Prospect Theory and Earnings Manipulation: Examination of Non-Uniform Relation between Earnings Manipulation and Stock Returns Using Quantile Regression

ABSTRACT

Using the prospect theory as a research framework, this paper makes contributions by demonstrating that managerial risk preference and stock return may influence a firm's earnings manipulation behavior. Specifically, this study argues that corporate executives may develop risk-averting (risk-seeking) attitudes because of high and positive (low and negative) stock returns. Under this scenario, managers may decide to actively manage the reported earnings in order to preserve gain (gamble on loss) on stock returns. On the other hand, firm executives may not actively manipulate their reported incomes when experiencing average and close-to-zero stock returns. Using quantile regression method to examine the relation between earnings manipulation and stock returns, this study finds that there is a significantly positive (negative) relation between earnings manipulation and stock returns at the high (low) stock returns quantiles. As predicated, such relation is not significant at the middle range of stock returns. To ensure the findings reported in this study are robust, we conduct several tests. In conclusion, we offer policy implications to regulators.

JEL classification:	G12; G32
Keywords:	Prospect theory, quantile regression, earnings manipulation, stock return, discretionary accruals
Data Availability:	Data analyzed in the study are collected from the public sources.

1. Introduction

This study postulates that the degree of earnings manipulation depends on managerial risk preference. Specifically, when firms enjoy gains or suffer from losses, corporate executives have higher incentives to manipulate earnings than experiencing average returns in capital markets. To examine this relation, we adopt the prospect theory, as the research framework, because it provides a theoretical foundation for our analysis. Applying the quantile regression (QR) and measuring gains and losses according to the stock returns, this study shows that the relation between earnings manipulation and stock returns is non-uniform and it varies significantly across various quantiles of the latter. As predicted, this relation is more pronounced in the tail regions than the central region of the stock returns. These results demonstrate that corporate executives are more inclined to take advantages of earnings manipulation tactic to preserve gains when enjoying high stock returns or to gamble on losses when suffering from low stock returns than experiencing the average returns.

Different from prior earnings management studies, we take managerial risk preference into consideration and build arguments according to the prospect theory. Examining the relation between the degree of earnings manipulation and the stock returns, the study points out that corporate executives may engage in risk-averting (risk-seeking) behavior when experiencing gains (losses). Moreover, we argue that earnings manipulation could either be a low-risk or a high-risk strategy from corporate executives' perspectives. In specific, this tactic could be a low-risk strategy if managers plan to use this tool to meet market expectation on earnings or to beat analyst forecasts. On the other hand, such behavior could be a high-risk undertaking if firm management anticipate that they would be punished when earnings management activities have been discovered by market participants. As Hall (2000) documents, equity shares have been incorporated in employment

contracts to incentivize corporate executives. As the agents of business entities, one would expect that these managers would pay close attention to stock returns, as market reactions will influence the value of their equity compensation. More importantly, we assume that firm executives may take risk-averting approach when experiencing gains in the stock markets. On the other hand, top management may engage in risk-seeking behavior when encountering losses in capital markets. Following these arguments, we predict that the degree of earnings management could be contingent upon the regions of the stock returns and the relation between earnings manipulation and stock returns could be non-uniform.

To examine this research inquiry, we adopt the QR approach (Koenker and Bassett, 1978). As documented in the literature, the ordinary least squares (OLS) and least-sum of absolute deviations (LAD) methods share the same limitation of constant coefficients. Hence, the inferences made according to these two statistical methods only reflect the conditional mean and medium distribution of the dependent variable. Consequently, the estimation results obtained with the OLS and LAD are not fully representative of the relation between earnings manipulation and returns on equity shares outside of the central region of return distribution. Instead of relying on these traditional econometric methods, this study embraces the QR because it can be used to evaluate the relation between the degree of earnings manipulation and magnitude of stock returns across the entire range of the latter. More importantly, the QR method provides a tool for us to explore whether corporate executives have different inclinations of earnings manipulation in the tail regions of stock returns.

This study uses the absolute value of discretionary accruals (i.e., $|DA|$) to gauge the degree of manipulation on the reported earnings. As shown in the literature, increasing $|DA|$ implies a higher level of manipulation on the reported income, and vice versa (e.g., Leuz, Nanda, and

Wysocki, 2003; Myers, Myers, and Omer, 2003; Jiraporn, Miller, Yoon, and Kim, 2008). As to the annual stock returns (*RETURN*), we obtain these values by calculating the compounded monthly returns on share equity over a 12-month period ending three months after the closing of the reporting period. While analyzing 20,350 firm–year observations collected from 2,290 non-financial U.S. companies between 1992 and 2010, we control the following factors: (1) market condition, measured by the annual returns of S&P 500 companies, (2) size of firm, calculated by the natural logarithm of a firm's total assets, (3) growth opportunities available to the studied firm, computed by the ratio between market value and book value of equity shares, and (4) momentum factor, accounted by the amount of lagged stock return. Employing the QR method, these observations are divided into 19 distinct quantiles with an increment of 5% between quantiles.

To ensure the robustness of empirical evidence reported in the study, we conduct several additional tests. First, we split the studied firms into two groups: (1) firms having high level of equity-based compensation and (2) firms having low level of equity-based compensation. This test allows us to discern the moderating effect of equity-based compensation on the relation between the degree of earnings manipulation and returns on equity shares (referred as $|DA|$–*RETURN* hereafter). Then, we investigate whether the empirical findings demonstrated in this research are sensitive to firm performance measure. To address this concern, we replace stock returns by Tobin's *Q*. Furthermore, we modify the specification of regression models by including both year and industry dummies. These specifications allow us to explore the effect of market condition across years and industries. Also, we take the positive versus negative manipulation of the reported income into account, since corporate executives may adjust the reported income upward or downward. Moreover, we divide data into two sub-periods, pre- versus post-Sarbanes Oxley Act (SOX) to find out whether the reported results are driven by the financial reporting and regulatory

environment. Finally, we take care of data outliers and potential measurement error in *DA* estimation. The results of these tests demonstrate that the empirical findings reported in this study are robust.

The remainder of this study is divided into several sections. Section 2 reviews the literature and develops research inquiries. Section 3 discusses the econometric approaches. Section 4 outlines samples, variables, and empirical models. Section 5 shows the results of empirical investigations and discusses their implications. Section 6 reports the findings of robustness tests. Section 7 summaries and conclude this research.

2. Literature review and research development

2.1 Studies on management's incentives for earnings manipulation

Corporate executives have incentives to manage the reported earnings and such activities tend to create market reactions. In specific, since investors may prefer to invest in firms with steady earnings, the literature has well documented that corporate executives may develop earnings management strategies in order to avoid earnings surprises (e.g., Payne and Robb 2000; Brown 2001; Burgstahler and Eames 2001). Moreover, investors tend to reward firms for meeting or beating earnings expectations. Therefore, corporate executives are likely to manage the reported earnings in order to meet or beat these expectations (e.g., Bartov et al., 2002; Skinner and Sloan, 2002). Matsumoto (2002) reports that managers of firms with higher institutional ownership, greater reliance on implicit claims with their stakeholders, and higher value-relevance of earnings are more likely to engage in earnings manipulations than entities without such characteristics. Frankela et al. (2002) document that there is a relation between earnings management and market reactions caused by the disclosure of audit fees. In addition, several studies show that mandatory

adoption of IFRS may affect executives' incentives to engage in earnings manipulation (e.g., Chen et al., 2010; Horton et al., 2012; Ahmed et al., 2013).

In spite of the empirical insights provided in prior studies, it is unclear whether corporate executives would develop earnings manipulation strategies when firms experience various levels of stock returns and whether such strategy is symmetric when firms encounter gains or loss in the markets. Referring to Bartov, et al. (2002), Matsumoto (2002) and Skinner and Sloan (2002), they have indicated that markets may have asymmetric responses to earnings surprises. In particular, their studies show that growth firms tend to suffer larger stock price decline when reporting negative earnings surprises. Consequently, executives working for these firms may have higher level of incentives to manipulate reported earnings than firms without such characteristics. Building on these studies, this study explores the relation between the degree of earnings manipulation and the level of stock returns. In particular, we take managerial risk preference into account and postulate that corporate executives would have higher incentives to manipulate earnings firms when enjoying gains or suffering from losses than those experience average returns in capital markets. To examine this relation, we adopt the prospect theory as the research framework.

2.2 Prospect theory

Referring to the literature, researchers have applied the prospect theory extensively to investigate individuals' decision-making under risks (e.g., Gomes, 2005; Levy et al., 2012; Kairies-Schwarz et al., 2017). As Kahneman and Tversky (1979) point out, individuals value gains and losses differently. More importantly, their risk preferences are asymmetric when encountering gains and losses. In general, people are less likely to gamble on gains but more willing to bet on

losses. Thus, individuals are inclined to act conservatively to preserve winning/gain situations. However, they are likely to bet when encountering losing/loss scenarios.

Following the arguments made in the prospect theory, researchers have conducted studies to examine individuals' choices among alternatives involving risks. Many support the predictions stipulated in the theory (e.g., Lehner, 2000; Kliger and Tsur, 2011), while others reject the notions proposed in the framework (e.g., Battalio et al., 1990; Miller and Bromiley, 1990; Levy and Levy, 2002). For example, Shefrin and Statman (1985) and Ferris et al. (1988) use the prospect theory to examine the disposition effect. Fiegenbaum (1990) and Sinha (1994) re-examine the risk-return relation based on the prospect theory. Benartzi and Thaler (1995) demonstrate that this theory is useful in explaining the equity premium puzzle. Moreover, Barberis et al. (2001), Zhang and Semmler (2009), and Levy et al. (2012) articulate that the prospect theory can be implemented to investigate the consequences of asset pricing. Also, Levy and Levy (2004) employ this theory to examine the implications of the Markowitz portfolio theory (1952), while Gomes (2005) use this theoretical framework to explore the implications of trading volume.

Building on the extant literature, this study postulates that corporate executives may develop a strategy and use earnings manipulation as a tool to manage income when facing gains or losses in capital markets. Specifically, managers are inclined to act conservatively by taking risk-averting route when encountering gains. They probably would behave aggressively by taking risk-seeking approach when experiencing losses. Because corporate executives may develop strategies on earnings manipulation and such strategies could be asymmetric when firms experience gains or losses in capital markets, the prospect theory offers a theoretical foundation for us to examine the non-uniform earnings manipulation behavior engaged by the corporate executives at different regions of stock returns.

2.3 Research development

This section develops research questions based on the prospect theory. As documented in the literature, corporate executives have incentives to manipulate the reported income (e.g., Dechow and Skinner, 2000; Kirschenheiter and Melumad, 2002). For example, executives can make adjustments to net incomes in order to avoid reporting a larger earnings surprise. This action mitigates the potential negative effect caused by lower inferred earnings precision on stock returns (e.g., Trueman and Titman, 1988; Subramanyam, 1996). Similarly, earnings manipulation also offers opportunities for executives to demonstrate a "desirable" stream of profits for future periods. While the literature has showed several factors which may influence how managers take action to manipulate earnings, none have explicitly considered individuals' risk preference, as the driver of their behavior. In particular, researchers have yet to explore the non-linear relation between earnings manipulations and stock returns because of managers' asymmetric risk preference.[1]

To make up this void in the literature, this study considers individuals' risk preference according to the prospect theory. Our arguments are presented as follows. First, it is a prevalent practice to include salary, benefits, performance bonus and equity-based incentives in executive contracts. More importantly, equity-based incentives have become a popular component of CEOs' compensation package (Brick et al., 2006; Larcker et al., 2007; Aboody et al., 2010). Because of its weight, executives may consider stock returns, a performance indicator, as part of the equity-based compensation specified in the employment contracts. Second, earnings manipulation can be either a safe or risky strategy. As companies enjoy positive returns on equity shares, executives

[1] Incentives derived from capital market could be one of primary determinants of earnings quality. These incentives include the need to raise capital and satisfy earnings targets set by analysts. In addition, there are several external factors, such as meeting capital requirements, complying political procedures, and fulfilling tax and non-tax regulation such as SOX 2002, which could also affect management behavior and the earnings quality reported in financial statements. Please refer to Dechow et al. (2010) for a detailed discussion on this line of research.

may manage the reported income either to meet market expectations and beat analyst forecasts. Under this scenario, earnings manipulation can be a safe strategy because it helps managers preserve gains in the market. Similarly, managers may manipulate the reported earnings to correct market perceptions when suffering from losses. In this case, manipulating the reported income becomes a risky undertaking for managers because it may deepen losses in the capital market if market investors detect it and punish firms accordingly. Taking these arguments together, it provides a foundation to support our conjecture regarding the association between the degree of earnings manipulation and the level of returns on firm's equity shares. That is, the relation between these two elements could be contingent upon whether firms experiencing positive or negative stock returns in the market.

In this study, we postulate that firm managers may develop risk-averting mentality when firms enjoy positive and higher than average stock returns. By managing the reported income, shareholders are likely to welcome this good corporate news and continue rewarding firms with superior stock returns. Hence, risk-averting executives working for firms with positive and higher than average stock returns (or a large rise in price) may perceive earnings manipulation as a low-risk strategy. As such, the degree of earnings manipulation would be more pronounced (e.g., $|DA|$ would increase from 2% to 4%) when stock return becomes increasingly positive (e.g., increase from 2% to 4%). Thus, we predict that there is a positive $|DA|$–*RETURN* relation when firms enjoy positive and higher than average stock returns (i.e., an increase in stock return from 2% to 4% would associate with an increase in $|DA|$ from 2% to 4%).

On the other hand, executives may embrace risk-seeking behavior when suffering from negative and lower than average stock returns. Managing earnings aggressively under this scenario becomes a high-risk strategy because executives may use these tactics to gamble on losses.

Moreover, this study argues that the degree of earnings manipulation would increase (e.g., |*DA*| would go up from 2% to 4%) when stock returns become more negative (e.g., drop from -2% to -4%). Following these logics, we anticipate that there is a negative |*DA*|–*RETURN* relation when firms suffer from negative and lower than average stock returns (i.e., a decrease in stock return from -2% to -4% would associate with an increase in |*DA*| from 2% to 4%).

Comparing to scenarios in the tail regions of stock returns, executives working for firms experiencing close-to-zero stock returns are unlikely to engage in high degree of income manipulation. Therefore, we expect that |*DA*|–*RETURN* relation would not be evident in the central region of stock returns distribution since executives probably would become risk-natural. Thus, they may not manage the reported earnings aggressively. Taking these discussions together, firm executives may leverage earnings manipulation either to preserve gains or to gamble on losses and extent of such manipulation may associate with firm's stock returns. Specifically, the |*DA*|–*RETURN* relation is positive (negative) when the stock return is high and positive (low and negative). Because the predicted |*DA*|–*RETURN* relation is non-uniform, the association between these two elements is consistent with what has been outlined in the prospect theory.

3. Econometric models

To test the non-uniform |*DA*|–*RETURN* relation across different regions of stock returns, researchers have adopted a two-step estimate procedure. This procedure allows researchers to partition the entire pool of samples according to the magnitude (or sign) of stock returns and then apply the OLS or LAD to each partitioned segment in order to make a comparative analysis among different data groups. This exogenous data partitioning process may lead to invalid outcomes driven by the "truncated samples" issue (Heckman 1979). In this study, we argue that the |*DA*|–*RETURN* relation should be analyzed by segmenting samples and such a relation is conditional on

rises or falls of stock returns. Hence, the sample segmentation and relation should be analyzed jointly. Since neither the OLS nor LAD fulfills this prerequisite, we adopt the QR approach. In the following discussions, we introduce the QR, highlight the differences between the OLS/LAD and QR models, and then explain why employing the QR method is proper when investigating our research inquiries.

3.1 QR model

To discuss how QR works, let's start with

$$y_{it} = x_{it}' \cdot \beta_\theta + u_{\theta it} \qquad \text{Eq. (1)}$$

where y_{it} is the explained variable (i.e., stock returns in this study) and x_{it} is the K X 1 vector of explanatory variables (including $|DA|$ and control variables) for the firm i and in time period t. In Eq. (1), θ is the quantile value of the y_{it} variable (i.e., stock return). This value measures a relative magnitude and has a range from 0% to 100%. For instance, the value of 50% quantile represents the median value. As the median value (i.e., θ = 50%) of stock returns is close to zero, the above 50% return quantiles could be considered as positive returns (an increase in stock price). On the other hand, the below 50% return quantiles could be viewed as negative returns (a decrease in stock price). The key feature of the QR approach is the *x-to-y* relation, measured by the beta coefficient β_θ, changes by the quantile value of the dependent variable, θ in (0%, 100%).

In particular, we estimate β_θ according to Eq. (2) below:

$$\begin{aligned} &\min \sum_{it:u_{\theta it}>0} \theta \times |u_{\theta it}| + \sum_{it:u_{\theta it}<0} (1-\theta) \times \left|u_{\theta it}\right| \\ &= \sum_{it:y_{it}-x_{it}'\cdot\beta_\theta>0} \theta \times |y_{it} - x_{it}'\cdot\beta_\theta| + \sum_{it:y_{i,t}-x_{it}'\cdot\beta_\theta<0} (1-\theta) \times |y_{it} - x_{it}'\cdot\beta_\theta|. \end{aligned} \qquad \text{Eq. (2)}$$

Eq. (2) shows the key advantage of the QR method. That is, the estimator vector of β_θ changes according to θ, the quantile value of the dependent variable (i.e., the y variable). By contrasting β_θ

estimates across various θ, we are able to examine whether the relation between the x and y variable is non-uniform across the entire distribution of the latter.[2]

Referring to the prior studies, researchers have employed QR method to investigate various issues in economics (Yu et al. 2003). More importantly, more and more researchers have become interested in employing this approach in business research including those in the Accounting and Finance fields.[3] To yield additional insights to the extant literature, this study investigates the $|DA|$–*RETURN* relation using the QR method.

3.2 OLS/LAD vs. QR models

This section provides a comparative analysis between OLS/LAD and QR models. To proceed, we first present the traditional non-quantile regression approach:

$$y_{it} = x_{it}' \cdot \beta + u_{it} \qquad \text{Eq. (3)}$$

We use the LAD to estimate β using Eq. (4) below:

$$\min \sum_{it} 1 \times |u_{it}| = \sum_{it} 1 \times |y_{it} - x_{it}' \cdot \beta| \qquad \text{Eq. (4)}$$

Comparing Eq. (4) with Eq. (2) reveals the difference between LAD and QR approaches. In particular, the LAD employs an equal weight (i.e., the value of 1) on positive and negative errors. By contrast, the QR adopts unequal weights on positive and negative errors (i.e., θ for positive errors and (1-θ) for negative errors). Moreover, the LAD estimators β are the special case of QR estimators β_θ under the restriction of θ = 50%. Figure 1 further illustrates the difference between the LAD and QR estimators. Also, Figure 1 demonstrates the advantages of QR by characterizing the dynamic β estimators in various regions of the dependent variable. It also shows that the LAD

[2] Since estimation of QR is well-documented in the literature, this study omits the details. Please refer to Koenker and Hallock (2001) for more detailed discussions.

[3] Yu et al. (2003) summarize research using QR method. More recently, Armstrong et al. (2015) also apply this regression method to investigate whether corporate governance would mitigate the degree of tax avoidance.

is to measure the central behavior of the distribution. Thus, it is unable to capture the behavior in the tail region of the distribution.

Moreover, the OLS estimator vector of β can be obtained from:

$$\min \sum_{it} 1 \times (u_{it})^2 = \sum_{it} 1 \times (y_{it} - x_{it}' \cdot \beta)^2 \qquad \text{Eq. (5)}$$

The comparison between Eq. (5) and (4) reveals the difference between the OLS and LAD methods. Specifically, the sum of the absolute and squared value of errors are at the minimum when using the LAD and OLS. Therefore, the LAD and OLS present the conditional median and mean function of the dependent variable (y_{it}) on the independent variables (x_{it}), respectively.

4. Samples, variables, and models

4.1 Samples

We obtain data from Compustat and the Center for Research in Security Prices (CRSP) database. Firms in the financial industries are excluded from analyses (SIC code 6000-6999) since $|DA|$ is not a proper measure of earnings manipulation for companies in this sector. Because of this exclusion, 2,290 non-financial firms in the United States with all required data from 1992 to 2010 are included in the study, which provides 20,350 firm–year observations for the statistical analyses.

4.2 Variables measurements

The annual stock return, the dependent variable in our analysis, is compounded monthly stock returns over a 12-month period ending three months after the closing of the fiscal year (Subramanyam, 1996). The stock prices used to compute the returns on equity shares are obtained from the CRSP. Following the approach specified in Kothari et al. (2005) study, we measure the degree of earnings manipulation using Eq. (6) below:

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

In Eq. (6), *TACC* represents the amount of total accruals while *TA* stands for the value of total assets, Moreover, $\Delta SALES$ represents the difference in net sales between years whereas ΔAR is calculated by taking the difference of net accounts receivable between years. In addition, *PPE* is the amount of net property, plant, and equipment. *ROA* represents the rate of return on total assets. The error term obtained from the regression model above is the amount of discretionary accruals (*DA*). It reflects the unexplained part of total accruals.

It should be noted that $|DA|$ is the absolute (unsigned) value of discretionary accruals. Since corporate executives may adjust earnings up or down, we analyze positive versus negative *DA* as part of the robustness tests. According to two-digit SIC code by year and by industry, we estimate *DA* using the modified Jones (1991) model.

4.3 Empirical model

We regress stock returns on earnings manipulation by incorporating several control variables: (1) market condition (*MKT*); (2) firm size (*SIZE*); (3) market value (*MB*); and (4) momentum factor (*MOM*). We include them in the regression analyses because these factors may influence the returns on a firm's equity shares (e.g., Fama and French, 1992 and 1993).

To examine the $|DA|$–*RETURN* relation, we implement Eq. (7):

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA|_{i,t} + \beta_2 MKT_{i,t} + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1} \qquad \text{Eq. (7)}$$

In Eq. (7), *RETURN* represents annual returns on equity shares and $|DA|$ is the amount of absolute discretionary accruals. Based on the four-factor CAPM model, we include *MKT*, *SIZE*, *MB* and *MOM* in Eq. (7). Table 1 provides a list of variable definitions.

[Please insert Table 1 here]

5. Empirical results

5.1 Descriptive statistics

Table 1 composes of Panels A and B. Panel A describes *RETURN*, |*DA*|, as well as *MKT*, *SIZE*, *MB*, and *MOM*, four control variables. As demonstrated, the mean of *RETURN* is 0.2177 (median = 0.0962, standard deviation = 0.8175). The mean of |*DA*| is 0.0585 (median = 0.0333, standard deviation = 0.1076). The median value (Q2) of *RETURN* is 9.62%. Comparing with Q1 (25% quantile = -16.52%) and Q3 (75% quantile = 39.91%), the median (50% quantile) of stock returns is close to zero. For the purpose of our investigations, this study treats the over-50% (under-50%) quantile value of stock returns as positive (negative) stock return. This classification allows us to examine the executives' earnings manipulation behaviors when they experience gains and losses situations.

The results of correlation coefficients analyses are provided in Panel B. This panel shows *RETURN* positively correlates with |*DA*| (coefficient = 0.025, *p*-value < 0.01). *MKT* (coefficient = 0.352, *p*-value < 0.01) and *MB* (coefficient = 0.215, *p*-value < 0.01) positively correlate with *RETURN*, whereas *SIZE* (coefficient = -0.091, *p*-value < 0.01) and *MOM* (coefficient = -0.111, *p*-value < 0.01) negatively correlate with *RETURN*.

5.2 Empirical results of QR model

We estimate OLS regression and use these results as benchmarks to compare to the findings from QR analysis. Table 2 presents the OLS coefficient and the estimated coefficient for |*DA*| at various *RETURN* quantiles. To simplify the presentation in Table 2, we did not provide the estimated coefficients of the control variables. According to the OLS estimate shown in the table, |*DA*| positively affects *RETURN* (coefficient = 0.232, *p*-value < 0.01). This evidence is consistent

with what has been reported in the prior studies. This result also supports the notion that the market tends to reward earnings manipulation behavior with positive returns (e.g., Healy and Palepu, 1993; Subramanyam, 1996; Dechow and Skinner, 2000; Beaver, 2002; Myers et al., 2007).

[Please insert Table 2 here]

Referring to the QR estimates illustrated in Table 2, the $|DA|$ coefficients are significantly negative in low *RETURN* quantiles. However, these coefficients become insignificant in middle *RETURN* quantiles. Moreover, $|DA|$ coefficients turn significantly positive in high *RETURN* quantiles. In the Table, we also present the results from the test of equality-of-slope parameters across various quantiles in the two right-most columns of table. These statistics show the inequalities of the $|DA|$ coefficient between the θ and $(1\text{-}\theta)$ quantiles. Based on F statistics, it shows that the pattern of quantile-varying coefficient on $|DA|$ is significant at the 1% level.

Figure 2 graphs the QR estimate of $|DA|$ coefficient with 95% confidence intervals. The OLS results are also graphed for comparison. As demonstrated in Figure 2, there is little overlap across quantiles of *RETURN*. Since the OLS provides a point estimate of the $|DA|$–*RETURN* relation, it captures the relation between two elements under average *RETURN*. Comparing with the QR estimates, it is evident that the OLS estimate fails to capture the $|DA|$–*RETURN* relation outside of the central regions of stock returns. Thus, the OLS estimate offers an incomplete description of the $|DA|$–*RETURN* relation. This issue is particularly pronounced at the relatively high/low *RETURN* quantiles when a firm encounters a sizable gain/loss in capital market.

[Please insert Figure 2 here]

Since a value higher (lower) than the median stock return quantile can be viewed as an increase (decrease) in stock price, QR results demonstrate that the pattern of the relationship between earnings manipulation and returns on equity shares is asymmetric across the entire stock

return distribution. Because there is a significant and positive |*DA*|–*RETURN* relation over 75% to 95% *RETURN* quantiles, it indicates that corporate executives probably would be more inclined to involve in earnings manipulation when firms experiencing a significant gain in stock returns. Hence, the |*DA*| accelerates as stock return increases. From the prospect theory perspective, this evidence suggests that firm executives may engage in earnings manipulation and use them as a low-risk strategy to stabilize a firm's future share prices, as they enjoy significantly higher than the average stock returns.

On the other hand, the |*DA*|–*RETURN* relation is significantly negative between 5% and 55% *RETURN* quantiles. Within this range, the negative |*DA*| coefficient increases as *RETURN* quantile goes down. This result indicates that the negative |*DA*|–*RETURN* relation strengthens as the stock return deteriorates. This finding signals that corporate executives may actively manage the reported earnings as well when their firms suffer in the capital markets (i.e., lower stock return quantiles). Taking from the prospect theory standpoint, this evidence is consistent with our earlier discussions. That is, executives may employ earnings manipulation to influence market participants' perception of a firm's future performance when experiencing significantly lower than the average stock returns.

5.3 Estimates of control variables

Figure 3 graphs the estimated coefficients of the four control variables with 95% confidence intervals. Several observations emerge from this figure. First, the OLS estimates are significant (i.e., the 95% confidence intervals do not overlap with zero). This finding reaffirms what researchers have articulated in their studies (e.g., Fama and French, 1992 and 1993). In addition, the result indicates that the four CAPM factors, *MKT*, *SIZE*, *MB,* and *MOM*, help to explain stock returns. Second, Figure 3 demonstrates that *MKT* and *MB* have significantly positive

coefficients, while *MOM*, the lagged return, has significantly negative coefficient across the entire return distribution. Finally, the coefficient on *SIZE* decreases monotonically from 5% to 95% return quantiles. Noticeably, it is significantly positive at lower, between 5% and 35%, stock return quantiles. On the other hand, the coefficient turns significantly negative at higher, between 50% and 95%, stock return quantiles.

[Please insert Figure 3 here]

Several implications can be drawn on control variables according to the QR results. First, the relation between *MKT*, *MB* and *RETURN* becomes stronger among firms experiencing a gain in high *RETURN* quantiles. Second, there is a significantly negative autocorrelation for stock returns in the pool of samples and it becomes more pronounced at higher *RETURN* quantiles. Finally, *SIZE* negatively relates to *RETURN* among firms experiencing an increase in share prices (i.e., higher *RETURN* quantiles). In contrast, *SIZE* positively relates to *RETURN* for firms suffering from a decrease in share price (i.e., lower *RETURN* quantiles).

6. Robustness tests

To ensure the results reported in Section 5 are robust, we carry out several additional tests. These analyses allow us to investigate (1) the effect of equity incentives on the |*DA*|–*RETURN* relation; (2) the relation between earnings manipulation and Tobin's *q*; (3) the effect of industry and year on the |*DA*|–*RETURN* relation; (4) the effect of upward versus downward earnings manipulation on the |*DA*|–*RETURN* relation; (5) the effect of SOX on the |*DA*|–*RETURN* relation; and (6) potential outliers and measurement errors when estimating the amount of *DA*.

6.1 Management incentive on earnings manipulation

Performance incentives stipulated in executive compensation contracts may affect the degree of earnings manipulation because executives may manage the reported incomes to influence stock prices (e.g., Dechow and Skinner, 2000; Beaver, 2002). Since firm executives are self-interest and in position to make financial reporting decisions, researchers have pointed out that managerial incentives could be a driver of earnings manipulation behavior.

To examine this inquiry, we measure the managerial incentives using the percentage of equity share stated in the managerial compensation as a proxy. Our conjecture is that firm executives may take stock returns into account if the equity-based pay constitutes a significant portion of their total compensation when determining whether, and to what extent, to manipulate earnings. If the portion of equity-based compensation specified in the executive contract is relatively insignificant, on the other hand, it is unlikely for corporate executives to take stock returns into account when contemplating whether to engage in earnings management. To examine this concern, we obtain the amount of total and equity-based (including restricted stocks and stock options) compensation awarded to CEO from the S&P's *ExecuComp* database. Then, we use these data to calculate the equity-based compensation ratio (i.e., amount of equity-based pay/amount of total pay). The result shows that the average percentage of equity-based compensation in the CEO contracts accounts for 41% of total compensation of executives among the studied firms.

We then use this percentage to divide observations into two subgroups: (1) equity constituting more than 41% of the compensation package as the high equity-based compensation group; and (2) equity constituting less than 41% of the compensation package as the low equity-based compensation group. Then, we estimate the QR and OLS separately for both subgroups.

Table 3 presents the results of estimation; whereas Panel A and Panel B of Figure 4 graph companies provide high versus low level of equity-based compensation to their executives.

Referring to Table 3 and Figure 4, firms reward their executives with high level of equity-based compensation has a significant and positive $|DA|$ according to the OLS estimate *(p-value* < 0.01). In contrast, the estimated $|DA|$ coefficient becomes insignificant when firms only provide low level of equity-based compensation *(p*-value = 0.101). This result indicates that corporate executives may (may not) take stock return (i.e., change in equity price) into consideration when the equity-based compensation constitutes a high (low) percentage of total rewards in their employment contracts. Then, we examine the QR results. The pattern of quantile-varying estimates diagrammed in Panels A and B of Figure 4 is in line with the $|DA|$–*RETURN* relation demonstrated in Section 5.2. Therefore, our argument with respect to the prospect theory holds when considering the impact of managerial incentive on earnings manipulation.

[Please insert Table 3 and Figure 4 here]

6.2 Using Tobin's q as an alternative measure of firm performance

In this subsection, we re-examine the relation between earnings manipulation and Tobin's *q* (Jiraporn et al., 2008).[4] Since earnings power among industries varies, we employ industry-adjusted, instead of using unadjusted, measures in our analysis. Accordingly, the industry-adjusted Tobin's *q* effectively controls for the potential industry effect. To obtain this measure, we calculate industry Tobin's *q* for all firms with the same first digit of SIC code as those of the sampled firms. Then, industry Tobin's *q* is subtracted from firm Tobin's *q* to produce industry-adjusted Tobin's *q*.

[4] Tobin's *Q* is obtained by calculating the ratio between (market value of equity + book value of preferred stock + book value of debt) and (book value of assets). In this computation, closing stock prices on the last trading day of the year are used to calculate market value of equity.

Finally, we incorporate six control variables in the regression model in accordance with what have been reported in the literature. This model is labelled as Eq. (8):

$$TOBIN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 INT_{i,t} + \beta_5 ROA_{i,t} + \beta_6 RD_{i,t} + \beta_7 INSIDER_{i,t} + \varepsilon_{i,t+1} \quad \text{Eq. (8)}$$

In Eq. (8) above, *SIZE* is the natural logarithm value of total assets; *LEV* is the ratio between the amount of debts and the amount of total assets; *INT* denotes a ratio between intangible assets and total assets; *ROA* is ratio between the amount of net income and the amount of total assets; *RD* is a ratio between the amount of research and development expenditures and the amount of sales revenue; and *INSIDER* represents the percentage of equity shares owned by corporate insiders.

Table 4 provides the OLS and the QR estimates of the relation between earnings manipulation and industry-adjusted Tobin's *q*. The statistics of the corresponding estimates are diagrammed in Figure 5. According to the result of OLS estimate, there is a significant and positive coefficient on |*DA*| (coefficient = 1.526, *p*-value < 0.01). We then examine whether the relation between |*DA*| and Tobin's *q* is non-uniform. As shown in Table 4, the |*DA*| estimate is significant and positive between 35% and 95% quantiles of Tobin's *q*. However, |*DA*| estimate turns insignificant between 15% and 30% quantiles of Tobin's *q*. Finally, the estimate becomes significantly negative between 5% and 10% quantiles of Tobin's *q*. The *F* statistics affirm the quantile-varying estimate pattern is significant. By comparing Figures 2 and 5, it demonstrates that the pattern of quantile-varying QR estimates on |*DA*| variable is robust when measuring firm performance using Tobin's *q*.

[Please insert Table 4 and Figure 5 here]

6.3 Industry and year effect on |DA|–RETURN relation

To find out whether industry and year affect our empirical results, we include these variables as dummies in the regression analysis. Using the first digit of SIC code to classify industries and incorporating year in the analyses allow us to further control the panel structure in the dataset. In Table 5, we report the |*DA*| estimate by incorporating industry and year dummies in the models. Figure 6 illustrates the QR and OLS estimates of |*DA*| with 95% confidence intervals.

[Please insert Table 5 and Figure 6 here]

As shown in Table 5, sign and significance of |*DA*| coefficients vary significantly across *RETURN* quantiles. Moreover, the *F* statistics support that inequalities in QR estimates of |*DA*| are significant over *RETURN* quantiles (please refer to the two right-most columns of Table 5). By comparing Figures 2 and 6, the quantile-varying pattern is robust with consideration of the industry and year dummies. In addition, we take industry-adjusted and market-adjusted stock returns into account when conducting these tests. These analyses also indicate that the results obtained from the examinations are resemble the QR findings reported in this study. Hence, the quantile-varying |*DA*|–*RETURN* relation reported in this study is robust when industry and year dummies are included in the analyses.

6.4 Upward versus downward earnings manipulation on |DA|–RETURN relation

So far, we have employed the absolute value of discretionary accruals, |*DA*|, to evaluate the quantile-varying |*DA*|–*RETURN* relation. However, firms may manage the reported income upwardly or downwardly. Therefore, it is imperative to take the sign of *DAs* into consideration when examining our research inquiries. For this analysis, we divide the pool of observations into two subgroups: (1) observations with positive *DAs*, which indicate upward earnings manipulation behavior, and (2) observations with negative *DAs*, which show downward earnings manipulation

compensation. We then re-investigate whether |*DA*|–*RETURN* relation changes across two subgroups of observations.

Panels A and B of Table 6 report the findings of estimation for positive *DA* and negative *DA*, respectively. The corresponding statistics are diagrammed in Figure 7. Comparing two panels of Table 6, the quantile-varying |*DA*|–*RETURN* relation is robust with respect to the sign of *DAs*.

[Please insert Table 6 and Figure 7 here]

6.5 SOX effect on |DA|–RETURN relation

As Cohen et al. (2005) report, the degree of earnings manipulation increases gradually until the passage of SOX. After its enactment, the degree of income manipulation declines significantly. This empirical evidence indicates that regulation may have significant effect on |*DA*|–*RETURN* relation. To consider this effect, we investigate whether the enactment SOX influences the quantile-varying |*DA*|–*RETURN* relation reported in this study. To analyze this effect, we divide our observations into two sub-periods: (1) the pre-SOX (1992~2001) and (2) the post-SOX (2003~2010).

Table 7 presents the results of this analysis. Panel A shows evidence of the pre-SOX period, while Panel B demonstrates findings of the post-SOX era. Comparing these two panels, we reaffirm the quantile-varying |*DA*|–*RETURN* relation reported in Section 5.2. The results of this analysis are diagrammed in Figure 8.

[Please insert Table 7 and Figure 8 here]

6.6 Potential outliers and possible measurement errors in estimating DA

As illustrated in Section 4.2, we use Eq. (6) to estimate a firm's |*DA*| according to the modified Jones model. All parameters of the model are estimated based on the industry observations. According to Klein (2002), it requires at least 10 firm–year observations with the

same two-digit SIC code to make estimates. Since the number of observations used to estimate the amount *DA* might be small, this section addresses potential outliers issue and concerns over the possible measurement errors.

For this examination, we first identify firm-year observations with the same two-digit SIC code in the Compustat. For industries with less than 50 observations, we remove them from analyses. As the result of this procedure, the number of observations drop significantly from 20,350 firm–year to 10,635 firm–year observations.[5] After this removal, we rerun the analysis. Table 8 shows the results of the |*DA*|–*RETURN* relation. We also graph the QR and OLS estimates in Figure 9. Comparing Figures 2 and 9, the quantile-varying pattern of |*DA*| estimates reported in the main analysis is robust. Hence, the potential outliers issue and concerns over the possible measurement errors for *DA* estimation should not affect our empirical findings.

[Please insert Table 8 and Figure 9 here]

7. Conclusions and directions of future research

This study argues that the degree of earnings manipulation is non-uniform across stock returns distribution. In particular, this relation would be more pronounced when firms experiencing gains or suffering from losses in capital markets. To examine these questions empirically, we adopt the prospect theory as the research framework by taking managerial risk preference into account. Applying the QR method, the results of our analyses indicate that the |*DA*|–*RETURN* relation is non-uniform and it varies significantly across the *RETURN* distribution. As predicted, the |*DA*|–*RETURN* relation is more pronounced in the tails regions than in the central region of the stock return distribution.

[5] This represents an approximately 48% drop in sample size.

Overall, the degree of earnings manipulation accelerates in the tail regions of returns on equity shares. This finding supports the notion that risk-averting executives may take earnings manipulation as a low-risk strategy and behave aggressively in managing the reported incomes when facing gain situations in capital markets. On the other hand, risk-seeking executives may perceive earnings manipulation as a high-risk strategy and decide to actively manipulate the reported income when experiencing loss in the capital markets. Hence, the $|DA|$–$RETURN$ relation strengthens in both tails of the stock return distribution. To ensure our empirical results are robust, we conduct several additional tests. These tests show consistent results with those reported in the main analysis.

This study makes theoretical and methodological contributions to the literature. It also offers policy implications to regulatory agencies. From the theoretical perspective, this study is the first research to examine the association of $|DA|$–$RETURN$ according to the prospect theory. As predicted, our results support the attributes outlined in the prospect theory. Moreover, the argument of managerial risk preference addressed in this study contributes to the literature on management's incentives for earnings manipulation behaviors. From the methodology perspective, we apply the QR to re-analyze the $|DA|$–$RETURN$ relation. This examination demonstrates that the OLS and LAD approach are ineffective to portray the managerial behavior when they encounter an extreme gain and loss in capital markets. Like what we have done to investigate the $|DA|$–$RETURN$ relation, it would be desirable for academicians to experiment other methods, as part of triangulation processes, to examine issues with inconclusive evidence reported in the literature.

Finally, this study provides policy implications to regulatory agencies. As documented in this study, the degree of earnings manipulation could accelerate when firms experiencing relatively high and positive stock returns or suffer from relatively low and negative performance in capital

markets. Moreover, these results appear to indicate that corporate executives may continue using earnings manipulation to deceive shareholders and other stakeholders. Thus, it is imperative for regulators to develop a viable regulatory framework according to the findings reported in this study, so they take enforceable actions to mitigate the potential consequences derived from the earnings manipulation.

Similar to other studies reported in the literature, researchers should interpret our empirical results with caution. One is our research hypothesis is built based on the argument that corporate executives may manipulate accounting information to enrich their personal utilities by taking risk preference into account. If this assumption is valid, our findings should have crucial implications for the usage of discretionary accruals in earnings management research because other unidentified factors also may motivate executives to engage in earnings management. Hence, it would be worthwhile to explore this possibility as part of their future research endeavors (e.g., Collins et al., 2017; Owens et al., 2017). Another issue is that the extant literature shows that firms may alter real activities, instead of using accounting accruals, to manipulate earnings (e.g., Roychowdhury 2006; Graham et al., 2005). To find out economic intuitions behind managerial choice between two earnings management methods, researchers are encouraged to conduct comparative studies, so they can find out how the tradeoff between accounting accruals and real activities management affects a firm's operations and its financial performance.

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Table 1
Descriptive statistics and correlation coefficients

Panel A: Descriptive statistics

	RETURN	|*DA*|	*DA*	*MKT*	*SIZE*	*MB*	*MOM*
Mean	0.2177	0.0585	-0.0075	0.0833	7.0813	0.9048	0.1889
Median	0.0962	0.0333	-0.0030	0.0973	6.9381	0.8392	0.0855
S.D.	0.8175	0.1076	0.1223	0.2279	1.6004	0.7452	0.7277
Skewness	6.8383	15.6586	7.8435	-0.2868	0.3419	0.6638	5.7698
Kurtosis	107.4732	542.2063	348.8974	2.6688	2.9583	6.2743	75.8313
Q1	-0.1652	0.0137	-0.0389	-0.0131	5.9319	0.4454	-0.1649
Q3	0.3991	0.0680	0.0277	0.1729	8.0947	1.3065	0.3701

Panel B: Correlation coefficients matrix

Variables	*RETURN*	|*DA*|	*DA*	*MKT*	*SIZE*	*MB*	*MOM*
RETURN	1.000						
|*DA*|	0.025**	1.000					
DA	0.023**	0.153**	1.000				
MKT	0.352**	-0.049**	-0.001	1.000			
SIZE	-0.091**	-0.145**	-0.034**	-0.052**	1.000		
MB	0.215**	0.061**	-0.017*	0.108**	-0.009	1.000	
MOM	-0.111**	0.110**	0.109**	-0.132**	-0.0864**	0.226**	1.000

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Variable definitions:

RETURN	=	Annual return of individual stock
|*DA*|	=	The absolute value of discretionary accruals
MKT	=	Annual return of S&P 500 Index
SIZE	=	The natural logarithm of a firm's total assets
MB	=	The ratio between market value and book value of a firm's equity shares
MOM	=	The lagged returns of a firm's equity shares

Table 2
The |*DA*|–*RETURN* relation across various quantiles of stock returns

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
5%	-0.646 (0.000)**	95%	2.586 (0.000)**	5% vs. 95%	31.86 (0.0000)**
10%	-0.590 (0.000)**	90%	1.132 (0.000)**	10% vs. 90%	41.98 (0.0000)**
15%	-0.594 (0.000)**	85%	0.586 (0.002)**	15% vs. 85%	42.96 (0.0000)**
20%	-0.532 (0.000)**	80%	0.403 (0.000)**	20% vs. 80%	66.74 (0.0000)**
25%	-0.488 (0.000)**	75%	0.225 (0.027)*	25% vs. 75%	50.82 (0.0000)**
30%	-0.419 (0.000)**	70%	0.019 (0.793)	30% vs. 70%	27.81 (0.0000)**
35%	-0.354 (0.000)**	65%	-0.052 (0.329)	35% vs. 65%	12.42 (0.0004)**
40%	-0.291 (0.000)**	60%	-0.086 (0.077)	40% vs. 60%	11.79 (0.0006)**
45%	-0.263 (0.000)**	55%	-0.152 (0.001)**	45% vs. 55%	16.79 (0.0000)**
50%	-0.217 (0.000)**	**OLS**	0.232 (0.000)**		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 3
The |*DA*|–*RETURN* relation across various quantiles of stock returns: High vs. low equity-based compensation

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
Panel A: High equity-based compensation					
5%	-0.518 (0.000)**	95%	2.872 (0.000)**	5% vs. 95%	17.32 (0.000)**
10%	-0.502 (0.000)**	90%	1.430 (0.027)*	10% vs. 90%	9.32 (0.002)**
15%	-0.430 (0.000)**	85%	0.475 (0.162)	15% vs. 85%	7.590 (0.006)**
20%	-0.435 (0.000)**	80%	0.215 (0.294)	20% vs. 80%	10.07 (0.002)**
25%	-0.367 (0.000)**	75%	0.034 (0.828)	25% vs. 75%	5.70 (0.017)*
30%	-0.344 (0.000)**	70%	-0.085 (0.380)	30% vs. 70%	4.69 (0.030)*
35%	-0.291 (0.000)**	65%	-0.078 (0.141)	35% vs. 65%	5.71 (0.017)*
40%	-0.229 (0.001)**	60%	-0.099 (0.020)*	40% vs. 60%	4.87 (0.027)*
45%	-0.169 (0.010)**	55%	-0.149 (0.010)**	45% vs. 55%	0.45 (0.500)
50%	-0.170 (0.000)**	**OLS**	0.211 (0.000)**		
Panel B: Low equity-based compensation					
5%	-0.616 (0.000)**	95%	1.213 (0.001)**	5% vs. 95%	25.20 (0.000)**
10%	-0.613 (0.000)**	90%	0.939 (0.037)*	10% vs. 90%	10.91 (0.001)**
15%	-0.661 (0.000)**	85%	0.592 (0.015)*	15% vs. 85%	25.79 (0.000)**
20%	-0.618 (0.000)**	80%	0.364 (0.150)	20% vs. 80%	15.03 (0.000)**
25%	-0.559 (0.000)**	75%	0.102 (0.603)	25% vs. 75%	9.00 (0.003)**
30%	-0.526 (0.000)**	70%	-0.015 (0.915)	30% vs. 70%	8.59 (0.003)**
35%	-0.410 (0.000)**	65%	-0.092 (0.349)	35% vs. 65%	9.90 (0.002)**
40%	-0.354 (0.000)**	60%	-0.169 (0.084)	40% vs. 60%	2.84 (0.092)
45%	-0.317 (0.000)**	55%	-0.236 (0.000)**	45% vs. 55%	1.630 (0.202)
50%	-0.274 (0.000)**	**OLS**	0.156 (0.101)**		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 4
The relation between |*DA*| and industry-adjusted Tobin's *Q* across various quantiles of Tobin's *Q*

$$TOBIN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 INT_{i,t} + \beta_5 ROA_{i,t} + \beta_6 RD_{i,t} + \beta_7 INSIDER_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
5%	-1.043 (0.000)**	95%	9.981 (0.000)**	5% vs. 95%	98.96 (0.0000)**
10%	-0.414 (0.011)*	90%	7.682 (0.000)**	10% vs. 90%	131.16 (0.0000)**
15%	-0.138 (0.227)	85%	5.785 (0.000)**	15% vs. 85%	115.90 (0.0000)**
20%	-0.016 (0.875)	80%	4.715 (0.000)**	20% vs. 80%	109.48 (0.0000)**
25%	0.083 (0.661)	75%	3.858 (0.000)**	25% vs. 75%	179.14 (0.0000)**
30%	0.343 (0.134)	70%	3.383 (0.000)**	30% vs. 70%	160.16 (0.0000)**
35%	0.628 (0.012)*	65%	2.796 (0.000)**	35% vs. 65%	111.37 (0.0000)**
40%	0.797 (0.000)**	60%	2.270 (0.000)**	40% vs. 60%	117.04 (0.0000)**
45%	1.086 (0.000)**	55%	1.780 (0.000)**	45% vs. 55%	29.13 (0.0000)**
50%	1.443 (0.000)**	**OLS**	1.526 (0.000)**		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 5
The |*DA*|–*RETURN* relation with year and industry dummies across various quantiles of stock returns

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + \textit{year dummies} + \textit{industry dummies} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
5%	-0.608 (0.000)**	95%	1.758 (0.000)**	5% vs. 95%	36.51 (0.0000)**
10%	-0.616 (0.000)**	90%	0.855 (0.007)**	10% vs. 90%	21.50 (0.0000)**
15%	-0.565 (0.000)**	85%	0.462 (0.005)**	15% vs. 85%	40.12 (0.0000)**
20%	-0.534 (0.000)**	80%	0.218 (0.189)	20% vs. 80%	20.78 (0.0000)**
25%	-0.498 (0.000)**	75%	0.055 (0.657)	25% vs. 75%	23.76 (0.0000)**
30%	-0.467 (0.000)**	70%	-0.094 (0.234)	30% vs. 70%	24.72 (0.0000)**
35%	-0.413 (0.000)**	65%	-0.136 (0.031)*	35% vs. 65%	25.45 (0.0000)**
40%	-0.380 (0.000)**	60%	-0.163 (0.005)**	40% vs. 60%	21.05 (0.0000)**
45%	-0.323 (0.000)**	55%	-0.243 (0.000)**	45% vs. 55%	11.08 (0.0009)**
50%	-0.307 (0.000)**	**OLS**	0.117 (0.017)*		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 6
The |*DA*|–*RETURN* relation across various quantiles of stock returns: Managing earnings upward or downward

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
Panel A: Upward earnings manipulation (Positive DA)					
5%	-0.499 (0.000)**	95%	3.498 (0.002)**	5% vs. 95%	12.15 (0.0005)**
10%	-0.347 (0.000)**	90%	2.011 (0.005)**	10% vs. 90%	11.01 (0.0009)**
15%	-0.324 (0.000)**	85%	1.021 (0.001)**	15% vs. 85%	17.96 (0.0000)**
20%	-0.202 (0.031)*	80%	0.686 (0.000)**	20% vs. 80%	16.41 (0.0001)**
25%	-0.183 (0.002)**	75%	0.641 (0.000)**	25% vs. 75%	24.61 (0.0000)**
30%	-0.142 (0.000)**	70%	0.519 (0.004)**	30% vs. 70%	13.08 (0.0003)**
35%	-0.141 (0.006)**	65%	0.286 (0.054)	35% vs. 65%	7.97 (0.0048)**
40%	-0.089 (0.063)	60%	0.224 (0.126)	40% vs. 60%	4.44 (0.0352)*
45%	-0.077 (0.172)	55%	0.079 (0.499)	45% vs. 55%	3.03 (0.0816)
50%	-0.053 (0.627)	**OLS**	0.458 (0.000)**		
Panel B: Downward earnings manipulation (Negative DA)					
5%	-0.756 (0.000)**	95%	1.349 (0.023)*	5% vs. 95%	11.92 (0.0006)**
10%	-0.735 (0.000)**	90%	0.586 (0.062)	10% vs. 90%	17.58 (0.0000)**
15%	-0.725 (0.000)**	85%	0.154 (0.349)	15% vs. 85%	24.03 (0.0000)**
20%	-0.717 (0.000)**	80%	-0.034 (0.809)	20% vs. 80%	21.86 (0.0000)**
25%	-0.677 (0.000)**	75%	-0.225 (0.035)*	25% vs. 75%	19.96 (0.0000)**
30%	-0.610 (0.000)**	70%	-0.265 (0.000)**	30% vs. 70%	23.57 (0.0000)**
35%	-0.558 (0.000)**	65%	-0.304 (0.000)**	35% vs. 65%	14.43 (0.0001)**
40%	-0.505 (0.000)**	60%	-0.341 (0.000)**	40% vs. 60%	11.83 (0.0006)**
45%	-0.457 (0.000)**	55%	-0.378 (0.000)**	45% vs. 55%	8.71 (0.0032)**
50%	-0.416 (0.000)**	**OLS**	-0.107 (0.174)		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 7
The |*DA*|–*RETURN* relation across various quantiles of stock returns: Pre- and post-Sarbanes Oxley eras

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
Panel A: Pre-SOX (1992~2001)					
5%	-0.668 (0.000)**	95%	2.994 (0.000)**	5% vs. 95%	44.56 (0.0000)**
10%	-0.699 (0.000)**	90%	1.475 (0.000)**	10% vs. 90%	25.90 (0.0000)**
15%	-0.641 (0.000)**	85%	0.914 (0.000)**	15% vs. 85%	55.74 (0.0000)**
20%	-0.583 (0.000)**	80%	0.450 (0.030)*	20% vs. 80%	25.50 (0.0000)**
25%	-0.531 (0.000)**	75%	0.222 (0.150)	25% vs. 75%	20.19 (0.0000)**
30%	-0.449 (0.000)**	70%	0.027 (0.759)	30% vs. 70%	25.20 (0.0000)**
35%	-0.324 (0.000)**	65%	-0.080 (0.184)	35% vs. 65%	9.05 (0.0026)**
40%	-0.288 (0.000)**	60%	-0.110 (0.026)*	40% vs. 60%	13.35 (0.0003)**
45%	-0.262 (0.000)**	55%	-0.148 (0.011)*	45% vs. 55%	8.21 (0.0042)**
50%	-0.263 (0.000)**	**OLS**	0.205 (0.000)**		
Panel B: Post-SOX (2003~2010)					
5%	-0.534 (0.000)**	95%	1.136 (0.006)**	5% vs. 95%	16.25 (0.0001)
10%	-0.525 (0.000)**	90%	0.687 (0.020)*	10% vs. 90%	15.59 (0.0001)**
15%	-0.426 (0.000)**	85%	0.564 (0.001)**	15% vs. 85%	32.83 (0.0000)**
20%	-0.424 (0.000)**	80%	0.260 (0.013)*	20% vs. 80%	40.38 (0.0000)**
25%	-0.461 (0.000)**	75%	0.267 (0.004)**	25% vs. 75%	41.86 (0.0000)**
30%	-0.423 (0.000)**	70%	-0.000 (1.000)	30% vs. 70%	9.73 (0.0018)
35%	-0.372 (0.000)**	65%	-0.154 (0.158)	35% vs. 65%	4.34 (0.0372)
40%	-0.331 (0.000)**	60%	-0.175 (0.086)	40% vs. 60%	2.36 (0.1243)
45%	-0.306 (0.000)**	55%	-0.192 (0.013)*	45% vs. 55%	2.63 (0.1046)
50%	-0.245 (0.002)**	**OLS**	0.045 (0.689)		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Table 8
The |*DA*|–*RETURN* relation across various quantiles of stock returns: Potential outliers and possible measurement errors

$$RETURN_{i,t+1} = \beta_0 + \beta_1 |DA_{i,t}| + \beta_2 MKT_t + \beta_3 SIZE_{i,t} + \beta_4 MB_{i,t} + \beta_5 MOM_{i,t} + u_{i,t+1}$$

Coefficient estimates on |DA|: QR vs. OLS				*Tests of equality across quantiles*	
Quant.	*Coeff. (p-value)*	*Quant.*	*Coeff. (p-value)*	*Quant.*	*F-statistic (p-value)*
5%	-0.553 (0.000)**	95%	2.828 (0.000)**	5% vs. 95%	41.53 (0.0000)**
10%	-0.551 (0.000)**	90%	1.413 (0.000)**	10% vs. 90%	30.16 (0.0000)**
15%	-0.553 (0.000)**	85%	0.653 (0.002)**	15% vs. 85%	32.55 (0.0000)**
20%	-0.496 (0.000)**	80%	0.464 (0.021)*	20% vs. 80%	19.39 (0.0000)**
25%	-0.431 (0.000)**	75%	0.269 (0.115)	25% vs. 75%	14.75 (0.0001)**
30%	-0.340 (0.000)**	70%	0.073 (0.588)	30% vs. 70%	7.45 (0.0064)**
35%	-0.307 (0.000)**	65%	-0.007 (0.924)	35% vs. 65%	12.79 (0.0004)**
40%	-0.229 (0.000)**	60%	-0.075 (0.085)	40% vs. 60%	6.19 (0.0128)*
45%	-0.197 (0.000)**	55%	-0.094 (0.088)	45% vs. 55%	6.01 (0.0143)*
50%	-0.147 (0.003)**	**OLS**	0.242 (0.000)**		

Notes: The ** and * denote a 1% and a 5% level of significance, respectively.

Figure 1
An illustrated example for the QR approach

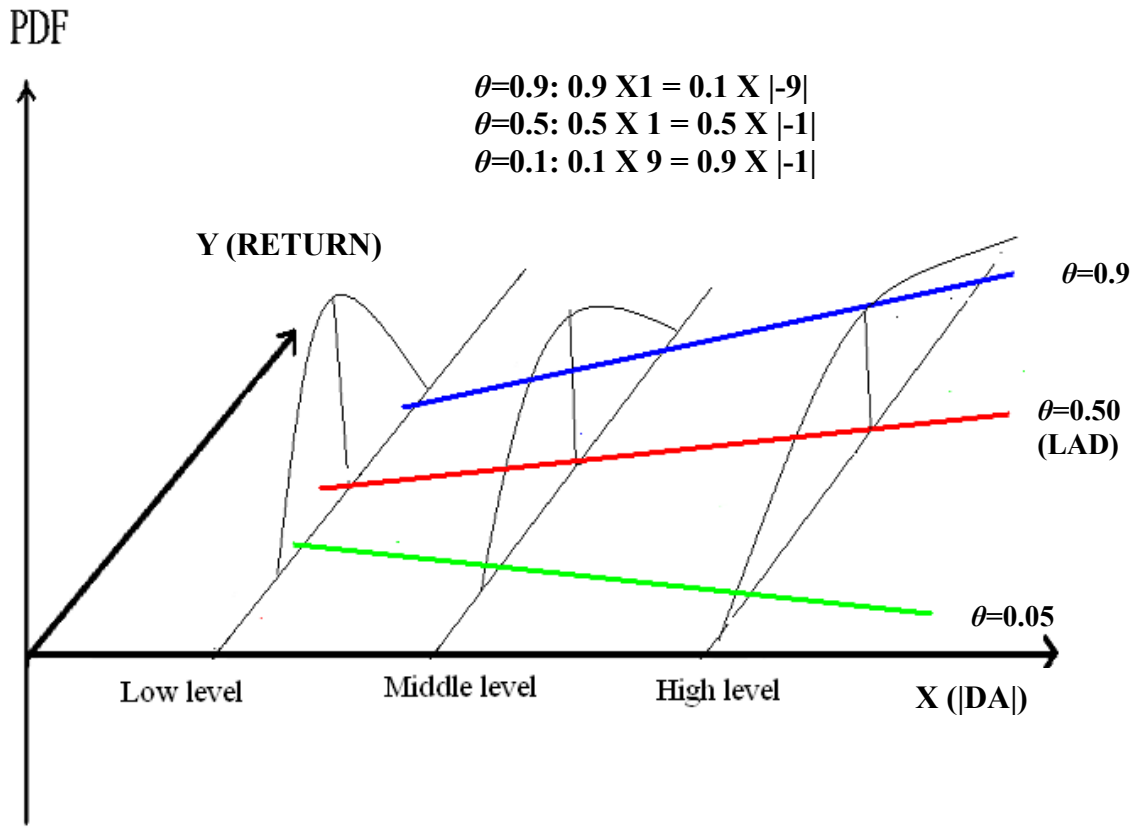


Figure 2
Coefficient estimates of |*DA*| across various quantiles of stock returns: QR vs. OLS

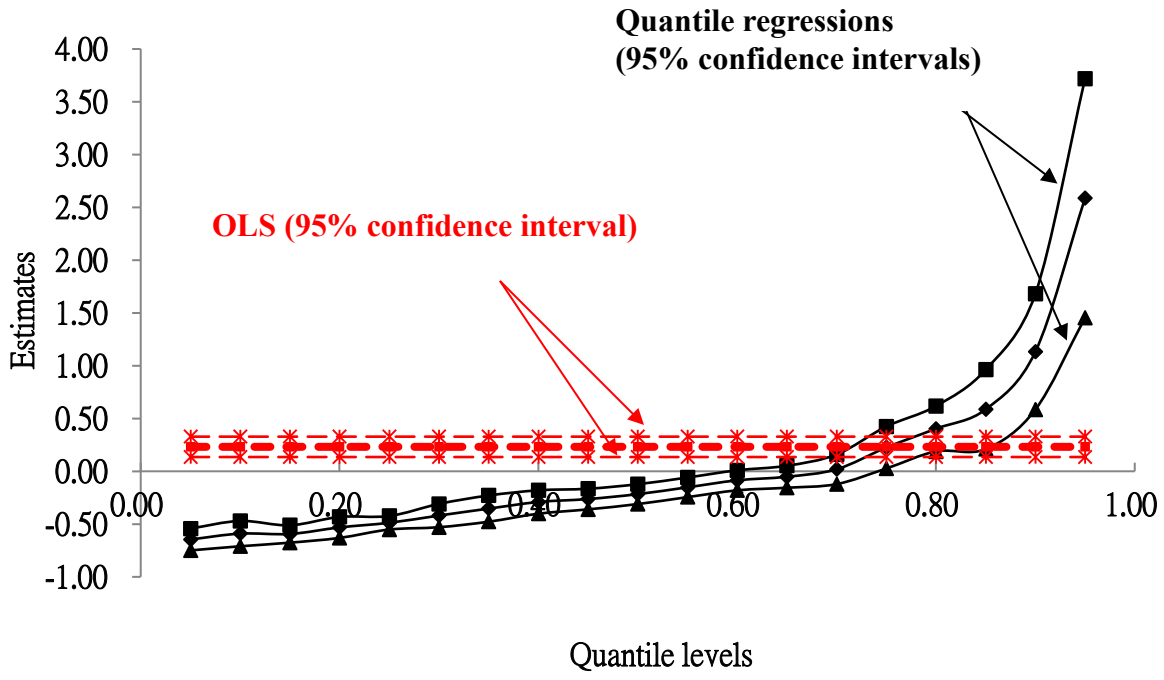
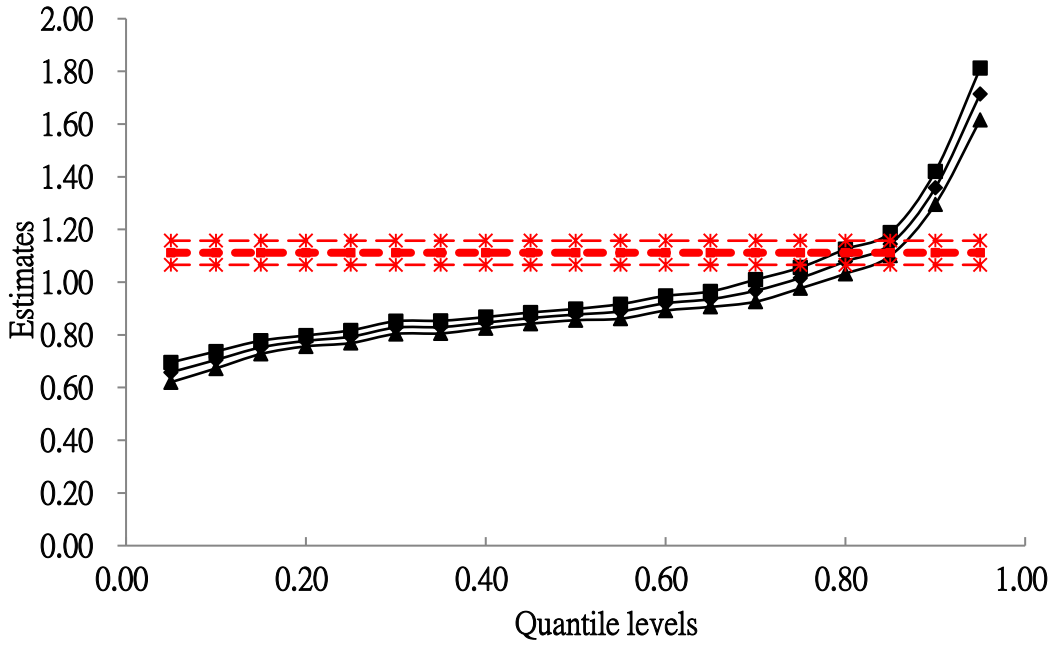
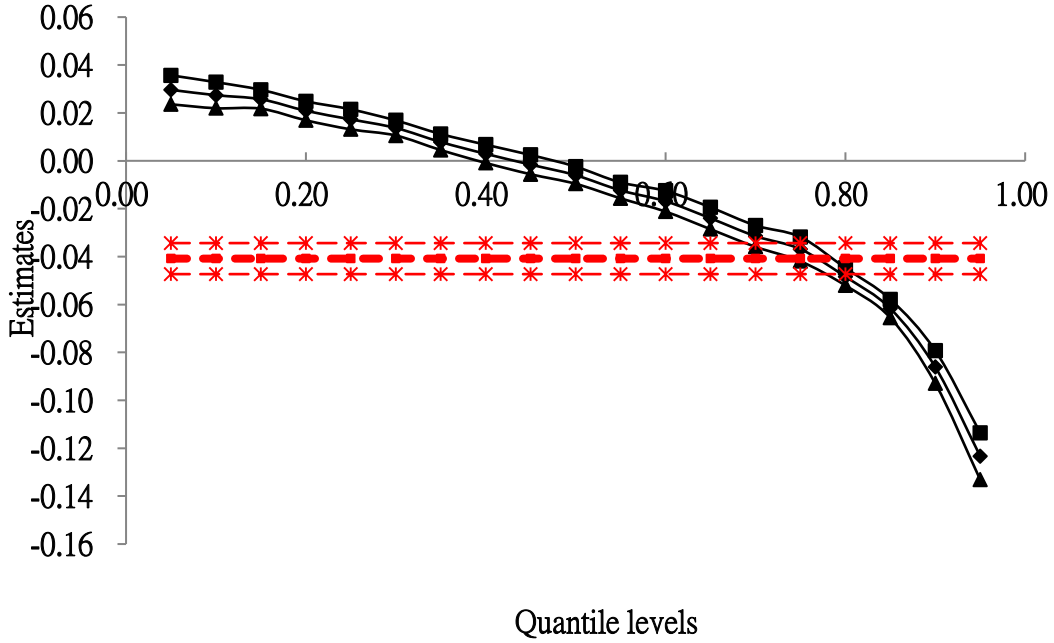


Figure 3
The QR and OLS estimates across various quantiles of stock returns for control variables

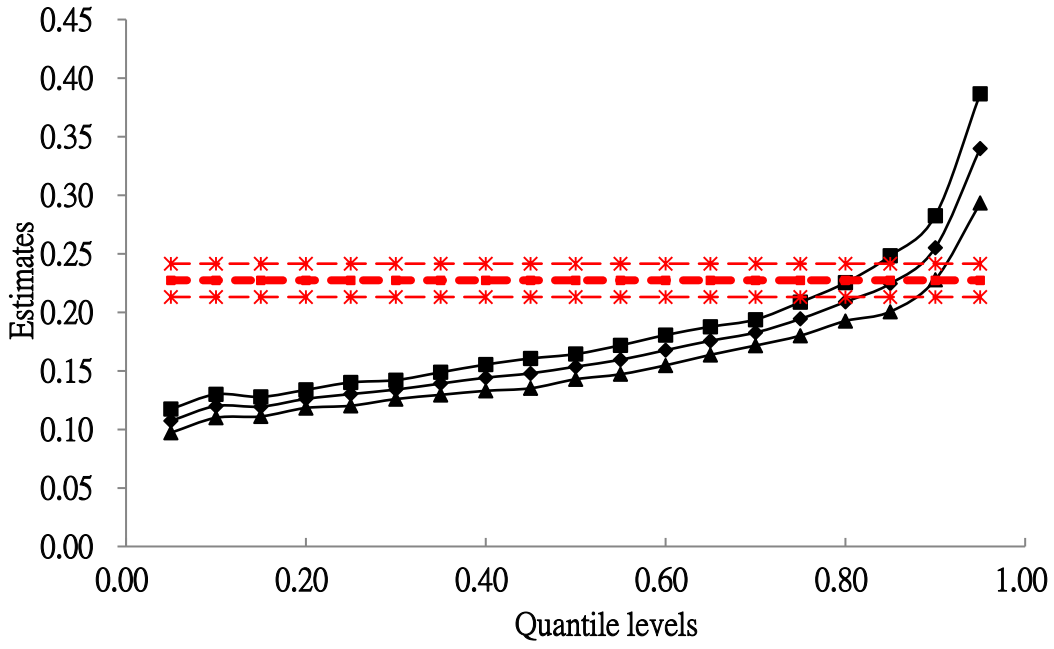
Panel A: Market return (*MKT*)



Panel B: Size of firm (*SIZE*)



Panel C: Market to book value ratio (*MB*)



Panel D: Lagged individual stock return (*MOM*)

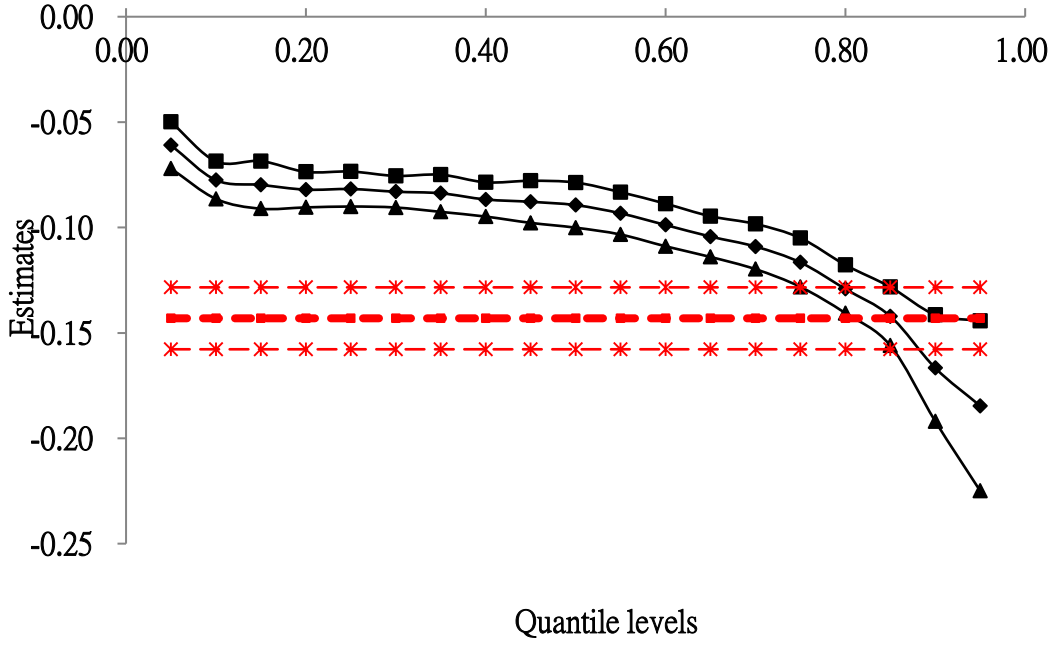
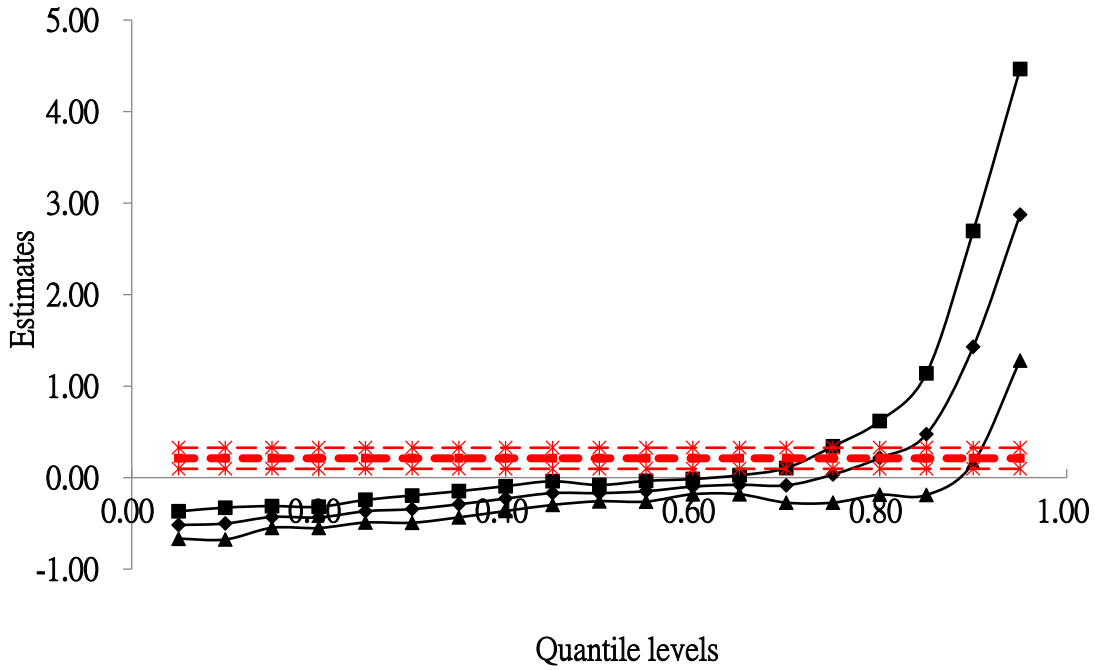


Figure 4
The QR and OLS estimates of |*DA*| across various quantiles of stock returns: High vs. low level of equity-based compensation

Panel A: Firms having high level of equity-based compensation



Panel B: Firms having low level of equity-based compensation

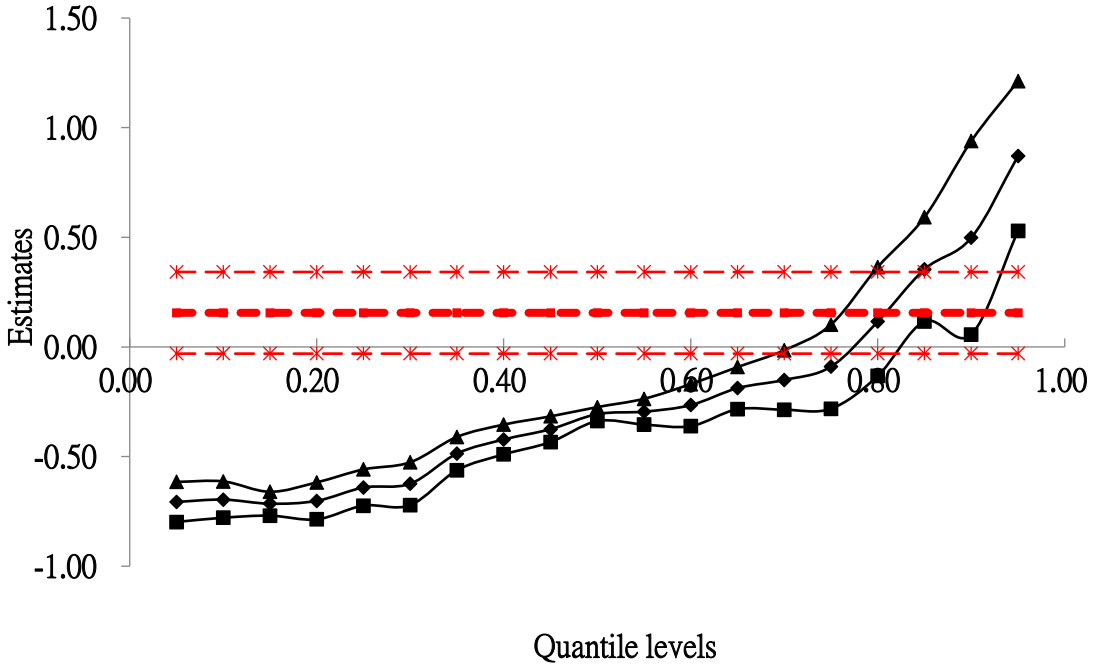


Figure 5
The QR and OLS estimates of |*DA*| across various quantiles of Tobin's *Q*:
Using industry-adjusted Tobin's *Q* as an alternative measure of performance

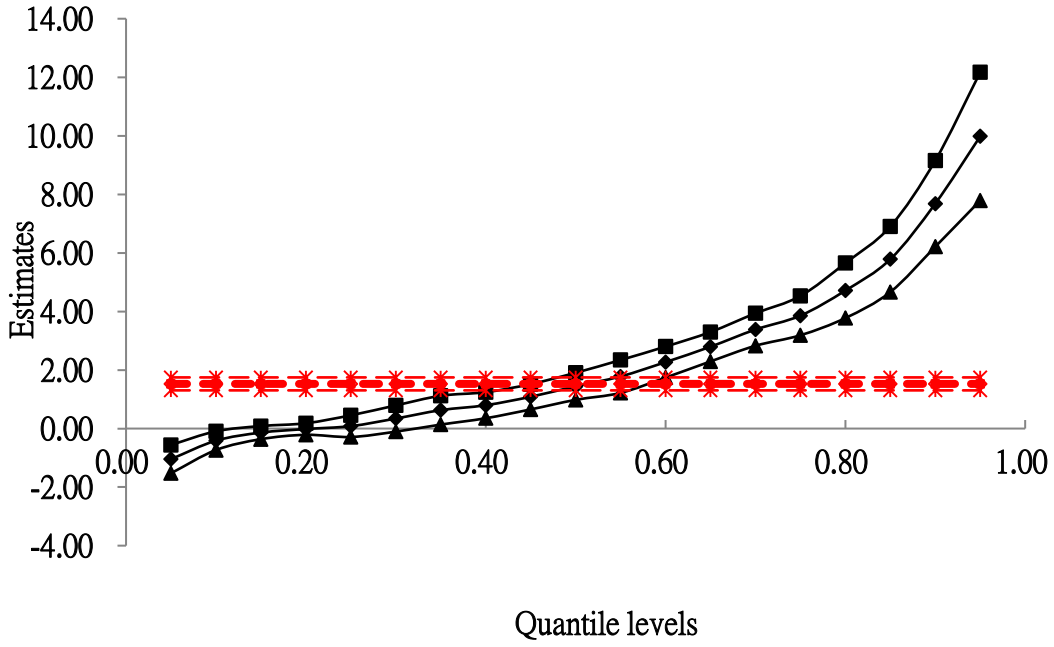


Figure 6
The QR and OLS estimates of |*DA*| across various quantiles of stock returns: With year and industry dummies

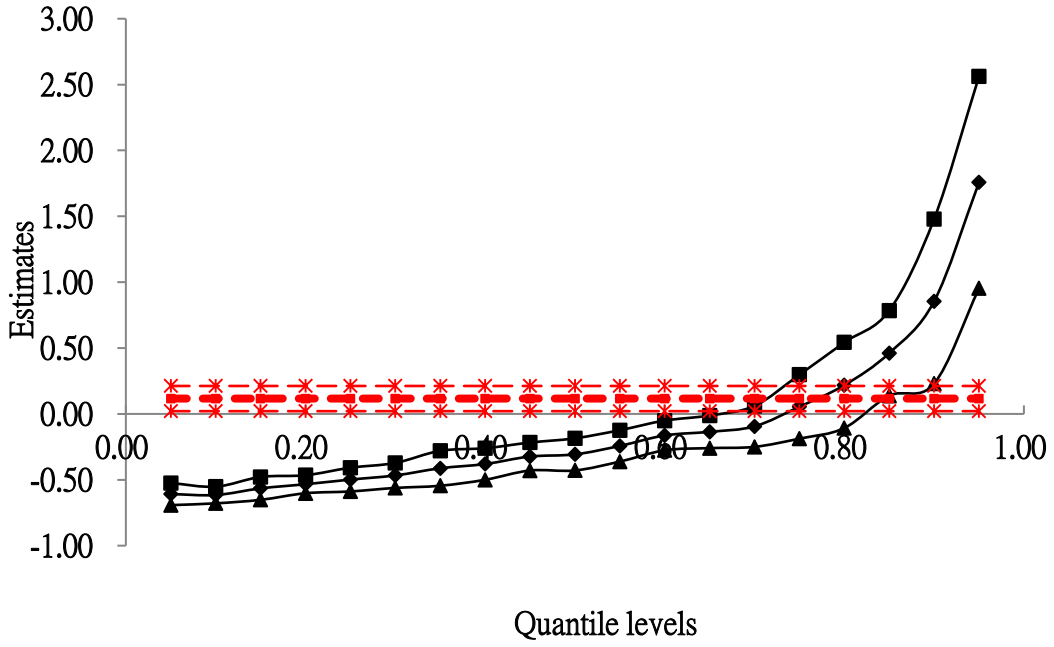
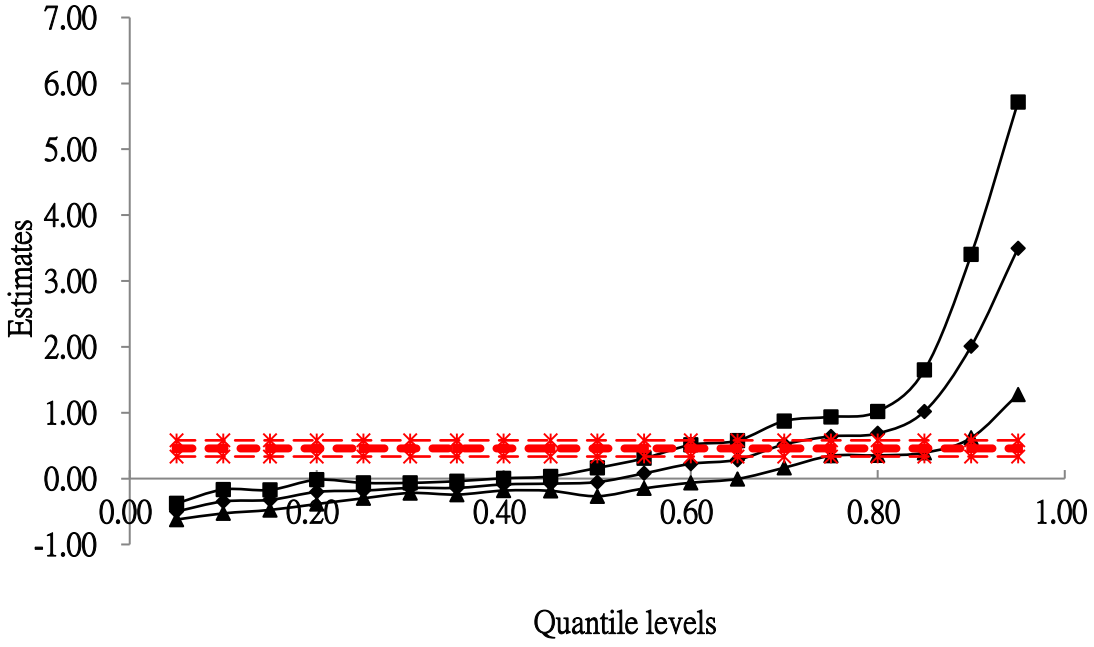


Figure 7
The QR and OLS estimates of |*DA*| across various quantiles of stock returns: Upward vs. downward earnings manipulation

Panel A: Upward earnings manipulation: Positive *DA*



Panel B: Downward earnings manipulation: Negative *DA*

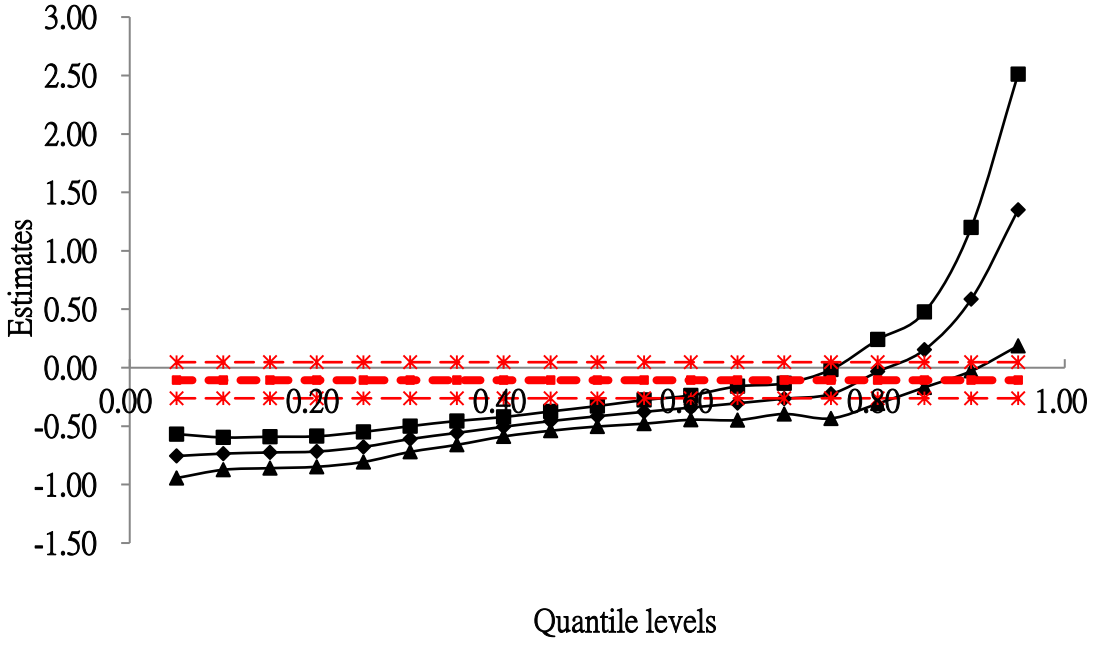
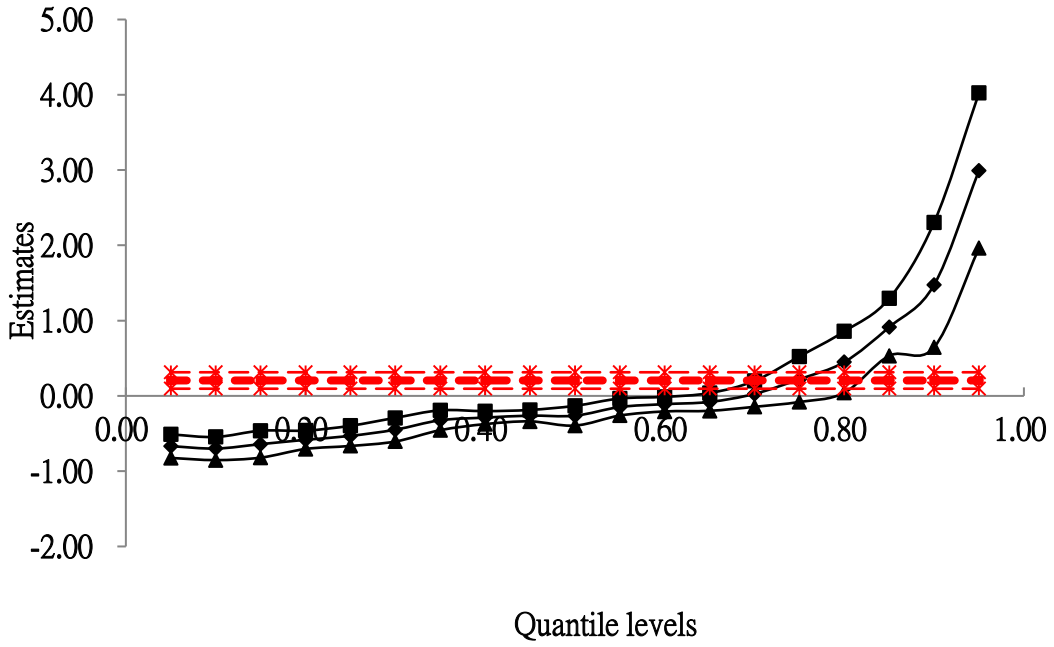


Figure 8
The QR and OLS estimates of |*DA*| across various quantiles of stock returns: Pre- vs. post-Sarbanes Oxley eras

Panel A: The pre-SOX (1992~2001)



Panel B: The post-SOX period (2003~2010)

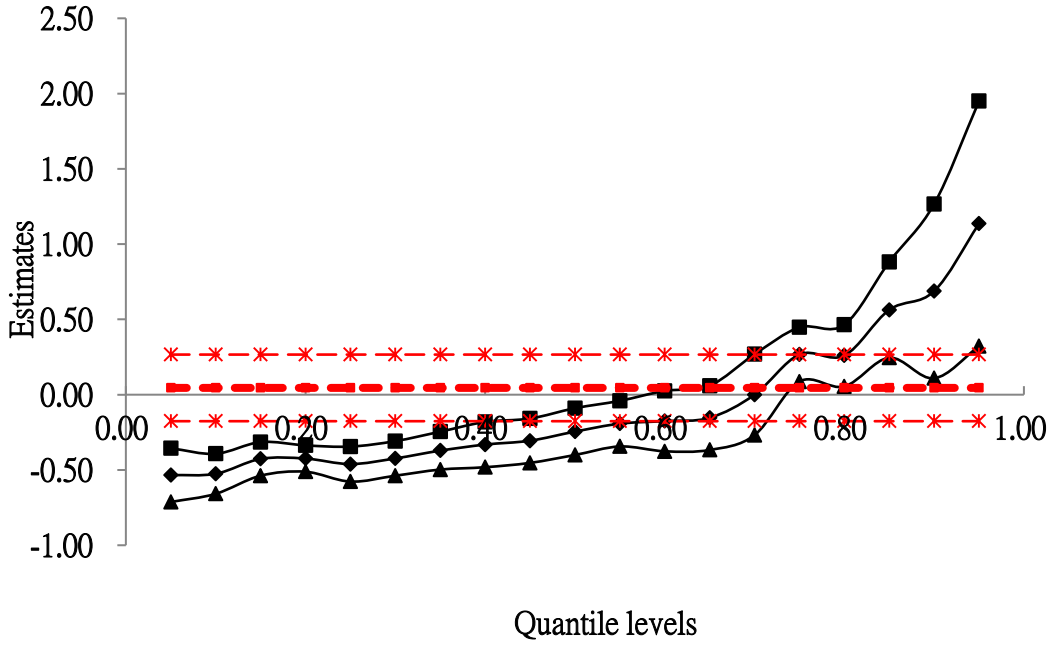


Figure 9
The QR and OLS estimates of |*DA*| across various quantiles of stock returns: Potential outliers and possible measurement errors