPO multiplied by the number of shares sold. The standard deviation of returns is measured over the 20 days following the IPO. Initial return is the return on the day that the firm's stock began trading publicly. The Z-statistic is based on the Wilcoxon two-sample rank-sums test.
1984 and the firms are followed for approximately three years.\textsuperscript{13} The initial observations are centered on January 1982, and 75\% fall between March 1980 and May 1983. Given that the observations are spread over calendar time and the most pronounced pattern in earnings response coefficients is concentrated in the first 12 to 18 months of the sample period, it seems unlikely that the results are calendar-period specific. However, caution should be exercised in generalizing the results to other time periods.

Finally, there may be industry concentration among IPO firms; for example, during the early 1980s, many IPOs occurred among energy and computer firms. Extreme industry clustering in my sample could limit the generalizability of results. Table 2, however, indicates little industry clustering. Manufacturing and services contribute the largest number of firms, but within those categories, the firms are spread across two-digit SIC codes. Therefore, the sample selection criteria imposed appear to have eliminated much of the industry clustering among IPOs.

3.2 METHODS

The primary metric that I use to test for changes in the stock price response to earnings over time is the earnings response coefficient (the coefficient from a regression of abnormal returns on unexpected earnings).\textsuperscript{14}

I test for changes in the earnings response coefficients by conducting cross-sectional regressions for each of the 12 sample quarters. The cross-sectional regressions yield 12 coefficient estimates, each of which can be viewed as an average of the individual firm coefficients for that observation and can be used to test for changes in earnings response coefficients over time. The earnings response coefficients are based on returns cumulated over two sets of event windows. The short window includes the day preceding and the day of the earnings announcement (two trading days). The long window extends from the day following the previous quarter's earnings announcement to the day of the current quarter's announcement.

\textsuperscript{13} In 70 cases, there is a quarter which would otherwise have been included in the sample, but for which an earnings announcement is not reported in the \textit{Wall Street Journal Index}. In those cases, it is not possible to conduct the tests based on the long event window (described more fully in the next section) for either the current quarter or the following quarter since the long event window extends from the day following the previous quarter's earnings announcement to the day of the current quarter's earnings announcement. Therefore, both quarters are excluded from the sample.

\textsuperscript{14} An alternative measure, the variance of stock returns, does not control for the sign and magnitude of unexpected earnings, so that changes in the stock price response to earnings caused by other factors, such as those predicted by the model in this paper, are less easily detected. Variance-based tests (not reported) based on Patell [1976] for a subsample of 40 firms and related research by Affleck-Graves, Fehrs, and Miller [1990] provide qualitatively similar results.
Table 2

Industry Composition of the Sample Firms

<table>
<thead>
<tr>
<th>SIC Code</th>
<th>Industry</th>
<th># of Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>0000-0999</td>
<td>Agriculture</td>
<td>2</td>
</tr>
<tr>
<td>1000-1499</td>
<td>Mining</td>
<td>17</td>
</tr>
<tr>
<td>1500-1999</td>
<td>Construction</td>
<td>2</td>
</tr>
<tr>
<td>2000-3999</td>
<td>Manufacturing</td>
<td>91</td>
</tr>
<tr>
<td>3400-3499</td>
<td>Fabricated Metals</td>
<td>6</td>
</tr>
<tr>
<td>3500-3599</td>
<td>Industrial Equipment</td>
<td>26</td>
</tr>
<tr>
<td>3600-3699</td>
<td>Electronic Equipment</td>
<td>30</td>
</tr>
<tr>
<td>3800-3899</td>
<td>Instruments</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>11</td>
</tr>
<tr>
<td>4000-4999</td>
<td>Transportation</td>
<td>7</td>
</tr>
<tr>
<td>5000-5199</td>
<td>Wholesale Trade</td>
<td>7</td>
</tr>
<tr>
<td>5200-5999</td>
<td>Retail Trade</td>
<td>11</td>
</tr>
<tr>
<td>5800-5899</td>
<td>Restaurants</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>3</td>
</tr>
<tr>
<td>6000-6999</td>
<td>Finance</td>
<td>5</td>
</tr>
<tr>
<td>7000-8999</td>
<td>Services</td>
<td>36</td>
</tr>
<tr>
<td>7000-7100</td>
<td>Hotels</td>
<td>3</td>
</tr>
<tr>
<td>7300-7399</td>
<td>Business Services</td>
<td>25</td>
</tr>
<tr>
<td>8000-8100</td>
<td>Health Services</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>4</td>
</tr>
<tr>
<td>Unidentified</td>
<td></td>
<td>22</td>
</tr>
<tr>
<td>Total</td>
<td>200</td>
<td></td>
</tr>
</tbody>
</table>

The sample comprises 200 firms which undertook IPOs between 1977 and 1982. Industry classification is based on the first nonzero SIC code reported in CRSP files.

The model does not indicate which window length is preferable because the issue cannot arise under the assumptions of the model. The model assumes that the market's expectation of earnings immediately prior to the earnings announcement is equal to the previous period's earnings adjusted for the estimated growth rate of earnings, and that all the information in current-period earnings arrives simultaneously on the earnings announcement data. In fact, previous research indicates that information about earnings arrives gradually over the course of the quarter and that some of this information may pertain to other quarters' earnings. The long window is preferable to the extent that earnings information arrives gradually, since it is likely to capture more of the resolution of uncertainty about current-period earnings. However, it is
also likely to capture the effect on returns of information pertaining to other quarters’ earnings. The short window, on the other hand, is preferable if the proportion of the uncertainty about the current quarter’s earnings which is resolved at the time of the earnings announcement is relatively high and a great deal of information about other quarters’ earnings is received during the course of the current quarter.

To estimate the earnings response coefficients, I use market-adjusted returns, computed by subtracting the return on the value-weighted index for the exchange on which the firm was traded at the time of the earnings announcement from the firm’s raw return. This computation assumes that sample firms have market model betas of one relative to the market index for the system on which they are traded (generally the NASDAQ). I adopt this approach since there are probably a substantial number of nontrading days for the sample firms and most NASDAQ securities were not required to provide transactions data during the sample period.

The earnings data I use are quarterly earnings per share before extraordinary items.\(^{15}\) As a proxy for unexpected earnings, I use the change in earnings from the same quarter in the previous year. This proxy is not entirely consistent with the model of the previous section, because there the value-relevant change in earnings was the quarter-to-quarter change, while here it is the change from the same quarter in the previous year, i.e., earnings follow a seasonal random walk with drift. My choice of the seasonal random walk is based on empirical evidence of a seasonal component to earnings. It is straightforward to show that the implications of the previous section also follow for a seasonal random walk with drift.

I do not adjust this proxy for the market’s estimate of the time-series parameter of earnings (\(\lambda_t^*\)) because this estimate is not observable. For specific time-series processes like the random walk with drift, it is possible to express \(\lambda_t^*\) in terms of past earnings and the first-period estimate of the parameter, \(\lambda_0^\dagger\).\(^{16}\) However, \(\lambda_0^\dagger\), which is likely to have a major impact on \(\lambda_t^*\) (especially for small \(t\)), is not observable.

\(^{15}\)The assumption that earnings follow a random walk with drift time-series process is likely to hold most closely for earnings before extraordinary items since extraordinary items are likely to be transitory. As a practical manner, very few of the sample firms reported extraordinary items, so the results are not likely to be sensitive to this choice.

\(^{16}\)For a random walk with drift, it is possible to assess the impact of excluding \(\lambda_{t-1}^*\) from the proxy for unexpected earnings by expressing equation (8) in terms of \((a_t - a_{t-1})\):

\[
P_t - P_{t-1} = R_{f_t}[1 + (t + k)(R_f - 1)]\lambda_{t-1}^* + \frac{1}{R_f - 1} + \frac{R_f}{(t + k)(R_f - 1)^2}(a_t - a_{t-1}).
\]

\(\lambda_{t-1}^*\) can be viewed as an omitted variable. Let \(\beta_1\) and \(\beta_2\) denote the coefficients from a multiple regression of \((P_t - P_{t-1})\) on \(\lambda_{t-1}^*\) and \((a_t - a_{t-1})\), and \(\beta_{a, a}\) denote the coefficient from a regression of \(\lambda_{t-1}^*\) on \((a_t - a_{t-1})\). Then, \(E(\hat{\beta}_2) = \beta_2 + \beta_1\beta_{a,a}\), where \(\hat{\beta}_2\) is the estimated coefficient from the simple regression of the price change on the change in earnings. In terms of the cross-sectional regression which follows, \(\beta_{a,a}\) will be positive and \(\beta_1\) will be negative, so that \(\hat{\beta}_2\) will be downward biased. Over time, \(\hat{\beta}_2\) will tend to increase, reducing the downward bias. Therefore, the effect of the omitted variable will run counter to the predicted decline in coefficients over time.
3.3 Regression Results

I estimate earnings response coefficients cross-sectionally with a regression of the following form:

\[ R_i = \alpha + \beta A_i + e_i \]

where \( R_i \) is the market-adjusted return over the event window for firm \( i \); \( A_i \) is the change in earnings per share from the same quarter in the previous year for firm \( i \), deflated by the price as of the day preceding the beginning of the event window; and \( \beta \) is the earnings response coefficient.

Given that each observation in the cross-section relates to a different firm, there are at least two potential problems with conducting an ordinary least squares (OLS) regression in this context; first, the residuals may be heteroscedastic, and, second, \( \alpha \) and \( \beta \) may vary across firms. Therefore, I perform a random coefficients estimation procedure based on the Hildreth and Houck [1968] model; results from OLS estimation (not reported) are very similar. The random coefficients model allows for cross-sectional variation in the coefficients and can be adapted to incorporate heteroscedasticity in the error term.

The random coefficients model I use assumes that the relation between returns and earnings can be expressed as follows:

\[ R_i = (\alpha + \nu_{\alpha,i}) + (\beta + \nu_{\beta,i})A_i + e_i \]

where \( \nu_{\alpha,i} \) and \( \nu_{\beta,i} \) are assumed to be normally distributed with \( E(\nu_{\alpha,i}) = E(\nu_{\beta,i}) = E(e_i) = 0 \) for all \( i \), \( E(\nu_{\alpha,i}\nu_{\beta,i}) = E(\nu_{\alpha,i}e_i) = E(\nu_{\beta,i}e_i) = 0 \) for all \( i \) and \( j \), and \( E(\nu_{\alpha,i}\nu_{\alpha,i}) = E(\nu_{\beta,i}\nu_{\beta,i}) = E(e_i e_j) = 0 \) for all \( i \neq j \). Equation (6) can be reexpressed as follows:

\[ R_i = \alpha + \beta A_i + \xi_i \]

where \( \xi_i = \nu_{\alpha,i} + \nu_{\beta,i}A_i + e_i \). Equation (7) could be estimated using OLS except that the error term is heteroscedastic since:

\[ E(\xi_i^2) = \sigma_{\alpha}^2 + A_i^2 \sigma_{\beta}^2 + \sigma_{e,i}^2 \]

where \( \sigma_{\alpha}^2 \) is the variance of \( \nu_{\alpha} \), \( \sigma_{\beta}^2 \) is the variance of \( \nu_{\beta} \), and \( \sigma_{e,i}^2 \) is the variance of \( e_i \). Therefore, the variance of \( \xi_i \) varies cross-sectionally based on differences in \( A_i^2 \) and \( \sigma_{e,i}^2 \).

Given values for \( \sigma_{\alpha}^2 \), \( \sigma_{\beta}^2 \), and \( \sigma_{e,i}^2 \), equation (7) could be estimated using weighted least squares. While \( \sigma_{\alpha}^2 \), \( \sigma_{\beta}^2 \), and \( \sigma_{e,i}^2 \) are not known, they can be estimated. From equation (8), \( E(\xi_i^2) \) is linear in \( A_i^2 \), \( \sigma_{\beta}^2 \) is known, and an estimate of \( \sigma_{e,i}^2 \), denoted \( \hat{\sigma}_{e,i}^2 \), can be obtained from a time-series regression of market-adjusted returns on the change in earnings for each firm. While the \( \xi_i^2 \)’s are not observable, it can be shown that the following relation holds (see, for example, Johnston [1984]):

\[ \zeta = M\xi \]

where \( \xi \) is the vector of true residuals, \( \zeta \) is the vector of observed residuals from the cross-sectional OLS regression, \( I \) is an identity matrix, \( X \) is a
200 × 2 matrix with ones in the first column and A₁’s in the second column, and M = I - (X(X’X)^⁻¹X’).

Let V denote a 200 × 3 matrix, with ones in the first column, A₁’s in the second column, and δ̂_{ε,i}’s in the third column. Then, equations (8) and (9) can be combined as follows:

\[ E(\xi) = \hat{M}V\sigma \]

where the dot over a term indicates that each element of that vector or matrix is squared and \( \sigma \) is the vector containing \( \sigma^2_{\alpha}, \sigma^2_{\beta}, \) and \( \Omega^2 \). The final element in \( \sigma \) is \( \Omega^2 \) rather than one because the V matrix contains \( \delta_{e,i} \) rather than \( \sigma_{e,i} \). I assume that \( \sigma_{e,i} \) is proportional to \( \delta_{e,i} \), with the constant of proportionality equal to \( \Omega \), which is assumed constant across firms for a given quarter, although it may vary between quarters.

The vector \( \sigma \) can be estimated by an OLS regression of \( \xi \) on \( \hat{M}V \). The resulting estimates of \( \sigma^2_{\alpha}, \sigma^2_{\beta}, \) and \( \Omega^2 \) can be used in conjunction with equation (8) to generate residual variance estimates for each observation, which in turn can be used as deflators in a weighted least squares estimation of equation (7)\(^{17}\).

3.3.1 Two-Day Event Window Results. Results of the 12 cross-sectional random coefficients model regressions for the two-day window are presented in table 3 and the estimated earnings response coefficients (with 90% confidence intervals) are plotted in figure 1. Consistent with prior results, the change in earnings explains only a small proportion of the variation in returns at the time of the earnings announcement. In addition, the point estimates for the earnings response coefficients are well below their theoretical counterparts. Easton and Zmijewski [1987] present evidence that this result may be due to measurement error in the proxy for unexpected earnings. That observation is consistent with the fact that, as the length of the event window is extended, the earnings response coefficient estimates increase substantially. Measurement error in unexpected earnings will be a concern in this study to the extent that it varies systematically for firms over time. That possibility is considered in more detail in the next section, in which I consider other potential explanations for the results.

The pattern of coefficient estimates in figure 1 is generally consistent with the prediction that the coefficients decline over time. The Pearson correlation between the coefficient estimates and the observation number is \(-0.74\), and the rank correlation is \(-0.79\), significant at the 0.01 level in a one-tailed test assuming independence. While these correlations are consistent with a decrease in the coefficients over time, they do not account for variable estimation error in the coefficients. Weighted least squares, with the weights based on the standard errors of the coefficient estimates, places the least weight on the observations which are measured

\(^{17}\) Because the random coefficients approach does not ensure that the variance estimates will be positive, I constrain any elements which have negative estimates to equal zero and reestimate the remaining elements. See Judge et al. [1985] for further discussion.
TABLE 3
Cross-Sectional Random Coefficients Model Regressions of Market-Adjusted Returns on the Change in Earnings for 12 Quarterly Earnings Announcements Following the IPO

<table>
<thead>
<tr>
<th>Sample Observation</th>
<th>Two-Day Window</th>
<th>Long Window</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>α</td>
<td>β</td>
</tr>
<tr>
<td>One</td>
<td>−0.002</td>
<td>1.156</td>
</tr>
<tr>
<td></td>
<td>(−0.492)</td>
<td>(3.934)</td>
</tr>
<tr>
<td>Two</td>
<td>0.004</td>
<td>0.615</td>
</tr>
<tr>
<td></td>
<td>(0.911)</td>
<td>(1.758)</td>
</tr>
<tr>
<td>Three</td>
<td>0.005</td>
<td>0.356</td>
</tr>
<tr>
<td></td>
<td>(1.310)</td>
<td>(2.115)</td>
</tr>
<tr>
<td>Four</td>
<td>0.003</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>(0.908)</td>
<td>(1.600)</td>
</tr>
<tr>
<td>Five</td>
<td>0.002</td>
<td>0.190</td>
</tr>
<tr>
<td></td>
<td>(0.387)</td>
<td>(1.734)</td>
</tr>
<tr>
<td>Six</td>
<td>−0.002</td>
<td>0.220</td>
</tr>
<tr>
<td></td>
<td>(−0.446)</td>
<td>(1.864)</td>
</tr>
<tr>
<td>Seven</td>
<td>−0.001</td>
<td>0.207</td>
</tr>
<tr>
<td></td>
<td>(−0.398)</td>
<td>(1.974)</td>
</tr>
<tr>
<td>Eight</td>
<td>0.004</td>
<td>0.282</td>
</tr>
<tr>
<td></td>
<td>(0.990)</td>
<td>(2.637)</td>
</tr>
<tr>
<td>Nine</td>
<td>−0.004</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(−0.931)</td>
<td>(2.069)</td>
</tr>
<tr>
<td>Ten</td>
<td>−0.003</td>
<td>0.154</td>
</tr>
<tr>
<td></td>
<td>(−0.824)</td>
<td>(1.815)</td>
</tr>
<tr>
<td>Eleven</td>
<td>0.002</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.470)</td>
<td>(1.041)</td>
</tr>
<tr>
<td>Twelve</td>
<td>−0.002</td>
<td>0.097</td>
</tr>
<tr>
<td></td>
<td>(−0.438)</td>
<td>(2.359)</td>
</tr>
</tbody>
</table>

The sample comprises 200 firms which undertook IPOs between 1977 and 1982. Estimation is based on the following random coefficients model estimated cross-sectionally for each of the 12 earnings announcements in the sample following the IPO:

\[ R_t = (\alpha + \alpha_i) + (\beta + \beta_i) \cdot A_t + \epsilon_t \]

where \( R_t \) denotes the return over a window which includes the day preceding and the day of the current quarter's earnings announcement for the two-day window and the return over a window which extends from the day following the previous quarter's earnings announcement to the day of the current quarter's earnings announcement for the long window. \( A_t \) denotes the change in earnings between the current quarter and the same quarter in the previous year, divided by price as of the day preceding the beginning of the event window. \( t \)-statistics are noted in parentheses.

with the most error. Results for the weighted least squares regression of the coefficient estimates on the observation number are consistent with a decrease in the coefficients over time:

\[ COEF_t = 0.362 - 0.026t + \epsilon_t \]

(3.686) \(-2.560\)

where \( COEF_t \) denotes the cross-sectional coefficient estimate and \( t \) denotes the quarter number (1 to 12);\(^{18}\) \( t \)-statistics are given in parentheses.

\(^{18}\) I also estimated this relation in a pooled time-series and cross-sectional regression, with very similar conclusions. Results from random coefficients model regressions based on the Swamy [1970] technique are generally consistent but weaker, probably because of the limited number of time-series observations available to estimate the firm-specific variances.
FIG. 1.—Cross-sectional estimates of earnings response coefficients: two-day event window. Stars denote slope coefficient estimates from the cross-sectional random coefficients model regression of market-adjusted returns on the change in earnings. Returns are cumulated over a window which includes the day preceding and the day of the current quarter’s earnings announcement. The independent variable is the change in earnings between the current quarter and the same quarter in the previous year, divided by price as of the day preceding the beginning of the event window. Vertical lines denote 90% confidence intervals.
The coefficient estimate for $t$ is of the predicted sign and significant at the 0.01 level in a one-tailed test.

The linear relation between observation number and coefficient estimate underlying the preceding regression can be valid only as an approximation since it implies that the earnings response coefficients would continue decreasing indefinitely, while the model in the previous section predicts that these coefficients will decrease at a decreasing rate. Based on (5), the earnings response coefficients are the following function of $t$:

$$\beta(t) = \left( a + \frac{b}{t + k} \right)$$  \hspace{1cm} (11)

where $t$ is the observation number and $k$ is related to the precision of the market’s estimate of the time-series parameter of earnings at the IPO.

Equation (11) cannot be estimated by a linear regression of $\beta(t)$ on $1/(t + k)$ because $k$ is not known.\(^{19}\) Although $a$, $b$, and $k$ could be estimated directly with a nonlinear regression, given the small sample size $I$ instead use linear approximations to equation (11). I consider three alternate estimation approaches, all of which yield similar results. The first is to estimate (11) for assumed values of $k$ ranging from 0 to 10 (i.e., 0 to 2½ year of equivalent data in terms of the model from the previous section).\(^{20}\) The conclusions from the analysis are not sensitive to the choice of $k$. Second, I consider a functional form based on a Taylor series expansion of equation (11) around $t_0$. Truncating after three terms yields a quadratic relation of the form $\beta(t) \approx \alpha + \gamma t + \delta t^2$. The model predicts $\beta'(t) < 0$ and $\beta''(t) > 0$. Third, I consider various transformations of the dependent and independent variables (e.g., logs, square roots, and reciprocals) which would imply a pattern in the coefficient estimates similar to the one predicted by the model.

I report results for the first approach with the earnings response coefficients assumed to be linear in the reciprocal of the observation number (i.e., $k$ is assumed to be zero). The advantage of this approach over the Taylor series approximation is that a positive coefficient on the independent variable implies earnings response coefficients which are monotonically decreasing over time, as predicted by the model. The Taylor series approximation, on the other hand, implies a quadratic relation between the earnings response coefficient and the observation

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\(^{19}\) If the IPO date is viewed as period 0, a potential proxy for $k$ is the number of earnings figures proved in the IPO filing with the SEC. However, that approach assumes that the only value-relevant data are the earnings numbers reported in the registration statement, and that earnings from periods prior to the IPO are as relevant to pricing the firm as later information.

\(^{20}\) Nonlinear weighted least squares regression of the relation in equation (11) yield estimates of $k$ of approximately 0 for the two-day window and 10 for the long window. Theoretically, the value should be the same for both windows. However, given the small data set and large standard errors on the estimates of $k$, these estimates should be viewed as suggestive only.
number. If, as predicted, the coefficient estimate on $t$ is negative and on $t^2$ is positive, the Taylor series approximation implies a relation between $\beta$ and $t$ which decreases initially but eventually reverses, contrary to the prediction of the model. In addition, the Taylor series approach can imply negative coefficient estimates even when the true coefficients are positive. The various transformations considered in the third approach also imply a monotonic relation, albeit arbitrary. Further, transformations involving the earnings response coefficients complicate the weighted least squares estimation.

I estimate the relation between the estimated earnings response coefficients and the reciprocal of the observation number by applying weighted least squares with the weights based on the standard errors of the coefficient estimates from the random coefficients model cross-sectional regressions. The estimated relation for the short event window is:

$$ COEF_t = -0.011 + 1.071(1/t) + \varepsilon_t $$

$$ (-0.390) \quad (5.384) $$

The estimated coefficient on $1/t$ is positive and significantly different from zero at the 0.01 level, consistent with the prediction of the model. The intercept is approximately zero and the coefficient on $1/t$ is approximately one, suggesting that the earnings response coefficients are approximately equal to the reciprocal of the observation number.

3.3.2 Long Event Window Results. As mentioned earlier, the long event window extends from the day following the previous quarter’s earnings announcement to the date of the current quarter’s earnings announcement. Results of the cross-sectional random coefficients model regressions, presented in table 3 and plotted in figure 2, provide evidence of a decline in the estimated earnings response coefficients over time.\textsuperscript{21} The Pearson correlation between the estimated coefficients from the random coefficients model and the observation number is $-0.61$. The rank correlation is $-0.50$, significant at the 0.05 level in a one-tailed test.

Results of the regression of the estimated coefficients from the random coefficients model on $t$ are consistent with a decrease in the earnings response coefficients over time:

$$ COEF_t = 1.898 - 0.135t + \varepsilon_t $$

$$ (3.588) \quad (-2.601) $$

\textsuperscript{21}Cross-sectional correlation among the regression residuals may be an issue for the long window tests. To assess the seriousness of the problem, I examine the pairwise residual correlations from the time-series regressions of returns on the change in earnings for a random subsample of 50 firms. The mean of the 1,225 resulting correlations is 0.0025 with an associated $t$-statistic of 0.333. Based on results in Bernard [1987], it seems unlikely that the correlations are of sufficient magnitude to alter the results substantially.
Fig. 2—Cross-sectional estimates of earnings response coefficients: long event window. Stars denote slope coefficient estimates from the cross-sectional random coefficients model regression of market-adjusted returns on the change in earnings. Returns are cumulated over a window extending from the day following the previous quarter's earnings announcement to the day of the current quarter's earnings announcement. The independent variable is the change in earnings between the current quarter and the same quarter in the previous year, divided by price as of the day preceding the beginning of the event window. Vertical lines denote 90% confidence intervals.
The coefficient estimate on the observation number is negative as predicted and significant at the 0.05 level \( t = -2.601 \). The results for a regression of the earnings response coefficient estimates from the random coefficients model on reciprocal of \( t \) are also consistent with the predictions of the model:

\[
COEF_t = 0.215 + 2.960(1/t) + e_t
\]

\[
(0.855) \quad (1.866)
\]

The estimated coefficient on \( 1/t \) is of the predicted sign and significantly different from zero at the 0.05 level in a one-tailed test \( t = 1.866 \). As for the short event window, the intercept is again approximately zero, but the coefficient on \( 1/t \) for the long window is larger, consistent with the fact that the earnings response coefficient estimates are generally larger for the long event window.

4. Alternative Explanations

In this section, I examine several potential alternative explanations for the observed pattern in earnings response coefficients including systematic changes in firm-specific factors (such as the information environment, risk, or the persistence, predictability, or composition of earnings) and changes in macroeconomic conditions. In general, none of these factors appears to explain the observed pattern in earnings response coefficients.

The model I present and test in the previous section assumes a very simple information environment for the firm in which all information about a given period’s earnings is communicated to the market through the earnings announcement. Alternatively, suppose that as the firm matures a larger portion of the information in earnings is impounded into price prior to the earnings announcement. Then, the change in quarterly earnings will become an increasingly poor proxy for unexpected earnings, resulting in additional measurement error in the independent variable and, therefore, lower earnings response coefficient estimates over time.

Direct evidence on this issue can be gained by considering a ratio (similar to the one in Freeman [1987]) designed to capture the proportion of information about earnings which is assimilated into price prior to the earnings announcement. The measure is based on the returns to a portfolio which is long in the sample firms with positive earnings changes for a given quarter \( A_{it} > 0 \) and short in the sample firms with negative earnings changes \( A_{it} < 0 \). The numerator is the return to the portfolio over the two-day window (the day preceding and the day of earnings announcement), and the denominator is the return over the long window
(extending from the day following the previous earnings announcement to the day of the current earnings announcement). 22

The result of the analysis is 12 ratios, one for each quarter, presented in table 4. There is no clear pattern over time; the median ratio is 0.23 for the first six observations and 0.32 for the last six. If anything, the proportion of earnings information which is incorporated into price prior to the earnings announcement may have decreased over time for the sample firms, which would tend to bias against finding the observed pattern in earnings response coefficients.

A less direct approach is to examine factors which might lead to differences in the firms' information environments over time. I consider three such factors based on previous research—firm size, dividend policy, and exchange listing. 23 Size has been frequently suggested as an important determinant of the information environment of the firm (see, for example, Atiase [1985; 1987], Bhushan [1989], Freeman [1987], and Kyle [1985]). If the benefits associated with information collection are increasing in firm size and the size of the sample firms tends to increase over time, the amount of information collected about the firms prior to the earnings announcement would also be expected to increase.

I measure size as the market value of equity from CRSP as of each of the 12 earnings announcement dates in the sample. Based on the data presented in table 4, there is little evidence of a systematic change in median firm size over the 12 quarters considered, although mean firm size increases 42% (from $81 million to $115 million). But the twelfth observation, the size of the median firm has decreased by 4% relative to the first quarter, suggesting that the increase in mean size is influenced by a small number of large firms. 24

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22 This formulation does not capture information about earnings which became available prior to the current quarter. In order to assess the effect of lengthening the cumulation period, I also consider the ratio with the denominator returns cumulated over periods of up to four quarters (i.e., I combine the return from the current quarter's long event window with returns from long windows for up to three preceding observations). Lengthening the cumulation period sacrifices the early observations since returns are generally not available prior to the first earnings announcement. The basic conclusions from the analysis are the same across all windows considered.

23 The list of variables considered is not exhaustive. Shores [1990] presents evidence that size and six other proxies for the level of interim information—number of financial analysts, number of interim earnings announcements, number of nonearnings announcements, percentage trading volume, number of market makers, and percentage bid–ask spread—are all correlated with the information content of earnings announcements across over-the-counter firms. However, the six other variables are all highly correlated with size and exhibit only modest incremental explanatory power.

24 The existing empirical evidence on firm size in this context is based on firms which differ vastly in size. For example, in Atiase [1985], the upper limit on the small firm subsample is $20 million, compared with a lower limit of $400 million for the large firm subsample. Relative to those extremes, the changes in firm size for the sample firms are relatively minor; the mean and median increase in size are 6% and 8%.
### Table 4
Descriptive Statistics for the Sample Firms by Quarter

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Information Ratio</th>
<th>Size ($000)</th>
<th>Beta</th>
<th>Change in EPS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Median</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>One</td>
<td>0.299</td>
<td>46,782</td>
<td>80,552</td>
<td>1.368</td>
</tr>
<tr>
<td>Two</td>
<td>0.195</td>
<td>48,854</td>
<td>83,177</td>
<td>1.340</td>
</tr>
<tr>
<td>Three</td>
<td>0.247</td>
<td>49,104</td>
<td>87,302</td>
<td>1.333</td>
</tr>
<tr>
<td>Four</td>
<td>0.208</td>
<td>49,383</td>
<td>92,542</td>
<td>1.342</td>
</tr>
<tr>
<td>Five</td>
<td>0.211</td>
<td>54,667</td>
<td>96,863</td>
<td>1.276</td>
</tr>
<tr>
<td>Six</td>
<td>0.258</td>
<td>53,364</td>
<td>104,023</td>
<td>1.265</td>
</tr>
<tr>
<td>Seven</td>
<td>0.152</td>
<td>54,543</td>
<td>116,611</td>
<td>1.265</td>
</tr>
<tr>
<td>Eight</td>
<td>0.374</td>
<td>52,089</td>
<td>119,995</td>
<td>1.254</td>
</tr>
<tr>
<td>Nine</td>
<td>0.162</td>
<td>50,797</td>
<td>127,838</td>
<td>1.254</td>
</tr>
<tr>
<td>Ten</td>
<td>0.385</td>
<td>46,963</td>
<td>124,644</td>
<td>1.178</td>
</tr>
<tr>
<td>Eleven</td>
<td>0.391</td>
<td>46,541</td>
<td>114,200</td>
<td>1.137</td>
</tr>
<tr>
<td>Twelve</td>
<td>0.272</td>
<td>44,768</td>
<td>114,693</td>
<td>1.068</td>
</tr>
</tbody>
</table>

The sample comprises 200 firms which undertook IPOs between 1977 and 1982. Information ratio is the ratio of the return over the two-day window to the return over the long window for a portfolio which is long in firms with positive earnings changes for the quarter and short in firms with negative earnings changes for the quarter. Size is the market value of outstanding equity based on the stock price as of the earnings announcement date and the most recent record of shares outstanding on CRSP. Beta is the beta estimate from CRSP. Change in EPS is the change in earnings per share from the same quarter in the previous year deflated by price as of two days prior to the current earnings announcement.

A second possibility relates to dividend policy. If firms began paying dividends during the sample period and dividends are informative about future earnings (as documented by Healy and Palepu [1988]), the change in earnings will be a poorer proxy for unexpected earnings following the dividend initiation and the stock price response to earnings will tend to decrease over time, particularly for the two-day window. Of the 200 sample firms, 9 initiated regular dividends during the sample period, so it is unlikely that the results are being driven by changes in dividend policy. I also conduct the OLS analysis for the two-day window excluding them, and the results are nearly identical to those for the entire sample.

Another possibility is that the sample firms may have changed exchange listings over time. Atiase [1985; 1987] and Grant [1980] provide evidence that exchange listing is a determinant of the magnitude of the stock price response to earnings. If firms change their listings to the NYSE or AMEX during the sample period, the information content of earnings will tend to decrease, particularly for the short event window. Of the 200 sample firms (all of which began trading on the NASDAQ), 31 switched to the NYSE or AMEX during the sample period. Results of the OLS analysis for the two-day event window excluding firms which switched exchanges are very similar to those for the entire sample.

A second potential explanation is that the risk of the firms has changed during the sample period. Easton and Zmijewski [1989] and Collins and Kothari [1989] suggest that earnings response coefficients are a decreasing function of the riskiness of the firm (as measured, for example, by beta from the Capital Asset Pricing Model). Therefore, an increase in
the riskiness of the sample firms could cause a decline in earnings response coefficients over time. To investigate risk changes, I analyze the annual market model betas for the sample firms reported in the CRSP files. If CRSP does not report a beta estimate for a year (typically because the firm had recently started trading on the exchange and, therefore, not enough data are available to estimate beta), I use the next reported estimate. Mean and median beta estimates for each quarter for the sample firms are reported in table 4. The decrease in median beta estimates over time is striking in that it is essentially monotonic. Subject to the caveat that beta is only one of many possible measures of risk, the evidence suggests that changes in risk for the sample firms should bias against finding the predicted pattern in earnings response coefficients.

A third potential explanation is that the persistence of earnings for the sample firms has changed over time. Extant theoretical and empirical research (see, for example, Kormendi and Lipe [1987], Easton and Zmijewski [1989], Collins and Kothari [1989], and Lipe [1990]) suggests that earnings response coefficients are positively correlated with earnings persistence. To test whether changes in persistence over time are driving the empirical results, I compare the first-order autocorrelation of the unexpected earnings series from the first six observations for each firm with the last six observations. There is no evidence of a systematic reduction in persistence between the two periods (the median change between the two periods is −0.005 with 101 of the firms exhibiting a reduction in autocorrelation).

A fourth possibility is that, consistent with the theoretical and empirical results in Lipe [1990], the decrease in earnings response coefficients is the result of a reduction in the predictability of earnings for the sample firms over time. To test this possibility, I compare the time-series variance of the unexpected earnings series over the first and last six observations for each of the sample firms. This variance increases over

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25 While persistence is not an issue for the random walk with drift time-series process, Appendix A considers an autoregressive time-series process for which earnings response coefficients vary cross-sectionally with persistence.

26 A related possibility is that the expected growth rate of earnings has decreased over time for the sample firms. While the model of the previous section does not imply differences in earnings response coefficients across firms with high and low expected earnings growth, Collins and Kothari [1989] provide evidence of a positive correlation between earnings response coefficients and a proxy for expected earnings growth. The intercepts from the earnings response coefficient regression provide a measure of expected growth since they represent the stock price response to no change in earnings (i.e., a negative intercept indicates that investors expected an increase in earnings). The fact that there is no evidence of an increase in the intercepts over time suggests that expected growth did not decrease during the sample period. Similarly, there is no pattern in the observed earnings changes provided in table 4 (e.g., the median earnings change for the first six observations is 0.0018 versus 0.0017 for the last six). Therefore, it seems unlikely that changes in the expected growth rate of earnings are driving the empirical results.
time for 122 of the firms. To test whether this decrease in predictability is responsible for the observed pattern in earnings response coefficients, I create two subsamples based on the sign of the change in variance and conduct the OLS regressions for each subsample individually. The pattern of decreasing earnings response coefficients persists for both of the subsamples (although, consistent with the results in Lipe [1990], it is more pronounced for the subsample with increasing variance). Therefore, the observed pattern in earnings response coefficients does not seem to be the result of decreased predictability over time.

A fifth alternative is that the decrease in earnings response coefficients is the result of decreases in the level of discretionary expenditures over time. Bublitz and Ettredge [1989] suggest that the stock price may respond less negatively to a dollar of research and development or advertising expense than to other types of expenses because the expenditures are expected to benefit future periods. As a result, the observed decrease in earnings response coefficients may be the result of reductions in research and development and advertising expenditures over time. To test that possibility, I compute research and development and advertising expense as a percentage of market value for the year of the firm's initial observation in the sample and the following three years. There is no evidence of a systematic decrease in research and development or advertising expense over time for those firms reporting nonzero levels of research and development and advertising. For example, the median level of research and development (advertising) expense as a percentage of market value of equity was 2.6%, 3.6%, 3.7%, and 5.1% (1.0%, 1.0%, 1.2%, and 1.5%) for the year of, and the three years following, the first observation in the sample.

A final possibility is that the observed pattern in earnings response coefficients was characteristic of firms more generally because of changes in macroeconomic conditions during the sample period. Variation in earnings response coefficients over time has been documented in numerous studies, including Beaver, Lambert, and Morse [1980], Rayburn [1986], and Freeman and Tse [1990], and has been linked to macroeconomic factors such as time-varying interest rates (Collins and Kothari [1989]). To ensure that the observed pattern in earnings response coefficients is not reflective of changing macroeconomic conditions, I compare the earnings response coefficient estimates for the sample firms with those from a random sample of firms from Freeman and Tse [1990].

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27 I am grateful to Robert Freeman for providing these data. Their cumulation periods (a four-day window beginning two days prior to the current quarter’s earnings announcement and a long window extending from two days after the preceding quarter’s earnings announcement to the day following the current quarter’s earnings announcement) differ slightly from the two-day window and long window considered in this study.
There is no apparent evidence of a systematic pattern in Freeman and Tse's [1990] earnings response coefficient estimates over the sample period that would explain the observed pattern in earnings response coefficients from this study. However, it is difficult to compare the two sets of earnings response coefficients since the 12 cross-sections considered in this study are not aligned in calendar time. A more formal comparison can be based on a weighted average of the earnings response coefficient estimates from Freeman and Tse for each of the 12 cross-sections in this study, with the weights determined by the proportion of the 200 observations in the cross-section which apply to a particular calendar quarter.\textsuperscript{28} Comparing each of the 12 earnings response coefficient estimates from the cross-sectional OLS regressions in this study with the weighted average earnings response coefficients from Freeman and Tse, there is no apparent evidence that the pattern in earnings response coefficients documented in this study was present for firms generally.\textsuperscript{29} Although there is slight evidence of a decline in the weighted average earnings response coefficients (e.g., the mean weighted average four-day earnings response coefficient is 0.127 for the first six observations versus 0.110 for the last six), it is not nearly large enough to explain the decrease in earnings response coefficients documented in this study.\textsuperscript{30} As a final check to ensure that the results are not time-period specific, I divide the firms into two subsamples based on the date of their first sample earnings announcement (i.e., before or after January 28, 1982). Evidence of a decline in earnings response coefficients persists in both subsamples, suggesting that the observed pattern in earnings response coefficients is robust to changes in the time period considered (at least to the limited extent considered here).

In summary, it does not appear that the alternatives considered in this section explain the observed pattern in earnings response coefficients over time. Of course, given that the list of alternatives considered is not

\textsuperscript{28} For example, if 75% of the observations from the first cross-section in this paper pertained to the first quarter of 1980 and the remainder pertained to the second quarter of 1980, and Freeman and Tse [1990] estimated earnings response coefficients of 1.0 and 2.0 for those two calendar quarters, respectively, the weighted average comparison earnings response coefficient would be \((0.75 \times 1.0) + (0.25 \times 2.0) = 1.25\). A similar computation would then be made for each of the 11 remaining cross-sections.

\textsuperscript{29} Because the early observations for a few of the sample firms occurred prior to 1980, approximately 3% of the observations cannot be matched with coefficients from the Freeman and Tse [1990] study; the conclusions do not appear to be sensitive to the exclusion of those firms.

\textsuperscript{30} I also replicate the analysis of the previous section on standardized earnings response coefficients, obtained by taking the difference between the earnings response coefficients from this study and the weighted average coefficients from Freeman and Tse [1990]. The pattern in standardized coefficients is virtually identical to that for the raw coefficient estimates reported in the previous section.
exhaustive and that in some cases the analysis is based on proxies for
unobservable variables, the possibility of alternative explanations cannot
be ruled out.

5. Conclusions

In this paper, I present a model in which investors learn about the
time-series parameter of a firm’s earnings process through observed
earnings. An implication of the model is that the informativeness of
earnings (as measured by the magnitude of the stock price response to
earnings) is greater when there is more uncertainty about the earnings
prospects for the firm. Therefore, for firms about which relatively little
is known (for example, newly traded firms), the magnitude of the stock
price response to earnings decreases over time as a longer time series of
earnings becomes available.

To provide evidence on that implication, I examine the stock price
response to quarterly earnings announcements for 200 firms over 12
quarters following their initial public offering dates. In general, the results
of the tests are consistent with the prediction that the earnings response
coefficients decrease over time, approaching a constant level. Evidence
from an analysis of alternate explanations for the observed pattern
suggests that the results are not driven by other factors which have been
shown to influence earnings response coefficients.

APPENDIX A

The analysis in the text assumes that earnings follow a random walk
with drift time-series process. From equation (5), earnings response
coefficients under that assumption vary only with \( t \), the length of the
earnings series used to estimate \( \lambda_i^* \). However, existing empirical evidence
suggests that earnings response coefficients are positively correlated with
the time-series persistence of earnings (see, for example, Kormendi and
Lipe [1987], Collins and Kothari [1989], Easton and Zmijewski [1989],
and Lipe [1990]). While there is no room for variation in persistence for
the random walk with drift process, an alternate time-series process for
earnings which has been considered in previous research (see, for exam-
ple, Ohlson [1990] and Easton and Zmijewski [1989]) and which implies
cross-sectional variation in earnings response coefficients based on per-
sistence is the following:

\[
a_{t+1} = (\theta + \epsilon_{t+1})a_t
\]

where \( \theta \) is the time-series parameter and the \( \epsilon_8 \) are serially uncorrelated
normally distributed error terms with \( E(\epsilon_t) = 0 \) and \( var(\epsilon_t) = \sigma_i^2 \). Similar
results follow for an autoregressive process with an additive error term.
Let $\theta^*_t$ denote investors' estimate of $\theta$ as of period $t$, and assume that investors' priors in period zero are diffuse. Assume further that price can be expressed in terms of earnings as in equation (1). Then, the price at time $t$ can be expressed as follows:

$$P_t = a_t \sum_{r=t}^{\infty} (R_F)^{-r-t} E_t(\theta^{-r-t}) = a_t \left( \frac{R_F}{R_F - \theta^*_t} \right) + c_t a_t$$  \hspace{1cm} (12)

where:

$$c_t = \frac{1}{t R_F^2} + \frac{1}{R_F^3} \left( \frac{3 \theta^*_t}{t} \right) + \frac{1}{R_F^4} \left( \frac{6 \theta^*_t}{t} + \frac{3}{t^2} \right) + \frac{1}{R_F^5} \left( \frac{10 \theta^*_t^2}{t} + \frac{15 \theta^*_t}{t^2} \right) + \cdots$$

Ignoring the second term in equation (12), let:

$$P_t^a = a_t \left( \frac{R_F}{R_F - \theta^*_t} \right).$$

Then:

$$P_t^a - P_{t-s}^a = a_t \left( \frac{R_F}{R_F - \theta^*_t} \right) - \theta^*_{t-1} a_{t-1} \left( \frac{R_F}{R_F - \theta^*_{t-1}} \right).$$  \hspace{1cm} (13)

An expression for the stock price response to earnings can be calculated by taking the partial derivative of equation (13) with respect to $a_t$:

$$\frac{\partial (P_t^a - P_{t-s}^a)}{\partial a_t} = \left( \frac{R_F}{R_F - \theta^*_t} \right) + \frac{a_t}{a_{t-1}} \left( \frac{R_F}{t (R_F - \theta^*_t)^2} \right).$$  \hspace{1cm} (14)

The first term in expression (14) would be the earnings response coefficient if $\theta$ were known and equal to $\theta^*_t$. The second term is the estimate of $\theta$ inherent in period $t$'s announced earnings multiplied by a term which is positive. Therefore, as time passes the second term in equation (14)
tends to zero. As was the case for the random walk with drift, the earnings response coefficient is decreasing in $t$, reducing in the limit to the case where $\theta$ is known.

The earnings response coefficient will vary cross-sectionally with both differences in the time-series parameter of earnings and the level of uncertainty. That will be the case because both terms in equation (14) are increasing in $\theta_t$'s. Therefore, in cross-sectional analysis, individual firm earnings response coefficients will be positively correlated with the $\theta_t$'s.

REFERENCES


