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Earnings co-movements and earnings manipulation

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Abstract This study develops a theory that predicts the lower the degree to which firms' earnings are correlated with the industry the greater the probability a firm will issue a biased signal of firm performance. The theory provides for causal predictions in our empirical tests in which we examine the probability a firm will be subject to an Accounting and Auditing Enforcement Release (AAER). The empirical findings provide support for the theory, even after controlling for various predictive variables from the literature, indicating the degree of earnings co-movements with the industry is in fact a causal factor in managers decisions to bias earnings reports. We further illustrate that low co-movement firms are less conservative than high co-movement firms, which provides an application of our theory to a broader setting. Overall, we provide both a theory and an empirical validation of the theory helping to discipline the thinking about earnings management and allowing for causal relations to be uncovered.

Keywords Accounting and auditing enforcement releases · Accounting theory · Earnings co-movements · Earnings management · Market earnings

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1 Introduction

The notion that corporate stewards bias their earnings reports to influence market beliefs is well accepted in the literature (See Dechow et al. 2010 for a review of the literature on earnings quality and earnings management). A recent stream of literature develops dynamic structural models to derive causal inferences regarding the drivers of earnings management and to guide empirical research in detecting and calibrating the extent of earnings management (i.e., Gerakos and Kovrijnykh 2013, Beyer et al. 2014, Zakolyukina 2014). We contribute to this line of research by investigating a potentially important determinant of earnings management – the degree to which a firm's earnings co-move with the industry, which in turn influences the ability of the market to unravel bias in reported earnings. In this respect, Fischer and Verrecchia (2000) and Heinle and Verrecchia (2016) provide theoretical insight by showing that a manager's ability to bias a report is a function of how much the market is able to infer about a firm from the reports made by other firms. In this paper, we build on these models to theoretically derive reporting bias as a function of the co-movement of a firm's earnings with aggregate industry earnings, which then provides us with a basis to formulate and test hypotheses with respect to assessing a manager's ability to bias an earnings signal.

Following Fischer and Verrecchia (2000) and Heinle and Verrecchia (2016), we study a privately informed manager's reporting decision using a model where the manager's primary incentive is to maximize stock price. For a reporting bias to arise endogenously in equilibrium in such a model, two conditions must hold: (i) the manager must have an incentive to influence share prices, and (ii) market participants have some uncertainty about the managers' incentives and so cannot fully back out the bias. These conditions mean that the manager benefits from biasing by causing share prices to move in a favorable manner. To the extent biasing is costly, a manager must choose a level of bias that balances the cost of being detected with the benefits from an increased stock price.

When earnings of firms in the same industry co-move, the market can infer information from industry earnings about the firm's true earnings and thus is better able to correct for the bias. As the market learns more about the true earnings realization of the firm from industry earnings, it relies less on the firm's own report, which then reduces the expected benefit to the manager from biasing earnings. This in turn reduces the equilibrium level of bias in the reports. In the extreme, when industry earnings are uncorrelated with a firm's earnings, price is entirely a function of firm-specific earnings, and there is a greater likelihood of earnings being biased given the incentives of the manager to maximize stock price. Thus our model predicts that the optimal level of bias in an earnings report is a decreasing function of the co-movement of a firm's earnings with aggregate industry earnings (hereafter, *co-movement*).

To empirically test this prediction, we consider firms receiving Accounting and Auditing Enforcement Releases (AAERs) from the Securities and Exchange Commission (SEC) as an ex post measure of biased reporting (consistent with the literature). Using a sample of AAERs over the period 1970–2011, we document significant relationships between the incidence of AAERs and earnings co-movements, consistent with the theory. The magnitude of the effect is economically significant with the likelihood of an AAER increasing by 7–10 percent from a one standard deviation decrease in earnings co-movement, even after controlling for earnings attributes and other predictive measures that have previously been shown to predict AAERs (Dechow et al. 2011; Francis et al. 2004). It is important to note that while we control for these variables from the literature, our theory is causal rather than predictive; that is, our co-movement variable is a causal factor in terms of the reporting bias, whereas the variables from the literature are meant to help identify whether bias is present rather than being causal determinants.

To further assess the robustness of co-movements as a determinant of biased reporting, we perform a series of subsample analyses based on three other measures of the information environment. Specifically, we split the sample based on high and low industry competition, firm age, and analyst coverage. Co-movements remain important determinants for firms characterized as being in low competition industries, younger firms, and high analyst coverage firms. The industry competition results are consistent with the notion that competition disciplines managers, thus limiting the role of co-movements in determining the biasing decision. Younger firms are characterized as having greater reliance on stock compensation, which is the primary incentive mechanism in the model. Finally, co-movements still influence biased reporting even in the presence of analyst coverage, which has been shown to reduce discretionary accrual behavior (Yu 2008). Overall, the subsample analyses help to illustrate where co-movements are most influential in managers' decisions to bias earnings and help to calibrate the robustness of the construct.

Finally, we investigate the relation between earnings co-movements and conservatism, which is a classic measure of bias in earnings reports. Our theory predicts that managers maximize stock price through biasing their earnings reports upwards, thus we hypothesize that low co-movement firms will be less conservative in their earnings reports. The findings are consistent with this prediction, with low co-movement firms exhibiting a 10 percent reduction in the asymmetric timeliness measure of Basu (1997) relative to high co-movement firms. Although conservatism is not as clear a signal of intentionally biased reporting as AAERs, extending the empirical validation of the theory to this broader test helps to provide a more general contribution to the literature, especially given the limited frequency of AAERs.

There are several caveats to our extension of existing theory and the empirical validation. First, our model is a single-period model in which the manager's incentives are shaped by stock price. Therefore our model can only speak to overstatement incentives. Because we do not account for time-varying preferences for stock prices using a multi-period setting, our model is not helpful in understanding when a manager might actually understate earnings. Nevertheless, we still expect firms to have the greatest flexibility to manage earnings (including understatements) whenever co-movements are low because the market learns less about the firm from other disclosures.

Second, although our results indicate that co-movements can be used to increase the efficiency of detecting earnings management, we note that co-movements require a significant time-series of earnings to calculate, whereas extant models (e.g., Dechow et al. 2011) are more parsimonious. We leave the development of a precise empirical methodology for incorporating co-movements in detecting earnings management to future research. Our purpose here is simply to illustrate that our predicted relation from the theory is empirically valid, even after including a large number of variables previously used to predict earnings management behavior.

Overall, this study contributes to the literature by theoretically establishing earnings co-movement as a driver of the bias in earnings signals and by providing empirical confirmation of the theory. By explicitly linking our empirical tests to theory, we provide a disciplining force on our hypotheses and are able to draw causal inferences from the findings, unlike much of the literature on earnings management.

The paper proceeds as follows. In the next section, we present an analytical adaptation of Heinle and Verrecchia (2016) to explicitly establish a causal link between earnings co-movements and reporting bias. In Section 3, we discuss data and variable measurements. In Section 4, we present our results, and in Section 5, we conclude.

2 Theoretical foundation

The issue of why reporting biases might arise in a rational expectations equilibrium has been the subject of many analytical models. For instance, in Fischer and Verrecchia (2000), Dye and Sridhar (2004), and Beyer (2009), the cost of biasing a report is conditional on idiosyncratic volatility of the firm's earnings—the greater the volatility, the lower the cost of bias and detection.[1] In Beyer et al. (2010) a manager's decision of whether to bias the disclosure depends on the extent to which information is obtainable from other sources.

Heinle and Verrecchia (2016) examine a model in which a firm's cash flows are correlated with the cash flows of other firms in the economy. They show that the greater the cross-correlations, the lower the benefit from biased reporting. In a similar vein, Strobl (2013) uses an agency framework with multiple firms with correlated earnings to examine the extent of earnings manipulation. He illustrates that the probability of manipulation is decreasing in the extent that a firm's earnings co-move with the market. Strobl (2013) extends the model to illustrate the circumstances under which earnings management can influence a firm's cost of capital.

Based on this intuition, we present a simple model that explicitly incorporates the effect earnings co-movements have on the bias in earnings signals, and we empirically test the implications from this model. A complication is that our empirical validation requires the construction of a measure that captures the theoretical construct of co-movements with some accuracy. Thus failure to detect bias in our earnings signals is not a sufficient condition to conclude that the theory is incorrect

[1] Many of these models also incorporate the notion that the market identifies the bias and will price protect accordingly as long as investors are rational and have perfect common knowledge of the manager's reporting objectives. When these assumptions are relaxed, reporting biases can influence prices in equilibrium (Fischer and Verrecchia 2000).

in employing co-movements. As a practical matter, we are forced to rely on proxies in empirical analysis. To the extent proxies measure the underlying constructs with error, we are biasing our empirical tests against finding an association consistent with our model and with the broader theoretical predictions.

2.1 Model

We present a model linking earnings co-movement with reporting bias using the frameworks of Heinle and Verrecchia (2016) and Fischer and Verrecchia (2000). Let $\tilde{e}$ represent the firm's true earnings. It is common knowledge that $\tilde{e}$ is normally distributed with mean 0 and variance σ^2. Let $\tilde{E}$ represent the market's assessment of the firm's earnings based on industry/market trends. We view $\tilde{E}$ as earnings of other similar firms in the industry and assume that $\tilde{E}$ is also distributed normally with mean 0 and variance σ_E^2. We assume the firm's earnings and the market earnings are related in the following way:[2]

$$\tilde{e} = \beta\tilde{E} + \tilde{u}, \text{ with } \tilde{u} \sim N(0, \sigma_u^2). \tag{1}$$

Thus the covariance between $\tilde{e}$ and $\tilde{E}$ is $\beta\sigma_E^2$; $Var(\tilde{e}) = \sigma^2 = \beta^2\sigma_E^2 + \sigma_u^2$, with $\beta^2\sigma_E^2$ and $\sigma_u^2 > 0$ representing the systematic risk and the firm-specific risk components, respectively.[3] The market publicly observes the realization of $\tilde{E}$.

As in Heinle and Verrecchia (2016) and Fischer and Verrecchia (2000), the manager has two pieces of private information, based on which he makes a report r. He privately observes a noisy signal $\tilde{s}$ of the firm's earnings $\tilde{e}$:

$$\tilde{s} = \tilde{e} + \tilde{\varepsilon}, \text{ with } \tilde{\varepsilon} \sim N(0, \sigma_\varepsilon^2). \tag{2}$$

The manager's incentive is tied to price via the parameter $\tilde{x}$ the realization of which is also private information to the manager. The market's beliefs about this parameter are assumed to be captured by a normal distribution with mean μ_x and variance σ_x^2 i.e., $\tilde{x} \sim N(\mu_x, \sigma_x^2)$. If the manager chooses to bias his report to inflate price, we assume that his biasing behavior will be additive, i.e, he will choose a reporting policy $R(x, s) = s + b$. However, biasing is not without cost, and this cost is adequately captured by the quadratic function $cb^2/2$, where $c > 0$.

We are looking for a linear equilibrium in which the bias and the price functions are of the form:

$$b(x, s) = \lambda_0 + \lambda_x x + \lambda_s s, \text{ and} \tag{3}$$

$$P(R(x, s) = r, E) = \alpha_0 + \alpha_r r + \alpha_E E. \tag{4}$$

[2]In essence, $\tilde{e}$ and $\tilde{E}$ are bivariate Normal with the mean vector μ and the variance covariance matrix Σ given by

$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \ \Sigma = \begin{bmatrix} \sigma^2 & \rho\sigma\sigma_E \\ \rho\sigma\sigma_E & \sigma_E^2 \end{bmatrix}.$$

Note that $\beta = \rho\sigma/\sigma_E$.

[3]We will assume that there is always a firm-specific risk component i.e., $\sigma_u^2 > 0$, which implictly places an upper bound on the extent of co-movement β i.e., $\beta < \bar{\beta} = \sigma/\sigma_E$.

Let $\langle \hat{\alpha}_0, \hat{\alpha}_r, \hat{\alpha}_I \rangle$ be the manager's conjectures of $\langle \alpha_0, \alpha_r, \alpha_E \rangle$, and the corresponding conjectured price be $\hat{P} = \hat{\alpha}_0 + \hat{\alpha}_r r + \hat{\alpha}_E E$. The manager will then choose the bias b to maximize:

$$\underset{b}{Max}\ \ x\hat{P} - \frac{cb^2}{2}.$$

The first-order condition yields

$$b(x, s) = \frac{\hat{\alpha}_r}{c}x. \tag{5}$$

Referring to Eq. 3, we then get $\lambda_0 = 0$, $\lambda_x = \frac{\hat{\alpha}_r}{c}$, and $\lambda_s = 0$.

Turning to the market's pricing function with the conjectures that $\hat{\lambda}_0 = \hat{\lambda}_s = 0$, $\hat{\lambda}_x = \frac{\hat{\alpha}_r}{c}$, the market price is simply the expected value of firm's earnings conditional on the manager's report, and the market's knowledge of industry earnings:

$$P = E\left[\tilde{e}|r, E\right].$$

Heinle and Verrecchia (2016) and Fischer and Verrecchia (2000) show that this structure yields a unique linear equilibrium in which the manager's and the market's conjectures are realized. The equilibrium price can be computed as

$$P = E\left[\tilde{e}|r, E\right] = \frac{\sigma_u^2}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}\left[r - \lambda_x\mu_x\right] + \frac{\beta\left[\sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}E.$$

Referring to Eq. 4, we have

$$\begin{aligned}
\alpha_r &= \frac{\sigma_u^2}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}, \\
\alpha_E &= \frac{\beta\left[\sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}, \text{ and} \\
\alpha_0 &= -\lambda_x\mu_x\alpha_r.
\end{aligned} \tag{6}$$

Observe that, when there is no earnings co-movement i.e., $\beta = 0$, $\alpha_E = 0$, and the market earnings does not play a role in equilibrium price. As β increases, the weight on the market earnings increases.

In determining the weight on the firm's report (α_r), the market filters out the systematic risk component $\beta^2\sigma_E^2$ from the total variance σ^2 (note that $\sigma_u^2 = \sigma^2 - \beta^2\sigma_E^2$). As β increases, a greater portion of the firm's total variance is explained by the systematic component, and the value-relevant portion of the firm's report decreases, and therefore α_r decreases. Put another way, α_r is increasing in the proportion of firm-specific variance in total variance, σ_u^2/σ^2 —for a given level of total variance, the weight on the firm's report is directly proportional to the firm-specific risk component. This, in turn, implies that α_r is decreasing in the R^2 from a regression of firm's earnings on the market earnings (as in Eq. 1).[4] Consequently, the incentive to bias decreases in the magnitude of β and in R^2. More formally (proof in Appendix):

[4]Theoretically, $R^2 \approx 1 - \sigma_u^2/\sigma^2 \equiv \beta^2\sigma_E^2/\sigma^2$.

Proposition 1 *The optimal bias $b(x, s; \beta)$ is decreasing in the magnitude of the earnings co-movement $|\beta|$, and in the R^2 from a regression of firm's earnings on the market earnings.*

A number of recent studies similarly model when managers will bias their earnings reports and then provide empirical validation of the models. For example, Gerakos and Kovrijnykh (2013) advances the notion that firms misreport to mitigate the impact of period-specific innovations in earnings (i.e., earnings shocks) to smooth earnings and meet performance targets. From their model, they predict that misreporting leads to a negative second-order autocorrelation in earnings. To the extent such period-specific performance shocks affect industry-wide performance because of industry-specific factors, their effects on firms' earnings will arguably be reflected in our co-movement parameter. Thus, by examining the impact of co-movement on misreporting, we are implicitly capturing the effects of performance shocks as well but only in the sense that co-movements are influenced by the earnings shocks.

Beyer et al. (2014) distinguishes between fundamental economic uncertainty (innovation) and accounting distortions/misreporting resulting from information asymmetry between investors and managers. They show that the noise added by earnings management to the reporting process is a significant determinant of accounting quality. In this paper, we do not focus on accounting quality per se; our objective is to point to a key determinant of misreporting rather than a more continuous quality measure that may be within the confines of generally accepted accounting principles.

Another related paper is Zakolyukina (2014), which uses a structural model to estimate "undetected" intentional manipulation when the manipulation incentives are primarily determined by the relative importance of the manager's equity holdings in the firm and his cash wealth. However, information provided by earnings co-movement on intentional manipulation is not modeled. In our model, it is precisely the equity incentives that result in earnings co-movement being an important determinant of intentional manipulation. Thus incorporating co-movement into a structural model such as in Zakolyukina (2014) could increase the efficiency of estimating intentional manipulation.

The movement of the literature towards providing theoretical links to earnings management is important because it imposes discipline on the hypotheses. The earnings management literature is often criticized for its lack of a theoretical basis, and as such, virtually any relation can be found when correlating with empirical measures like discretionary accruals. However, exactly what the findings mean is often questionable (Ball 2013). The goal in our study is to extend the literature by developing an explicit model using earnings co-movement as the disciplining force on managers.

3 Empirical measurement and sample selection

Our model identifies two alternate measures of earnings co-movement to test the hypothesis that reporting bias and earnings co-movement are negatively related. The first measure is the *magnitude* of a firm's earnings beta as estimated from regressing the firm's earnings on industry level earnings. A second measure is the (adjusted)

R^2 from this regression—we expect the reporting bias to decrease in R^2. We have no a priori reason to prefer one measure over the other. As a practical matter, the prior literature on co-movements uses the R^2 measure.[5] We also present our main results using the R^2, but we check the robustness of our results using the earnings beta measure, which we discuss below in Section 4.4.

In constructing the empirical co-movement construct, we follow Beaver et al. (1970) and use quarterly earnings before extraordinary items (Compustat IBQ) divided by beginning of the quarter market value of equity (Compustat PRCCQ*CSHOQ). Next, we create a value weighted earnings portfolio, where the weights are the beginning of calendar quarter market values of equity on an industry basis using the Fama-French 48 industry classification.[6] We then use this industry portfolio to estimate a regression of firm quarterly earnings scaled by beginning of the quarter market value of equity on the value-weighted industry earnings measure and capture the adjusted R^2 from this model as our measure of earnings co-movements ($CoMove$), consistent with the theory developed in Section 2. These co-movements are calculated over 20 quarters, with a requirement of at least 10 quarters of earnings data needed to be included in the sample. We use the value of $CoMove$ as of the end of the prior year in all empirical specifications to be sure that the variable is observable to both the market and the manager at the time of evaluating the earnings signal in question.

Table 1, Panel A, provides descriptive statistics on earnings co-movements over the 1970–2011 sample period.[7] Accounting and stock market return data is sourced from the Compustat Quarterly Fundamentals and CRSP files, respectively. Our final sample is made up of 82,758 firm-year observations that include both firms with and without AAERs that have all the necessary data to estimate a logistic regression of the probability of an AAER. All non-indicator variables are winsorized at the 1^{st} and 99^{th} percentiles.

We use AAERs as an empirical measure of an observable signal of bias in the earnings signal. The existence of an AAER is really a reflection of a joint probability that (i) there has been a material misstatement (bias) that (ii) the SEC has identified and (iii) has successfully prosecuted the case. Given the SEC's limited resources it is more likely to pursue enforcement actions against higher profile firms. As such AAERs do not identify every firm that is biasing its earnings report, and thus the empirical tests are actually biased against finding significant results to the extent that other firms are also managing their earnings but are not prosecuted by the SEC. In our sample, 530 firm-year observations are subject to an AAER, which represents

[5] See Brown and Kimbrough (2011) and Gong et al. (2013) among others, for similar measures.

[6] Inferences are unchanged if we use market level earnings instead of and in addition to industry level earnings. We elect to use industry level co-movements since firms are typically evaluated on an industry basis rather than versus the entire market.

[7] The sample is restricted to this period because of the need for AAER data obtained from Dechow et al. (2011) for our primary tests. We conduct sub-period analyses as robustness tests to ensure the results are consistent over time and there is nothing systematically biasing the results by using the entire sample period in the reported tables.

Table 1 Descriptive Statistics

	Mean	Std Dev	p1	Q1	Median	Q3	p99
$AAER$	0.0064	0.0795	0.0000	0.0000	0.0000	0.0000	0.0000
$CoMove$	0.1651	0.1963	0.0000	0.0184	0.0840	0.2456	0.7998
$lnMVE$	5.0500	2.2336	0.4919	3.3682	4.9555	6.6154	10.5107
$rsst$	0.0276	0.1598	−0.5187	−0.0235	0.0297	0.0841	0.5701
Δrec	0.0132	0.0615	−0.1851	−0.0090	0.0083	0.0355	0.2229
Δinv	0.0098	0.0535	−0.1709	−0.0041	0.0012	0.0243	0.1982
$soft_assets$	0.5352	0.2322	0.0519	0.3611	0.5648	0.7188	0.9436
Δcs	0.1343	0.4188	−0.6672	−0.0228	0.0827	0.2078	1.9415
Δroa	−0.0027	0.1236	−0.4639	−0.0292	0.0003	0.0243	0.4675
$issue$	0.8784	0.3268	0.0000	1.0000	1.0000	1.0000	1.0000
Δemp	−0.0566	0.2880	−1.2355	−0.1392	−0.0473	0.0435	0.8427
$leasedum$	0.7556	0.4297	0.0000	1.0000	1.0000	1.0000	1.0000
ret_t	0.0625	0.6061	−0.8817	−0.2910	−0.0393	0.2490	2.9761
ret_{t-1}	0.0675	0.6210	−0.8702	−0.2942	−0.0411	0.2510	3.1221
$lnOperCyc$	4.6901	0.7227	2.2725	4.2971	4.7671	5.1638	6.3639
$NegEarn$	0.2812	0.4059	0.0000	0.0000	0.0000	0.5000	1.0000
σCFO	0.1038	0.1273	0.0084	0.0371	0.0648	0.1149	0.8445
$\sigma sales$	0.1941	0.1812	0.0122	0.0760	0.1383	0.2469	1.0379
$beta$	0.9948	0.6650	−0.7336	0.5826	0.9566	1.3606	3.0655
σret	0.0466	0.0400	0.0027	0.0204	0.0354	0.0596	0.2229

Notes: This table presents the descriptive statistics of the full sample (N = 82,742) over the period 1970–2011. All independent variables are measured as of the end of the prior fiscal year in order to make sure they are observable at the time the dependent variables in the remaining tables are measured. $AAER$ is a dummy variable for whether a firm is subject to an AAER for that financial year, $CoMove$ is our measure of earnings co-movement, which is the adjusted R^2 from firm-specific regressions of quarterly net income (Compustat IBQ) scaled by beginning of the quarter market value of equity (Compustat PRCCQ*CSHOQ) regressed on value-weighted industry level earnings where the weights are determined by the beginning of the quarter market value of equity and the industry is defined as the Fama-French 48 industries. We require at least 10 and include up to 20 quarterly observations to calculate $CoMove$ and use the value of $CoMove$ as of the beginning of the fiscal year in all tables. $lnMVE$ is our measure of size, taken as the log of market value of equity (Compustat CSHO * PRCCF), $rsst$ is the working capitals accruals from Richardson et al. (2005) (($\Delta WC + \Delta NCO + \Delta FIN$)/Average AT, where WC = (ACT-CHE)-(LCT-DLC), NCO = (AT-ACT-IVAO)-(LT-LCT-DLTT), and FIN=(IVST+IVAO)-(DLTT+DLC+PSTK)), Δrec is the change in receivables (Δ RECT/Average AT), Δinv is the change in inventory (Δ INVT/Average AT), $soft\_assets$ is the percentage of soft asset ((AT-PPENT-CHE)/AT), Δcs is the percentage change in cash sales (CS = SALE-(Δ RECT), Δroa is the change in ROA (ΔIB/Average AT), Δemp is the change in employees (percentage change in employees (EMP) less the percentage change in assets (AT)), $leasedum$ is a dummy variable for the presence of operating leases as determined if MRC1+MRC2+MRC3+MRC4+MRC5 is greater than 0, $issue$ is a dummy variable for the issuance of debt determined if SSTK or DLTIS is greater than 0, ret is the market adjusted buy and hold return, $lnOperCyc$ is the log of the operating cycle, where operating cycle is the sum of days in accounts receivable ((average RECT*365)/SALE) and days in inventory ((average INVT*365)/COGS), $NegEarn$ is the proportion of years with negative earnings (IB) in the last ten years, σCFO is the standard deviation of cash flows from operations (CFO/AT) over the prior five years, $\sigma sales$ is the standard deviation of sales (SALE/AT) over the prior five years, $beta$ is risk, and σret is the standard deviation of monthy returns (RET).

0.6% of the sample, which is slightly larger than the 0.4% of observations with an AAER in Dechow et al. (2011).[8]

The mean (median) earnings co-movement (*CoMove*) is 0.16 (0.08) with a standard deviation of 0.19. Thus industry level earnings explains approximately 16 percent of the variation in firm-specific earnings on average with a range of close to 80 percent. Overall, there is significant variation in the ability of industry level earnings to explain firm-specific earnings, which is exactly the feature of the accounting environment that is modeled in the previous section.

Table 1 also contains variables identified in the literature as being related to the probability of having an AAER. Note that our measure of co-movements is theoretically related to the probability of biasing an earnings signal, and thus we have identified a causal link between the properties of the information environment and the probability of biasing a reporting signal. This is quite different from developing a model to best predict when earnings management has occurred, along the lines of Dechow et al. (2011). In extant prediction models, the purpose or nature of the earnings management is not modeled, but rather accounting relationships that emerge from empirical regularities are used to help detect the presence of earnings management. In our model, we explicitly lay out the objectives of the manager to maximize share price and illustrate the co-movement's role in the ability and desire to bias the earnings signal. Nevertheless, we include the predictive variables in the regression from the literature to illustrate the incremental effect of co-movement.

The following variables are adopted from Dechow et al. (2011): the Richardson et al. (2005) measure of accruals ($rsst$), the change in receivables (Δrec), the change in inventories (Δinv), the percentage of soft assets ($soft\_assets$), change in cash sales (Δcs), change in ROA (Δroa), issuance of debt ($issue$), change in the number of employees (Δemp), the presence of operating leases ($leasedum$), current market adjusted returns (ret_t), and lagged market adjusted returns (ret_{t-1}). We also include additional variables that have also been used in the earnings management literature. For instance, Francis et al. (2004) includes operating cycle (*lnOperCyc*), the incidence of negative earnings (*NegEarn*), variation in cash flows (σCFO) and sales ($\sigma sales$) to capture expected variation in accrual quality. For our purposes, we expect these variables to also be related to the variation in the relationship between industry earnings and firm earnings; thus we include them in the model to make sure that the co-movement variable is incremental to variables already used in the literature.

All the variables from Dechow et al. (2011) have similar values as in their study, which is also true of the inherent accrual quality control variables from Francis et al. (2004). Table 1 further reports statistics on returns betas, which on average are approximately 1, consistent with a long history of finance-related studies. Finally, we also include the natural logarithm of market value of equity (*lnMVE*) to capture firm size and return beta ($beta$) and return volatility (σret) to control for additional market-based notions of risk.

[8]The larger percentage of AAERs in our sample is a function of the construction of co-movements, which requires significant time-series to calculate. Given the SEC tends to prosecute more high profile cases of earnings management, AAER firms tend to be maintained in our sample, whereas smaller non-AAER firms are eliminated because of variable construction leaving a larger percentage of AAERs.

Table 2 Correlation Matrix

	$CoMove$	$rsst$	Δrec	Δinv	$soft\_assets$	Δcs	Δroa	$issue$	Δemp	$Leasedum$	Ret_t	Ret_{t-1}	$Beta$	$lnOperCyc$	$NegEarn$	σCFO	$\sigma Sales$	$lnMVE$	σRet
$CoMove$		**0.007**	*−0.007*	0.017	−0.075	−0.013	0.019	*0.008*	−0.012	−0.069	0.015	−0.010	0.056	*0.008*	−0.065	−0.062	−0.072	0.135	−0.031
$rsst$	0.011		0.331	0.283	0.025	0.197	0.317	0.069	−0.252	*−0.008*	0.189	0.220	**0.005**	−0.038	−0.196	−0.091	0.010	0.155	−0.069
Δrec	**−0.002**	0.366		0.338	0.123	0.199	0.152	0.083	−0.139	**0.006**	0.163	0.132	0.011	−0.022	−0.110	−0.030	0.039	0.069	−0.039
Δinv	0.023	0.338	0.328		0.116	0.232	0.079	0.083	−0.081	−0.011	0.101	0.141	0.011	0.032	−0.155	−0.039	0.020	0.046	−0.053
$soft\_assets$	−0.067	0.030	0.135	0.114		−0.026	−0.016	−0.011	0.030	0.187	−0.027	−0.018	**−0.001**	0.384	−0.045	**−0.006**	0.177	−0.146	0.044
Δcs	0.015	0.326	0.308	0.356	**−0.001**		0.145	0.076	−0.028	0.014	0.104	0.150	0.035	−0.098	0.020	0.079	0.028	0.066	0.028
Δroa	**0.005**	0.247	0.154	0.079	**−0.006**	0.210		**−0.005**	−0.157	**0.002**	0.269	−0.020	**0.006**	−0.045	0.166	0.010	0.009	0.048	**0.001**
$issue$	*0.008*	0.078	0.088	0.082	−0.011	0.115	**−0.006**		−0.054	0.104	0.040	0.091	0.080	−0.028	−0.041	−0.021	−0.033	0.265	−0.012
Δemp	−0.025	−0.195	−0.163	−0.114	0.024	−0.056	−0.082	−0.062		**0.006**	−0.115	−0.102	**−0.001**	**0.000**	0.064	**0.007**	**−0.004**	−0.075	**−0.004**
$Leasedum$	−0.059	−0.010	**0.002**	−0.016	0.183	**0.000**	**0.001**	0.104	0.033		0.029	0.024	0.091	−0.022	0.112	0.082	0.124	0.059	0.088
Ret_t	0.028	0.227	0.171	0.108	−0.040	0.177	0.364	0.041	−0.102	**0.003**		−0.026	0.030	−0.041	0.014	0.016	0.017	0.130	0.166
Ret_{t-1}	*0.009*	0.263	0.156	0.163	−0.030	0.217	*0.009*	0.102	−0.106	**−0.005**	0.030		0.045	−0.042	−0.152	**0.003**	0.021	0.120	−0.023
$Beta$	0.054	0.023	0.020	0.017	*0.009*	0.041	**0.007**	0.084	**0.003**	0.105	**−0.002**	**0.005**		0.036	0.085	0.060	0.031	0.117	0.115
$lnOperCyc$	−0.010	−0.033	**0.003**	0.074	0.374	−0.112	−0.054	−0.032	**−0.004**	**0.003**	−0.074	−0.072	0.045		0.045	0.038	−0.135	−0.142	0.062
$NegEarn$	−0.063	−0.262	−0.139	−0.186	−0.018	−0.126	0.052	−0.039	0.152	0.132	−0.148	−0.262	0.085	0.059		0.370	0.179	−0.266	0.301
σCFO	−0.093	−0.065	−0.033	−0.061	0.125	−0.038	0.011	−0.056	0.058	0.129	−0.084	−0.097	0.088	0.150	0.451		0.310	−0.219	0.243
$\sigma Sales$	−0.067	0.015	0.035	0.017	0.220	*0.009*	*0.009*	−0.034	0.017	0.164	−0.048	−0.047	0.061	−0.071	0.226	0.441		−0.255	0.167
$lnMVE$	0.109	0.166	0.075	0.059	−0.161	0.139	0.050	0.267	−0.082	0.058	0.209	0.206	0.130	−0.174	−0.287	−0.361	−0.310		−0.227
σRet	−0.024	−0.053	−0.032	−0.050	0.059	*−0.009*	**0.004**	**−0.001**	0.031	0.104	*0.008*	−0.096	0.159	0.082	0.301	0.291	0.193	−0.221	

Notes: This table presents the Pearson (Spearman) correlations above (below) the diagonal for the full sample (N = 73,161). All correlations are significant at the 1% unless presented in bold (italic) typeface where they are not significant (significant at the 5% level). All variables are defined as in Table 1.

Table 2 reports the correlations between the variables with Pearson (Spearman) correlations above (below) the diagonal. All variables are measured as of the end of the prior year so that we can properly assess the probability of an AAER, given the observable values of the independent variables. Most correlations are significant at the 1 percent level because of the large sample size. However, more importantly, the correlations with *CoMove* tend to be quite small, with the largest Pearson (Spearman) correlation occurring with *lnMVE* of 0.11 (0.14). In general, the correlations with *CoMove* are intuitive in that they indicate co-movements are greater for larger and less volatile firms. Nevertheless, most other variables exhibit significantly higher correlations often in excess of 0.25 with some other variables in the model, indicating that *CoMove* appears to be capturing something inherently different from the other variables.

4 Results

4.1 Earnings co-movements and AAERS

We adapt the model from Dechow et al. (2011) and estimate a logistic regression of the incidence of an AAER on all the variables from Table 1. The model includes both violators and non-violators in the sample with the resulting coefficients indicating either increasing or decreasing probabilities of receiving an AAER. Similar to Dechow et al. (2011), we present results where we progressively add more variables to illustrate the degree to which the *CoMove* variable is influenced by the inclusion of additional controls. We report significance tests (Wald chi-square statistics in parentheses and p-value indicators) based on a two-sided alternative to be conservative, even though many of the variables have clear predictions either from theory (*CoMove*) or from the literature. Thus significance at the 10 percent level based on a two-sided alternative can be interpreted as significant at the 5 percent level if the variable has a clear predicted relationship with AAERs, as in the coefficient on *CoMove*, which we expect to be negative. All p-values are calculated after clustering by industry. Table 3 presents the results.

The first thing to note is that the results on all the variables from Dechow et al. (2011) are generally consistent with their results. However, a number of coefficients lose their significance including Δinv, Δrec , and Δroa. These differences stem from the exclusion of a number of observations from our sample as a result of the requirements for calculations of earnings co-movements and stock return betas. In untabulated findings, we confirm the results in Dechow et al. (2011) on a larger sample that is not subject to the data requirements to calculate the co-movement variable. This serves to highlight the trade-offs in designing tests of earnings management. The model in Dechow et al. (2011) is meant to represent a parsimonious empirical model to identify earnings management that has occurred without requiring extensive data to estimate, whereas the purpose of our investigation is to examine the extent to which earnings co-movements provide causal information about the probability of biasing an earnings signal.

Table 3 Logistic Regression of Determinants of AAERs

	(1)	(2)	(3)	(4)	(5)
$Intercept$	−9.3718***	−9.7209***	−9.7415***	−11.0017***	−11.2906***
	(948.40)	(908.07)	(806.41)	(446.03)	(457.56)
$CoMove$	−0.5333**	−0.4275*	−0.3436*	−0.3889*	−0.4565*
	(5.12)	(3.25)	(2.95)	(3.09)	(3.26)
$lnMVE$	0.3636***	0.3557***	0.3554***	0.4165***	0.4234***
	(319.81)	(295.64)	(255.71)	(287.30)	(284.51)
$rsst$	0.4007	0.2923	−0.0903	−0.0214	−0.0249
	(2.29)	(1.04)	(0.08)	(0.01)	(0.01)
Δrec	0.5801	0.7633	0.9516	0.8074	0.8816
	(0.56)	(0.95)	(1.30)	(1.06)	(1.26)
Δinv	−0.9600	−0.8984	−1.2767	−0.9065	−0.9054
	(1.11)	(0.95)	(1.66)	(0.90)	(0.90)
$soft_assets$	2.6020***	2.3816***	2.5574***	2.4277***	2.4881***
	(137.19)	(107.90)	(107.26)	(90.58)	(94.40)
Δcs	0.1292***	0.1387***	0.1226**	0.0787	0.0754
	(9.18)	(10.03)	(5.31)	(2.07)	(1.83)
Δroa	− 0.7345**	−0.8583	−0.8440**	−0.7523**	−0.6256*
	(4.65)	(6.75)	(4.89)	(5.51)	(3.80)
$issue$	0.7538***	0.6415**	0.5707**	0.5474**	0.5063*
	(9.04)	(6.52)	(4.55)	(4.18)	(3.57)
Δemp		−0.0847	−0.1316	−0.0895	−0.0778
		(0.63)	(1.33)	(0.71)	(0.54)
$leasedum$		0.7184***	0.6197***	0.5390***	0.4993***
		(21.57)	(14.92)	(11.18)	(9.58)
ret_t			0.0872	0.0377	−0.0180
			(1.08)	(0.22)	(0.05)
ret_{t-1}			0.2542***	0.2261***	0.1940***
			(12.53)	(10.53)	(7.81)
$lnOperCyc$				0.1485*	0.1279
				(3.56)	(2.61)
$NegEarn$				0.4074***	0.2576*
			;	(8.55)	(3.21)
σCFO				0.8363**	0.7020*
				(5.57)	(3.75)
$\sigma sales$				0.9218***	0.8342***
				(11.54)	(9.28)
$Beta$					0.2727***
					(14.39)
σret					3.5777***

Table 3 (continued)

	(1)	(2)	(3)	(4)	(5)
					(7.82)
LogLikelihood	516.70	528.98	481.66	519.29	543.23
N	82,742	80,263	70.491	70,491	70,491

Notes: The table presents the results of estimating a logistic model of the determinants of receiving an AAER over the period 1982–2011, where *CoMove* is defined as the adjusted R^2 from regressions estimating the firm's earnings betas. All variables are as defined in Table 1. Wald chi-squares are provided in parentheses. ***/**/* represent significance at the 1%/5%/10% levels using industry-clustered standard errors.

Focusing on the coefficient on *CoMove* in Table 3, the results indicate that the greater the co-movement of earnings the lower is the probability of being subject to an AAER, regardless of the number of controls in the model. In other words, firms with greater earnings co-movements do not have the flexibility to manipulate earnings since detection is relatively easy—stakeholders can simply look to the industry to determine the firm's earnings in the extreme scenario. The economic magnitude indicates that a one unit change in *CoMove*, i.e., a move from no correlation with industry earnings to perfect correlation, results in a 34–53 percent change in the odds of having an AAER. Alternatively, a one standard deviation change would result in a 7–10 percent change in the odds of being detected and prosecuted for manipulating earnings depending on the model. Regardless of the metric used, the economic magnitude is large, providing a strong support for the notion that earnings co-movements are a causal factor in the probability of biasing an earnings signal.

4.2 Additional analysis on AAERs

In the model in Section 2, earnings co-movement is the primary variable of interest in determining the probability of biasing an earnings' signal. As previously described, the motivation underlying the theory is that managers of low co-movement firms have more flexibility to bias their signals, since less can be learned about their earnings from other firms' signals. Co-movements are in essence a measure of the information environment of firms, with low co-movement firms having lower information environments. A natural question then is whether the influence of co-movements varies across other partitions of the information environment. We elect to use industry competition, firm age, and analyst coverage as three other popular measures of the information environment from the literature. We split the sample based on above/below median values for each of these variables and re-estimate the full regressions from Table 3 to examine how the influence of other potential determinants of earnings management behavior influence the effect of co-movements on AAERs.[9] Note, ex ante we do not necessarily expect co-movements to systematically vary

[9]To ensure that the partitions capture different aspects of the information environment, we correlated the indicator variables used to create the partitions for each variable. In untabulated findings, the highest

across these subsample splits; rather, we are interested in the variation in the *influence* of co-movements across the partitions. As explained below, each of the additional information environment variables has countervailing forces leading to uncertain predictions about the direction of the influence on co-movement's effect on AAERs across the various subsamples. This is another reason we focus on co-movements in our primary tests given the clear theoretical implications on biased reporting. Nevertheless, it is important to investigate the robustness of co-movement as a determinant of earnings management, which is the purpose of the subsample analyses.

4.2.1 Product market competition

Product market competition is often viewed as a disciplining mechanism that curbs agency problems and increases economic efficiency (Shleifer and Vishny 1997). Fama (1980) observes, "the firm is disciplined by competition from other firms, which forces the evolution of devices for efficiently monitoring the performance of the entire team and of its individual members." Giroud and Mueller (2010) provides evidence that competition inhibits managerial slack. Balakrishnan and Cohen (2012) argues that financial misreporting is a manifestation of the agency problem between shareholders and corporate executives and finds evidence that product market competition constrains misreporting. This line of research indicates that we should expect co-movement to have a greater influence on the probability of AAERs in the low competition subsample since high competition mitigates incentives to bias reports.

On the other hand, the model assumes managers' objectives are to maximize stock price, which in turn provides incentives to bias earnings' signals. Research on product market competition has shown that pay-for-performance sensitivity is higher for more competitive environments (e.g., Aggarwal and Samwick 1999, Cunat and Guadalupe 2005) leading to the prediction that co-movements have a greater influence on the probability of AAERs in highly competitive industries, since incentives to bias earnings are lower in the low competition subsample. Ex ante, it is unclear which effect dominates, thus we empirically investigate the issue in Table 4.

We partition our sample of AAER observations into two subsamples based on the level of industry-competition, as measured by the Herfindahl-Hirschman Index(HHI) (i.e., above and below sample median).[10]

correlation in terms of magnitude is 0.07 between age and analyst coverage indicating that the variables are capturing quite different aspects of firms' environments.

[10]The literature has identified problems with the HHI as a measure of competition, including the lack of inclusion of private firms, staleness of codes, and potential endogeneity concerns. See, for example, Karuna (2007), Ali et al. (2014), and Hoberg and Phillips (2010). We elect to use the HHI since it corresponds well to our industry definitions and is available for the entire sample period. Many of the new competition measures are only available since the mid-1990s or for a subset of industries. Furthermore, a number of studies cited concerning the countervailing forces of competition use the HHI, including Aggarwal and Samwick (1999) and Balakrishnan and Cohen (2012), indicating it best aligns with the referenced literature.

Table 4 presents the results from the re-estimation of Table 3 across the low and high competition subsamples. The mean (median) co-movement is 0.180 (0.096) for the low competition subsample and 0.161 (0.079) for the high competition subsample. The coefficient of *CoMove* (-0.791, $p < 0.05$) is reliably negative for the low competition subsample, but we cannot reject the null that this coefficient is zero for the high competition subsample. Furthermore, the effect is stronger than in the full sample setting in Table 3, indicating that co-movement's influence on biased reporting is increased in markets characterized as relatively low competition. This result supports the notion that competition moderates the impact of earnings co-movement on misreporting incentives, indicating stock price incentives are large enough in the low competition sample to induce reporting bias when co-movements are similarly low.

4.2.2 Firm age

Referring to our theoretical framework in Section 2, an important factor in the association between earnings co-movement and reporting bias is the extent to which the manager's objective function is tied to stock price (as captured by x in the model). All else equal, the weaker this link, the less pronounced is the incentive of managers to issue biased reports. While the precise extent of this link may be unknown (as assumed in the model), the literature provides some guidance on when (i.e., for which firms) this link is likely stronger. For example, firm age is known to play a significant role in the extent to which managers care about stock price. De Angelis and Grinstein (2015) provides evidence that firm age is negatively related to the weight placed on market-based measures on executive compensation contracts. Ittner et al. (2003) observes that "relative to more traditional firms, (younger) new economy firms provide a larger proportion of compensation in the form of equity grants, have more unexercised stock options as a percent of total shares outstanding." Forsyth et al. (2007) shows that younger firms are more likely to award stock options to their executives.

Again, in the context of our analysis, these studies imply that earnings co-movement should be more of a factor for younger firms–relative to older, more mature firms—in determining to what extent managers engage in biased reporting. Although firm age is a coarse measure of the extent of stock-based compensation to managers, obtaining actual compensation related information for the entire sample of firms is not possible at this time. [11] With that said, to the extent that firm age captures characteristics other than executive compensation, the predicted direction of co-movements on AAERs becomes unclear. However, to the extent that firm age reflects differences in stock-based compensation incentives, we have clear predictions and thus interpret any reported results as being consistent with the theory.

To test this hypothesis, we partition our sample of AAER observations into two subsamples based on firm age, using firm incorporation dates as in Fink

[11] Execucomp excludes many of the sample firms, and we do not have access to broader databases like Equilar.

Table 4 Logistic Regression of Determinants of AAERs

	Competition		Firm Age		Analyst Following	
	Low	High	Low	High	Low	High
Intercept	−11.6797***	−10.3085***	−11.7771***	−10.8443***	−13.0691***	−10.3495***
	(213.94)	(125.96)	(187.79)	(180.70)	(191.29)	(176.27)
CoMove	−0.7906**	−0.2153	−0.7787**	−0.2098	0.1867	−0.7244**
	(5.13)	(0.25)	(4.09)	(0.30)	(0.20)	(4.70)
lnMVE	0.4200***	0.4373***	0.4916***	0.3625***	0.5136***	0.3529***
	(136.96)	(94.49)	(151.41)	(74.84)	(145.39)	(86.72)
rsst	−0.1843	−0.1490	−0.2871	−0.0330	−0.1683	0.0068
	(0.24)	(0.08)	(0.22)	(0.01)	(0.18)	(0.00)
Δrec	−0.1847	1.8650	−2.5086*	2.6175***	0.5144	1.0201
	(0.03)	(2.08)	2.86)	(6.95)	(0.20)	(0.69)
Δinv	−0.5514	−0.3932	0.9702	−1.1231	1.6887	−2.8147*
	(0.17)	(0.06)	(0.29)	(0.78)	(1.51)	(3.53)
$soft_{a}ssets$	2.9697***	2.1773***	3.9595***	1.2242***	2.2397***	2.6438***
	(74.57)	(21.90)	(81.10)	(11.72)	(26.95)	(59.88)
Δcs	0.0551	0.0918	0.0838	0.0465	0.1023	0.0945
	(0.48)	(0.61)	(0.39)	(0.42)	(1.94)	(0.92)
Δroa	−0.6169	−0.2505	−1.8255*	−0.4976	−0.6068	−0.4157
	(2.19)	(0.15)	(4.01)	(1.82)	(2.01)	(0.54)
issue	1.0881**	−0.1374	0.1776	0.7106	0.4749	0.7313
	(4.57)	(0.15)	(0.23)	(2.38)	(1.26)	(2.57)
Δemp	0.0407	−0.3940**	−0.1247	−0.0904	−0.2531*	0.2396
	(0.07)	(5.14)	(0.29)	(0.50)	(3.34)	(1.63)
leasedum	0.3934*	0.5420*	0.6042**	0.2156	1.4395***	0.0713
	3.12)	(3.55)	(5.07)	(0.92)	(15.28)	(0.14)
ret_t	0.0167	−0.1224	−0.0360	−0.0208	−0.0608	0.0135
	(0.02)	(0.63)	(0.05)	(0.04)	(0.26)	(0.01)
ret_{t-1}	0.1831*	0.0903	0.0625	0.2182**	0.2387**	0.0878
	(3.72)	(0.47)	(0.18)	(6.22)	(5.84)	(0.63)
lnOperCyc	0.0837	−0.0056	−0.0239	0.2464**	0.1929	0.0527
	(0.66)	(0.00)	(0.04)	(4.63)	(1.89)	(0.25)
NegEarn	0.4006**	−0.0903	0.4233*	0.1053	0.0612	0.3066
	(4.75)	(0.10)	(3.23)	(0.26)	(0.07)	(2.29)
σCFO	1.0651**	0.3815	−3.2728**	1.1654***	1.0787**	0.4491
	(5.38)	(0.25)	(4.33)	(8.50)	(4.73)	(0.61)
$\sigma sales$	0.2021	1.8126***	0.6764	1.1220***	1.1754***	0.7118*
	(0.27)	(16.25)	(1.68)	(10.19)	(8.33)	(3.10)
Beta	0.4318***	0.2836**	0.4160***	0.3675***	0.2312**	0.2844***
	(20.61)	(4.48)	(10.46)	(14.40)	(4.37)	(7.31)
σret	3.4728**	2.3431	6.1306***	1.7450	3.7948**	4.6391**
	(4.30)	(0.88)	(7.52)	(1.03)	(4.05)	(5.83)
LogLikelihood	331.94	178.93	348.11	193.79	280.21	202.06
N	29,869	25,418	28,000	27,298	27,339	30,985

Notes: The table presents the results of estimating a logistic model of the determinants of receiving an AAER over the period 1982–2011 using model (5) from Table 3. Age is defined as firm age based on Fink et al. (2010). Competition is based on the Herfindahl index using sales within Fama French 48 industry, and Analyst Following is the mean of analyst following over years $t-2$ to t. High (low) samples are based on above (below) median values within industry-year. All variables are as defined in Table 1. Wald chi-squares are provided in parentheses. ***/**/* represent significance at the 1%/5%/10% levels using industry-clustered standard errors.

et al. (2010). We again re-estimate the logistic regression for each of these subsamples. Table 4 presents the results. The mean (median) co-movement is 0.181 (0.096) for the low age subsample and 0.161 (0.079) for the high age subsample. The coefficient on co-movement (-0.779, $p < 0.05$) is reliably negative for the low age subsample, but we cannot reject the null that this coefficient is zero for the high age subsample. This result is consistent with the prior literature's notion that younger firms focus more on stock-based compensation, and as such, co-movement plays a greater role in determining whether or not to bias an earnings signal.

4.2.3 Analyst following

Analyst following is typically viewed by the literature as proxying for the degree to which a firm is in the public eye and how much public information is available about a firm. There is a large literature on the influence of analysts on firm behavior, with results indicating that analysts help reduce information asymmetry, serve as external monitors to firm managers, and reduce discretionary accruals (Brennan and Subrahmanyam 1995, Hong et al. 2000, Yu 2008, among others). These findings predict a decreased influence for earnings co-movement on the probability of AAERs for high analyst coverage firms. However, there are other studies that document analysts induce myopic behavior on the part of managers, including too heavy a focus on short-term stock returns and willingness to sacrifice long-run economic performance to meet analyst forecasts (Graham et al. 2005; Bradshaw et al. 2006). In turn, these findings lead to the prediction that the influence of co-movements will be greater in the high analyst following subsample since stock price incentives to manipulate earnings are strongest. Regardless of the predicted direction, analyst following is often used to characterize the information environment and thus raises an interesting question of whether co-movement will still be a determinant of the biasing behavior of firms even in the presence of considerable analyst following?

To investigate the impact of analyst following on our results, we partition our sample of AAER observations into two subsamples based on analyst following (i.e., above and below median analyst following, where analyst following is determined by a three-year moving average). We reestimate the logistic regression for each of these subsamples, with results presented in the final two columns of Table 4. The mean (median) co-movement is 0.156 (0.077) for the low following subsample and 0.178 (0.094) for the high following subsample. The coefficient on co-movement (-0.724, $p < 0.05$) is reliably negative for the high following subsample, but we cannot reject the null that this coefficient is zero for the low following subsample. The results indicate that co-movement is a major driver of reporting behavior even for firms under scrutiny from the analyst community. It is surprising that co-movement is not an important factor for the low analyst following subsample, given these firms are typically characterized as low information environments. We do not have a reasonable explanation for the lack of results here other than AAERs are typically leveled against larger, more high profile firms potentially limiting the importance of co-movements as a determinant in this subsample.

4.3 Conservatism

Although AAERs represent clear signals of reporting bias, they are infrequent since the SEC has limited resources and only pursues cases that provide the greatest cost benefit trade-off. However, there are more subtle forms of bias in financial reporting arising, for instance, from conservatism and the opportunistic use of discretionary accruals. It is instructive to examine whether earnings co-movement explains such bias, as predicted by our framework in a broader setting. We choose to investigate conservatism as a second measure of bias in the earnings report simply because conservatism is an important property of financial reporting systems and has attracted much attention in the literature over the last two decades. In particular, the literature has highlighted various useful features of conservatism that stem primarily from contracting benefits (Watts 2003). At a general level, conservatism represents a particular form of bias in earnings and most commonly refers to the asymmetric treatment of losses and gains, resulting in greater timely recognition of losses.

Accordingly, we investigate the relation between co-movements and conservatism. Given our model is one in which managers' incentives are tied to stock price, we expect low co-movement firms to exhibit less conservatism than higher co-movement firms. The reason is that, with less earnings co-movement, market participants learn less about a firm's true earnings from industry earnings, which provides managers with the opportunity to prop up stock price by, for instance, accelerating (delaying) recognition of gains (losses). This in turn reduces the asymmetry between gains and losses.

To test this prediction, we apply a Basu (1997) reverse regression of earnings on returns, an indicator for negative returns, and the interaction of the two. To assess the effect of earnings co-movements, we split the full sample into high and low co-movement samples based on the median within-industry value at the end of year $t-1$, which helps avoid continuous interaction terms that are difficult to interpret as well as separating the measurement of co-movement from conservatism since contemporaneous measures would be influenced by the same economic events. As previously noted, we expect low co-movement firms to be less conservative on average, i.e., the asymmetric timeliness coefficient (coefficient on the interaction of returns and the indicator for negative returns, which measures the incremental association between earnings and negative returns) is expected to be smaller compared to the same coefficient for high co-movement firms.

We present the results in Panel A of Table 5. As expected, we document that the asymmetric timeliness for negative returns is smaller in the low co-movement sample (0.35) compared with the high co-movement sample (0.41), with the difference significant at less than the 1% level. The total coefficient on negative returns is 0.33 (0.37) for low (high) co-movement firms, which represents a 10 percent reduction in conservatism across the two subsamples. Overall, low co-movement firms are

Table 5 Conservatism and Earnings Co-Movements

	Low Co-Movements	High Co-Movements	Difference
Panel A: Full Sample			
Intercept	0.0665***	0.0684***	0.0019
	(38.09)	(35.66)	
D	−0.0045	−0.0087***	−0.0042
	(−1.47)	(−2.59)	
Ret	−0.0201***	−0.0458***	−0.0257***
	(−7.27)	(−15.21)	
$Ret * D$	0.3521***	0.4131***	0.0610***
	(45.07)	(47.75)	$AdjR^2$
$AdjR^2$	0.0952	0.0899	
N	38,389	39,442	
Panel B: Low Analyst Sample			
Intercept	0.0652***	0.0622***	−0.0030
	(22.43)	(19.66)	
D	−0.0031	−0.0063	−0.0032
	(−0.60)	(−1.14)	
Ret	−0.0147***	−0.0273***	−0.0126*
	(−3.34)	(−5.85)	
$Ret * D$	0.2912***	0.3451***	0.0539***
	(21.77)	(23.73)	
$AdjR^2$	0.0810	0.0825	
N	10,860	11,566	
Panel C: High Analyst Sample			
Intercept	0.0666***	0.0677***	0.0011
	(31.75)	(31.45)	
D	0.0025	0.0001	−0.0024
	(0.68)	(0.03)	
Ret	−0.0180***	−0.0331***	−0.0151***
	(−4.71)	(−8.78)	
$Ret * D$	0.2647***	0.2925***	0.0278*
	(25.56)	(28.24)	
$AdjR^2$	0.0921	0.0942	
N	11,235	11,964	

Notes: The table presents the results of estimating a Basu (1997) model, where the dependent variable is earnings per share (scaled by opening price), *Ret* is the 12-month buy-and-hold raw return ending three months after the balance sheet date, and *D* is an indicator for negative returns. The sample is split into high and low co-movement samples based on the *CoMove* in the prior period. Panel B (C) partitions the sample based on low (high) analyst following partitioned on below (above) median analyst coverage within industry-year. Standard errors are presented in parentheses. ***/**/* represent significnace at the 1%/5%/10% levels using industry-clustered standard errors.

less conservative than high co-movement firms, which is consistent with the AAER results where firms with lower co-movements are more likely to report aggressive earnings. [12]

To further investigate the impact of co-movement on the extent of conditional conservatism we detect in reported earnings, we split the sample into two subsamples based on the level of analyst following (i.e., above and below median analyst following, where analyst following is determined by a three-year moving average), and repeat the analysis in Panel A of Table 5 for each of these subsamples. Both conservatism and analyst coverage have been shown to reduce the information asymmetry between managers and investors (LaFond and Watts 2008; Ahmed and Duellman 2007; Brennan and Subrahmanyam 1995; Hong et al. 2000). Thus the robustness of the influence of co-movements on conservatism in the face of monitoring by analysts is an empirical question, which we address with sample partitions.

Panels B and C of Table 5 present the results. As we can see from these panels, the asymmetric timeliness for negative returns is reliably smaller for low co-movement firms compared with high co-movement firms for both analyst following subsamples, indicating that low (high) co-movement decreases (increases) the level of conservatism, regardless of the extent to which a firm is followed by the analyst/investment community. Thus co-movement's influence on conservative financial reporting is robust across differing analyst coverage environments, highlighting the importance of co-movements in determining the degree to which managers bias their earnings reports in this fashion.

4.4 Sensitivity analysis

The theory developed in Section 2 identifies two measures of co-movements: (1) the (adjusted) R^2 from a regression of firm earnings on industry-level earnings, which is our primary measure, and (ii) the *magnitude* of a firm's earnings beta from the same regression. The findings are robust to using the magnitude of the earnings beta, which results in a coefficient estimate of -0.0314 and p-value of 0.01 in untabulated tests replicating column 1 from Table 3. The econonomic significance of the results are also similar, with a one standard deviation change in the absolute earnings beta resulting in an 8–11 percent change in the odds of having an AAER. However, unlike the *CoMove* variable, the earnings beta measure is sensitive to the inclusion of other risk factors like the standard deviation of cash flows and sales, return beta, and the standard deviation of returns. When these additional risk factors are included in the model, earnings beta loses significance, indicating that it is capturing risk-related concepts as opposed to the probability of biasing an earnings signal stemming from co-movements with the industry. Nevertheless, the additional risk-related con-

[12]We do note that the coefficient on *Ret* in both samples is negative, which differs from the results presented in Basu (1997), but is consistent with a number of more recent studies investigating conservatism (see Martin and Rowchowdhury 2015 and Banker et al. 2016, among others). In untabulated analysis, we document a similar positive coefficient to Basu (1997) if we limit the sample to the years in Basu (1997) with no change to the inferences on the co-movement subsamples.

trol variables have not been theoretically modeled, and thus we cannot theoretically assess how their inclusion will affect the causal association between co-movement and reporting bias. While it is not our intent to provide the best model for determining AAERs, our empirical findings appear to indicate that adjusted R^2 measures of co-movements better capture the causal effect of co-movement on reporting bias. We leave further refinements of the co-movement measure to future research.

Approximately 30 percent of sample observations have negative earnings beta coefficients meaning their earnings move opposite to industry-level earnings. Given the very different nature of these counter-cyclical firms, we re-estimate all results (including those using $CoMove$ as the empirical measure), splitting the sample into positive and negative earnings beta observations with no change in inferences.

In addition to altering the measurement of the co-movement variable, we perform a variety of robustness tests related to our results. First, we include the financial statement comparability measure developed in De Franco et al. (2011), which uses both returns and earnings to determine firm comparability. This is clearly related to our earnings co-movement variable but is different in the sense that it estimates whether the earnings report is comparable based on the information provided in returns. This measure requires stringent data requirements and reduces the sample size by 40 percent. Nevertheless, the coefficient on $CoMove$ is slightly stronger, while the coefficient on the De Franco et al. (2011) comparability measure varies across all our analysis from positive and insignificant to negative and significant. Given these varying results, we simply conclude that the results on earnings co-movements are robust to the inclusion of other measures of financial statement comparability.

We also replicate our results with a number of different returns-based betas. Specifically, we include a measure of downside risk (Ang et al. 2006) and a sentiment beta which captures a firm's sensitivity to market-wide sentiment (Glushkov 2006).[13] The inclusion of both these measures does not alter the inferences. Overall, the results are robust to the inclusion of a variety of control variables, partitions of the data, and measurement concerns.

5 Conclusions

We provide a theory that directly attributes the probability of biasing an earnings signal to the degree to which firm-specific earnings are related to industry-level earnings. The intuition for the theory is the less the market learns about firm earnings from other firms, the greater the reliance on firm-specific earnings. Under the assumptions that managers try to maximize stock price and the market cannot unwind all earnings management, managers of firms whose earnings co-move less with the market will be more likely to bias their earnings signals. Using AAERs as a proxy for biased

[13] The sentiment beta proposed by Glushkov (2006) is essentially the Carhart four-factor model including a sentiment factor from Baker and Wurgler (2006) estimated over rolling 60-month periods, with the coefficient on the sentiment factor capturing how sensitive a firm's returns are to market wide sentiment (Coulton et al. 2016).

earnings, the empirical findings support the theory, with firms that do not co-move with the market experiencing up to a 53 percent increase in the odds of having an AAER relative to firms that co-move perfectly with the market. Finally, firms with lower co-movement of earnings with the industry have less conservative earnings, compared with the sample of firms with high earnings co-movement, which is again consistent with the predictions from the theory.

Overall, our theory and results help provide a causal link between earnings co-movements and the conditions under which firms are more likely to manipulate earnings. Our study is notable in that we explicitly consider competing information from other firms in the market in documenting the likelihood of earnings manipulations. Most other empirical studies on earnings management implicitly assume firms operate in isolation and do not consider other firms when making their earnings management decisions. Our study provides a sort of calibration of how much and when firms consider other information in making decisions, but the literature needs much more work on this subject. By appealing to theory, the empirical results in this study provide for clear insights that are often lacking in the earnings management literature using discretionary accrual models. Developing more refined theories and empirical measures of earnings co-movements represents a fruitful area for future research. For instance, determining whether co-movements are primarily related to cash flows versus accruals could help academics, regulators, and auditors better isolate earnings management activities. In general, using information available from resources outside the firm will be helpful in understanding and motivating when managers might choose to bias their financial performance. The current study provides a preliminary step in this process opening the door for a variety of future research paths.

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Appendix 1: Proof of Proposition 1

Proof Note that

$$\begin{aligned}
\alpha_r &= \frac{\sigma_u^2}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]} = \frac{\sigma^2 - \beta^2\sigma_E^2}{\left[\sigma^2 - \beta^2\sigma_E^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]} < 1, \\
\alpha_E &= \frac{\left[\sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}{\left[\sigma_u^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]}, \text{ and} \\
\alpha_0 &= -\lambda_x\mu_x\alpha_r. \qquad (7)
\end{aligned}$$

With $\lambda_x = \frac{\alpha_r}{c}$,

$$\begin{aligned} \alpha_r &= \frac{\left[\sigma^2 - \beta^2\sigma_E^2\right]}{\left[\sigma^2 - \beta^2\sigma_E^2 + \sigma_\varepsilon^2 + \lambda_x^2\sigma_x^2\right]} \qquad (8) \\ &= \frac{\sigma^2 - \beta^2\sigma_E^2}{\left[\sigma^2 - \beta^2\sigma_E^2 + \sigma_\varepsilon^2 + \left(\frac{\alpha_r}{c}\right)^2\sigma_x^2\right]} \\ \Leftrightarrow \\ &\frac{\sigma_x^2}{c^2}\alpha_r^3 + \left(\sigma^2 - \beta^2\sigma_E^2 + \sigma_\varepsilon^2\right)\alpha_r - \left(\sigma^2 - \beta^2\sigma_E^2\right) = 0, \qquad (9) \end{aligned}$$

The optimal reporting bias is given by Eq. 5:

$$b(x, s) = \frac{\alpha_r}{c}x.$$

Our interest is to sign $\frac{db(x,s)}{d\beta}$:

$$\frac{db(x, s)}{d\beta} = \frac{x}{c}\frac{d\alpha_r}{d\beta}.$$

Differentiating Eq. 9 with respect to β,

$$\left[\frac{3\sigma_x^2}{c^2}\alpha_r^2 + \left[\sigma^2 - \beta^2\sigma_E^2 + \sigma_\varepsilon^2\right]\right]\frac{d\alpha_r}{d\beta} + 2\beta\sigma_E^2(1 - \alpha_r) = 0.$$

Noting that $\sigma^2 - \beta^2\sigma_E^2 = \sigma_u^2 > 0$ (where σ_u^2, the firm-specific risk component is always positive by assumption—see footnote 3), the coefficient of $d\alpha_r/d\beta$ is positive. With $0 < \alpha_r < 1$, the term $2\beta\sigma^2(1 - \alpha_r)$ is positive if $\beta > 0$, and it must be that $\frac{d\alpha_r}{d\beta} < 0$, which yields $\frac{db(x,s)}{d\beta} < 0$. The term $2\beta\sigma^2(1 - \alpha_r)$ is negative if $\beta < 0$, in which case it must be that $\frac{d\alpha_r}{d\beta} > 0$, which yields $\frac{db(x,s)}{d\beta} > 0$. Combining these two effects, it can be seen that $\frac{d\alpha_r}{d|\beta|} < 0$, and therefore $\frac{db(x,s)}{d|\beta|} < 0$, i.e., the reporting bias is *decreasing* in the magnitude of the earnings co-movement. It can also be seen that $\frac{d\alpha_r}{d\sigma_u^2} > 0$ and $\frac{db(x,s)}{d\sigma_u^2} > 0$. $\square$

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