Post-Earnings Announcement Drift and the Dissemination of Predictable Information*

LEONARD C. SOFFER, Northwestern University

THOMAS LYS, Northwestern University

Abstract
Building on the work of Bernard and Thomas 1990, we develop a model to infer the degree to which the information in an earnings announcement is incorporated into investors' expectations for the subsequent earnings announcement at any point in time between the two announcements. We are unable to reject the null hypothesis that investors' earnings expectations are based on a seasonal random walk and reflect none of the implications of the immediately prior earnings announcement up to 15 trading days after that announcement. By mid-quarter, expectations are significantly more sophisticated than a seasonal random walk. Two trading days before the next earnings announcement, as much as one half of the information in the prior earnings announcement is reflected in earnings expectations. We also find that the dissemination of information, albeit predictable information, speeds the incorporation of prior earnings information into earnings expectations.

Our results suggest that as information about future earnings that could have been discerned from the earlier announcements (because past earnings surprises predict future ones) is disseminated in a more transparent form, investors revise their earnings expectations to reflect this information. Thus, the investors' expectations appear to incorporate more and more of the serial correlation in earnings surprises as the quarter progresses, even though they do not consider per se the serial correlation in earnings surprises in forming their expectations.

Accepted by John Wild. This paper was presented at the 1997 Contemporary Accounting Research Conference, generously sponsored by: the CGA-Canada Research Foundation, CGA-Ontario, the Canadian Institute of Chartered Accountants, the Ernst & Young Foundation, and the Society of Management Accountants of Ontario. Financial support from the Accounting Research Center at the J. L. Kellogg Graduate School of Management, Northwestern University is gratefully acknowledged. We thank John Wild (associate editor), Jacob Thomas and Larry Brown (discussants), and two anonymous reviewers for their comments. We also thank Ray Ball, Mary Barth, John Core, John Hand, Rachel Hayes, Roby Lehavy, Ramu Thiagarajan, Beverly Walther, and Ross Watts for their input. Finally, we thank seminar participants at the 1997 Contemporary Accounting Research Conference, the 1997 Big 10 Research Conference, the Massachusetts Institute of Technology, Northwestern University, Ohio State University, the University of Rochester, the 1996 Stanford University Accounting Research Summer Camp, Vanderbilt University, and the University of Wisconsin.

Contemporary Accounting Research Vol. 16 No. 2 (Summer 1999) pp. 305-31 ©CAAA
Condensed

Ball et Brown (1968) ont été les premiers à faire porter leurs recherches sur les mouvements réactifs postérieurs à l’annonce des résultats. D’autres se sont par la suite interrogés sur la robustesse des conclusions de Ball et Brown ou ont analysé dans quelle mesure les mouvements réactifs observés étaient attribuables aux méthodes de recherche utilisées plutôt qu’à la non-efficience du marché. Trente ans de recherche ont démontré l’extrême robustesse du mouvement réactif que l’on continue d’attribuer à une apparente non-efficience du marché. L’existence du mouvement réactif étant établie, les chercheurs ont orienté leurs analyses vers l’analyse des raisons comportementales et institutionnelles de cette non-efficience. Bernard et Thomas (1990), par exemple, constatent que les manifestations et l’importance des rendements anormaux des quatre trimestres postérieurs aux annonces de résultats sont reliées aux autocorrélations des erreurs prévisionnelles d’un modèle de marché aléatoire saisonnier naïf relatif aux attentes de résultats. Ils montrent en outre qu’une quantité disproportionnée de ces rendements anormaux se produisent aux environs des annonces de résultats subséquentes. Leurs constatations permettent de croire que le processus du mouvement réactif comporte deux étapes. La première est celle des erreurs dans la détermination du cours des actions immédiatement après les annonces de résultats en raison de l’incapacité des investisseurs à tenir pleinement compte des répercussions des résultats courants sur les résultats futurs. La seconde étape consiste dans la correction progressive du cours à mesure que les investisseurs révisent leurs attentes en ce qui a trait aux résultats futurs. C’est à cette étape que les auteurs observent des rendements anormaux qui peuvent être prévus grâce à l’information relative aux résultats antérieurs.

Dans le compte rendu de leurs recherches, les auteurs s’intéressent plus particulièrement à deux questions principales. En premier lieu, ils mesurent la difficulté qu’ont les investisseurs à incorporer immédiatement dans leurs attentes l’information contenue dans une annonce de résultats (première étape). En second lieu, ils analysent quand et comment ces attentes de résultats sont révisées de manière à incorporer l’information qui aurait pu être tirée de l’annonce de résultats antérieure (seconde étape).

L’analyse de ces questions exige l’inférence du niveau des attentes de résultats à divers moments entre les annonces de résultats. Contrairement aux chercheurs précédents, qui vérifiaient la convergence des rendements et de niveaux particuliers d’attentes de résultats, les auteurs élaborent un modèle permettant d’inférer le niveau des attentes à partir des rendements des actions. Ils permettent, en outre, la variation intertemporelle de la mesure dans laquelle les attentes reflètent l’information relative aux résultats antérieurs, entre les annonces de résultats consécutives, ce qui rend possible l’étude du moment où les attentes deviennent plus élaborées.

La première des deux équations du modèle proposé par les auteurs relie les résultats inattendus aux résultats inattendus décalés. La deuxième équation relie les résultats anormaux aux résultats inattendus antérieurs et subséquents. Le ratio des estimations du coefficient dans la deuxième équation donne la valeur estimée du coefficient de corrélation sériale implicite des attentes de résultats des investisseurs. Ce ratio est conjugué à la corrélation sériale réelle des résultats, que l’on estime dans la première équation, ce qui permet d’évaluer la mesure dans laquelle les attentes de résultats des investisseurs saisissent les répercussions des résultats courants sur les résultats futurs.

Les constatations des auteurs ajoutent à celles de Bernard et Thomas (1990). Ces derniers ont conclu que les investisseurs n’incorporent pas entièrement la corrélation sériale à leurs attentes de résultats. À l’aide de leur modèle, les auteurs montrent qu’immédiatement après une annonce de résultats, les investisseurs n’incorporent à peu près aucune de ses répercussions sur les résultats futurs. Les conclusions des auteurs
raccordent également les constatations de Bernard et Thomas (1990) et celles, apparemment dissemblables, de Ball et Bartov (1996) qui affirment que leurs conclusions « écartent les théories selon lesquelles les investisseurs agissent comme s’ils ignoraient, dans leur naïveté, les principaux attributs du comportement des résultats ». Ball et Bartov constatent que les investisseurs incorporent l’information relative aux résultats antérieurs dans leurs attentes mais sous-estiment l’ampleur de la corrélation sériale d’environ 50 pour cent. Si l’observation de Ball et Bartov selon laquelle les investisseurs tiennent expressément compte de la corrélation sériale mais l’estiment de façon erronée est juste, alors l’importance de cette erreur d’estimation devrait être à peu près constante tout au long du trimestre. Bien que Ball et Bartov consignent le fait que les attentes des investisseurs ne sont pas totalement naïves immédiatement avant l’annonce de résultats suivante, en raison de la fenêtre de rendements qu’ils utilisent, ils demeurent silencieux en ce qui a trait aux attentes à n’importe quel autre moment. Les constatations des auteurs indiquent toutefois que l’importance de l’erreur d’estimation varie de façon systématique au cours du trimestre. Deux jours de marché précédant l’annonce de résultats suivante, les auteurs constatent que leurs observations rejoignent celles de Ball et Bartov. La proportion de la corrélation sériale saisie dans les attentes est cependant beaucoup plus faible tôt dans le trimestre et elle est à peu près nulle au début du trimestre.

Pour rapprocher la conclusion de Ball et Bartov de celle des auteurs, il faudrait supposer que les investisseurs tiennent compte de la corrélation sériale dans les résultats mais qu’ils commettent, dans l’estimation de cette corrélation des erreurs d’importance variable tout au long du trimestre. Immédiatement après une annonce de résultats, les investisseurs utilisaient un coefficient de corrélation sériale de zéro, réviseraient lentement leurs attentes (à un niveau d’efficience de 50 pour cent) avant la fin du trimestre, et reviendraient ensuite à un coefficient de zéro au trimestre suivant.

Les auteurs proposent une autre explication. Les conclusions de Bernard et Thomas (1990), celles de Ball et Bartov (1996) et l’évolution des attentes que documentent les auteurs convergent toutes vers l’hypothèse selon laquelle les investisseurs ignorent la corrélation sériale dans les résultats inattendus. Les investisseurs révisent leurs attentes au cours du trimestre à mesure que leur parvient de l’information qu’ils perçoivent comme étant nouvelle, même si cette information aurait pu être tirée de résultats inattendus antérieurs. Cette explication, tout comme celle de Ball et Bartov, repose sur un certain degré d’irrationalité des investisseurs. Les auteurs l’estiment néanmoins plus plausible.

Les auteurs soumettent à un autre test l’hypothèse voulant que la diffusion de l’information entraîne la révision des attentes en analysant comment les investisseurs incorporent les répercussions des résultats antérieurs sur les résultats futurs. Ils énoncent l’hypothèse selon laquelle les attentes ne deviennent pas simplement plus élaborées mais tiennent compte de l’information relative aux résultats futurs à mesure qu’elle est diffusée. Dans une certaine mesure, il aurait été possible de fonder les attentes sur l’information relative aux résultats antérieurs. À mesure que les attentes sont révisées, elles semblent donc tenir compte de plus en plus de la corrélation sérielle des résultats inattendus, peu importe que les investisseurs prennent expressément ou non en considération les propriétés des séries chronologiques. Les auteurs formulent l’hypothèse selon laquelle la rapidité avec laquelle la correction des cours se produit est en relation positive avec le volume d’information mis à la disposition des investisseurs au sujet d’une entreprise. Ils perfectionnent leur modèle en y insérant les différences transversales dans le volume d’information au sujet des entreprises. Leurs constatations confirment cette hypothèse.

Dans l’ensemble, les conclusions des auteurs donnent à penser que les investisseurs ne prennent pas explicitement en considération la corrélation sériale mais procèdent plutôt
à la révision de leurs attentes à mesure que l’information — qu’ils auraient pu prévoir — est mise à leur disposition, ce qui donne lieu à un mouvement réactif postérieur à l’annonce de résultats.

1. Introduction
Ball and Brown (1968) first documented post-earnings announcement drift. Subsequent researchers sought either to examine the robustness of Ball and Brown’s findings or to investigate the extent to which drift was observed because of the research methods used rather than because of a market inefficiency. After 30 years of research, drift has been shown to be very robust, and it remains an apparent market inefficiency. Having accepted the existence of drift, researchers have shifted their investigations to examinations of the behavioral and institutional reasons for this inefficiency. Bernard and Thomas (1990), for example, find that the signs and magnitudes of abnormal returns in the four quarters subsequent to earnings announcements are related to the autocorrelations of forecast errors from a naive seasonal random walk earnings expectations model. In addition, they show that a disproportionately large amount of these abnormal returns occur around the subsequent earnings announcements. Their results suggest that drift is a two-stage process. The first stage is the mispricing of shares immediately after earnings announcements because of investors’ failure to incorporate fully the implications of current earnings for future earnings. The second stage is a gradual price correction as investors update their expectations of future earnings. It is in this second stage that we observe abnormal returns that are predictable using prior earnings information.

In this paper, we focus on two main questions. First, we investigate the extent to which investors’ expectations fail to capture immediately the information in an earnings announcement (first stage). Second, we analyze when and how earnings expectations are revised to reflect information that could have been discerned from the prior earnings announcement (second stage).

Analyzing these questions requires that we infer the level of earnings expectations at various points in time between earnings announcements. Thus, in contrast to prior literature, which has tested whether returns are consistent with particular levels of earnings expectations, we develop a model to infer the level of expectations from stock returns. Our model allows a parameter representing the degree to which future earnings expectations reflect the implications of prior earnings to vary from completely ignoring to fully incorporating them. This allows us to infer the level of earnings expectations from the data, and to estimate the degree to which expectations fail to capture available information. Further, we allow the degree to which expectations reflect prior earnings information to vary intertemporally between consecutive earnings announcements. This enables us to study when expectations become more sophisticated. Finally, we augment the model to include cross-sectional differences in the amount of information flow about firms to study how the price correction occurs.

Our results extend those of Bernard and Thomas 1990. Bernard and Thomas concluded that investors do not fully incorporate serial correlation in their earnings expectations. Using our model, we show that immediately after an
earnings announcement, investors incorporate essentially *none* of its implications for future earnings. Our results also reconcile Bernard and Thomas 1990 and the seemingly disparate findings of Ball and Bartov 1996, who argue that their results "rule out theories in which investors act as if naively unaware of the principal attributes of earnings behavior." Ball and Bartov found that investors do incorporate prior earnings information in their expectations, but underestimate the magnitude of the serial correlation by about 50 percent. If Ball and Bartov's conclusion that investors formally consider but mis-estimate serial correlation is correct, then the degree of this mis-estimation should be roughly constant throughout the quarter. While Ball and Bartov document that expectations are not completely naive just before the next earnings announcement, because of the returns window they use, their result is silent on expectations at any other point in time. However, our results show that the magnitude of the mis-estimation varies systematically during the quarter. At two trading days before the next earnings announcement, we find results consistent with Ball and Bartov. However, the proportion of serial correlation impounded in expectations is much smaller earlier in the quarter, and it is about zero at the beginning of the quarter.

To reconcile the Ball and Bartov conclusion with our results, one would have to assume that investors consider, but inaccurately estimate the magnitude of, the serial correlation in earnings by varying degrees throughout the quarter. Immediately after an earnings announcement, investors would use a serial correlation coefficient of zero, slowly update their expectations (to a 50 percent efficient level) by the end of the quarter, and then revert to a coefficient of zero in the following quarter.

We propose an alternative explanation. Bernard and Thomas (1990), Ball and Bartov (1996), and the evolution of expectations we document are all consistent with investors who are unaware of serial correlation in earnings surprises. Such investors update their expectations during the quarter as information they perceive to be new arrives, even though that information could have been discerned from the prior earnings surprise. This explanation, just like Ball and Bartov's, relies on some degree of investor irrationality. However, we believe that this explanation is more plausible.

We further test the hypothesis that the dissemination of information drives expectations revisions by investigating how investors incorporate the implications of prior earnings for future earnings. We conjecture that expectations do not simply become more sophisticated. Rather, as information about future earnings is released, expectations reflect that information. To some extent, that information could have been predicted from prior earnings information. Thus, as expectations are updated, they begin to appear as if they take the serial correlation of earnings surprises into account, whether investors formally consider the time series properties or not. Our conjecture suggests that the speed with which the price correction occurs is positively related to the volume of information made available about a firm. We find evidence consistent with our conjecture.

The remainder of the paper is organized as follows. Section 2 summarizes the post-earnings announcement drift literature. Section 3 discusses our models and results. Section 4 concludes the paper.
2. Post-earnings announcement drift

Beginning with the seminal paper of Ball and Brown 1968, researchers have documented that post-earnings announcement stock returns are related to the size and magnitude of the prior earnings surprises. (See also Foster, Olsen, and Shevlin 1984, Bernard and Thomas 1989, and Freeman and Tse 1989.) As a result, it is possible to earn abnormal returns of roughly 3 to 4 percent in the 60-day period following earnings announcements by going long (short) in firms with the most favorable (unfavorable) earnings surprises. This phenomenon, often referred to as post-earnings announcement drift, is robust to time period, company size, exchange, and general market movements.

Recently, researchers have begun to investigate why the mispricing that leads to drift occurs. Rendleman, Jones, and Latané (1987) and Freeman and Tse (1989) show that much of the observed drift is explained by a predictable response to subsequent earnings announcements. Bernard and Thomas (1990) conclude that the predictable response occurs because investors' earnings expectations do not fully incorporate the serial correlation in seasonally differenced earnings. Consistent with Bernard and Thomas, Bartov (1992) argues that the market's failure to characterize correctly the time series properties of earnings fully explains drift in the entire period between earnings announcements. Together, these papers point toward the inefficient use of the information contained in earnings announcements as the first stage in the creation of drift.

Abarbanell and Bernard (1992), in seeking to determine what expectations investors use, follow an approach similar to Bernard and Thomas 1990 in that they compare the magnitude of the observed drift to what one would predict given an assumed earnings expectations level. The major difference between Abarbanell and Bernard and Bernard and Thomas is that Abarbanell and Bernard use Value Line forecasts as a proxy for investors' earnings expectations, while Bernard and Thomas use a seasonal random walk. Abarbanell and Bernard find that the drift is greater than what would be implied by investors' reliance on Value Line forecasts, and that expectations for the subsequent earnings announcement are closer to a seasonal random walk than are the Value Line forecasts. These results suggest that security analyst behavior may partially explain post-earnings announcement drift. Shane and Brous (1996) find that both stock prices and analyst earnings forecast revisions underreact to non-earnings information, and that the underreactions are not significantly different from each other. They argue that analysts fail to incorporate all available information in making their forecasts and investors rely on those forecasts, making prices informationally inefficient.

Ball and Bartov (1996) show that investors do incorporate, but not fully, past earnings changes in forming their expectations for the next earnings announcement. Their regressions use returns beginning two trading days prior to the next earnings announcement. Thus when they infer expectations, those expectations are as of two trading days before the next earnings announcement. By this time, investors have adjusted their earnings expectations so that they incorporate some of the serial correlation in seasonally differenced earnings. While the Ball and Bartov results show that expectations are not a seasonal random walk by two
trading days before the next earnings announcement, little is known about the level of expectations earlier in the quarter, or what mechanism causes expectations to become more sophisticated.

3. Empirical model and results
We first describe our data. We then show that seasonally differenced earnings are serially correlated in our sample. Next, we develop a model to infer the degree to which the implications of this serial correlation have been impounded into investors’ earnings expectations at any point in time. We estimate the model and document how investors’ earnings expectations change in 15-day intervals between earnings announcements. We then relate the extent to which earnings expectations incorporate prior earnings information to the volume of information dissemination.

Sample selection and data
Our sample consists of all companies that have a December 31 fiscal year-end and that are listed on the New York or the American Stock Exchange. Quarterly earnings per share amounts and earnings announcement dates are obtained from COMPUSTAT. Abnormal returns are obtained from the Center for Research in Security Prices (CRSP) and are the CRSP beta-adjusted returns series. Twenty-five thousand, seven hundred and nine company-quarters relating to 798 distinct companies had the necessary earnings and return data. To measure information flow, we obtain 71,232 trade recommendations issued by 215 sell-side analyst firms from Zacks Investment Research (ZIR). These recommendations were issued in 11,660 (45 percent) of the 25,709 company-quarters for 509 (64 percent) of the 798 companies. We note that the distribution of trade recommendations (53.5 percent buys, 38.0 percent holds, 8.5 percent sells) is similar to the results in Francis and Soffer 1997.1 Further, the mean three-day cumulative abnormal returns (CARs) around the recommendation date for each of the three categories are consistent with basic intuition; that is, CAR(buy) > CAR(hold) > CAR(sell). (An F-test rejects the equality of the three means; $F = 61.2$, degrees of freedom = 2 and 71,229; $p = 0.0000$).

Information contained in current earnings for future earnings
For company $j$ and quarter $t$, we compute earnings surprise ($\Delta EPS_{jt}$) as the seasonally differenced quarterly earnings per share from continuing operations ($EPS_{jt} - EPS_{jt-4}$), adjusted for stock dividends and stock splits and deflated by the absolute value of $EPS_{jt-4}$. To reduce the impact of outliers, we winsorize $\Delta EPS_{jt}$ at $\pm 1$.2 Panel A of Table 1 provides descriptive statistics for this metric, showing that, on average, $\Delta EPS_{jt}$ is slightly positive. (Mean = 0.044; median = 0.067).

We estimate the correlation between successive earnings surprises with the following pooled, time series, cross-sectional regression.$^3$

$$\Delta EPS_{jt} + 1 = \alpha + \beta \cdot \Delta EPS_{jt} + \epsilon_{1,j}$$ (1)
Panel B of Table 1 reports the results. Consistent with prior research, our sample exhibits significant positive serial correlation of seasonally differenced earnings per share. For the entire sample of 25,709 company-quarters with valid data, $\hat{\beta} = 0.4027$, while $\hat{\beta} = 0.3750$ for the 11,660 company-quarters containing at least one analyst recommendation and $\hat{\beta} = 0.4191$ for the 14,049 company-quarters having no recommendations. The $F$-statistic for the equality of both $\alpha$ and $\beta$ across the two subsamples is 6.89 (degrees of freedom = 2 and 25,705; $p < 0.01$). Although the serial correlations of the two subsamples differ statistically, both are similar in magnitude to those reported in Bernard and Thomas 1990.

**Inferring the degree to which prior earnings information has been incorporated in earnings expectations**

In an efficient market, investors' earnings expectations would reflect the serial correlation of earnings described in (1): $\bar{E}_{t+\tau}(\Delta EPS_{j,t+1} | \Delta EPS_{j,t}) = \alpha + \beta \Delta EPS_{j,t}$, where $t + \tau$ is a date between consecutive earnings announcement dates $t$ and $t + 1$ ($0 \leq \tau < 1$). Rather than assuming any particular level to which investors' expectations incorporate prior earnings information, we explicitly allow investors to incorporate all, some, or none of the serial correlation of earnings in their

**TABLE 1**

<table>
<thead>
<tr>
<th>Serial correlation of earnings surprises</th>
</tr>
</thead>
</table>

**Panel A:** Descriptive statistics for $\Delta EPS_{j,t}$

<table>
<thead>
<tr>
<th>Mean</th>
<th>0.044</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation</td>
<td>0.595</td>
</tr>
<tr>
<td>25th percentile</td>
<td>-0.308</td>
</tr>
<tr>
<td>Median</td>
<td>0.067</td>
</tr>
<tr>
<td>75th percentile</td>
<td>0.368</td>
</tr>
</tbody>
</table>

**Panel B:** Regression estimates

Model: $\Delta EPS_{j,t+1} = \alpha + \beta \cdot \Delta EPS_{j,t} + e_{t,j}$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>Greater than zero</th>
<th>Zero</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CONSTANT$</td>
<td>0.0304</td>
<td>0.0319</td>
<td>0.0301</td>
</tr>
<tr>
<td>$t$-statistic</td>
<td>8.89</td>
<td>6.76</td>
<td>6.15</td>
</tr>
<tr>
<td>$\Delta EPS_{j,t}$</td>
<td>0.4027</td>
<td>0.3750</td>
<td>0.4191</td>
</tr>
<tr>
<td>$t$-statistic</td>
<td>70.22</td>
<td>43.08</td>
<td>54.75</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.14</td>
<td>0.16</td>
<td>0.18</td>
</tr>
<tr>
<td>$N$</td>
<td>25,709</td>
<td>11,660</td>
<td>14,049</td>
</tr>
</tbody>
</table>

Notes:

$\Delta EPS_{j,t} =$ Company $j$'s seasonally differenced earnings per share deflated by the absolute value of earnings per share at $t - 4$. 
expectations. We depart further from prior literature by allowing the extent to which investors have incorporated the serial correlation of earnings to vary intertemporally between earnings announcement dates. Thus, we model investors' earnings expectations as of \( t + \tau \) conditional on prior earnings as

\[
E_{t+\tau}(\Delta EPS_{j,t+1} \mid \Delta EPS_{j,t}) = \alpha^*_{t+\tau} + \beta^*_{t+\tau} \cdot \Delta EPS_{j,t}
\]  

(2)

\( \beta^*_{t+\tau} \) measures the level of serial correlation implicit in investors' expectations for the subsequent earnings announcement as of \( t + \tau \). We expect \( \beta^*_{t+\tau} \) to be between zero (investors ignore serial correlation) and \( \beta \) (investors fully impound serial correlation), where \( \beta \) is the actual serial correlation coefficient [see equation (1)], and to be increasing through the quarter as \( \tau \) varies from zero to one.

Because \( E_{t+\tau}(\Delta EPS_{j,t+1} \mid \Delta EPS_{j,t}) \) is not observable, equation (2) cannot be used to estimate \( \beta^*_{t+\tau} \). Therefore, we develop a model that allows us to infer \( \beta^*_{t+\tau} \) from stock returns subsequent to \( t + \tau \). We postulate that the abnormal return between \( t + \tau \) and \( t + 1 \) is a linear function of the difference between the actual earnings announced at \( t + 1 \) and investors' expectations of those earnings as of \( t + \tau \), both normalized on \( |EPS_{j,t-3}| \). That is,

\[
CAR(t+\tau, t+1)_j = \gamma + \delta_{t+\tau} \cdot \frac{1}{|EPS_{j,t-3}|} \cdot [EPS_{j,t+1} - E_{t+\tau}(EPS_{j,t+1} \mid \Delta EPS_{j,t})] + \epsilon_{2,j}
\]

where \( CAR(t + \tau, t + 1)_j \) is company \( j \)'s cumulative abnormal return between \( t + \tau \) and \( t + 1 \). Subtracting \( EPS_{j,t-3} \) from both \( EPS_{j,t+1} \) and its expectation gives

\[
CAR(t + \tau, t + 1)_j = \gamma + \delta_{t+\tau} \cdot [\Delta EPS_{j,t+1} - E_{t+\tau}(\Delta EPS_{j,t+1} \mid \Delta EPS_{j,t})] + \epsilon_{2,j}
\]

(4)

Substituting (2) into (4) and rearranging leads to

\[
CAR(t + \tau, t + 1)_j = (\gamma - \delta \cdot \alpha^*_{t+\tau}) + \delta \cdot \Delta EPS_{j,t+1} - \delta \cdot \beta^*_{t+\tau} \cdot \Delta EPS_{j,t} + \epsilon_{2,j}
\]

(5)

(5) indicates that \( \beta^*_{t+\tau} \) can be estimated by taking the negative of the ratio of the estimated coefficients on \( \Delta EPS_{j,t} \) and \( \Delta EPS_{j,t+1} \). Importantly, estimating the level of serial correlation implicit in investors' earnings expectations at different points in time requires the use of different returns windows. To infer expectations at \( t + \tau \), the returns window must run from \( t + \tau \) to \( t + 1 \), the date the actual information is disclosed.

The estimator of \( \delta (= \delta_{t+\tau}) \) and the estimator of \( -\delta \cdot \beta^*_{t+\tau} (= \hat{\lambda}) \) in our model are mean-zero random variables, so our estimate of \( \beta^*_{t+\tau} \) (the negative of the ratio of the estimates of \( \delta \) and \( -\delta \cdot \beta^*_{t+\tau} \)) does not have a well-defined distribution. Therefore, we re-estimate our model using the direct estimation method described in Mishkin 1983. Appendix 1 describes this procedure. As discussed in this appendix, our OLS estimates of \( \beta^*_{t+\tau} \) are identical to those using direct estimation, although the
t-statistics differ from the OLS t-statistics, which are biased. We present the
direct-estimation t-statistics with our results. The Mishkin procedure also allows
us to perform a likelihood ratio test on the cross-equation restriction that $\beta = \beta_r^*$, which we are unable to do using OLS.

**Results**
We estimate equation (5) at 15-day intervals between earnings announcements. Panel
A of Table 2 reports regression results for returns accumulation periods with starting
dates between $t$ and $t+1$ quarter – 2 trading days. When the returns accumulation
period begins immediately after the earnings announcement, the estimate of $-\delta \cdot \beta^*_r$, the coefficient on $\Delta EPS_{j,t}$, is not significantly different from zero ($t = 0.88$). However, the coefficient estimate becomes negative as $\tau$ increases and it is significantly
different from zero from $\tau = 30$ trading days ($t = -2.57$) onward. By two trading days
before the next earnings announcement, $\hat{\beta} = -0.0042$ ($t = -7.18$).

Panel B of Table 2 reports the values of $\beta^*_r$ implied by our regression results. It also reports direct-estimation t-statistics for the hypothesis that investors’
earnings expectations incorporate none of the information in the announcement
($\beta^*_r = 0$). Up to 15 trading days following an earnings announcement, we cannot
reject the null hypothesis that investors’ expectations incorporate none of the
information in the announcement. However, $t$-tests reject the null hypothesis that $\beta^*_r = 0$ from $\tau = 30$ trading days on. Finally, likelihood ratio tests reject the null hypothesis that investors’ earnings expectations incorporate all of the information
in prior earnings ($\beta^*_r = \beta$) for all values of $\tau$. Together, these tests indicate that (a)
immediately after an earnings announcement, essentially none of the information
in prior earnings is impounded in investors’ expectations for the next earnings
announcement, (b) by mid-quarter, some of this information is incorporated in
investors’ earnings expectations, and (c) investors’ earnings expectations never
incorporate all the information contained in $\Delta EPS_{j,t}$. The implied values of $\beta^*_r / \beta$, which measure the degree to which investors’ expectations incorporate the
implications of current earnings for future earnings, indicate that although investors’ expectations become more sophisticated over time, only about half of
the serial correlation is incorporated in expectations by two trading days prior to
the next earnings announcement.

**Comparison to Bernard and Thomas and Ball and Bartov**
Our results indicate that $\beta^*_r / \beta$ is monotonically increasing throughout the quarter
and that a disproportionate amount of the increase occurs around the subsequent
earnings announcement ($t + 1$). This pattern is similar to the CAR pattern in
Bernard and Thomas 1990. However, it is not the case that our findings are a mere
restatement of the Bernard and Thomas results. For $\beta^*_r / \beta$, to be just a simple
rescaling of $CAR(t, t + \tau)$, the values shown in the Bernard and Thomas graph,
two conditions must hold. First, it would have to be the case that investors
completely ignore serial correlation immediately after an earnings announcement.
In other words, $\beta^*_r = 0$ for $\tau = 0$. While we do not find $\beta^*_r$ to be significantly
different from zero at $\tau = 0$, this is a new result of our analysis and cannot be
TABLE 2
The relation between cumulative abnormal returns and earnings surprises regression results for various values of \( \tau \)

Model: \( \text{CAR}(t + \tau, t + 1) = (\gamma - \delta \cdot \alpha^t) + \delta \cdot \Delta \text{EPS}_{j,t+1}^t - \delta \cdot \beta_t^t \Delta \text{EPS}_{j,t}^t + \varepsilon_{2j} \)

<table>
<thead>
<tr>
<th>Variable</th>
<th>( t )</th>
<th>( t + 15 ) days</th>
<th>( t + 30 ) days</th>
<th>( t + 45 ) days</th>
<th>( t + 1-2 ) days</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-0.0187</td>
<td>-0.0148</td>
<td>-0.0117</td>
<td>-0.0085</td>
<td>-0.0004</td>
</tr>
<tr>
<td>( t )-statistic</td>
<td>-19.19</td>
<td>-17.41</td>
<td>-15.27</td>
<td>-12.94</td>
<td>-1.17</td>
</tr>
<tr>
<td>( \Delta \text{EPS}_{j,t+1}^t )</td>
<td>0.0545</td>
<td>0.0486</td>
<td>0.0422</td>
<td>0.0315</td>
<td>0.0197</td>
</tr>
<tr>
<td>( t )-statistic</td>
<td>30.75</td>
<td>31.07</td>
<td>30.03</td>
<td>25.97</td>
<td>33.84</td>
</tr>
<tr>
<td>( \Delta \text{EPS}_{j,t}^t )</td>
<td>0.0016</td>
<td>-0.0019</td>
<td>-0.0036</td>
<td>-0.0046</td>
<td>-0.0042</td>
</tr>
<tr>
<td>( t )-statistic</td>
<td>0.88</td>
<td>-1.21</td>
<td>-2.57</td>
<td>-3.76</td>
<td>-7.18</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>( N )</td>
<td>25,709</td>
<td>24,697</td>
<td>24,469</td>
<td>23,066</td>
<td>24,640</td>
</tr>
</tbody>
</table>

Panel B: Implied Values

| Implied \( \beta_x^t \) | -0.0287 | 0.0391 | 0.0861 | 0.1468 | 0.2127 |
| \( t \)-statistic* | -0.87 | 1.23 | 2.66 | 3.97 | 7.68 |
| Likelihood ratio statistic (\( \beta_x^t = \beta \)) | 201.36 | 151.06 | 109.20 | 58.84 | 50.24 |
| \( p \)-value[\( \chi^2(1) \)] | .0000 | .0000 | .0000 | .0000 | .0000 |
| Implied \( \beta_x^t / \beta \) | -0.0713 | 0.0971 | 0.2138 | 0.3645 | 0.5282 |

Notes:
* Directly estimated using non-linear least squares. See Appendix 1 for a discussion of this method.

\( \text{CAR}(t + \tau, t + 1)_j \) = Company \( j \)'s cumulative abnormal return between the intermediate date \( t + \tau \) and the next earnings announcement date.

\( \Delta \text{EPS}_{j,t}^t \) = Company \( j \)'s seasonally differenced earnings per share deflated by the absolute value of earnings per share at \( t - 4 \).

Inferred from the results in Bernard and Thomas. Second, the coefficient on \( \Delta \text{EPS}_{j,t+1}^t \) would have to be invariant to \( \tau \). Appendix 2 explains why we expect that not to be the case, and panel A of Table 2 confirms our expectation empirically. As a result, it is possible to conclude from the Bernard and Thomas results that expectations are not fully efficient. However, it is not possible to infer the degree to which investors have impounded the serial correlation of seasonally differenced earnings into their expectations. Thus, our results extend, rather than replicate, the Bernard and Thomas findings.

Examining how \( \beta_x^t \) changes with \( \tau \) provides a link between Bernard and Thomas 1990 and Ball and Bartov 1996. Ball and Bartov argue that investors do
incorporate, but not completely, the implications of prior earnings. Their results are based on regressions of three-day CARs around the next earnings announcement on past and future earnings surprises. In terms of our model, Ball and Bartov find that $0 < \beta_\tau < \beta$ when $\tau = +1$ quarter $-2$ trading days. Like Ball and Bartov, we reject the conjecture that investors' earnings expectations are based on a seasonal random walk model immediately prior to the subsequent earnings announcement. In fact, we find the magnitude of $\beta_\tau$ to be similar to Ball and Bartov's result, and further show that the difference is statistically significant. However, Ball and Bartov's conclusion that investors partially incorporate prior earnings information is valid only as of the beginning of their returns accumulation period, which is two trading days prior to the subsequent earnings announcement. Estimating earlier expectations requires the use of a returns accumulation period that begins earlier. When we use wider returns windows to infer expectations earlier in the quarter, we find that $\beta_\tau$ is smaller, and that it is not significantly different from zero when $\tau \leq 15$ trading days. That is, we cannot reject the null hypothesis that immediately after an earnings announcement, investors' expectations are based on a seasonal random walk.

**Model refinements and sensitivity tests**

*Sensitivity of model to one-lag assumption*

We examined the sensitivity of our analysis to the assumption of a single-lag relation for seasonally differenced earnings. Earnings certainly follow a more complicated process and investors may also use a more sophisticated expectations model. As a result, our estimators of $\beta$ and $\beta_\tau$ may be biased. However, under fairly general conditions, this bias affects the estimators of $\beta$ and $\beta_\tau$ in the same manner, leaving the ratio $\beta_\tau / \beta$, which measures the degree to which serial correlation is incorporated in expectations, virtually unaffected. Thus, our inferences about the degree to which the information in prior earnings is incorporated into expectations, which are based on $\beta_\tau / \beta$, are robust to the actual time series process and form of investors' expectations. Further, $\beta_\tau / \beta$ can be interpreted as a weighted average of the extent to which investors have incorporated information from the immediately prior earnings surprise and additional lagged surprises that are correlated with the first lag. Thus we capture, in a single measure, the degree to which all information correlated with the first lag is incorporated into earnings expectations. The weights in this measure depend on the serial correlation coefficients, but for reasonable correlation structures, most of the weight is on the first lag. We present this analysis in Appendix 3.

To confirm that our results are not sensitive to our use of a single lag, in addition to providing the analysis in Appendix 3, we reran our model using four lags and the three-day returns window, as in Ball and Bartov. We obtained results similar to theirs. The coefficients on $\Delta EPS_{jt+1}$, $\Delta EPS_{jt}$, $\Delta EPS_{jt-1}$, $\Delta EPS_{jt-2}$, and $\Delta EPS_{jt-3}$ were positive, negative, negative, negative and positive, respectively. We also found the ratio of the implied $\beta_\tau$ to $\beta$ for lag 3 to be greater than one, consistent with Ball and Bartov. We reran our model using four lags for all
of our earlier expectations dates as well. We found similar patterns in those tests, but with generally smaller implied values of $\beta^*_r$.

**Effect of the release of information unrelated to prior earnings**

Our model of earnings expectations (2) ignores information that investors obtain between earnings announcements that is useful in predicting $\Delta EPS_{j,t+1}$ but that is unrelated to the serial correlation of earnings and is therefore unpredictable based on prior earnings. In Appendix 2, we augment equation (2) to include this additional information in the expectation and then examine how the returns equation (5), which we use to estimate $\beta^*_r$, is affected. The analysis shows that this refinement to the model does not change the fact that we can infer the degree to which earnings expectations reflect the serial correlation by taking the negative of the ratio of the two regression coefficients. It also explains the intraquarter changes in the estimates of the intercept and the coefficient on $\Delta EPS_{j,t+1}$ in the results in Table 2. The importance of this analysis is that it shows that the appropriate divisor for estimating $\beta^*_r$ is the estimate of $\delta$ for the same returns window.

**Sensitivity to homogeneity assumption**

Our model assumes homogeneity across all observations, which is unlikely to hold. In particular, different patterns of seasonality and different levels of permanence of earnings shocks are likely to exist in different industries. We examine the sensitivity of our analysis to our homogeneity assumption by partitioning the sample by two-digit SIC codes. Panel A of Table 3 presents a summary of the results for the 10 two-digit SIC codes having the greatest number of observations in our sample. The serial correlation coefficient ($\beta$) is, on average, similar to the results for our pooled regression. Industry-specific estimates of $\beta$ range from 0.1674 to 0.5705, with the mean (median) 0.4411 (0.4555). Our estimates of $\beta^*_r$ vary across industry, but are generally increasing in $r$, as in the pooled regressions. The mean (median) value of $\beta^*_r / \beta$ is $-0.7637$ ($0.2066$) at $r = 0$ and $0.5586$ ($0.6422$) at $r = 1$ quarter – 2 trading days. By this last intermediate date, nine of the ten industry groups show a positive value of $\beta^*_r / \beta$, and the $t$-statistic is above 2.00 in magnitude for five of the 10 industries.

We also partition our sample by quarter to determine the extent to which different quarters exhibit different behavior. The results of this analysis are presented in panel B of Table 3. $\beta$ is lower for the fourth quarter subsample. Further, $\beta^*_r$ increases more quickly for that quarter, and even exceeds $\beta$ by $r = 1$ quarter – 2 trading days.

**Effect of information dissemination on investors’ expectations**

Next we expand our model to investigate the impact of information dissemination on investors’ expectations. We rewrite $\beta^*_r$ as $\beta^*_j, r$ and allow it to vary cross-sectionally with the amount of information that has been disseminated about the firm since the last earnings announcement. We use $NRECS(t, t + \tau)$, the number of analyst trade recommendations that were issued between $t$ and $t + \tau$, as a proxy for the volume of information dissemination.
TABLE 3
The relation between cumulative abnormal returns and earnings surprises regression results for various values of \( \tau \)

Models: 
\[
\Delta EPS_{j,t+1} = \alpha + \beta \cdot \Delta EPS_{j,t} + \epsilon_{i,j}
\]
\[
CAR(t + \tau, t + 1) = (\gamma - \delta \cdot \alpha^* + \beta \cdot \Delta EPS_{j,t+1} - \delta \cdot \beta^* \cdot \Delta EPS_{j,t} + \epsilon_{2,j})
\]

Panel A: Summary of individual industry regressions
\( \hat{\beta}_\tau \) when beginning of returns accumulation period is

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Mean ( \beta )</th>
<th>Mean ( t )</th>
<th>Mean ( t + 15 ) days</th>
<th>Mean ( t + 30 ) days</th>
<th>Mean ( t + 45 ) days</th>
<th>Mean ( t + 1-2 ) days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.4411</td>
<td>-0.7637</td>
<td>-0.1073</td>
<td>0.0769</td>
<td>0.1531</td>
<td>0.5586</td>
</tr>
<tr>
<td>Median</td>
<td>0.4555</td>
<td>0.2066</td>
<td>0.1460</td>
<td>0.4312</td>
<td>0.2664</td>
<td>0.6422</td>
</tr>
<tr>
<td>( t )-statistics</td>
<td>Mean</td>
<td>13.88</td>
<td>0.17</td>
<td>0.38</td>
<td>0.79</td>
<td>0.71</td>
</tr>
<tr>
<td>Median</td>
<td>14.01</td>
<td>0.17</td>
<td>0.40</td>
<td>1.26</td>
<td>0.54</td>
<td>1.80</td>
</tr>
<tr>
<td>Number positive (out of 10)</td>
<td>10</td>
<td>6</td>
<td>6</td>
<td>7</td>
<td>7</td>
<td>9</td>
</tr>
</tbody>
</table>

Panel B: Summary of individual quarterly regressions
\( \hat{\beta}_\tau \) when beginning of returns accumulation period is

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Coefficient ( \beta )</th>
<th>( t )-statistic</th>
<th>( t + 15 ) days</th>
<th>( t + 30 ) days</th>
<th>( t + 45 ) days</th>
<th>( t + 1-2 ) days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quarter 1</td>
<td>0.4733</td>
<td>41.97</td>
<td>-0.0701</td>
<td>-0.0352</td>
<td>-0.0729</td>
<td>0.0375</td>
</tr>
<tr>
<td>Quarter 2</td>
<td>0.4528</td>
<td>39.32</td>
<td>-0.0177</td>
<td>-0.0093</td>
<td>-0.0521</td>
<td>0.0329</td>
</tr>
<tr>
<td>Quarter 3</td>
<td>0.4216</td>
<td>32.22</td>
<td>0.1098</td>
<td>0.1656</td>
<td>0.3967</td>
<td>0.3485</td>
</tr>
<tr>
<td>Quarter 4</td>
<td>0.3076</td>
<td>24.70</td>
<td>-0.37</td>
<td>0.0191</td>
<td>0.0878</td>
<td>0.1084</td>
</tr>
<tr>
<td>( t )-statistic</td>
<td>1.14</td>
<td>0.57</td>
<td>1.18</td>
<td>-0.60</td>
<td>-3.50</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.6</td>
<td>0.32</td>
<td>0.76</td>
<td>-0.43</td>
<td>-2.53</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.22</td>
<td>0.13</td>
<td>0.3967</td>
<td>0.3485</td>
<td>0.0203</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.076</td>
<td>0.0191</td>
<td>0.0878</td>
<td>0.1084</td>
<td>0.2119</td>
<td>0.4139</td>
</tr>
<tr>
<td></td>
<td>0.37</td>
<td>-1.39</td>
<td>-2.10</td>
<td>-4.42</td>
<td>-3.54</td>
<td>-0.28</td>
</tr>
<tr>
<td>Notes:</td>
<td>( t )-statistics are for ( \beta = 0 ) and ( \delta \cdot \beta^* = 0 ).</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( CAR(t + \tau, t + 1) ) = Company ( j )'s cumulative abnormal return between the intermediate date ( t + \tau ) and the next earnings announcement date.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \Delta EPS_{j,t} ) = Company ( j )'s seasonally differenced earnings per share deflated by the absolute value of earnings per share at ( t - 4 ).</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
If information dissemination causes expectations to be revised, then $\beta_{r,R}$ will be positive.

We use the number of analyst recommendations as our measure of information flow because these generally include narrative explanations of recent developments at the company. Also, they often include an earnings forecast, as well as other information that will be useful to investors trying to forecast earnings or make investment decisions. In using the number of analyst recommendations in the regressions, we do not suggest that it is the analyst recommendations per se that cause the revision. We use the recommendation count simply as a measure of information flow. Arguably, there are other measures of information flow. As discussed later, using an earnings forecast count does not alter the results qualitatively.

Replacing $\beta_{r}$ in (5) with the expression in (6) results in

$$CAR(t + \tau, t + 1)_{j} = (\gamma - \delta \cdot \alpha_{r}) + \delta \cdot \Delta EPS_{j,t+1} - \delta \cdot \beta_{r,0} \cdot \Delta EPS_{j,t} - \delta \cdot \beta_{r,R} \cdot NRECS(t, t + \tau)_{j} \cdot \Delta EPS_{j,t} + \epsilon_{2,j}$$

Results

Panel A of Table 4 reports the distribution of recommendations broken down by 15-day periods between earnings announcements. There are more reports issued just after an earnings announcement (1 to 15 trading days) and just before the next one (≥ 46 trading days). An independence test indicates that the level of recommendation and the period in which it is published are not independent ($\chi^2(6) = 21.22; p = 0.0017$). This results from slightly higher (lower) frequencies of buys and sells (holds) in both the 1 to 15 trading days and the ≥ 46 trading days periods. Panel B of Table 4 reports the distribution of the number of trade recommendations per company-quarter for the 11,660 company quarters with at least one trade recommendation. The mean (median) number of trade recommendations per company-quarter is 6.1 (5.0).

We estimate equation (7) for $\tau$ ranging from 15 trading days to one quarter minus two trading days. Table 5 reports our results, including the earlier results for $\tau = 0$ and for which, by construction, $NRECS(t, t + \tau)_{j} = 0$ for all firms. The estimate of $-\delta \cdot \beta_{r,R}$ is negative and statistically significant for all non-zero values of $\tau$ (marginally so for $\tau = 45$ trading days and $\tau = 1$ quarter – 2 trading days), implying that the value of $\beta_{r,R}$ is positive and that the dissemination of information facilitates the incorporation of prior earnings information into earnings expectations. Our estimate of $\beta_{r,0}$ is smaller (in absolute value) than was our estimate of $\beta_{r}$ in the original model, although it is still significantly different from zero at $\tau = 45$ trading days and $\tau = 1$ quarter – 2 trading days. Directly estimated $t$-statistics confirm the OLS results.

Our results indicate that the dissemination of information speeds the incorporation of serial correlation in earnings expectations. When the volume of information was not modeled, we found no significant difference between investors’
TABLE 4
Trade recommendation descriptive statistics

Panel A: Intertemporal Distribution of Trade Recommendations

<table>
<thead>
<tr>
<th>Trade recommendation*</th>
<th>Total</th>
<th>1–15 days</th>
<th>16–30 days</th>
<th>31–45 days</th>
<th>≥ 46 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy</td>
<td>38,082</td>
<td>(53.5)</td>
<td>(54.0)</td>
<td>(53.2)</td>
<td>(52.3)</td>
</tr>
<tr>
<td>Hold</td>
<td>27,084</td>
<td>(38.0)</td>
<td>(37.3)</td>
<td>(38.6)</td>
<td>(39.2)</td>
</tr>
<tr>
<td>Sell</td>
<td>6,066</td>
<td>(8.5)</td>
<td>(8.7)</td>
<td>(8.2)</td>
<td>(8.5)</td>
</tr>
<tr>
<td>Total</td>
<td>71,232</td>
<td>(27.4)</td>
<td>(23.4)</td>
<td>(21.3)</td>
<td>(27.9)</td>
</tr>
</tbody>
</table>

Panel B: Distribution of number of recommendations per company-quarter

<table>
<thead>
<tr>
<th>NRECS</th>
<th>Number of company-quarters</th>
<th>Frequency %</th>
<th>Cumulative frequency %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1,688</td>
<td>14.48</td>
<td>14.48</td>
</tr>
<tr>
<td>2</td>
<td>1,310</td>
<td>11.24</td>
<td>25.71</td>
</tr>
<tr>
<td>3</td>
<td>1,173</td>
<td>10.06</td>
<td>35.77</td>
</tr>
<tr>
<td>4</td>
<td>1,138</td>
<td>9.76</td>
<td>45.53</td>
</tr>
<tr>
<td>5</td>
<td>1,026</td>
<td>8.80</td>
<td>54.33</td>
</tr>
<tr>
<td>6</td>
<td>869</td>
<td>7.45</td>
<td>61.78</td>
</tr>
<tr>
<td>7</td>
<td>771</td>
<td>6.61</td>
<td>68.40</td>
</tr>
<tr>
<td>8</td>
<td>681</td>
<td>5.84</td>
<td>74.24</td>
</tr>
<tr>
<td>9</td>
<td>570</td>
<td>4.89</td>
<td>79.13</td>
</tr>
<tr>
<td>10</td>
<td>514</td>
<td>4.41</td>
<td>83.53</td>
</tr>
<tr>
<td>11</td>
<td>428</td>
<td>3.67</td>
<td>87.20</td>
</tr>
<tr>
<td>12</td>
<td>301</td>
<td>2.58</td>
<td>89.79</td>
</tr>
<tr>
<td>13</td>
<td>277</td>
<td>2.38</td>
<td>92.16</td>
</tr>
<tr>
<td>14</td>
<td>221</td>
<td>1.90</td>
<td>94.06</td>
</tr>
<tr>
<td>15</td>
<td>174</td>
<td>1.49</td>
<td>95.55</td>
</tr>
<tr>
<td>16</td>
<td>120</td>
<td>1.03</td>
<td>96.58</td>
</tr>
<tr>
<td>17</td>
<td>92</td>
<td>0.79</td>
<td>97.37</td>
</tr>
<tr>
<td>18</td>
<td>69</td>
<td>0.59</td>
<td>97.96</td>
</tr>
<tr>
<td>19</td>
<td>60</td>
<td>0.51</td>
<td>98.47</td>
</tr>
<tr>
<td>20</td>
<td>39</td>
<td>0.33</td>
<td>98.81</td>
</tr>
<tr>
<td>21</td>
<td>39</td>
<td>0.33</td>
<td>99.14</td>
</tr>
<tr>
<td>22</td>
<td>24</td>
<td>0.21</td>
<td>99.35</td>
</tr>
<tr>
<td>23</td>
<td>18</td>
<td>0.15</td>
<td>99.50</td>
</tr>
<tr>
<td>24</td>
<td>15</td>
<td>0.13</td>
<td>99.63</td>
</tr>
<tr>
<td>25–38</td>
<td>43</td>
<td>0.37</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td>11,660</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
* Test of independence of recommendation level and period: $\chi^2(6) = 21.22$

$NRECS =$ Number of trade recommendations per company-quarter.

$p$-value = 0.0017
TABLE 5
The relation between cumulative abnormal returns and earnings surprises regression results including information flow

Model:

\[
\text{CAR}(t + \tau, t + 1)_j = (\gamma - \delta \cdot \tilde{\alpha}_j) + \delta \cdot \Delta EPS_{j,t+1} - \delta \cdot \tilde{\beta}_{t,R} \cdot NRECS(t, t+\tau) \cdot \Delta EPS_{j,t} + \varepsilon_{2,j}
\]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Beginning of returns accumulation period</th>
<th>t</th>
<th>t + 15 days</th>
<th>t + 30 days</th>
<th>t + 45 days</th>
<th>t + 1–2 days</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td></td>
<td>-0.0187</td>
<td>-0.0148</td>
<td>-0.0116</td>
<td>-0.0084</td>
<td>-0.0004</td>
</tr>
<tr>
<td>t-statistic</td>
<td></td>
<td>-19.19</td>
<td>-17.34</td>
<td>-15.18</td>
<td>-12.87</td>
<td>-1.10</td>
</tr>
<tr>
<td>(\Delta EPS_{j,t+1})</td>
<td></td>
<td>0.0545</td>
<td>0.0485</td>
<td>0.0422</td>
<td>0.0315</td>
<td>0.0197</td>
</tr>
<tr>
<td>t-statistic</td>
<td></td>
<td>30.75</td>
<td>31.03</td>
<td>29.98</td>
<td>25.91</td>
<td>33.82</td>
</tr>
<tr>
<td>(\Delta EPS_{j,t})</td>
<td></td>
<td>0.0016</td>
<td>-0.0005</td>
<td>-0.0021</td>
<td>-0.0034</td>
<td>-0.0036</td>
</tr>
<tr>
<td>t-statistic</td>
<td></td>
<td>0.88</td>
<td>-0.26</td>
<td>-1.31</td>
<td>-2.44</td>
<td>-5.56</td>
</tr>
<tr>
<td>(NRECS(t, t+\tau) \cdot \Delta EPS_{j,t})</td>
<td></td>
<td>-0.0023</td>
<td>-0.0013</td>
<td>-0.0007</td>
<td>-0.0020</td>
<td></td>
</tr>
<tr>
<td>t-statistic</td>
<td></td>
<td>-2.12</td>
<td>-2.31</td>
<td>-1.91</td>
<td>-1.81</td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td></td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>(N)</td>
<td></td>
<td>25,709</td>
<td>24,697</td>
<td>24,469</td>
<td>23,066</td>
<td>24,640</td>
</tr>
<tr>
<td>Implied (\beta_{t,0})</td>
<td></td>
<td>-0.0287</td>
<td>0.0090</td>
<td>0.0489</td>
<td>0.1078</td>
<td>0.1852</td>
</tr>
<tr>
<td>t-statistic(^*) ((\beta_{t,0} = 0))</td>
<td></td>
<td>0.26</td>
<td>1.33</td>
<td>2.53</td>
<td>5.85</td>
<td></td>
</tr>
<tr>
<td>Implied (\beta_{t,0} / \beta)</td>
<td></td>
<td>-0.0713</td>
<td>0.0231</td>
<td>0.1207</td>
<td>0.2674</td>
<td>0.4599</td>
</tr>
<tr>
<td>Implied (\beta_{t,R})</td>
<td></td>
<td>0.0460</td>
<td>0.0318</td>
<td>0.0215</td>
<td>0.0126</td>
<td></td>
</tr>
<tr>
<td>t-statistic(^*) ((\beta_{t,R} = 0))</td>
<td></td>
<td>2.09</td>
<td>2.34</td>
<td>1.90</td>
<td>1.81</td>
<td></td>
</tr>
<tr>
<td>Implied (\beta_{t,R} / \beta)</td>
<td></td>
<td>0.1157</td>
<td>0.0777</td>
<td>0.0536</td>
<td>0.0313</td>
<td></td>
</tr>
<tr>
<td>Mean of (NRECS(t + \tau))</td>
<td></td>
<td>0.79</td>
<td>1.48</td>
<td>2.18</td>
<td>2.78</td>
<td></td>
</tr>
<tr>
<td>SD of (NRECS(t + \tau))</td>
<td></td>
<td>1.47</td>
<td>2.47</td>
<td>3.37</td>
<td>4.28</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
* Directly estimated using non-linear least squares. See Appendix 1 for a discussion of this method.

\(\text{CAR}(t + \tau, t + 1)_j\) = Company \(j\)'s cumulative abnormal return between the intermediate date \(t + \tau\) and the next earnings announcement date.

\(\Delta EPS_{j,t}\) = Company \(j\)'s seasonally differenced earnings per share deflated by the absolute value of earnings per share at \(t - 4\).

\(NRECS(t, t + \tau)_j\) = The number of analyst reports for company \(j\) issued between \(t\) and \(t + \tau\).
expectations and a seasonal random walk until halfway through the quarter. These results, however, show that as early as 15 trading days after an earnings announcement, expectations incorporate information from prior earnings if there have been analyst reports about the company. The fact that \( \beta_{r0}^* \) is not driven to zero is likely due to the imperfection with which information flow is measured.

**Sensitivity tests**

We also used two alternative measures of information flow in our model: forecasts of earnings for quarter \( t+1 \) and all earnings forecasts. In both cases, the forecast count was based on those forecasts released after the first earnings announcement and on or before the intermediate date \( t + \tau \). For the forecasts of quarter \( t+1 \), our estimates of \( \beta_{r0}^* \) and \( \beta_{rR}^* \) followed patterns similar to those presented in Table 5. \( \beta_{r0}^* \) increased in \( \tau \), while \( \beta_{rR}^* \) declined, although the \( \tau \)-statistics for \( \beta_{rR}^* \) were lower than when \( NRECS \) was used, and \( \beta_{rR}^* \) was marginally significant only for \( \tau = 45 \) trading days. When all earnings forecasts were used, again the coefficient patterns were similar, and \( \beta_{rR}^* \) was significant at conventional levels, except for \( \tau = 1 \) quarter – 2 trading days.

We also performed other robustness tests. To allow for a diminishing level of information with additional recommendations, we used \( \log[NRECS(t,t + \tau) + 1] \) in place of \( NRECS(t,t + \tau) \). We found no qualitative difference in results. We also augmented the regressions with \( \log(\text{total assets}) \) to control for correlation between size and the number of recommendations available, again with no effect on the results.

In addition, we re-estimated all of our models on three subsamples partitioned on size. We sorted company-quarters on total assets and partitioned the sample into thirds, eliminating company-quarters that did not have returns data for every 15-day interval in our tests, so that we had identical partitions for every value of \( \tau \). Again, the patterns of \( \beta_{rR}^* \) were similar to the full sample. The magnitudes of \( \beta_{rR}^* \) were similar in all three groups, although the results were more significant for the middle and large firms, due to less cross-sectional variation in \( NRECS(t,t + \tau) \) for small firms.

Finally, we augmented equation (7) to include four variables designed to capture the level of the recommendations being made, both before and during the returns accumulation period. These variables captured the percentage of recommendations in a company-quarter that were buys and sells, both before and after date \( t + \tau \). For these tests, observations were limited to company-quarters having at least one recommendation between \( t \) and \( t + \tau \) and at least one recommendation between \( t + \tau \) and \( t + 1 \). If any portion of the drift were related to investors' failure to incorporate information in prior earnings for future stock recommendations, the coefficient on \( \Delta EPS_{j,t}^* \) would decline when we added the recommendation level variables to the specification. There was no such decline, and our results remained qualitatively unchanged for all four non-zero values of \( \tau \).

4. Conclusion

We view drift as a two-stage process involving a mispricing of information in earnings and a subsequent price correction, and investigate when and how the
mispricing is corrected. We develop a two-equation model to infer investors' earnings expectations from stock returns. The first equation relates earnings surprise to lagged earnings surprise. The second equation relates abnormal returns to prior and subsequent earnings surprises. The ratio of the coefficient estimates in the second equation provides an estimate of the serial correlation coefficient implicit in investors’ earnings expectations. This ratio is used in conjunction with the actual serial correlation of earnings, which is estimated in the first equation, to assess the degree to which investors’ earnings expectations impound the implications of current earnings for future earnings.

Using this model, up to 15 trading days after an earnings announcement, we are unable to reject the null hypothesis that investors’ earnings expectations do not reflect any of the implications of prior earnings for future earnings. Thus, securities are priced as if investors’ expectations of earnings are based on a seasonal random walk. As time passes, earnings expectations begin to incorporate some, but not all, of the serial correlation. By mid-quarter, although expectations are clearly more sophisticated than those implied by a seasonal random walk, they still do not fully reflect the implications of prior earnings for future earnings. By two trading days before the next announcement, as much as one half of the serial correlation is reflected in expectations.

We investigate the determinants of the speed with which the implications of prior earnings are reflected in investors’ earnings expectations. We find that the dissemination of information speeds the incorporation of prior earnings information into earnings expectations. These results suggest that the dissemination of information allows investors to incorporate into their expectations information that they already possess but that they cannot or do not process efficiently.

Inferring expectations requires that the regression of returns on earnings surprises control for contemporaneous earnings, as Ball and Bartov did. However, the extent to which expectations appear to incorporate prior information depends on the point in time between earnings announcements that expectations are taken. While Ball and Bartov show that expectations partially reflect serial correlation, their conclusion pertains to two trading days before the next earnings announcement, the beginning of the returns window in their regressions. Our additional results that expectations are less sophisticated earlier in the quarter are inconsistent with Ball and Bartov’s claim that their findings refute theories based on investors who are unaware of the time series properties of earnings. The logical extension of the Ball and Bartov conclusion would be that our results are caused by investors who incorporate time series analysis in their expectations, but with a bias that varies in degree intertemporally. Investors would become more sophisticated through the quarter, but revert to a naive seasonal random walk model immediately after an earnings announcement. We believe that our results are more plausibly explained by investors who do not incorporate into their expectations information requiring an understanding of the time series properties of earnings, and who therefore are surprised in a predictable fashion as information that could have been discerned from the prior earnings announcement is disseminated in a more transparent manner.
Appendix 1: Direct estimation of $\beta^P$

$\beta^P$ is estimated from OLS regression results using the ratio of two mean-zero random variables. Because this ratio does not have a well-defined distribution under the null hypothesis, obtaining a test statistic for the parameter is problematic. This appendix explains the direct estimation procedure we use to avoid this problem.

Under the null hypothesis that $\delta = 0$ and $\beta^r = 0$, our estimators of $\delta$ and $-\delta \cdot \beta^r$ are mean-zero random variables and approximately normally distributed, so our estimate of $\beta^P$ (the negative of the ratio of the estimates of $-\delta \cdot \beta^r$ and $\delta$) does not have a well-defined distribution. Therefore, we re-estimate our model using the method described in Mishkin 1983. This procedure estimates the following system:

\[
\begin{bmatrix}
\text{CAR}(t + \tau, t + 1)^{n \cdot 1} \\
\theta \cdot \Delta EPS_{t+1}^{n \cdot 1}
\end{bmatrix} = (\gamma - \delta \cdot \alpha^*_t)^{n \cdot 1} + \delta \cdot \begin{bmatrix}
\Delta EPS_{t+1}^{n \cdot 1} \\
0^n_{1 \cdot 1}
\end{bmatrix} + \hat{\beta} \cdot \begin{bmatrix}
\theta^{n \cdot 1} \\
\Delta EPS^{n \cdot 1}
\end{bmatrix} + \hat{\theta} \cdot \epsilon^{n \cdot 1}
\] (A1.1)

where the superscript $n \cdot 1$ indicates an $n$-by-1 vector. Thus, each of the vectors in (A1.1) has dimension $2n$-by-1. This system is block-diagonal, and if $\theta = 1$ it is equivalent simply to stacking OLS regressions of equations (5) and (1). In that case, the coefficient estimates for this system would be identical to those obtained if separate OLS regressions were run on the two equations. However, by estimating the system jointly, the variances of the error terms ($e_1$ and $e_2$) are restricted to be the same in the two equations. If that is not a valid restriction, the standard errors and $t$-statistics would be biased, even though the coefficient estimates would not be.

We set $\theta$ equal to the square root of the ratio of the sum of squared residuals from separate OLS regressions of equations (5) and (1). This rescales the second equation so that the variances of the error terms are identical for the two equations, resulting in standard errors and $t$-statistics that are identical to those obtained from separate OLS regressions on the two equations. The coefficient estimates are unaffected by this rescaling.

If that were the end of the procedure, there would be no benefit to using it, since the coefficient estimates and $t$-statistics are identical to OLS on the separate equations. However, this approach has two advantages. First, if (A1.1) is estimated using non-linear least squares rather than OLS, we can obtain $t$-statistics for $\beta^P$ rather than for $\hat{\theta}$. Thus, we avoid the problem that the distribution of the ratio of two mean-zero random variables is not well defined. Second, using non-linear least squares we can estimate this system with the cross-equation restriction $\beta^r = \beta$ imposed, and obtain a likelihood ratio statistic for that restriction.
Because the restricted system does not have a linear representation, such a test is not possible using OLS. Thus, this procedure provides statistical tests that, as of any intermediate date \( t + \tau \), investors completely ignore \((\hat{\beta}_r = 0)\) and fully impound \((\beta_r^* = \beta)\) prior earnings information in their expectations.

As a technical note, avoiding the division of coefficient estimates is less important when the \( t \)-statistic on \( \hat{\delta} \), the denominator, is high (in absolute value). In this case, \( \hat{\delta} \) is nearly constant and, as a result, the following approximate equality holds: \( \text{SE}(\hat{\beta}_r^*) = \text{SE}(\hat{\delta})/\hat{\delta} \). The directly estimated standard error of \( \hat{\beta}_r^* \) is approximately equal to the OLS standard error of the coefficient on \( \Delta EPS_{j,t} \) divided by the coefficient on \( \Delta EPS_{j,t+1} \). Thus the OLS \( t \)-statistic on \( \hat{\delta} \) is very close to the negative of the directly-estimated \( t \)-statistic on \( \hat{\beta}_r^* \). In our tests, the \( t \)-statistic on \( \delta \) is generally around 30 and, consistent with this fact, the directly-estimated \( t \)-statistics on \( \hat{\beta}_r^* \) and the negative of the OLS \( t \)-statistics on \( \hat{\delta} \) are very close to each other.

Appendix 2: The effect of the release of information unrelated to prior earnings

Because earnings surprises are serially correlated, the earnings surprise in period \( t \) is predictable from the earnings surprise in period \( t - 1 \). As a result, some of the information about next quarter’s earnings surprise that comes out during the quarter is predictable using the prior earnings information.

In addition to this predictable component, information comes out during the quarter that is not predictable using prior earnings information. This information, which is orthogonal to the prior earnings information, allows investors to revise their expectations from what would be implied by their use of the time series properties of earnings (or their use of information that was predictable using time series properties) alone.

This appendix shows that inclusion of this orthogonal information in the model affects the expected levels of the model’s coefficients, and explains the differences in the coefficients we observe for different values of \( \tau \). Moreover, the appendix shows that despite the fact that inclusion of this orthogonal information affects the levels of the model’s coefficients, it does not affect estimation of \( \beta_r^* \), the variable of interest. Therefore, our conclusions are not altered by the fact that our basic model does not include the orthogonal information.

We parameterize the proportion of the information about the next earnings surprise that is unrelated to prior earnings surprise and that is known as of \( t + \tau \) as \( \mu_r^* \), and rewrite the expectation as

\[
E_{t+\tau}(\Delta EPS_{j,t+1} | \Delta EPS_{j,t}; I_{j,t}) = \alpha_r^* + \beta_r^* \cdot \Delta EPS_{j,t} + \mu_r^* \cdot [\Delta EPS_{j,t+1} - (\alpha_r^* + \beta_r^* \cdot \Delta EPS_{j,t})] \tag{A2.1}
\]

where \( I_{j,t} \) is the information about firm \( j \) (other than \( \Delta EPS_{j,t} \)) that is known at \( t + \tau \). \( \mu_r^* \) measures the extent to which information about the next earnings an-
nouncement that is uncorrelated with prior earnings is known by investors. We expect \( \mu^* \) to be increasing in \( \tau \) and assume values between zero (investors have no information about subsequent earnings other than their time series estimates) and one (investors know \( \Delta EPS_{j,t+1} \) with certainty).

Our returns equation (5) then becomes

\[
CAR(t + \tau, t + 1) = [\gamma - \delta \cdot (1 - \mu^* \cdot \alpha^*)] + \delta \cdot (1 - \mu^* \cdot \Delta EPS_{j,t+1}) - \delta \cdot (1 - \mu^* \cdot \beta^* \cdot \Delta EPS_{j,t}) + \varepsilon_{2j}
\]  

We cannot separately identify \( \delta \) and \( \mu^* \) in equation (A2.2). However, assuming that (a) \( \mu^* \) is between zero and one for all \( \tau \), (b) \( \mu^* \) is increasing in \( \tau \), and (c) \( \delta \) is positive, we predict that the intercept coefficient in (A2.2) is increasing in \( \tau \) and that the coefficient on \( \Delta EPS_{j,t+1} \) is positive and declining in \( \tau \). While these predictions are not our central research question, results consistent with them will provide some assurance about our model specification.

Our analysis shows that \( \mu^* \) in (5) is replaced by \( \delta \cdot (1 - \mu^*) \) in (A2.2). Importantly, this shows that incorporating information that is orthogonal to the information in prior earnings has the same effect on the coefficients on \( \Delta EPS_{j,t} \) and \( \Delta EPS_{j,t+1} \). Therefore, even in this more complete model, the negative of the ratio of the coefficients on \( \Delta EPS_{j,t} \) and \( \Delta EPS_{j,t+1} \) is still an estimator of \( \beta^* \). The arrival of orthogonal information cannot account for the differences in our estimates of \( \beta^* \) for different values of \( \tau \). For ease of notation, we describe results in the text in terms of the original model presented in the text. We refer to the refined model in this appendix only when the predictions differ from the model in the text, which is when we examine differences in the coefficients (not the ratio of coefficients) for different values of \( \tau \).

**Appendix 3: Properties of \( \beta^*/\beta \) estimate when time series model is underspecified**

This appendix investigates the consequences of using only one lag in our earnings expectations model, when earnings follow a time series process containing more than one lag. We show that the resulting biases of the estimators of \( \beta^* \) and \( \beta \) are of similar magnitudes. As a result, the effect of the bias on the ratio of these estimators is mitigated. Further, \( \lim(\beta^*/\beta) \) approximates a weighted average of the ratio of the true coefficients and corresponding ratios for the omitted lagged terms.

To illustrate, we assume the true time series of earnings has two lags and derive the properties of our one-lag based estimators. The result generalizes for additional lags. For ease of exposition and without loss of generality, the intercept terms are omitted from this analysis.
Two-lag model
Assume that the true earnings generating process is such that earnings surprises are described by the following equation (omitting the \( j \) subscript for ease of notation):

\[
\Delta EPS_{t+1} = \beta \cdot \Delta EPS_t + \lambda \cdot \Delta EPS_{t-1} + \epsilon_t
\]  
(A3.1)

and investor expectations are described by

\[
E^{\prime}_{t+1} (\Delta EPS_{t+1} | \Delta EPS_t; \Delta EPS_{t-1}) = \beta^* \cdot \Delta EPS_t + \lambda^* \cdot \Delta EPS_{t-1}
\]  
(A3.2)

Cumulative abnormal returns are given by (omitting \("(t + \tau, t + 1)\)" from the expression for \(CAR\), for ease of notation):

\[
CAR = \delta \cdot \Delta EPS_{t+1} - \delta \cdot \beta^* \cdot \Delta EPS_t - \delta \cdot \lambda^* \cdot \Delta EPS_{t-1} + \epsilon_2
\]  
(A3.3)

Equations (A3.1) through (A3.3) correspond to equations (1), (2), and (5) in the text, respectively. The next three sections derive the probability limits of \( \hat{\beta} \), \( \hat{\beta}^* \), and \( \hat{\beta}^* / \hat{\beta} \), respectively, when the \( t - 1 \) terms are omitted erroneously from the regressions.

**Probability limit of \( \hat{\beta} \)**
Let \( \hat{\beta} \) be the OLS estimator of \( \beta \) in (A3.1) when the second lag (\( \Delta EPS_{t-1} \)) is omitted from the regression.

\[
\hat{\beta} = \beta + \lambda \cdot \frac{\sum \Delta EPS_t \cdot \Delta EPS_{t-1}}{\sum \Delta EPS_t^2} + \frac{\sum \Delta EPS_t \cdot \epsilon_t}{\sum \Delta EPS_t^2}
\]  
(A3.4)

Taking the probability limit \( (\text{plim}) \) of (A3.4), and noting that

\[
\text{plim} \left( \frac{\sum \Delta EPS_t \cdot \Delta EPS_{t-1}}{\sum \Delta EPS_t^2} \right) = \text{plim} \left( \frac{\sum \Delta EPS_{t+1} - \Delta EPS_t}{\sum \Delta EPS_t^2} \right)
\]  
(A3.5)

\[
\text{plim} (\hat{\beta}) = \frac{\beta}{1 - \lambda}
\]

If \( \lambda > 0 \), as one would expect, then \( \hat{\beta} \) is biased upward.

**Probability limit of \( \hat{\beta}^* \)**
If (A3.3) is estimated excluding the \( \Delta EPS_{t-1} \) term from the regression, the coefficient estimates are
\[
\begin{bmatrix}
\beta \\
\phi
\end{bmatrix}
= \begin{bmatrix}
\sum \Delta EPS_{t+1}^2 & \sum \Delta EPS_{t+1} \cdot \Delta EPS_t \\
\sum \Delta EPS_{t+1} \cdot \Delta EPS_t & \sum \Delta EPS_t^2
\end{bmatrix}^{-1}
\begin{bmatrix}
\sum \Delta EPS_{t+1} \cdot CAR \\
\sum \Delta EPS_t \cdot CAR
\end{bmatrix},
\]

implying
\[
\hat{\beta} \cdot \sum \Delta EPS_{t+1} \cdot CAR - \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR
\]

Substituting (A3.3) for CAR, taking probability limits and substituting (A3.5) for plim(\hat{\beta}),

\[
\begin{align*}
\text{plim}(\hat{\beta}^*_\tau) &= \frac{\beta \cdot \sum \Delta EPS_{t+1} \cdot CAR - \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR}{\sum \Delta EPS_{t+1} \cdot CAR - \hat{\beta} \cdot \sum \Delta EPS_t \cdot CAR},
\end{align*}
\]

Substituting (A3.3) for CAR, taking probability limits and substituting (A3.5) for plim(\hat{\beta}),

\[
\begin{align*}
\text{plim}(\hat{\beta}^*_\tau) &= \frac{\beta \cdot \sum \Delta EPS_{t+1} \cdot CAR - \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR}{\sum \Delta EPS_{t+1} \cdot CAR - \hat{\beta} \cdot \sum \Delta EPS_t \cdot CAR},
\end{align*}
\]

where
\[
\phi = \sum \Delta EPS_{t+1} \cdot \sum \Delta EPS_{t-1} \cdot \sum \Delta EPS_t^2.
\]

Substituting (A3.1) for \(\sum \Delta EPS_{t+1}\) in the expression for \(\phi\) and taking the probability limit results in

\[
\text{plim}(\phi) = \frac{\beta^2}{1 - \lambda} + \lambda
\]

Finally, substituting (A3.7) into (A3.6) and simplifying gives

\[
\text{plim}(\hat{\beta}^*_\tau) = \frac{\beta \cdot \hat{\beta}^* \cdot \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR}{1 - \lambda \cdot \sum \Delta EPS_t^2}.
\]

If, as we expect, \(\lambda > \lambda^*_\tau > 0\), then \(\hat{\beta}^*_\tau\) is positively biased. As a result, \(\hat{\beta}^*_\tau / \hat{\beta}\) may be biased in either direction.

**Probability limit of \(\hat{\beta}^*_\tau / \hat{\beta}\)**

Using (A3.8) and (A3.5),

\[
\text{plim}(\hat{\beta}^*_\tau / \hat{\beta}) = \frac{\beta \cdot \hat{\beta}^* \cdot \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR}{\beta \cdot \sum \Delta EPS_{t+1} \cdot CAR - \sum \Delta EPS_{t+1}^2 \cdot \sum \Delta EPS_t \cdot CAR},
\]

where
\[
\omega_1 = \frac{1 - \lambda}{1 - \lambda \cdot \sum \Delta EPS_t^2} \quad \text{and} \quad \omega_2 = \frac{\lambda \cdot (1 - \lambda)}{1 - \lambda \cdot \sum \Delta EPS_t^2}.
\]
To explore the effect on $\beta^*_\tau / \beta$ of omitting the second lag, we substitute, as an example, the first- and second-lag correlation coefficient estimates of 0.34 and 0.19 reported by Bernard and Thomas 1990 for $\beta$ and $\lambda$ in (A3.9).

Table A3.1 shows the values of $\text{plim} (\beta^*_\tau / \beta)$ for various levels of $\lambda^*_\tau / \lambda$ and $\beta^*_\tau / \beta$. It is reasonable to assume that $\Delta \text{EPS}_{t+1} | \Delta \text{EPS}_t; \Delta \text{EPS}_{t-1}$ than is $\Delta \text{EPS}_t$. That is, $\beta^*_\tau / \beta < \lambda^*_\tau / \lambda < 1$. In other words, we expect $\beta^*_\tau / \beta$ to arise from underlying values of $\beta^*_\tau / \beta$ and $\lambda^*_\tau / \lambda$ that are below and to the left of the diagonal (shown in bold face) in Table A3.1. This means that when $\beta^*_\tau / \beta = 0.00$, we estimate it to be between 0.0000 and 0.1597, when $\beta^*_\tau / \beta = 0.25$, we estimate it to be between 0.2432 and 0.3697, and so on. Although our estimates of $\beta^*_\tau / \beta$ are biased upwards, the bias is decreasing in $\beta^*_\tau / \beta$. Thus the bias reduces the likelihood of our finding the ratio $\beta^*_\tau / \beta$ to be increasing over the quarter, as we do.

Note that $\beta^*_\tau / \beta$ is approximately a weighted average of $\beta^*_\tau / \beta$ and $\lambda^*_\tau / \lambda$. Up to this point, we have discussed the bias in $\beta^*_\tau / \beta$ in terms of the difference between $\text{plim} \beta^*_\tau / \beta$ and $\beta^*_\tau / \beta$. Another interpretation, however, is that $\beta^*_\tau / \beta$ is an estimate of the weighted average of $\beta^*_\tau / \beta$ and $\lambda^*_\tau / \lambda$. Then the appropriate comparison to determine bias is between $\beta^*_\tau / \beta$ and $\omega_1 \cdot \beta^*_\tau / \beta + \omega_2 \cdot \lambda^*_\tau / \lambda$, where $\omega_1$ and $\omega_2$ are the “true weights” that should be placed on the weighted average. That is, they are the values of $\omega_1$ and $\omega_2$ with $\lambda$ substituted in for $\lambda^*_\tau$. The Bernard and Thomas estimates of $\lambda$ correspond to an $\omega_1$ of 0.8403 and $\omega_2$ of 0.1597. In that case, bias arises only if $\lambda^*_\tau < \lambda$, which causes the weights not to equal $\omega_1$ and $\omega_2$.

Table A3.2 indicates that if one interprets $\beta^*_\tau / \beta$ as an estimate of a weighted average of $\beta^*_\tau / \beta$ and $\lambda^*_\tau / \lambda$, then the bias induced by omitting the second lag from the model is very small relative to the estimates we obtained. For example, Table 2 in the text reports values of $\beta^*_\tau / \beta$ that vary from −0.0713 (for $\tau = 0$) to 0.5282 (for $\tau = 1$ quarter − 2 trading days), whereas the largest (in magnitude) bias in Table A3.2 is −0.0092.

### Table A3.1

<table>
<thead>
<tr>
<th>$\lambda^*_\tau / \lambda$</th>
<th>0.00</th>
<th>0.25</th>
<th>0.50</th>
<th>0.75</th>
<th>1.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00</td>
<td>0.0000</td>
<td>0.2025</td>
<td>0.4050</td>
<td>0.6075</td>
<td>0.8100</td>
</tr>
<tr>
<td>0.25</td>
<td>0.0388</td>
<td>0.2432</td>
<td>0.4475</td>
<td>0.6519</td>
<td>0.8562</td>
</tr>
<tr>
<td>0.50</td>
<td>0.0784</td>
<td>0.2846</td>
<td>0.4908</td>
<td>0.6970</td>
<td>0.9033</td>
</tr>
<tr>
<td>0.75</td>
<td>0.1186</td>
<td>0.3268</td>
<td>0.5349</td>
<td>0.7430</td>
<td>0.9512</td>
</tr>
<tr>
<td>1.00</td>
<td>0.1597</td>
<td>0.3697</td>
<td>0.5798</td>
<td>0.7899</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
### TABLE A3.2

Bias in estimates weighted averages of $\beta_t / \beta$ and $\lambda_t / \lambda$ for various combinations of $\beta_t / \beta$ and $\lambda_t / \lambda$ (assuming $\beta = 0.34$ and $\lambda = 0.19$)

<table>
<thead>
<tr>
<th>$\lambda_t / \lambda$</th>
<th>0.00</th>
<th>0.25</th>
<th>0.50</th>
<th>0.75</th>
<th>1.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00</td>
<td>0.0000</td>
<td>-0.0076</td>
<td>-0.0152</td>
<td>-0.0227</td>
<td>-0.0303</td>
</tr>
<tr>
<td>0.25</td>
<td>-0.0011</td>
<td>-0.0068</td>
<td>-0.0126</td>
<td>-0.0183</td>
<td>-0.0240</td>
</tr>
<tr>
<td>0.50</td>
<td>-0.0015</td>
<td>-0.0053</td>
<td><strong>-0.0092</strong></td>
<td>-0.0131</td>
<td>-0.0169</td>
</tr>
<tr>
<td>0.75</td>
<td>-0.0012</td>
<td>-0.0041</td>
<td>-0.0050</td>
<td><strong>-0.0070</strong></td>
<td>-0.0089</td>
</tr>
<tr>
<td>1.00</td>
<td>0.0000</td>
<td>-0.0001</td>
<td>-0.0001</td>
<td>0.0000</td>
<td><strong>0.0000</strong></td>
</tr>
</tbody>
</table>

The analysis in this appendix implies that we can interpret our estimate of $\beta_t / \beta$ as a weighted-average of $\beta_t / \beta$ and additional omitted lags. Importantly, the biases in our estimates under this interpretation are small relative to the estimates themselves.

### Notes

1. Francis and Soffer obtained their recommendations directly from a sample of analyst reports. The similarity of our distribution to theirs indicates that our (larger) sample is representative even though it is collected from a secondary source.
2. None of our tests are affected significantly if we exclude observations rather than winsorize.
3. Brown and Rozell (1979) model seasonally differenced earnings as $\Delta EPS_{jt + 1} = \alpha + \beta \Delta EPS_{jt} + \gamma \epsilon_{t+4} + \epsilon_{jt}$. Following Bernard and Thomas' (1990) suggestion that investors' expectations resemble a seasonal random walk, we drop the $\epsilon_{t+4}$ term from our model.
4. Equation (1) is a pooled, time-series and cross-sectional regression. As a result, $R^2 = \hat{\beta}^2$, whereas $R^2 = \beta^2$ would hold for a single, large-sample time series regression. Further, because our sample sizes are sufficiently large, the estimates for $\beta$ reported in Table 1 are not subject to the estimation biases discussed in Lys, Sabino, and Jacob (1996).
5. Sloan (1996) uses a similar model to examine whether the information in cash and accrual components of current earnings are incorporated into stock prices differentially.
6. If $\Delta EPS_{jt + 1}$ is excluded from the specification, the coefficient on $\Delta EPS_{jt}$ for starting date $t$ is positive and significant ($t = 14.17$), confirming the existence of drift in our sample.
7. The intercept coefficient increases and the coefficient on $\Delta EPS_{jt + 1}$ decreases as $\tau$ goes from 0 to 1 quarter minus 2 trading days. These changes in the coefficients are as predicted by our analysis in Appendix 2. However, as noted in that appendix, our ability to estimate $\beta_t$ using the negative of the ratio of the two slope coefficients in our regression is unaffected by these intraquarter changes in the coefficients.
8. In separate tests not reported in this paper, we used an ordered trinomial logit model to show that trade recommendation levels are in fact predictable using...
\[ \Delta EPS_{jt} \]. In addition, when \( \Delta EPS_{jt+1} \) was added to the right-hand side, both \( \Delta EPS_{jt+1} \) and \( \Delta EPS_{jt} \) were significant. Thus, recommendations contain both old and new information.

References