Effects of earnings management strategy on earnings predictability: A quantile regression approach based on opportunistic versus efficient earnings management

ABSTRACT

This study argues that the managerial choice of earnings management strategy may be contingent upon a firm's information asymmetry and such a strategy affects the firm's earnings predictability. Measuring the information asymmetry by earnings predictability based on the subsequent dispersion in analysts' forecasts and employing a quantile regression to analyze 28,383 U.S. firm-year observations obtained from 1988 to 2014, this study reports that the effect of earnings management strategy on earnings predictability is non-uniform. Specifically, the amount of absolute discretionary accruals negatively (positively) relate to the subsequent dispersion in analysts' forecasts in the low (high) quantiles of the latter. These results support our hypothesis that a firm may implement efficient or opportunistic earnings management strategies according to the degree of information asymmetry between the firm's management and corporate outsiders.

JEL classification: G12; G32

Keywords: Discretionary accruals, analysts' forecasts dispersion, quantile regression

Data Availability: Data analyzed in the study are collected from public sources

1. Introduction

Earnings management is prevalent among business organizations (Graham et al., 2005). However, the causes and consequences of such activities have yet to be conclusively established (e.g., Dechow, 1994; Dechow and Skinner, 2000). Some argue that firms use earnings management as a tool to communicate their financial potentials to interested parties (i.e., efficient earnings management). However, others assert that managers may behave opportunistically by taking advantage of earnings management to maximize their utilities (i.e., opportunistic earnings management).

We argue that the managerial choice of an efficient or opportunistic earnings management approach is contingent upon the level of information asymmetry between market participants and a firm's corporate executives. In particular, firms with low information asymmetry may encourage managers to adopt an efficient earnings management strategy to convey a firm's future financial performance to the intended audiences. On the other hand, firms with high information asymmetry may motivate corporate executives to adopt an opportunistic earnings management strategy because market participants may not have convenient access to a firm's transactions or sufficient time and effort to discern the nature of business activities. Consequently, we hypothesize that earnings management strategy can be beneficial or harmful to earnings predictability. Moreover, we postulate that the effect of earnings management on earnings predictability may not be uniform across business entities and the strength of this association between these two elements depends on the degree of information asymmetry.

For the examinations, we use the absolute value of discretionary accruals ($|DA|$), adjusted by industry, as a proxy to measure earnings management. To gauge earnings predictability, we use the industry-adjusted analysts' forecasts dispersion (*DISP*). To test the non-uniform association between them, we employ the quantile relapse (QR) technique, which has been broadly adopted by scholars to investigate issues in economics, finance, and accounting since Koenker and Basset created it in 1978.

Employing |*DA*| and *DISP* and analyzing 28,383 observations obtained from 4,981 S&P 500, mid-cap, and small-cap companies in the U.S., we consider 19 distinct quantiles with an increment of 0.05 between quantiles. The empirical evidence obtained from our analyses demonstrates that the relation between |*DA*| and *DISP* is not uniform across the quantile values of the latter. In particular, there is a negative relation between |*DA*| and *DISP* in low quantiles of *DISP*. On the other hand, there is a positive relation between |*DA*| and *DISP* in high quantiles of *DISP*. The empirical results provide evidence to support our argument.

To ensure the robustness of the results reported in the study, we conduct several additional tests. First, we use idiosyncratic risk (*IRISK*) as the measure of return predictability. Then, we consider the small-sample problem in estimating *DISP* and |*DA*|. We also take the regulatory environment into account to examine the impact of the Sarbanes–Oxley (SOX) Act. Also, we incorporate a year dummy to investigate the year-fixed effect. Moreover, we consider the sign of discretionary accruals. According to the results from these additional tests, the empirical findings reported in this study are robust.

The remainder of this paper proceeds as follows. Section 2 reviews the literature and develops research questions. Section 3 discusses the econometric models. Section 4 describes samples, variables, and the regression model. Section 5 presents the empirical findings and discusses the implications of the empirical results. Section 6 shows the findings of the robustness tests. Finally, Section 7 summarizes the study and offers conclusions.

2. Literature review and research questions

2.1 Efficient versus opportunistic earnings management

There are two types of earnings management strategy: efficient and opportunistic earnings management (Scott, 2000). Proponents of efficient earnings management claim that managers use discretionary accruals to improve the quality of reported earnings by communicating proprietary information to market participants. Consistent with this view, Healy and Palepu (1993) point out that corporate executives prefer to incorporate as much impact from current economic events and private information into current-period earnings as possible. To achieve this objective, managers can leverage discretionary accruals to reveal their private knowledge to market participants, even when capital markets have been considered efficient. In this case, earnings management would improve the predictability of a firm's performance (Chaney et al., 1998). Subramanyam (1996) also suggests that the inherent flexibility in the GAAP offers an effective channel for corporate executives to strengthen the value relevance of reported earnings. Through these discretionary accruals, management can convey private information about a firm's future profitability that is not fully captured in nondiscretionary accruals to market participants. Moreover, Dechow and Skinner (2000) indicate that managerial discretion in accounting numbers could be one of the critical avenues for managers to bring undisclosed information about the firm to light. Similarly, Sankar and Subramanyam (2001), Krishnan (2003), Tucker and Zarowin (2006), and Hann et al. (2007) find evidence supporting the concept of efficient earnings management because such a strategy strengthens communication between the firm management and corporate outsiders.

On the other hand, an opportunistic earnings management strategy allows managers to take advantage of the discretions in accounting principles, make accounting choices, and report opportunistically for personal gains. For instance, managers may have incentives to increase the value of their equity holdings. Thus, they could be motivated to manipulate accounting earnings to achieve this objective. Consistent with this view, Burgstahler and Dichev (1997) indicate that managers can leverage earnings management either to avoid reporting operating losses of the current period or to prevent declines in earnings in the future. In addition, Balsam et al. (2002) find a negative relation between unexpected discretionary accruals and stock returns around earnings announcements. These results imply that the market regards discretionary accruals as part of the opportunistic behavior taken by executives to manage the reported earnings. Other well-known scholars, including Dye (1988), Trueman and Titman (1988), Teoh et al. (1998a, 1998b, 1998c), Burgstahler and Dichev (1997), and Burgstahler and Eames (2006) also support the notion that executives may manage earnings opportunistically. The literature appears to indicate that managerial choice of earnings management strategy could either be efficient or opportunistic.

2.2 Development of research questions

While researchers have investigated the issue of efficient versus opportunistic earnings management strategies, to our knowledge, none has yet explicitly drawn a non-uniform link between earnings management strategies and earnings predictability. In particular, prior studies do not jointly consider the managerial incentive to use efficient or opportunistic earnings management strategies when the degree of information asymmetry varies among firms. To address these voids in the literature, this study distinguishes these two types of earnings management techniques and links them to firms with various levels of information asymmetry. Measuring the degree of information asymmetry by the dispersion in analysts' forecasts, we build our arguments because prior studies have documented a significant association between earnings predictability and information asymmetry. For instance, Brown and Han (1992), Barron et al. (1998), and Affleck-Graves et al. (2002) report that firms with more (less) predictable earnings may be associated with lower (higher) information asymmetry. Moreover, Krishnaswami and Subramaniam (1999), Richardson (2000), Thomas (2002) and Maskaraa and Mullineaux (2011) suggest that researchers can use earnings predictability, measured by analysts' forecast dispersion, as a proxy for information asymmetry.

As discussed earlier, efficient earnings management can be a viable avenue for managers to communicate proprietary information to market participants; whereas opportunistic earnings management behavior refers to managerial manipulation with the purpose to achieve a specified earnings target to maximize certain individuals' utilities. Given the diverse nature of these two earnings management strategies, this study argues that these strategies could have divergent (non-uniform) impacts on earnings predictability. Moreover, whether managers use earnings management to communicate private information about firm profitability or adopt earnings management to serve personal interests may depend on the scenarios encountered. In particular, the choice between earnings management strategies would vary according to the degree of information asymmetry of a firm. For firms with low information asymmetry, it offers a conducive setting for investors to spend time and effort, examine relevant information, and to make proper assessments of a firm's operations. Under this scenario, manipulating earnings opportunistically could be a risky proposition because such activities are likely to be detected by market participants. To avoid this undesirable situation from happening, corporate executives may choose to engage in efficient earnings management instead. On the other hand, when information asymmetry between the firm's management and corporate outsiders is high, it could be costly for market participants to invest time and effort to dig into relevant information about the affected firm to efficiently monitor managerial actions. Therefore, high information asymmetry situation encourages corporate executives to manage earnings opportunistically.

Furthermore, prior studies have documented that the relationship between corporate governance and information asymmetry, i.e., high information asymmetry associating with weak corporate governance (e.g., Vafeas, 2000; Kanagaretnam et al., 2007; Dey, 2008). In this case, corporate executives may manage earnings opportunistically to deceive market participants. This undertaking worsens the earnings predictability. On the other hand, firms with low information asymmetry are likely to have strong corporate governance. Under this environment, corporate executives may actively seek for avenues to communicate their financial potentials to market participants. In this case, managers may choose the efficient earnings management strategy since it allows them to reveal information that is yet to be fully incorporated into the financial statements provided to their users. By taking this action, it would improve earnings predictability.

Measuring the information asymmetry by earnings predictability using the degree of dispersion in analysts' forecasts, firms with low information asymmetry are likely to employ efficient earnings management, and such a strategy could enhance earnings predictability. As a result, the degree of dispersion in analysts' forecasts narrows. Therefore, we predict that there would be a negative association between |*DA*| and *DISP* in low quantiles of *DISP*. In contrast, firms with high information asymmetry are inclined to use opportunistic earnings management and such a strategy could worsen earnings predictability. Consequently, the degree of dispersion in analysts' forecasts widens. Hence, we predict that there would be a positive association between |*DA*| and *DISP* in high quantiles of *DISP*.

To investigate the non-uniform impact of earnings management on earnings predictability, one can employ a two-step estimate procedure to examine this relation. Applying this procedure requires the partitioning of the sample via a chosen factor. In the context of this study, this factor is information asymmetry measured by *DISP*. Upon completing this procedure, researchers can then apply a traditional optimization method, such as OLS or LAD, to fit the data and perform comparative analyses between the partitioned segments. Implicitly, this two-step analysis methodology assumes that the partitioning process is exogenous. In reality, however, the sample segmentation and relation between earnings management and *DISP* should be analyzed jointly when such a relation is conditional on an increase or a decrease in *DISP*. Therefore, it is imperative for us to implement a research method that provides a proper setting, so that we can (1) analyze the assumed relation over a range of values of *DISP* and (2) address the endogeneity issue regarding traditional two-step methods. Since neither OLS nor LAD fulfills this prerequisite for our examination, we adopt the QR approach for data analyses.

3. Econometric models

3.1 OLS and LAD models

To understand the differences between the traditional OLS and LAD approaches as well as the QR approach, let (y_{it}, x_{it}), i = 1, 2…, N and t = 1, 2…, T, be a sample population, where subscript i denotes the ith firm and t denotes the tth period. In this study, the explained variable, y_{it}, represents a firm's earnings predictability and x_{it} is a K x 1 vector of explanatory variables for y_{it}. When dealing with panel data, the traditional linear model is represented as follows:

$$y_{it} = x_{it}'\cdot\beta + u_{it}, \tag{1}$$

where β is a K x 1 vector of unknown parameters to be estimated.

The OLS estimator vector of β is obtained from:

$$\min \sum_i (u_{it})^2 = \sum_i (y_{it} - x_{it}'\cdot\beta)^2 . \tag{2}$$

while the LAD estimator vector is obtained from:

$$\min \sum_i | u_{it} | = \sum_i | y_{it} - x_{it}' \cdot \beta |. \tag{3}$$

As the error terms in Equations (2) and (3) are equally weighted, $x_{it}'\beta$ denotes the conditional mean and median functions in the OLS and LAD, respectively.

Equation (1) implies a constant loading on each identified determinant of the dependent variable. In particular, the values of all the elements in the K x 1 vector, β, are fixed across all firms, which is a potential limitation of this model as it ignores the tail regions of the dependent variable. We will show in the next section how the QR approach mitigates this inherent limitation.

3.2 Quantile regression model

In spite of the popularity of the OLS and LAD methods in academic research, their major flaw is that the parameter estimates from these models only provide the conditional mean and median of the dependent variable thereby ignoring the behavior of the dependent variable in the tail regions. Though several random coefficient models have been proposed to mitigate this problem, we choose the QR because the parameter of the explanatory variable can be expressed as a monotonic function of a single, scalar random variable. Thus, it captures systematic influences of the conditional variables on the location, scale, and shape of the conditional distribution of the response.

To illustrate how the QR allows us to investigate the effect of earnings management on earnings predictability across the entire distribution of the latter, assume that there is a linear relationship between the θth quantile of the explained variable y_{it} and the explanatory variables x_{it}. Under this assumption the conditional QR model can be written as follows:

$$y_{it} = x_{it}'\cdot\beta_\theta + u_{\theta it}. \tag{4}$$

In the model above, the β_θ is the unknown vector of parameters to be estimated for different values of θ in (0,1), and the $u_{\theta it}$ is the error term assumed to be drawn from a continuously differentiable distribution function. By allowing us to change the value of θ from zero to one the QR approach enables us to trace the whole distribution of y conditional on x. In particular, the following equation shows the estimator for β_θ.

$$\begin{aligned} &\min \sum_{it:u_{\theta it}>0} \theta\times|u_{\theta it}| + \sum_{it:u_{\theta it}<0} (1-\theta)\times|u_{\theta it}| \\ &= \sum_{it:y_{it}-x_{it}'\cdot\beta_\theta>0} \theta\times|y_{it}-x_{it}'\cdot\beta_\theta| + \sum_{it:y_{it}-x_{it}'\cdot\beta_\theta<0} (1-\theta)\times|y_{it}-x_{it}'\cdot\beta_\theta|. \end{aligned} \tag{5}$$

This minimization problem can be solved using linear programming techniques, in spite of the estimators in Equation (5) not having an explicit form.[1]

Equation (5) shows the major feature and advantage of QR technique over OLS (Equation 2) and LAD (Equation 3). Note that in Equation (5) the estimator vector of β_θ varies with θ. By varying θ, we can thus characterize the dynamic estimator vector, β_θ, in various regions of the explained variable. We also note by comparing Equation (5) with Equation (3) that LAD is just a special case of the QR model with θ set at 0.50. As a special case, the LAD estimator does not consider the behavior of residuals in the tail region of the dependent variable.

4. Sample, variables, and empirical model

4.1 Sample

We obtained financial statement data from Compustat and analyst forecast data from Institutional Brokers Estimate Service (I/B/E/S) database collected by the Center for Research in

[1] Please refer to Koenker (2000) and Koenker and Hallock (2001) for detailed discussions.

Security Prices (CRSP). Because the amount of discretionary accrual is not an appropriate measure for earnings management among financial firms, we exclude companies with Standard Industrial Classification (SIC) codes between 6000 and 6999 from the pool of observations. After this exclusion, the final pool of samples consists of 28,383 firm-year observations from 4,981 non-financial U.S. companies. The sample period starts from 1988 and ends in 2014.

4.2 Measures of earnings predictability

Following the literature (e.g., Butler and Lang, 1991; Affleck-Graves et al., 2002; Payne and Thomas, 2003; Behn et al., 2008; Barron et al., 2009), we use the dispersion of analysts' forecasts (*DISP*) to measure earnings predictability. To calculate the *DISP*, we apply Equation (6) below:

$$Dispersion\ of\ Analysts'Forecast\ \ (DISP) = \frac{Standard\ Deviation\ of\ Analysts'\ Earnings\ Forecasts}{|\ Mean\ Analysts'\ Earnings\ Forecast|} \tag{6}$$

Because the standard deviation of the analysts' forecasts increases with the average of the analysts' forecasts, we normalize the standard deviation of analysts' earnings forecasts by the absolute value of the average earnings forecast made by analysts. To compute *DISP*, we remove observations of firms with a "zero" average earnings forecast because it results in a zero of the denominator in the above equation for a given company (e.g., Diether et al., 2002; Payne and Thomas, 2003).

Then, we employ the industry-adjusted *DISP* to control for the potential industry effect. There are several reasons to control for this effect. First, using the industry-adjusted measure of financial or accounting variables is commonly found in the literature (e.g., Berger and Ofek, 1995; La Porta et al., 2002; Powell and Stark, 2005). Second, the amount of discretionary accrual, which is the explanatory variable in the regression, is estimated by the industry. Therefore, applying an industry-adjusted *DISP* is appropriate to ensure the consistency of measurement. Finally, variability in the forecast errors and mean/median levels of *DISP* exists across industries (Cheong and Thomas, 2011). Therefore, using industry-adjusted *DISP* is suitable for our examination.

To derive the value of the industry-adjusted *DISP*, we subtract industry *DISP* from a specific firm's *DISP*. In Panel A of Table 1, we present the mean and median of *DISP* by industry. Then, we test the *DISP* across industries and display the results in Panel B. As shown in the panel, the statistics obtained from the Kruskal–Wallis test indicate that the variation in *DISP* across industries is significant (p-value < 0.0001). This result also supports our decision to use industry-adjusted *DISP* for the analyses.

[Insert Table 1 about here]

4.3 Measures of earnings management

Earnings management is not always observable by market participants. Therefore, we use discretionary accruals as a proxy for this variable (e.g., Cheng and Warfield, 2005; Bergstresser and Philippon, 2006; Larcker et al., 2007; Chi and Gupta, 2009; Datta et al., 2013). Because managers can manipulate the reported earnings upward or downward, we adopt the absolute (unsigned) value of discretionary accruals to gauge the degree of earnings management. To ensure the robustness of empirical results reported in the stud, we then analyze the effects of earnings management on earnings predictability using the signed values of discretionary accruals.

To estimate the number of discretionary accruals, we employ a cross-sectional version of the modified Jones (1991) model by controlling for the firm's performance. We adopt this revised measure because Kothari et al. (2005) report that performance-matched discretionary accruals enhance the reliability of the inferences made in earnings management research.[2] To estimate the number of discretionary accruals by year–industry based on two-digit SIC, we use the following equation:

$$\frac{TACC_{i,t}}{TA_{i,t-1}} = \alpha_0 \frac{1}{TA_{i,t-1}} + \alpha_1 \frac{\Delta SALE_{i,t} - \Delta AR_{i,t}}{TA_{i,t-1}} + \alpha_2 \frac{PPE_{i,t}}{TA_{i,t-1}} + \alpha_3 ROA_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

In Equation (7), *TACC* equals total accrual and *TA* is the number of total assets. $\Delta SALES$ equals the change in net sales and ΔAR represents the change in net accounts receivable. *PPE* is the amount of net property, plant, and equipment, and *ROA* equals the rate of return on assets. Finally, ε represents an error term. Regarding the subscripts *i* and *t*, these denote the firm and year, respectively. The discretionary accruals (*DA*) are the residuals obtained from Equation (7).

4.4 Empirical model

This study examines the effect of earnings management on earnings predictability. Thus, the explained variable, *DISP*, represents the dispersion in analysts' forecasts for the year immediately after the discretionary accruals are measured. The explanatory variable is the amount of |*DA*|. In addition to explained and explanatory variables, we include the firm size (*SIZE*), the book-to-market ratio (*BM*), and the financial leverage (*LEV*) as control variables. We control the effects of these variables in the regression analyses because the literature has indicated that these factors may affect the amount of firm's reported earnings (e.g., Boot and Thakor, 1993; McLaughlin et al., 1998). By considering this argument, we develop the following model to test the impact of |*DA*| on *DISP*:

$$DISP_{i,t} = \beta_0 + \beta_1 |DA|_{i,t-1} + \beta_2 SIZE_{i,t-1} + \beta_3 BM_{i,t-1} + \beta_4 LEV_{i,t-1} + u_{i,t} \tag{8}$$

[2] Since some prior studies on earnings management estimate discretionary accruals using the original Jones model (without controlling for firm performance), we replicate all the regressions using this alternative measure of discretionary accruals. The results (not tabulated) are similar to those reported in the tables and figures.

In Equation (8), *DISP* represents the dispersion in analysts' forecasts; whereas |*DA*| is the absolute value of discretionary accruals. Moreover, *SIZE* equals the natural logarithm of total assets and *BM* is a ratio between the book value of equity and the market value of equity. *LEV* is a ratio between total liabilities and total assets. Table 2 provides the definitions of these variables.

[Insert Table 2 about here]

5. Empirical results

5.1 Descriptive statistics

Panel A of Table 2 presents the descriptive statistics of explained, explanatory and control variables. The mean (median) of *DISP* is 0.1523 (0.0499). The skewness of *DISP* is 4.3635, which is significant. We also note that the descriptive statistics of *DISP* reported in the panel are consistent with those in Diether et al. (2002). As to the explanatory variable, the mean (median) of |*DA*| equals 0.1032 (0.0516).[3] Regarding the mean (median) of *SIZE*, *BM*, and *LEV*, it equals 6.8348 (6.7621), 0.5425 (0.4701), and 0.2510 (0.2392), respectively.

Panel B of Table 2 reports the Pearson Correlation coefficients of all the variables included in Equation (8). As shown in the Panel, *DISP* is positively and significantly correlated with |*DA*|, with a relatively small coefficient of 0.0965. Some control variables are also significantly correlated with each other. Since the highest absolute correlation coefficient observed between *SIZE* and *BM* is 40.20%, this implies that multicollinearity is not a serious issue in our analysis.

[3] We collect sufficient data from Compustat to estimate discretionary accruals using Equation (7). By construction, the average *DA* is close to zero. Our empirical results are not sensitive to the population of firms used to estimate discretionary accruals.

5.2 Quantile-varying effect of earnings management on earnings predictability

We compare the QR results with those obtained from OLS and LAD regressions. The result of LAD regression is the same as that of QR at the 0.5 quantile of *DISP*. Because we adopt a multiple regression method, the explanatory variable, and three control variables are included in the QR analysis as well. Our primary focus of this study is to examine the effect of |*DA*| on *DISP*. Thus, we present the estimation results of the |*DA*| variable in Table 3. For simplicity, we do not tabulate the estimates of the control variables and the intercept terms.

Table 3 shows that the coefficient of OLS regression on |*DA*| equals 0.0730 (p-value < 0.0001). However, the QR results show that the coefficient on |*DA*| varies widely in magnitude across the *DISP* quantiles. The coefficient increases from −0.0724 at the 0.05 quantile to 0.5496 at the 0.95 quantile. Moreover, they are significantly positive (negative) at the 0.65–0.95 (0.05–0.45) quantiles and become insignificant at the 0.50–0.60 quantiles. Note that the LAD estimate of this coefficient equals −0.0042 (p-value = 0.209), which reflects the QR result at the 0.50 quantile. Also, we test the equality-of-slope parameters across quantiles. We present the results of this comparison in the two right-most columns of Table 3. The statistics show the significance of differences between slope estimates at the θ against $(1-\theta)$ quantiles. The results of the *F*-tests reveal that the differences across firms in various *DISP* quantiles are significant at the 1% level in all cases.

To understand the variation in the estimated coefficient of |*DA*| across the quantiles of *DISP*, we plot the 95% confidence intervals of the coefficient estimates of |*DA*| in Figure 1. For comparison, we show the OLS coefficient estimate. Since the OLS estimate is a single measure of the effect of earnings management on earnings predictability, it only focuses on the mean behavior in the central region of distribution without considering the impact of the |*DA*| in the tail regions of the *DISP* distribution. Moreover, the positive |*DA*| coefficient at the very high *DISP* quantiles (0.90 and 0.95) and the negative |*DA*| coefficient at the low *DISP* quantiles (0.05 to 0.45) do not overlap with the same confidence intervals of the OLS estimate. These suggest that the OLS estimate does not capture the impact of |*DA*| on *DISP* at very high nor very low quantiles of *DISP*. Finally, the OLS estimate, in which data are pooled without considering the heterogeneity in firms, may produce an incorrect inference as to the effect of earnings management on earnings predictability for firms with extremely high or low levels of information asymmetry.

[Insert Table 3 and Figure 1 about here]

5.3 Discussions

There are several findings reported in the study worth of discussions in details. First, results reported in this study are consistent with those reported in prior studies. In particular, a firm with low (high) earnings predictability is usually associated with high (low) information asymmetry. Second, we argue that information asymmetry could influence the earnings management strategies adopted. In particular, firms with high information asymmetry between executives and corporate outsiders are likely to behave opportunistically in earnings management. Under this scenario, market participants may be "fooled," at least temporarily. Accordingly, firm management may exploit market participants because these individuals probably do not have sufficient resources or available avenues to evaluate relevant information. In other words, market investors cannot adequately monitor managerial actions or detect their earnings management behavior. Since managers working for firms with high information asymmetry are inclined to behave opportunistically in earnings management, such activities have a negative impact on earnings predictability, thus increasing dispersion in analysts' forecasts. On the other hand, executives working for firms with low information asymmetry are likely to leverage the efficient earnings management strategy. In this condition, corporate executives may use earnings management effectively to improve their communication with market participants regarding a firm's financial potentials. As a result, this type of earnings management could have a positive influence on earnings predictability, hence decreasing the dispersion in analysts' forecasts.

Finally, as shown in Table 3 and Figure 1, the positive impact of |*DA*| on *DISP* monotonically decreases as the quantile levels of the *DISP* decrease. While the QR estimates of |*DA*| are significantly positive at the 1% level between the 0.65 and 0.95 quantiles of *DISP*, these estimates become insignificant between the 0.50 and 0.60 quantiles and then turn significantly negative in the 0.05 to 0.45 quantiles. These findings are consistent with the notion that earnings management improves (worsens) the contents of communication for firms associated with low (high) information asymmetry. In particular, the efficient earnings management strategy could dominate when firms have relatively low information asymmetry. This leads to a positive impact of earnings management on earnings predictability as evidenced by the negative association between |*DA*| and *DISP*. On the other hand, firms with high information asymmetry may be inclined to undertake an opportunistic earnings management strategy. In this case, manipulating earnings has a negative impact on earnings predictability, supported by a positive association between |*DA*| and *DISP* reported in this study.

6. Robustness tests

6.1 Return predictability: Idiosyncratic risk

So far, we use *DISP* as the explained variable in the analysis (e.g., Krishnaswami and Subramaniam, 1999; Richardson, 2000; Thomas, 2002; Maskaraa and Mullineaux, 2011). However, some studies also employ idiosyncratic risk (*IRISK*) as an explained variable to measure a firm's information asymmetry (e.g., Barry and Brown, 1985; Dierkens, 1991; Moeller et al., 2007). To test whether our reported result is robust in this regard, we rerun the regressions using *IRISK*, as the explained variable.

To estimate *IRISK*, we follow Fu (2009) and Ang et al. (2009) by employing the daily Fama–French (1993) three-factor model:

$$R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + s_i \times SMB_{i,t} + h_i \times HML + e_{i,t}, \tag{9}$$

$R_{i,t}$ and $R_{m,t}$ are the daily excess returns of the $i-th$ stock and broad market portfolio at time t, respectively. $SMB_{i,t}$ is the return of the small stock portfolio minus the return of the big stock portfolio. $HML_{i,t}$ is the return on a portfolio of high book-to-market stocks minus the return on a portfolio of low book-to-market stocks. Equation (9) is estimated yearly by regressing daily excess returns of individual stocks on the daily Fama–French three factors.[4] The *IRISK* of a stock is the standard deviation of the regression residuals from Equation (9).

The results for the regression of |*DA*| on *IRISK* are graphed in Figure 2. Overall, the quantile-varying pattern of the coefficients on |*DA*| for the regression of *IRISK* is similar to that of the regression of |*DA*| on *DISP* demonstrated in Table 3 and Figure 1.

[Insert Figure 2 about here]

6.2 Small-sample issue in estimating DISP and |DA|

To make sure that the reported results are not driven by firms with small numbers of analysts, we use the 10th percentile of our sample as a threshold to filter out firms with small numbers of analyst earnings forecasts. To address the issue of a limited number of firm-year observations in an industry, we also remove firms in the industries with fewer than 40 firm-year observations when estimating abnormal accruals. Following these sample selection procedures,

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_ library.html

the number of observations drops from 28,383 to 22,345. The results are shown in Figure 3. After considering the small number of analysts and a limited number of firm-year observations in a given industry, the pattern of quantile-varying estimates for the effect of earnings management on earnings predictability is robust. This finding is supported by comparing Figure 3 with Figure 1.

[Insert Figure 3 about here]

6.3 Regulatory environment: Passage of SOX

As Cohen et al. (2008) report, the degree of earnings management increases steadily until the passage of SOX, followed by a significant decline after its enactment. DeBoskey and Jiang (2012) also point out that audit expertise may contribute to this phenomenon because auditors effectively mitigate the degree of earnings management during the post-SOX period. To consider this factor, we examine whether the passage of SOX influences the quantile-varying relation between earnings management and earnings predictability. For this investigation, we only include observations obtained after the passage of SOX in 2002. Therefore, this analysis covers data collected from 2003 to 2014. Applying this criterion to this analysis, the number of firm-year observations drop from 28,383 to 11,683. The results of the impact of $|DA|$ on *DISP* during the post-SOX period are graphed in Figure 4. Comparing Figure 4 with Figure 1, we find that the non-uniform effect of earnings management on earnings predictability is robust during the post-SOX period.

[Insert Figure 4 about here]

6.4 Year effects

The sample period starts from 1988 and ends in 2014. To capture the potential effect of economic conditions across years on the relation between $|DA|$ and *DISP*, we include a year dummy in the regression models and rerun the statistical analyses. In total, there are 16-year dummies, one for each year during the studied period. The empirical results are graphed in Figure 5, which shows our conclusion is intact after considering year effects.

[Insert Figure 5 about here]

6.5 Upward vs. downward earnings management

So far, we have used the absolute value of discretionary accruals, |*DA*|, to test the relation between earnings management and earnings predictability. However, firms can make upward or downward adjustments to their reported earnings. Therefore, it is imperative to consider this factor in the study. To address this issue, we divide the pool of observations into two subgroups according to the signed values of *DA*: (1) observations with a positive *DA*, which indicates upward earnings management, and (2) observations with a negative *DA*, which shows downward earnings management. Then, we re-investigate how the QR model behaves between these two subgroups of observations.

Panels A and B of Figure 6 report the results of the estimation for observations related to upward earnings management (positive *DA*) and downward earnings management (negative *DA*), respectively. Comparing the two panels of Figure 6, the quantile-varying |*DA*|–*DISP* relation is robust concerning the signed values of *DA*.

[Insert Figure 6 about here]

7. Summary and conclusions

Examining 28,383 non-financial firm-year observations in the U.S. from 1988 to 2014, the QR results reported in this study show that the effect of |*DA*| on *DISP* varies significantly across the distribution of *DISP*. Specifically, we find that there is a positive (negative) relation between |*DA*| and *DISP* at the high (low) quantiles of *DISP*. Overall, the empirical results reported in this study support our hypothesis that management may utilize an effective (opportunistic) earnings management strategy when a firm has low (high) information asymmetry.

This study makes the following contributions to the literature. From the perspective of efficient versus opportunistic earnings management, the quantile-varying relation between earnings management and earnings predictability demonstrated in this study supports our argument that efficient and opportunistic earnings management behaviors coexist in firms, and corporate executives can use them as reporting strategies to achieve their objectives. More importantly, the managerial choice between these earnings management strategies depends on the information asymmetry between corporate executives and market participants. In particular, managers tend to utilize efficient (opportunistic) earnings management when information asymmetry in a firm is low (high). From the research methodology point of view, this study shows that traditional optimization methods, namely the OLS and LAD, are only valid to capture the behavior of firms with a mean or median level of information asymmetry. Outside the middle range, the OLS and LAD may not be useful in fully portraying the effects of earnings management on earnings predictability. In contrast, QR allows researchers to discover the relation between earnings management and earnings predictability in the tail regions of the latter.

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Table 1
Dispersion in analysts' forecasts across industries

Panel A: Mean and median value of dispersion

Two-digit SIC code	Industry	# of Obs.	Mean	Median
01 – 09	Agriculture, Forestry and Fishing	85	0.1713	0.0576
10 – 14	Mining	1,466	0.3476	0.1561
15 – 17	Construction	196	0.2969	0.1209
20 – 39	Manufacturing	14,853	0.1456	0.0497
40 – 49	Transportation and Public Utilities	3,849	0.1405	0.0504
50 – 59	Wholesale and Retail	3,422	0.1032	0.0326
70 – 79	Business and Personal Services	3,344	0.1656	0.0446
80 – 89	Health and Social Services	1,090	0.1039	0.0295
91 – 99	Public Administration	78	0.2049	0.0800

Panel B: Kruskal-Wallis test of the difference among industries

Chi-square statistic	Degree of freedom	p-value
2085.1607	8	0.0000

In this table, we define nine industries based on the two-digit SIC code. The dispersion in analysts' earnings forecasts is conducted as the standard deviation of analysts' earnings forecasts scaled by the absolute value of their mean. We obtain analysts' forecast earnings per share data from Institutional Brokers Estimate Service (I/B/E/S) detailed database. The table reports average dispersion in analysts' forecasts across industries. Importantly, the Kruskal-Wallis Chi-square statistic shows the difference among industries is significant.

Table 2
Descriptive statistics and correlation coefficients of variables

Panel A: Descriptive statistics of variables

	DISP	*IRISK*	*|DA|*	*SIZE*	*BM*	*LEV*
Mean	0.1523	2.8235	0.1032	6.8348	0.5425	0.2510
Median	0.0499	2.4034	0.0516	6.7621	0.4701	0.2392
Standard	0.3136	1.5889	0.1594	1.7504	0.3613	0.1741
Skewness	4.3635	1.3781	3.8435	0.2001	1.4137	0.5681
Kurtosis	25.1003	5.1281	21.7283	2.5587	5.8972	3.0004
Minimum	0.0057	0.3892	0.0007	2.8275	-0.2661	0.0000
Maximum	2.6847	10.3143	1.5190	11.4745	2.3480	0.8801

Panel B: Correlation coefficients of variables

	DISP	*IRISK*	*|DA|*	*SIZE*	*BM*	*LEV*
DISP	1.0000					
IRISK	0.2730	1.0000				
|DA|	0.0965	0.1291	1.0000			
SIZE	-0.3438	-0.6072	-0.0791	1.0000		
BM	0.2960	0.1738	-0.1011	-0.4020	1.0000	
DEBT	0.0718	-0.0650	-0.1247	0.0613	0.0730	1.0000

Variable definitions:

DISP	=	The standard deviation of analysts' earnings forecasts scaled by the absolute value of their mean
IRISK	=	The standard deviation of the residual of the Fama-French (1993,1996) three-factors CAPM model, Equation (9)
|DA|	=	The absolute value of discretionary accruals (*DA*) Total accruals less nondiscretionary accruals Residual from a the regression of Equation (7)
SIZE	=	The natural logarithm of the total assets of the firm
BM	=	The book value of equity divided by market capitalization
LEV	=	Total liabilities/total assets

This study uses a sample of U.S. firms over the 17-year period from 1998 to 2014. The financial firms (i.e., SIC codes between 6000 and 6999) are excluded. The overall sample consists of a total of 4,981 firms and a total of 28,383 annual observations. The two databases used in this study are Institutional Brokers Estimate System (I/B/E/S) and COMPUSTAT.

Table 3
The impact of earnings management on earnings predictability

$$DISP_{i,t} = \beta_0 + \beta_1 |DA_{i,t-1}| + \beta_2 SIZE_{i,t-1} + \beta_3 BM_{i,t-1} + \beta_4 LEV_{i,t-1} + u_{i,t}$$

Estimated results of quantile regression				*Statistical tests of the equality of slope estimates across various quantiles*	
Quantile	*Estimate (p-value)*	*Quantile*	*Estimate (p-value)*	*Quantile*	*Estimate (p-value)*
0.05	-0.0724 (0.000)**	0.95	0.5496 (0.000)**	0.05 vs. 0.95	36.21 (0.0000)**
0.10	-0.0108 (0.000)**	0.90	0.3117 (0.000)**	0.10 vs. 0.90	62.00 (0.0000)**
0.15	-0.0129 (0.000)**	0.85	0.1394 (0.000)**	0.15 vs. 0.85	39.67 (0.0000)**
0.20	-0.0147 (0.000)**	0.80	0.0947 (0.000)**	0.20 vs. 0.80	48.04 (0.0000)**
0.25	-0.0166 (0.000)**	0.75	0.0496 (0.000)**	0.25 vs. 0.75	31.82 (0.0000)**
0.30	-0.0157 (0.000)**	0.70	0.0309 (0.000)**	0.30 vs. 0.70	61.48 (0.0000)**
0.35	-0.0150 (0.000)**	0.65	0.0160 (0.000)**	0.35 vs. 0.65	103.44 (0.0000)**
0.40	-0.0134 (0.000)**	0.60	0.0079 (0.071)	0.40 vs. 0.60	45.53 (0.0000)**
0.45	-0.0106 (0.000)**	0.55	0.0000 (0.995)	0.45 vs. 0.55	13.51 (0.0002)**
0.50	-0.0042 (0.209)	**OLS**	0.0730 (0.000)**		

The ** denotes significance at the 1% level. *DISP* is the industry-adjusted dispersion in analysts' forecasts following the year that the discretionary accruals are calculated; |*DA*| is the absolute discretionary accrual; *SIZE* is the firm size; *LEV* is the leverage, and *B/M* is the book-to-market of equity. The data source is same as in Table 2.

Figure 1
Coefficient estimates and 95% confidence intervals of absolute discretionary accruals (|*DA*|): QR vs. OLS

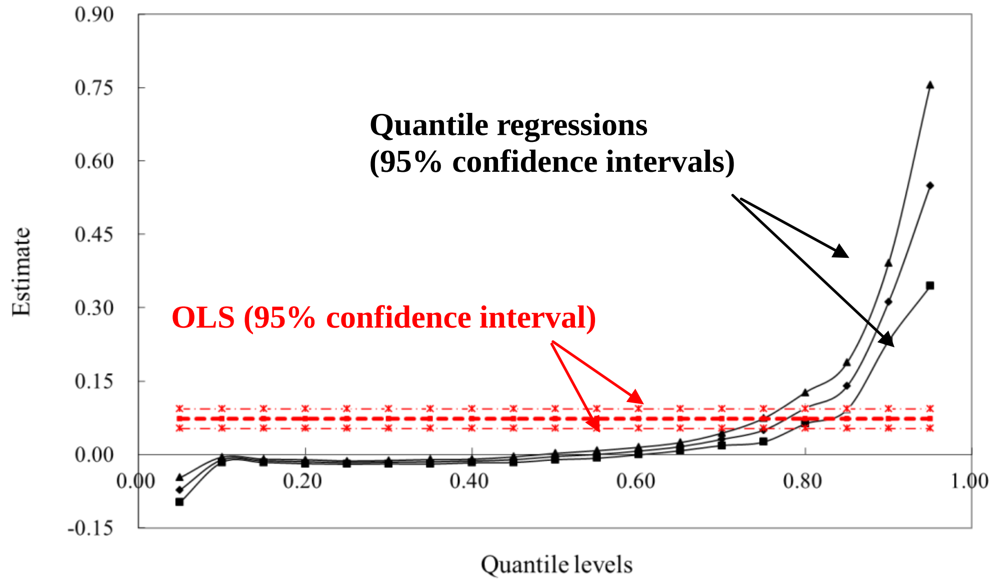


Figure 2
Coefficient estimates and 95% confidence intervals of |*DA*|: Using idiosyncratic risk as an alternative proxy of information asymmetry

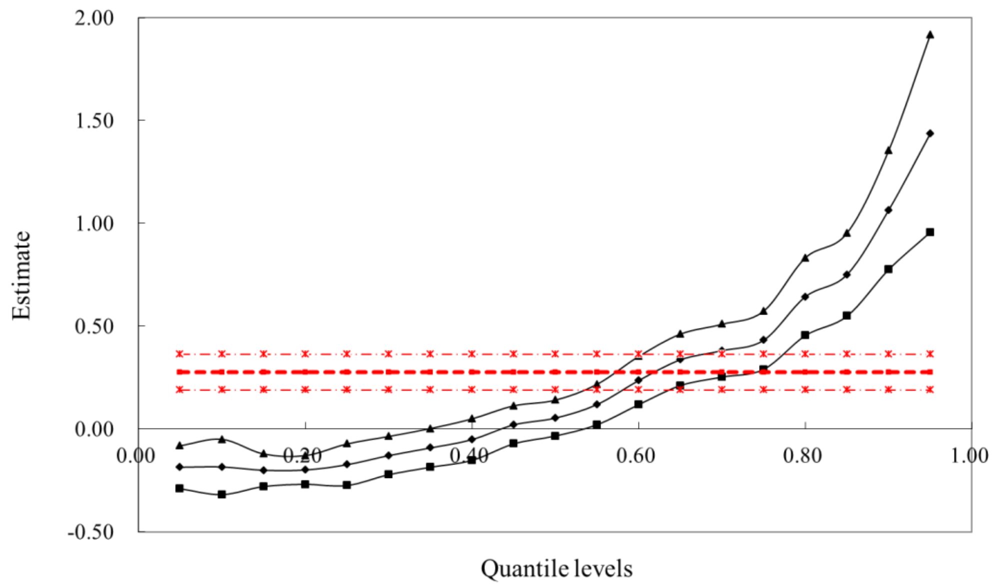


Figure 3
Coefficient estimates and 95% confidence intervals of |*DA*|: After controlling a small number of analysts and observations in estimating accruals

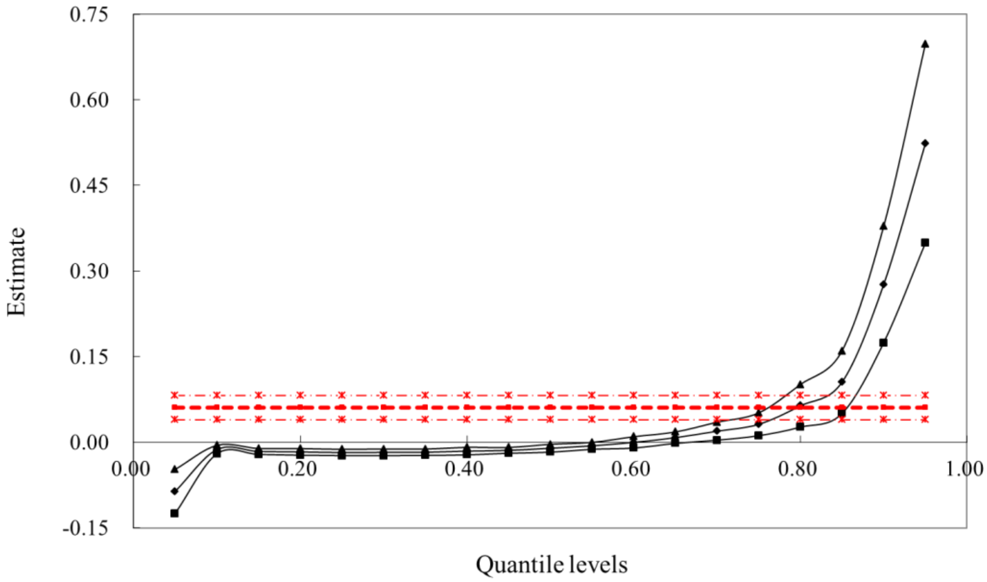


Figure 4
Coefficient estimates and 95% confidence intervals of |*DA*|:
The effect of Sarbanes Oxley Act

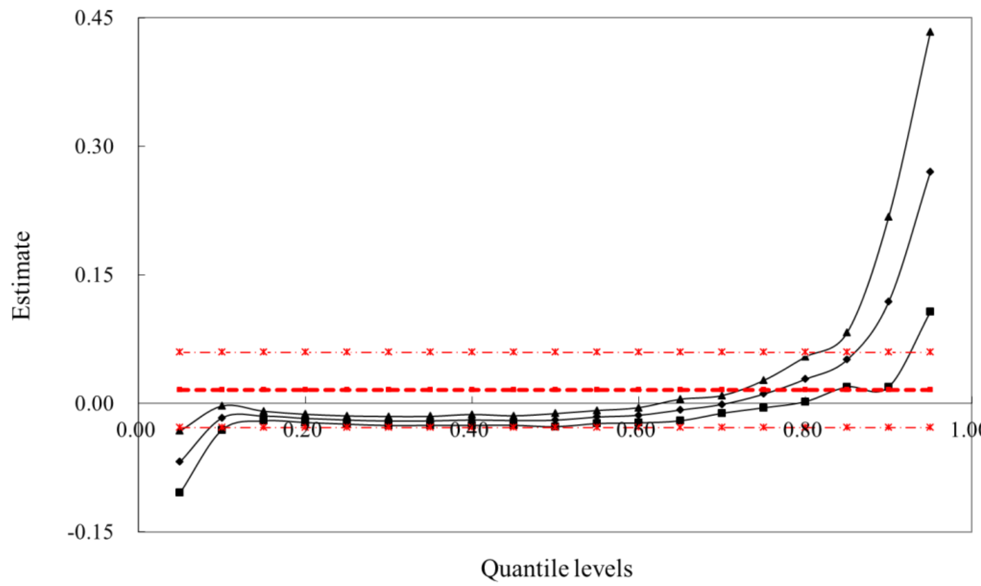


Figure 5
Coefficient estimates and 95% confidence intervals of |*DA*|: Year effects

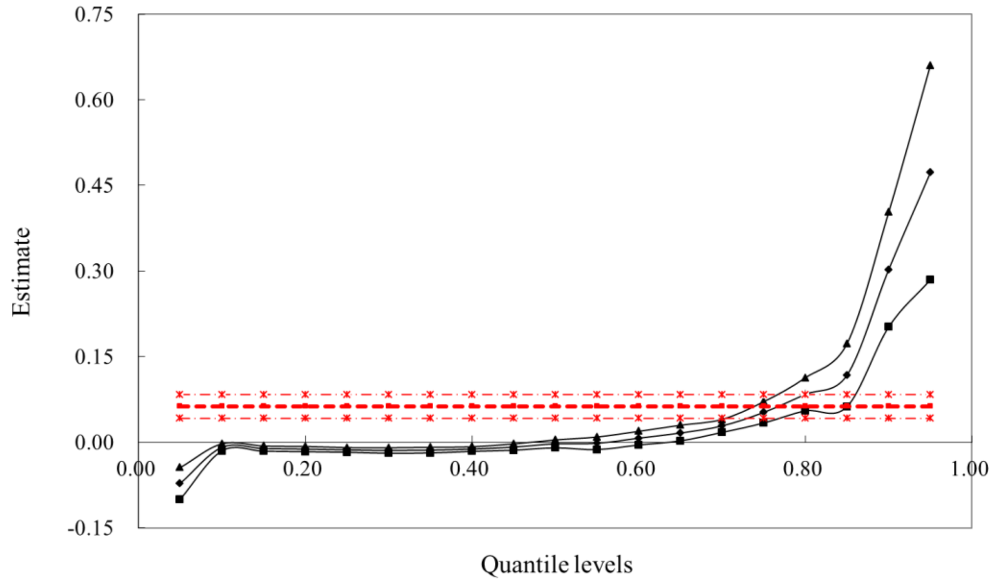
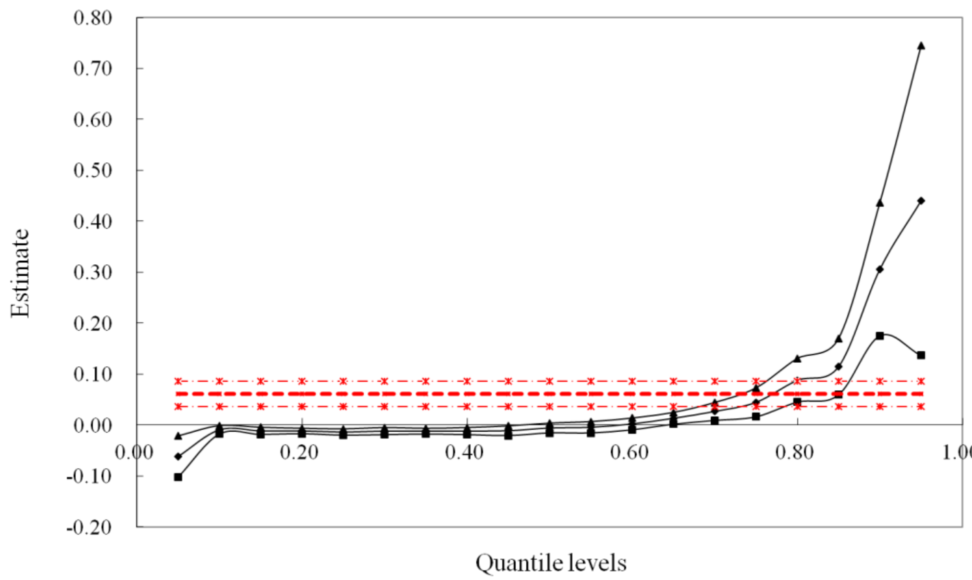


Figure 6
Coefficient estimates and 95% confidence intervals of |*DA*|:
Upward versus downward earnings management

Pane A: Upward earnings management (Positive *DA*)



Pane B: Downward earnings management (Negative *DA*)