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Executive Equity Compensation and Earnings Management: A Quantile Regression Approach

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Abstract

Prior research has investigated the association between executive equity compensation and earnings management but the evidence is not conclusive. We investigate this question using the quantile regression approach which allows the coefficient on the independent variable (equity compensation) to shift across the distribution of the dependent variable (earnings management). Based on a sample of 18,203 U.S. non-financial firm-year observations from 1995 to 2008, we find that chief executive officer (CEO) equity compensation is positively associated with the absolute value of discretionary accruals at all quantiles of absolute discretionary accruals, but the association becomes weaker as the quantile decreases. The association between CEO equity compensation and signed values of discretionary accruals is positive (negative) when the discretionary accruals are at the high (medium and low) quantiles. The results are robust to alternative measures of equity incentives and earnings management and alternative model specifications. Overall, the quantile regression results suggest that equity compensation motivates income-increasing earnings management when the firm has low financial reporting quality, but mitigates income-increasing earnings management when the financial reporting quality is high. The results also demonstrate that the least-squares and least-sum optimization techniques which are used commonly in prior research do not capture the behavior of firms at the high and low quantiles of financial reporting quality.

Keywords: Equity incentives, executive compensation, quantile regression, earnings management, discretionary accruals

JEL classification: G12; G32

Data Availability: All data are obtained from publicly available sources.

1. Introduction

Whether equity compensation motivates corporate executives to manage earnings has been debated for years. Academic research also has investigated this question but the evidence is not conclusive. Most studies find a positive association between the chief executive officer (CEO) equity compensation and earnings management, using proxies such as discretionary accruals and restatement of financial report, but some others do not find a positive association. These different results are obtained despite that the studies use similar proxies for equity incentives and earnings management. However, research design could be a factor that causes the different results. It is common in prior studies on equity compensation and earnings management to use a matched-pairs sample where a restating firm is matched with a non-restating firm using a small number of variables such as firm size and industry classification. Instead of using this common approach, Armstrong et al. (2009) use a propensity score matching process and find some evidence that the level of CEO equity incentives has a modest negative relationship with the incidence of accounting irregularities.

Our study adds to the research on CEO equity compensation and earnings management by investigating their relationship across the entire distribution of earnings management using the quantile regression, which does not require the regression coefficients to be constant. In empirical research, the constant-coefficient regression models, such as the ordinary least squared (OLS) and least-sum of absolute deviations (LAD), are used extensively. However, these models only describe the average behavior of the dependent variable (i.e., central distribution tendency) and the resulting coefficient estimates are not necessarily indicative of the size and nature of the effects of the independent variables on the tails of the dependent variable's distribution. In addition, the analytical framework in prior research tends to assume an unconditional distribution of firm observations. This form of "sample truncation" may yield invalid empirical results (Heckman, 1979).

The quantile regression (hereafter, QR) approach was developed by Koenker and Basset (1978) and used widely in recent economics and finance research. *Quantile* describes a division of observations into intervals based on the values of the data. The QR model is a random-coefficient model in which the parameter of the independent variable can be expressed as a monotonic function of a single scalar random variable, hence capturing the systematic influences of the independent variables on the location, scale, and shape of the conditional distribution of the dependent variable. The QR approach can be used to examine whether the traditional optimization techniques fail to address the behaviors in the tail regions of the dependent variable's distribution (e.g., at the 0.05 or 0.95 quantile).[1] This approach differs from segmenting the dependent variable into subsets according to its unconditional distribution and then doing least squares fitting on these subsets. To the extent that the sample segmentation and the relation between equity compensation and earnings management are jointly determined, using QR can address the potential problem in prior studies that assume segmentation of the sample is exogeneous.

We use discretionary accruals as a proxy for earnings management, where positive (negative) values imply income-increasing (income-decreasing) earnings management and larger absolute values imply more extreme earnings management. We measure equity compensation as the fair value of stock options and restricted stock granted to the CEO scaled by the CEO's total compensation. The sample

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[1] As discussed below, the QR model minimizes a sum of weighted absolute residuals. For example, the results at the 0.90 quantile are estimated when the positive (negative) residuals are given a 90 (10) percent of weight. The LAD results are the same as the QR results at the 0.50 quantile where the positive and negative residuals are equally weighted.

consists of 18,203 observations of U.S. non-financial firms (S&P 500 and medium and small cap) for the period from 1995 to 2008. We perform the QR at 19 quantiles, starting from quantile 0.05 and increasing by 0.05 each time up to quantile 0.95.

In the OLS regression of absolute discretionary accruals, we find the coefficient on equity compensation to be significantly positive. The QR results also show a significantly positive coefficient on equity compensation at all quantiles of absolute discretionary accruals, but the coefficient decreases monotonically as the quantile decreases, and becomes very small at the low quantiles. The coefficients at any two adjoining quantiles are significantly different from each other, indicating that the relation between equity compensation and earnings management varies with the likelihood of earnings management.

In the OLS regression of signed values of discretionary accruals, we find the coefficient on equity compensation to be statistically insignificant. However, the QR results show that the coefficient on equity compensation increases monotonically as the quantile of signed values of discretionary accruals increases. The coefficient is significantly negative at the 0.05 to 0.65 quantiles, statistically insignificant at the 0.70 to 0.80 quantiles, and significantly positive at the 0.85 to 0.95 quantiles.

Taken together, the QR results show that equity compensation is positively associated with absolute and signed values of discretionary accruals only at the high quantiles of these two accruals measures (i.e. low financial reporting quality). At the medium and low quantiles of signed values of discretionary accruals, equity compensation is negatively associated with discretionary accruals. The results are robust to alternative measures of discretionary accruals and equity incentives (such as lagged equity compensation to total compensation, and pay-for-performance sensitivity) and alternative model specifications. Overall, the results suggest that equity compensation motivates income-increasing earnings management in firms with characteristics associated with lower financial reporting quality. Conversely, in firms with high financial reporting quality, equity compensation mitigates income-increasing earnings management. The results also demonstrate that the least-squares and least-sum optimization techniques used commonly in prior research do not capture the behavior of firms at the extreme quantiles of financial reporting quality.

Our study contributes to the literature in several ways. First, we employ a methodology that recognizes heterogeneity in the dependent variable of the regression (earnings management) and considers the entire distribution of the variable, hence producing results that cannot be observed under the OLS and LAD approaches. Second, we use an empirical model that produces quantile-varying estimators rather than relying on a single measure of conditional central tendency, thereby linking equity compensation and earnings management in a continuous and smooth manner. Taking advantage of the less restrictive research design and empirical model, our study provides evidence that helps to explain the inconsistent findings in prior research concerning the relationship between CEO equity compensation and earnings management.

The rest of the paper proceeds as follows. Section 2 reviews related studies and develops the research questions. Section 3 discusses the theoretical models. Section 4 describes the sample, variables, and empirical model. Section 5 discusses the empirical results. Section 6 discusses the results for robustness tests and alternative specifications. Section 7 summarizes and concludes the paper.

2. Related Studies and research questions

2.1 Studies on equity compensation and earnings management

Prior studies have investigated the association between CEO equity compensation and earnings management extensively. Most studies find positive associations. For example, Larcker, Richardson, and Tuna (2007) find a positive association between compensation mix (equity compensation divided by total compensation) and discretionary accruals, and Bergstresser and Philippon (2006) find a positive association between incentive ratio and discretionary accruals. Some studies, however, do not find a statistically significant association between equity compensation and earnings management (Erickson, Hanlon, and Maydew 2006; Baber, Kang, and Liang 2007). There is also research showing that the association is negative. Armstrong, Jagolinzer, and Larcker (2010) find some evidence that accounting irregularities occur less frequently at firms where CEOs have relatively higher levels of equity incentives.

Some studies further investigate the association between the components of equity compensation and earnings management. Harris and Bromiley (2007), Burns and Kedia (2006), and Efendi, Srivastava, and Swanson (2007), find positive associations only for option-related compensation, Cheng and Warfield (2005) find positive associations for unvested options and stock ownership, and Johnson, Ryan, and Tian (2009) find positive associations for vested stock holdings. O'Connor et al. (2006) find that the association is positive for option-related equity components only when conditioned on the board of directors' composition and compensation structure.

2.2 Development of research questions

Our study differs from prior research on the association between equity compensation and earnings management in that our analysis incorporates the potential influences of financial reporting quality on the association. Prior studies document a link between corporate governance and financial reporting quality (e.g., Dechow et al.

1996; Beasley 1996; Klein 2002), and a link between corporate governance and executive compensation (e.g., Core, Holthausen, and Larcker 1999). Therefore, firms with characteristics associated with low financial reporting quality likely have poor corporate governance, which can lead to inefficient compensation contracts (particularly stock options grants) that increase the manager's incentives to engage in earnings management.

Whether equity compensation motivates earnings management also depends on the costs and benefits of earnings management, but the costs and benefits are likely to vary with the firm's financial reporting quality. When financial reporting quality is lower, the expected costs of earnings management would be lower, as the (poor) corporate governance is less likely to deter earnings management and detection of earnings management is less likely to surprise the market participants. On the other hand, the expected benefits of earnings management would also be lower if the market participants perceive the financial reports to be of lower quality and discount the reported numbers accordingly. Prior research has not provided theoretical guidance on how the costs and benefits of earnings management vary with the quality of financial reporting, but if such variation exists, whether equity compensation motivates earnings management could also depend on the quality of financial reporting.

To investigate the conditional relationship between equity compensation and earnings management, one might think of a two-step estimation procedure which has been used in prior studies but on issues different from ours. The typical procedure is that in the first step the sample is partitioned on a factor, such as financial reporting quality in the context of our study, and in the second step the traditional optimization techniques (such as OLS or LAD) are used to fit the data and conduct comparative analyses between the partitioned segments. This two-step analysis implicitly assumes that the partitioning process is exogenous. However, to the extent that the link between equity compensation and earnings management is conditional on the firm's financial reporting quality, the sample segmentation and the link between equity compensation and earnings management should be analyzed jointly.

Based on the above discussion, we aim to investigate whether (and how) the association between equity compensation and earnings management varies with the perceived financial reporting quality of the firm. To investigate this question, it is necessary to employ a methodology that can analyze the association over a range of the values of the conditioned variable (financial reporting quality). Neither the OLS and LAD approach, nor the two-step estimation procedure mentioned above, can satisfy the need, but the quantile regression approach can. In the next section we discuss the properties of the OLS, LAD, and quantile regression models, and demonstrate that the quantile regression approach is an appropriate method to use in our study.

3. Theoretical models

3.1 OLS and LAD models

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. The dependent variable, y_{it}, is a proxy for the firm's earnings management, and x_{it} is a K×1 vector of explanatory variables for y_{it}. When the data have a panel structure, the following equation represents a fixed-effects model:

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

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

The non-quantile model in Equation (1) is potentially limited due to the use of a constant loading in each identified determinant of the explained variable. Specifically, once the final result is derived from Equation (1), the values of all the elements in the K×1 vector, β, are fixed across all firms.

Using the OLS optimization technique, we can obtain the estimator vector of β from the following equation:

$$\min \sum_{i} (u_{it})^2 = \sum_{i} (y_{it} - x_{it}' \cdot \beta)^2 . \qquad (2)$$

As to the β estimate in the LAD model, the sum of absolute errors can be minimized by following the model below:

$$\min \sum_{i} | u_{it} | = \sum_{i} | y_{it} - x_{it}' \cdot \beta |. \qquad (3)$$

In Equations (2) and (3), the error terms are equally weighted, hence $x_{it}' \cdot \beta$ represents the conditional mean and the conditional median functions in the OLS and LAD optimization techniques, respectively.

3.2 Quantile regression model

A major limitation of the OLS and LAD models is that their estimates provide only one measure of the central distribution tendency of the dependent variable and fail to consider the behavior of the dependent variable in the tail regions. To address this issue, various random-coefficient models have emerged as viable alternatives in the field of statistical application. The quantile regression (QR hereafter) model is one of those alternatives. We employ the QR approach in this study because the parameter of the independent variable can be expressed as a monotonic function of a single, scalar, random variable. The QR model captures systematic influences of the conditioning variables on the location, scale, and shape of the conditional distribution of the response. Therefore, implementing the QR model allows us to explore whether the traditional optimization techniques fail to address the behaviors in the tail regions of the dependent variable's distribution (i.e., when the quality of financial reporting is very high or low).

Assume that the θth quantile of the conditional distribution of the dependent variable, y_{it}, is linear in x_{it}, the conditional QR model can be expressed as follows:

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

$$Quant_\theta(y_{it}|x_{it}) \equiv \inf\{y : F_{it}(y|x)\theta\} = x_{it}{}'\cdot\beta_\theta\ , \tag{4}$$

$$Quant_\theta(u_{\theta it}|x_{it}) = 0$$

where $Quant_\theta(y_{it}|x_{it})$ denotes the θth conditional quantile of y_{it} on the regressor vector x_{it}; β_θ is the unknown vector of parameters to be estimated for different values of θ in (0,1); and $u_{\theta it}$ is the error term assumed to be drawn from a continuously differentiable distribution function, $F_{u\theta}(.|x)$, and density function, $f_{u\theta}(.|x)$. The value F_{it} $(.|x)$ denotes the conditional distribution of the dependent variable conditional on x. By varying the value of θ from 0 to 1, the QR approach allows users to trace the entire distribution of y conditional on x.

The estimator for β_θ is obtained from:

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

Although the estimators in Equation (5) do not have an explicit form, the minimization problem can be solved using linear programming techniques.[2]

Comparing Equation (5) with Equations (2) and (3) reveals a major feature of the QR technique: the estimator vector of β_θ varies with θ. By comparing the behaviors with different θ further, one can characterize the dynamic estimator vector, β_θ, in various regions of financial reporting quality. A comparison of Equation (5) with Equation (3) also reveals that the LAD estimator is a special case of the quantile-varying estimator at the 0.50 quantile. Because the LAD estimators only represent a special case of the quantile-varying estimator, they denote a single measure of the central distribution tendency, without considering the behavior of residuals in the tail region.

The QR approach has been widely used in many areas of applied economics and econometrics, such as wage structure (Buchinsky, 1994, 1995; Mueller, 2000; Angrist, et al., 2006; Chernozhukov and Hansena, 2006), earnings mobility (Trede, 1998; Eide and Showalter, 1999; Gosling, et al., 2000), and educational quality issues (Eide and Showalter, 1998; Levin, 2001). There is also growing interest in employing QR in finance research. Applications in this field include works on Value at Risk (Taylor, 1999; Chernozhukov and Umantsev, 2001; Engle and Manganelli, 2004), option pricing (Morillo, 2000), the cross section of stock market returns (Barnes and Hughes, 2002), mutual fund investment styles (Bassett and Chen, 2001), hedge fund strategies (Meligkotsidou, Vrontos, and Vrontos, 2009), and bankruptcy prediction (Li and Miu, 2010). This study serves as the first attempt to apply the QR models in the research on CEO equity compensation and earnings management.

In this study, we use the design-matrix bootstrap method to estimate the

[2] See Koenker (2000) and Koenker and Hallock (2001) for related discussions.

standard error of the coefficients in the QR model.[3] In a Monte Carlo study, Buchinsky (1994) recommends bootstrap methods for studies with relatively small samples because bootstrap methods are robust when changes are made in bootstrap sample size relative to the data sample size.[4] Furthermore, we use the percentile method proposed by Koenker and Hallock (2001) to construct confidence intervals for each parameter in β_θ, where the intervals are computed from the empirical distribution of the sample of the bootstrapped estimates.[5] In comparison with standard asymptotic confidence intervals, the bootstrap percentile intervals are not symmetric around the underlying parameter estimate.[6] Therefore, these bootstrap procedures can be extended to handle the joint distribution of various QR estimators, which allows us to test equality of the parameters across various quantiles (Koenker and Hallock 2001).

4. Sample, variables, and empirical model

4.1 Sample

Our sample consists of U.S. non-financial firms with the required financial and compensation data available from Compustat and ExecuComp for the period from 1995 to 2008. We exclude financial firms (SIC 6000-6999) as discretionary accruals are not appropriate measures of financial reporting quality (earnings management) for them. The final sample consists of 18,203 firm-year observations from 2,320 unique firms.

4.2 Measures of financial reporting quality and equity compensation

Earnings management is pervasive (Graham et al. 2005) but not always

[3] Two approaches are generally used to estimate the covariance matrix of the regression parameter vector. The first derives the asymptotic standard errors of the estimators, while the second uses bootstrap methods to compute standard errors and construct confidence intervals.
[4] Appendix A provides details of the bootstrap estimate of the standard error.
[5] See Buchinsky (1998) for a detailed discussion of the percentile method.
[6] This is useful when the true sampling distribution is not symmetric.

observable. However, firms with larger accruals are more likely to have restatements (Richardson et al. 2003). Following prior studies related to ours (e.g., Bergstresser and Philippon 2006; Larcker, Richardson, and Tuna 2007), we use discretionary accruals as a measure of earnings management. We estimate discretionary accruals using a cross-sectional version of modified Jones model after controlling for prior performance, as Kothari, Leone, and Wasley (2005) find that performance-matched discretionary accrual measures enhance the reliability of the inferences from earnings management research. Specifically, we estimate the following equation by year-industry (2-digit SIC):

$$\frac{TACC_{i,t}}{TA_{i,t-1}} = \alpha_0 \frac{1}{TA_{i,t-1}} + \alpha_1 \frac{\Delta SALE_{i,t} - \Delta AR_{i,t}}{TA_{i,t-1}} + \alpha_2 \frac{PPE_{i,t}}{TA_{i,t-1}} + \alpha_3 ROA_{i,t-1} + \varepsilon_{i,t}, \quad (6)$$

where *TACC* equals total accruals, *TA* equals total assets, $\Delta SALES$ equals change in net sales, ΔAR equals change in net accounts receivable, *PPE* equals net property, plant, and equipment, *ROA* equals rate of return on asset, and ε is an error term. The subscripts, *i* and *t*, denote firm and year, respectively. Total accruals are separated into two components: (i) nondiscretionary accruals, which equal the fitted value of total accruals obtained from estimating Equation (6), and (ii) discretionary accruals (denoted by *DA*), which equal the residuals from estimating Equation (6).

We measure equity incentives (denoted by *EQCOM*) as total value of the CEO's stock-based compensation (restricted stock and stock options) divided by total compensation.[7] This measure is termed compensation mix in some studies (e.g., Larcker, Richardson, and Tuna 2007). The value of stock options is computed based on the Black-Scholes model as of the date the options are granted.

[7] As discussed later, we obtain qualitatively similar results when measuring equity incentives by the pay-for-performance sensitivity.

4.3 Empirical model

The empirical model we estimate is a regression of discretionary accruals on equity compensation and a set of control variables, including the book-to-market ratio (a proxy for growth opportunities), net cash flows from operations, leverage, and size. Prior studies have found associations between these factors and accruals (e.g., Becker et al. 1998; Francis and Krishnan 1999; Myers, Myers, and Omer 2003; Menon and Williams 2004). The model we estimate is as follows:

$$|DA_{i,t}| \text{ or } DA_{i,t} = \beta_0 + \beta_1 EQCOM_{i,t} + \beta_2 BM_{i,t} + \beta_3 OCF_{i,t} + \beta_4 LEV_{i,t} + \beta_5 SIZE_{i,t} + \varepsilon_{i,t}, \quad (7)$$

where *DA* equals discretionary accruals and *EQCOM* equals equity compensation (both are defined previously), *BM* equals book value of equity divided by market value of equity, *OCF* equals net cash flows from operations divided by lagged total assets, *LEV* equals total liabilities divided by total assets, and *SIZE* equals natural logarithm of total assets. See Table 1 for detailed variable definitions.

Earnings can be managed upward or downward depending on the manager’s incentives. When the magnitude of earnings management is a concern but the direction is not, the absolute value of discretionary accruals is an appropriate measure of earnings management. However, if income-increasing earnings management is a more serious concern than income-decreasing earnings management, it is more appropriate to investigate the signed (raw) values of discretionary accruals. We think it is important to analyze both situations, so we investigate both absolute and signed values of discretionary accruals.

5. Empirical results

5.1 Descriptive statistics

Table 1, Panel A, presents descriptive statistics of the variables. The mean and median of *DA* equals -0.0116 and -0.0055, respectively.[8] The mean and median of |*DA*| equals 0.0690 and 0.0367, respectively. In view of the distribution of *DA*, it is an expected result that the mean of |*DA*| is much greater than the median. The mean (median) of *EQCOM* equals 0.4210 (0.4502), which indicate that on average, the CEOs in our sample receive more than 40 percent of their total pay in the form of equity compensation. Except for the book-to-market value of equity, the other control variables have symmetric distributions.

Table 1, Panel B, presents the Pearson correlation coefficients. *EQCOM* is positively correlated with |*DA*| and negatively correlated with *DA*. These two coefficients are statistically significant, though the magnitude is not large (both below 0.02). Net cash flows from operations, leverage, and firm size are negatively correlated with |*DA*|, and leverage is positively correlated with *DA*. Some of the control variables are correlated with each other, but a high correlation coefficient is observed only between leverage and size.

5.2 Equity incentives and absolute discretionary accruals

Our study concentrates on the QR analysis, but we also estimate the OLS and LAD regressions for the purpose of comparison with the QR results. Note that LAD regression is the same as QR at the 0.5 quantile of the dependent variable.

Table 2 presents the estimated coefficient for equity compensation when the dependent variable equals absolute discretionary accruals (|*DA*|). Panel A shows that in the OLS regression, the coefficient on *EQCOM* equals 0.0247 (*t*-value = 3.45),

[8] We estimate discretionary accruals based on the entire ExecuComp population with sufficient data from Compustat for estimating Equation (6). By construction, the average *DA* should be close to zero. However, some of the ExecuComp firms are not in our final sample due to lack of other data required for estimating the main regression in Equation (7). Our empirical results are not sensitive to the population of firms used to estimate discretionary accruals.

consistent with prior research findings that equity incentives are positively associated with earnings management. The coefficient on *EQCOM* in the LAD regression equals 0.0157 (*t*-value = 12.39, see the result for quantile 0.5), consistent with the OLS estimate.[9]

The QR results in Panel A of Table 2 show that the coefficient on *EQCOM* is significantly positive at all quantiles of |*DA*|, increasing monotonically from 0.0017 at the 0.05 quantile to 0.0973 at the 0.95 quantile. Panel B shows that the coefficient at any two adjoining quantiles is significantly different from each other. However, despite its statistical significance, the coefficient on *EQCOM* is very small at the low quantiles. For example, based on the inter-quartile range of *EQCOM* (= 0.506), the coefficient on *EXCOM* at the 0.05 and 0.10 quantile translates into a |*DA*| of only 0.086 percent and 0.157 percent, respectively, of lagged total assets.

We replicate the regressions after replacing the raw values of *EQCOM* by decile rankings scaled to range between zero and one. The results (not tabulated) indicate that the coefficient on *EQCOM* is significantly positive at all quantiles of |*DA*|. It increases monotonically from 0.0015 at the 0.05 quantile to 0.0748 at the 0.95 quantile. These results are similar to those shown in Table 2.

To better understand the variation of the coefficient on equity incentives across the quantiles, we plot the 95% confidence intervals of the coefficient estimates in Figure 1. The figure also shows the OLS coefficient estimate for comparison. None of the confidence intervals for the QR estimates overlap with zero, which is expected given that the coefficient on *EQCOM* is significantly positive at all quantiles. The confidence intervals at the 0.80-0.95 quantiles do not overlap with those at the 0.55-0.65 quantiles, which in turn do not overlap with those at the 0.05-0.40 quantiles. The

[9] The difference between the conditional median estimate (0.0157 in the LAD regression) and mean estimate (0.0247 in the OLS regression) can be partially due to the asymmetric conditional density and a strong effect exerted on the least squares fit by the possible outlier observations in the sample.

95% confidence interval for the OLS estimate overlaps with only the QR estimates' confidence intervals at the 0.35-0.80 quantiles. These findings show that the OLS estimate does not capture the relation between CEO equity incentives and earnings management at the high and low quantiles of absolute discretionary accruals (i.e., when the quality of financial reporting is very low or very high).

Taken together, the results in Table 2 and Figure 1 suggest that, on average, higher equity incentives are associated with more extreme earnings management. But the association is weaker when the firm has characteristics suggesting higher financial reporting quality. When the quality of financial reporting is very high, the association between equity incentives and earnings management becomes economically trivial, and the OLS method overestimates the association.

To conserve space, instead of tabulating the results for the control variables at different quantiles, we plot the coefficient estimates and their 95% confidence intervals in Figure 2. The figure shows that the coefficient on the book-to-market value of equity is not statistically significant at all quantile. The coefficient on *OCF* is significantly negative at the 0.90 and 0.95 quantiles but is indistinguishable from zero at the other quantiles, suggesting that net operating cash flows is negatively associated with absolute discretionary accruals only when absolute discretionary accruals are very high. The coefficient on *LEV* is significantly negative at all quantiles but much more negative at the 0.95 quantile. The coefficient on *SIZE* is always significantly negative and decreases monotonically with the quantile level. For *OCF* and *LEV*, the 95% confidence intervals of the coefficient at the 0.05-0.10 quantiles have no overlap with those at the 0.90-0.95 quantiles. The 95% confidence intervals of the coefficient on *SIZE* at the high (0.70-0.95) quantiles have no overlap with each other and with those at the low (0.05-0.60) quantiles. Overall, the QR results show that the associations of net operating cash flows, leverage, and size with earnings management are much stronger when the firm has lower financial reporting quality.[10]

5.3 Equity incentives and signed values of discretionary accruals

We replicate the above OLS and QR analyses using the signed values of discretionary accruals (*DA*) as the dependent variable. The results for equity incentives are presented in Table 3. Note that since the median (quantile 0.50) of *DA* is close to zero, *DA* at the 0.55 quantile or above (0.45 quantile or below) in Table 3 are positive (negative).

Panel A of Table 3 shows that, in the OLS regression of *DA*, the coefficient on *EQCOM* equals -0.0121 (*t*-value = -1.62). The LAD estimate of this coefficient equals -0.0162 (*t*-value = -10.67, see the QR result at the 0.50 quantile in the same panel). The QR results show that the coefficient on *EQCOM* increases monotonically with the quantile level of *DA*, ranging from -0.0919 at the 0.05 quantile to 0.0266 at the 0.95 quantile, and the coefficient is significantly negative (positive) at the 0.05-0.65 (0.85-0.95) quantiles. Panel B shows that the coefficient at any two adjoining quantiles is significantly different from each other.

When we replicate the regressions after replacing the raw values of *EQCOM* by decile rankings scaled to range between zero and one, we find that the coefficient on *EQCOM* increases monotonically from -0.0788 at the 0.05 quantile to 0.0208 at the 0.95 quantile (results not tabulated). The coefficient is significantly negative (positive) at the 0.05-0.70 (0.80-0.95) quantiles. These results are qualitatively similar to those shown in Table 3.

Figure 3 plots the 95% confidence intervals of the OLS and QR coefficient estimates for *EQCOM* when the dependent variable equals *DA*. The 95% confidence

[10] The detailed test results for equality of the parameter estimates between quantiles are available from the authors upon request.

intervals at the very high (0.90 and 0.95) and low (0.05 to 0.20) quantiles have no overlap with the 95% confidence interval of the OLS estimate. Therefore, consistent with the results from regression of |*DA*|, the findings in Table 3 and Figure 3 show that the OLS estimate does not capture the relation between CEO equity incentives and earnings management at the high and low quantiles of raw values of discretionary accruals. Overall, the QR results show a positive association between equity incentives and income-increasing earnings management only when the firm has characteristics suggesting poor financial reporting quality (*DA* at high quantiles). When the quality of financial reporting is relatively good, equity incentives are negatively associated with income-increasing earnings management.

The control variables' coefficient estimates and the 95% confidence intervals of the estimates are plotted in Figure 4. The figure shows a generally similar pattern of variation of the coefficients and their confidence intervals over the quantiles of *DA* when compared with Figure 2. The only differences are that net operating cash flows has a significantly negative coefficient at all quantiles of *DA*, and the coefficient on firm size is significantly positive at the low quantiles of *DA*. Overall, the QR results show higher associations of net operating cash flows and leverage with income-increasing earnings management when the firm has lower financial reporting quality. Firm size is positively (negatively) associated with income-increasing earnings management when the firm has high (low) financial reporting quality.

6. Robustness tests

We conduct various tests to check the robustness of the primary results discussed above. The tests include using alternative measures of discretionary accruals and CEO equity incentives, controlling for additional confounding factors in the regressions, using an instrumental variable approach to address the potential endogeneity problem, and using a first-difference specification (i.e., changes model).

6.1 Using alternative measures of discretionary accruals and equity incentives

In the empirical analysis discussed above, we use discretionary accruals adjusted for lagged performance, following the argument by Kothari, Leone, and Wasley (2005) that performance-matched discretionary accrual measures enhance the reliability of the inferences from earnings management research. Since some prior studies on equity compensation and earnings management estimate discretionary accruals using modified Jones model, we replicate all the regressions using this alternative measure of discretionary accruals. The results (not shown) are similar to those reported in the tables and figures. We also obtain similar regression results using discretionary accruals adjusted for contemporaneous performance.

In the primary analysis we measure CEO equity incentives as total value of restricted stock and stock options granted to the CEO divided by total compensation. Some prior studies measure CEO equity incentives in a different way, such as the pay-for-performance sensitivity and the value of stock options granted divided by total compensation. Therefore, we replicate the regressions using these two alternative measures of equity incentives.

Following the method in Core and Guay (2002), and Broussard, Buchenroth, and Pilotte (2004), we define pay-for-performance sensitivity (*PPS*) as the partial derivative of the Black-Scholes option value with respect to the stock price.[11] However, to mitigate the potential problem of heteroskedasticity, we use the natural logarithm instead of the raw value.

[11] Data on the Black-Scholes stock option values are no longer available on ExecuComp after 2006. To ensure use of consistent estimation method for option values across years, our analysis using PPS is limited to the 1995-2006 period.

Table 4, Panel A, shows the results for the regression of |*DA*| on *PPS*. The OLS coefficient estimate for *PPS* is positive but not significantly different from zero. The QR results show that the coefficient on *PPS* is positive but not statistically significant at most of the below-median quantiles of |*DA* (except the 0.10 and 0.15 quantiles). However, the coefficient is significantly positive at all of the above-median quantiles and increases with the quantile level. Untabulated results show that the coefficient at each of the 0.65-0.95 quantiles is significantly different from the coefficient at each of the 0.05-0.60 quantiles.

Table 4, Panel B, shows the results for the regression of *DA* on *PPS*. The OLS coefficient estimate for *PPS* is negative but not significantly different from zero. The QR results show that the coefficient on *PPS* is significantly negative at or below the 0.40 quantile and is significantly positive at the 0.95 quantile. Untabulated results show that the coefficient at the 0.95 quantiles is significantly different from the coefficient at the other quantiles.

Overall, the results when measuring the CEO equity incentives by pay-for-performance sensitivity are qualitatively similar to those reported in Tables 2 and 3 for *EQCOM*. We also obtain similar results (not shown) when measuring the CEO equity incentives by the ratio of stock option grants to total compensation (Hanlon, et al. 2003).

6.2 Controlling for additional confounding factors

In the robustness tests we further control for several factors that could be associated with discretionary accruals. Those factors include firm age, auditor type, and audit opinion. Prior studies find that firms that are older or audited by a Big-N auditor tend to have lower accruals, whereas firms that receive a qualified audit opinion tend to have higher accruals. We measure firm age as the length of time (in years) since the first year the firm's financial data are available on Compustat.[12] Auditor type is an indicator variable which equals one if the firm is audited by a Big-N auditor an zero otherwise. Audit opinion is an indicator variable which equals one if the firm receives a qualified audit opinion and zero otherwise. We also include a set of indicator variables to control for the year effects. The results are similar to those reported in Tables 2 and 3 after we include the above control variables in the regressions.

6.3 Other robustness tests

Endogeneity could be a concern in empirical tests when the dependent and independent variables are contemporaneous. To address this problem, we follow prior studies to use the lagged value of equity compensation as an instrumental variable for *EQCOM* and estimate the same QR model. The regression results (not tabulated) are similar to those reported in the tables.

In the primary analyses we regress the level of discretionary accruals on the level of equity incentives (equity-based compensation divided by total compensation). This type of "levels model" could be subject to the correlated omitted variables problem and may not be as powerful as the "changes model." To address this concern, we take the first difference of the variables in Equation (7) and estimate QR for the new model. The regression results (not tabulated) are still similar to those reported in the tables.

In summary, we conduct various robustness tests and find the QR results to be largely consistent with those based on the models and measures of variables in the primary analyses. The quantile-varying relationships between equity incentives and

[12] We do not use the firm's real age as it is not practical to collect such data manually for a large sample.

earnings management appear to be robust.

7. Summary and conclusions

The widespread use of equity-based compensation in executive compensation packages has raised concerns that excessive equity compensation motivates earnings management. A number of studies examine this issue but the evidence is not conclusive. Our study contributes to this line of research by using a less restrictive methodology and providing evidence that helps to reconcile the inconsistent results among the prior studies. Specifically, we investigate the association between equity compensation and earnings management using the quantile regression, which allows the parameter estimates to vary over the distribution of the dependent variable. Unlike the OLS and LAD regressions which rely on the central tendency distribution of the dependent variable, the quantile regression also examines the dependent variable at the tails of the distribution, thus facilitating an investigation of the relationship between equity compensation and earnings management across the entire distribution of the firms' financial reporting quality.

We use discretionary accruals as a proxy for earnings management, where higher (positive) accruals imply more income-increasing earnings management and larger absolute discretionary accruals imply more extreme earnings management. We measure equity compensation as the total value of restricted stock and stock options granted to the CEO divided by the CEO's total compensation, but we also use other measures in the robustness tests. Our sample consists of 18,203 non-financial firm-year observations in the U.S. (S&P 500 and medium and small cap) during the period from 1995 to 2008.

The quantile regression results show that the association between equity compensation and discretionary accruals varies substantially across the distribution of the firms' financial reporting quality (accruals), and some of the quantile regression results are very different from the OLS regression results. We find that equity compensation is positively associated with absolute discretionary accruals, but the association is much stronger at the high quantiles of absolute discretionary accruals and is economically trivial at the low quantiles. We also find that equity compensation is positively associated with signed values of discretionary accruals only at the very high quantiles of discretionary accruals, but it is negatively associated with signed values of discretionary accruals at the low quantiles. The regression results are robust to alternative measures of discretionary accruals and equity incentives and alternative model specifications.

Overall, the evidence in our study suggests that equity compensation motivates income-increasing earnings management only when the firm has characteristics associated with lower financial reporting quality. We find no evidence that equity compensation motivates earnings management when the firm's financial reporting quality is high. Our quantile regression results also demonstrate that the OLS and LAD optimization techniques only capture the behaviors of firms with financial reporting quality at the medium quantiles. Outside this range, the OLS and LAD methods are more likely to overestimate (underestimate) the association between equity compensation and earnings management as the firm's financial reporting quality moves towards the high (low) end.

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Appendix A: The bootstrap estimate of the standard error

Assume we have a real-valued estimator $\hat{\beta}$ ($X_1, X_2, ..., X_n$), which is a function of n independently and identically distributed observations:

$$X_1, X_2, ..., X_n \overset{iid}{\sim} F, \tag{A1}$$

F being an unknown probability distribution on a space κ. Having observed $X_1 = x_1$, $X_2 = x_2$, ..., $X_n = x_n$, we wish to obtain an estimate of the standard error of $\hat{\beta}$.

The true standard error of $\hat{\beta}$ is a function of F, n, and the form of the estimator $\hat{\beta}$, say

$$\sigma(F, n, \hat{\beta}(.,.,...,.)) = \sigma(F). \tag{A2}$$

This last notation emphasizes that, knowing n and the form of $\hat{\beta}$, the true standard error is only a function of the unknown distribution F.

The bootstrap estimate of the standard error, $\hat{\sigma}_B$, is simply

$$\hat{\sigma}_B = \sigma(\hat{F}), \tag{A3}$$

where $\hat{F}$ is the empirical probability distribution

$$\hat{F}: mass \frac{1}{n} \quad on \quad x_i, \qquad i=1, 2, \ldots, n. \tag{A4}$$

In practice, the function $\sigma(F)$ is usually impossible to express in simple form, and $\hat{\sigma}_B$ must be evaluated using a Monte Carlo algorithm:

Step 1. Construct $\hat{F}$ as at (A4).

Step 2. Draw a bootstrap sample from $\hat{F}$,

$$X_1^*, X_2^*, \ldots, X_n^* \overset{iid}{\sim} \hat{F}, \tag{A5}$$

and calculate $\hat{\beta}^* = \hat{\beta}(X_1^*, X_2^*, \ldots, X_n^*)$.

Step 3. Independently repeat Step 2 some number B times, obtaining bootstrap replications $\hat{\beta}^*(1)$, $\hat{\beta}^*(2)$,…, $\hat{\beta}^*(B)$, and calculate

$$\hat{\sigma}_B = \left[\sum_{b=1}^{B} \frac{[\hat{\beta}^*(b) - \hat{\beta}^*(\cdot)}{B-1} \right]^{1/2}, \tag{A6}$$

where

$$\hat{\beta}^*(\cdot) = \sum_{b=1}^{B} \hat{\beta}^*(b) / B. \tag{A7}$$

As $B \rightarrow \infty$, the right-hand side of (A6) converges to $\sigma(\hat{F})$.

Table 1
Descriptive statistics and correlation coefficients of variables

Panel A: Descriptive statistic of variables

Variable	Mean	Standard Dev.	Q1	Median	Q3
DA	-0.0116	0.2882	-0.0429	-0.0055	0.0302
|*DA*|	0.0690	0.2801	0.0161	0.0367	0.0734
EQCOM	0.4210	0.2941	0.1528	0.4502	0.6588
BM	0.5859	6.1828	0.2632	0.4251	0.6409
OCF	0.1135	0.1400	0.0618	0.1078	0.1670
LEV	0.5020	0.2037	0.3529	0.5190	0.6525
SIZE	7.1923	1.5826	6.0631	7.0552	8.1983

Panel B: Correlation coefficients of variables

Variable	*DA*	|*DA*|	*EQCOM*	*BM*	*OCF*	*LEV*
|*DA*|	-0.6146**					
EQCOM	-0.0167*	0.0188*				
BM	0.0007	-0.0006	-0.0001			
OCF	0.0062	-0.1430**	0.0282**	-0.0228**		
LEV	0.0157*	-0.0617**	-0.0376**	0.0181*	-0.1320**	
SIZE	-0.0099	-0.0634**	0.1898**	0.0038	0.0613**	0.4471**

Variable definitions:

DA	=	Discretionary accruals (Total accruals less nondiscretionary accruals)
|*DA*|	=	Absolute value of *DA*
EQCOM	=	Value of restricted stock and stock options granted to the CEO divided by total compensation
BM	=	Book value of common equity/Market value of equity
OCF	=	Net cash flows from operations/divided by total assets
SIZE	=	Natural logarithm of book value of total asset
LEV	=	Total liabilities divided by total assets

The sample consists of 18,203 firm-year observations (2,320 unique firms) for the period from 1995 to 2008. * and ** denotes statistical significance at the 0.05 and 0.01 levels, respectively.

Table 2
Results from regression of absolute discretionary accruals (|*DA*|) on equity compensation and control variables – OLS and quantile regressions at various quantile levels of |*DA*|

$$|DA_{i,t}| = \beta_0 + \beta_1 EQCOM_{i,t} + \beta_2 BM_{i,t} + \beta_3 OCF_{i,t} + \beta_4 LEV_{i,t} + \beta_5 SIZE_{i,t} + \varepsilon_{i,t},$$

	Panel A: Regression results for equity compensation (*EQCOM*)				Panel B: Results for test of equality of coefficient on *EQCOM* between quantiles		
	Coefficient	t-value	p-value	Adjusted-R^2	Quantiles compared	F-statistics	p-value
OLS	0.0247	3.45	0.001	0.0278			
Quantile				Pseudo R^2			
0.05	0.0017	3.85	0.000	0.003			
0.10	0.0031	5.55	0.000	0.005	0.10 vs. 0.05	10.22	0.001
0.15	0.0046	5.51	0.000	0.006	0.15 vs. 0.10	12.73	0.000
0.20	0.0053	6.51	0.000	0.008	0.20 vs. 0.15	2.94	0.086
0.25	0.0066	8.29	0.000	0.010	0.25 vs. 0.20	9.89	0.002
0.30	0.0083	8.16	0.000	0.012	0.30 vs. 0.25	12.13	0.000
0.35	0.0094	8.15	0.000	0.014	0.35 vs. 0.30	3.85	0.049
0.40	0.0108	9.08	0.000	0.017	0.40 vs. 0.35	9.47	0.002
0.45	0.0132	9.90	0.000	0.019	0.45 vs. 0.40	19.75	0.000
0.50 (**LAD**)	0.0157	12.39	0.000	0.021	0.50 vs. 0.45	19.45	0.000
0.55	0.0184	10.13	0.000	0.023	0.55 vs. 0.50	14.53	0.000
0.60	0.0209	9.72	0.000	0.026	0.60 vs. 0.55	15.47	0.000
0.65	0.0247	9.83	0.000	0.028	0.65 vs. 0.60	17.27	0.000
0.70	0.0276	12.70	0.000	0.031	0.70 vs. 0.65	10.59	0.001
0.75	0.0333	10.01	0.000	0.033	0.75 vs. 0.70	13.91	0.000
0.80	0.0403	9.37	0.000	0.036	0.80 vs. 0. 75	15.36	0.000
0.85	0.0480	12.45	0.000	0.038	0.85 vs. 0.80	13.47	0.000
0.90	0.0634	8.99	0.000	0.041	0.90 vs. 0.85	10.21	0.001
0.95	0.0973	6.48	0.000	0.048	0.95 vs. 0.90	12.39	0.000

See Table 1 for variable definitions and sample descriptions. Panel A presents coefficient estimates, t-values, and p-values for equity compensation (*EQCOM*). Panel B presents *F*-statistics and p-values for tests of equality of coefficient for *EQCOM* between the indicated two quantiles of |*DA*|. Only the results for *EQCOM* are presented in this table.

Table 3
Results from regression of signed values of discretionary accruals (*DA*) on equity compensation and control variables – OLS and quantile regressions at various quantile levels of *DA*

$$DA_{i,t} = \beta_0 + \beta_1 EQCOM_{i,t} + \beta_2 BM_{i,t} + \beta_3 OCF_{i,t} + \beta_4 LEV_{i,t} + \beta_5 SIZE_{i,t} + \varepsilon_{i,t},$$

	Panel A: Regression results for equity compensation (*EQCOM*)				Panel B: Results for test of equality of coefficient on *EQCOM* between quantiles		
	Coefficient	t-value	p-value	Adjusted-R^2	Quantiles compared	F-statistics	p-value
OLS	-0.0121	-1.62	0.105	0.001			
Quantile				Pseudo R^2			
0.05	-0.0919	-10.37	0.000	0.035			
0.10	-0.0629	-16.40	0.000	0.037	0.10 vs. 0.05	14.96	0.000
0.15	-0.0466	-21.39	0.000	0.040	0.15 vs. 0.10	37.24	0.000
0.20	-0.0386	-18.11	0.000	0.042	0.20 vs. 0.15	49.90	0.000
0.25	-0.0303	-16.68	0.000	0.043	0.25 vs. 0.20	26.85	0.000
0.30	-0.0249	-15.73	0.000	0.043	0.30 vs. 0.25	34.40	0.000
0.35	-0.0219	-15.37	0.000	0.042	0.35 vs. 0.30	10.98	0.001
0.40	-0.0196	-13.25	0.000	0.042	0.40 vs. 0.35	11.35	0.001
0.45	-0.0177	-15.00	0.000	0.043	0.45 vs. 0.40	4.16	0.041
0.50 (**LAD**)	-0.0162	-10.67	0.000	0.044	0.50 vs. 0.45	2.46	0.117
0.55	-0.0130	-9.93	0.000	0.045	0.55 vs. 0.50	21.36	0.000
0.60	-0.0088	-4.99	0.000	0.047	0.60 vs. 0.55	25.84	0.000
0.65	-0.0052	-2.68	0.007	0.049	0.65 vs. 0.60	18.50	0.000
0.70	-0.0027	-1.22	0.223	0.052	0.70 vs. 0.65	7.08	0.008
0.75	0.0007	0.29	0.772	0.055	0.75 vs. 0.70	10.26	0.001
0.80	0.0044	1.49	0.136	0.058	0.80 vs. 0. 75	12.78	0.000
0.85	0.0074	2.43	0.015	0.063	0.85 vs. 0.80	2.21	0.137
0.90	0.0111	3.05	0.002	0.070	0.90 vs. 0.85	2.29	0.131
0.95	0.0266	4.33	0.000	0.081	0.95 vs. 0.90	10.30	0.001

See Table 1 for variable definitions and sample descriptions. Panel A presents coefficient estimates, t-values, and p-values for equity compensation (*EQCOM*). Panel B presents *F*-statistics and p-values for tests of equality of coefficient for *EQCOM* between the indicated two quantiles of |*DA*|. Only the results for *EQCOM* are presented in this table.

Table 4
Results from regression of absolute and signed values of discretionary accruals (|*DA*| and *DA*, respectively) on pay-for-performance sensitivity (*PPS*) and control variables – OLS and quantile regressions at various quantile levels of |*DA*| and *DA*

$$|DA_{i,t}| \text{ or } DA_{i,t} = \beta_0 + \beta_1 PPS_{i,t} + \beta_2 BM_{i,t} + \beta_3 OCF_{i,t} + \beta_4 LEV_{i,t} + \beta_5 SIZE_{i,t} + \varepsilon_{i,t}$$

	Panel A: Dependent variable = |*DA*|				Panel B: Dependent variable = *DA*			
	Regression results for *PPS*				Regression results for *PPS*			
	Coefficient ($\times 10^3$)	t-value	p-value	Adjusted-R^2	Coefficient ($\times 10^3$)	t-value	p-value	Adjusted-R^2
OLS	0.1147	1.43	0.153	0.030	-0.0335	-0.39	0.699	0.012
Quantile				Pseudo R^2				Pseudo R^2
0.05	0.0019	0.85	0.395	0.002	-0.1606	-6.71	0.000	0.025
0.10	0.0070	2.52	0.012	0.004	-0.0912	-4.61	0.000	0.028
0.15	0.0118	1.70	0.089	0.006	-0.0590	-2.52	0.012	0.032
0.20	0.0047	0.59	0.553	0.007	-0.0690	-3.49	0.000	0.037
0.25	0.0104	1.41	0.158	0.009	-0.0507	-3.29	0.001	0.039
0.30	0.0152	1.54	0.125	0.011	-0.0373	-3.60	0.000	0.041
0.35	0.0163	1.38	0.167	0.014	-0.0258	-2.32	0.020	0.042
0.40	0.0171	1.32	0.188	0.016	-0.0188	-1.78	0.075	0.043
0.45	0.0161	1.54	0.123	0.019	-0.0103	-0.60	0.552	0.045
0.50 (**LAD**)	0.0233	2.04	0.041	0.020	-0.0011	-0.04	0.968	0.047
0.55	0.0288	2.74	0.006	0.022	-0.0255	-0.90	0.368	0.049
0.60	0.0329	3.47	0.001	0.024	-0.0166	-0.65	0.513	0.052
0.65	0.0458	6.07	0.000	0.026	-0.0099	-0.41	0.683	0.055
0.70	0.0550	5.75	0.000	0.028	-0.0004	-0.02	0.986	0.059
0.75	0.0558	7.04	0.000	0.030	-0.0106	-0.50	0.617	0.063
0.80	0.0765	11.61	0.000	0.033	0.0036	0.13	0.900	0.068
0.85	0.1021	6.42	0.000	0.035	0.0086	0.23	0.815	0.073
0.90	0.1529	10.78	0.000	0.039	0.0269	1.50	0.134	0.081
0.95	0.2054	6.13	0.000	0.044	0.0733	2.98	0.003	0.091

PPS equals the partial derivative of the Black-Scholes option value for the stock options held by the CEO with respect to the stock price. See Table 1 for definition of other variables. Panels A and B present coefficient estimates, t-values, and p-values for equity compensation (*EQCOM*) in the regression of |*DA*| and *DA*, respectively. Only the results for *PPS* are presented in this table. The sample period for the tests in this table is from 1995 to 2006.

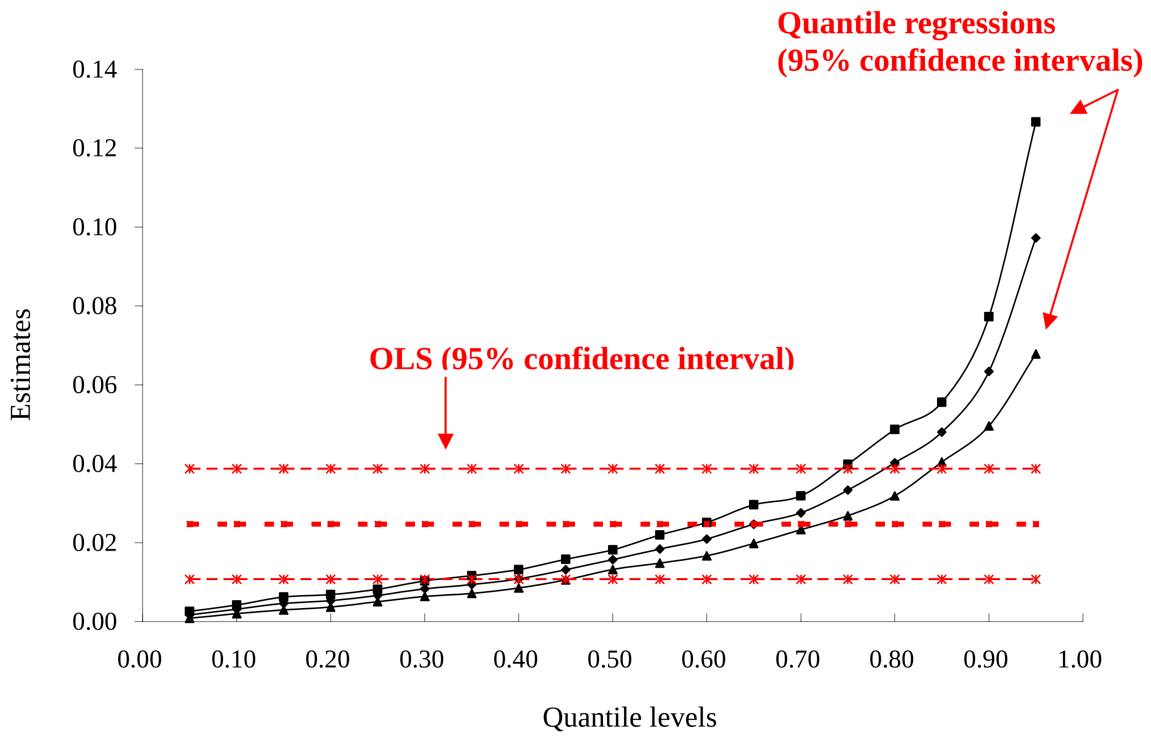

Figure 1 Coefficient estimates and 95% confidence intervals for equity compensation (*EQCOM*) in the regression of absolute discretionary accruals (|*DA*|)

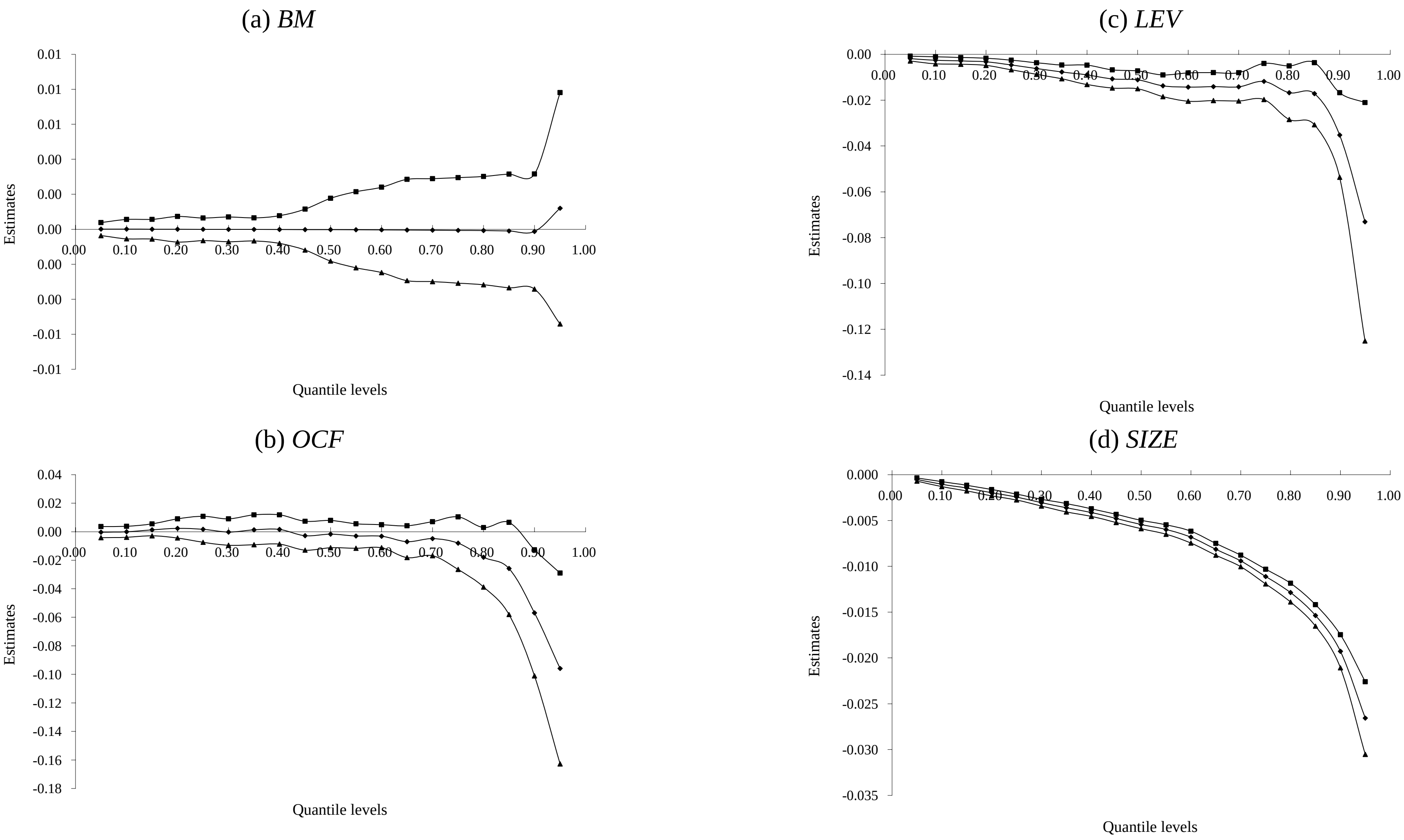

Figure 2 Coefficient estimates and 95% confidence intervals for book-to-market ratio (*BM*), net cash flows from operations (*OCF*), leverage (*LEV*), and size (*SIZE*) in the quantile regressions of absolute discretionary accruals

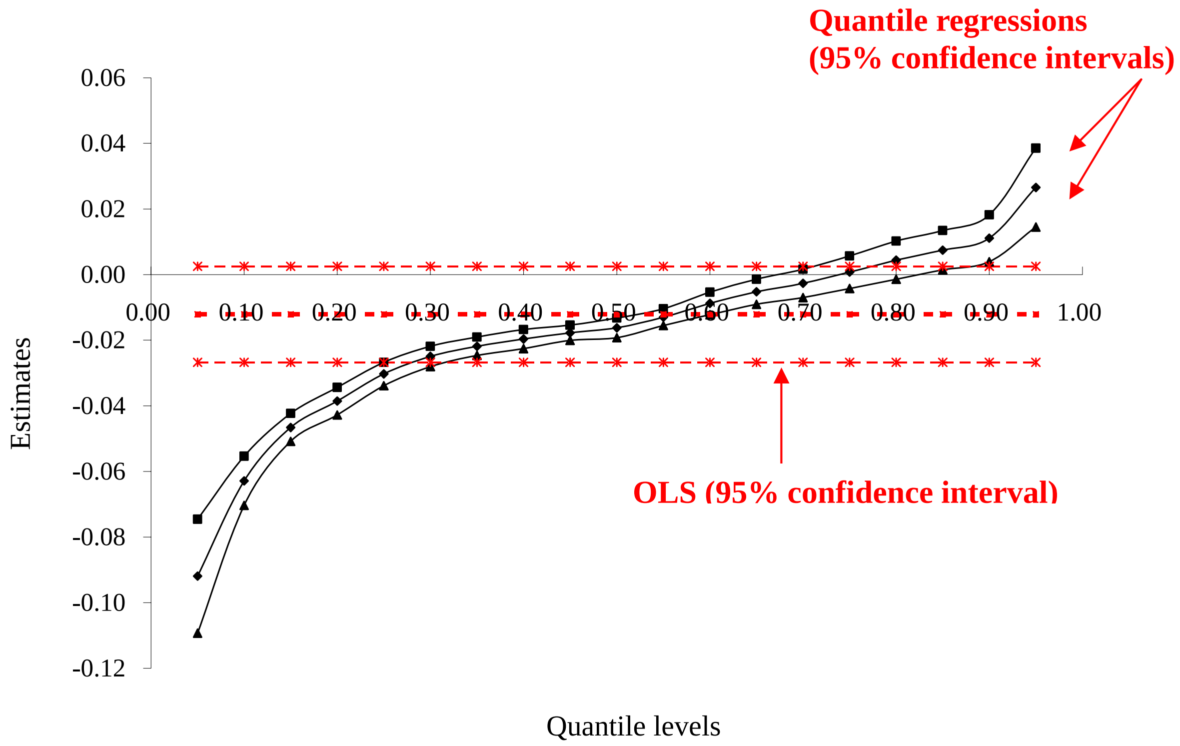

Figure 3 Coefficient estimates and 95% confidence intervals for equity compensation (*EQCOM*) in the regression of signed values of discretionary accruals (*DA*)

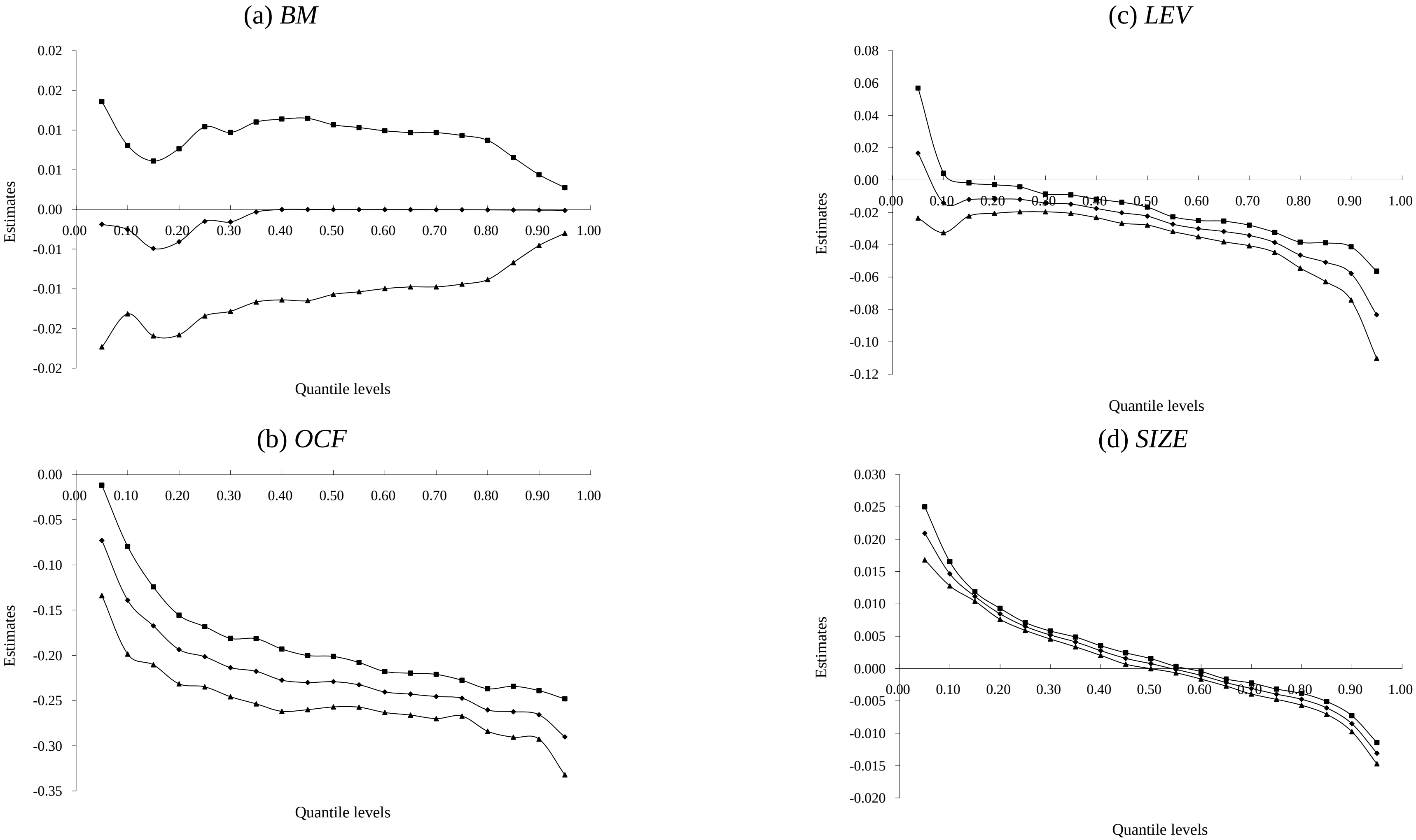

Figure 4 Coefficient estimates and 95% confidence intervals for book-to-market ratio (*BM*), net cash flows from operations (*OCF*), leverage (*LEV*), and size (*SIZE*) in the quantile regressions of signed values of discretionary accruals