Improving the estimation of discretionary accruals – the cycle approach

Che-Wei Chiu, PhD
Winona State University

Po-Chang Chen, PhD
Miami University

Yuqian Wang, PhD
Winona State University

ABSTRACT

The paper proposes a new estimation approach to cross-sectional accrual models with the objective of reducing the measurement error in discretionary accruals resulting from violation of the homogeneous accrual generating process in an industry (Dopuch, Seethamraju, Mashruwala and Zach, 2012). Applying the cycle approach to four commonly-used discretionary accrual measures, the paper shows that discretionary accruals estimated using the new approach have less measurement errors than those estimated by the traditional approach without the cycle adjustment, especially in industries where firms' operating cycles are more varied. The paper also provides empirical evidence that discretionary accruals estimated using the cycle approach have superior ability in detecting earnings management, as measured by SEC Accounting and Auditing Enforcement Release (AAER).

Keywords: discretionary accruals, earnings management, and operating cycle.

INTRODUCTION

Discretionary accruals have been widely used in the accounting and finance literature to examine a firm's earning management behavior or earnings quality (e.g., Francis, LaFond, Olsson, and Schipper, 2005; Fang, Huang and Karpoff, 2016; Kothari, Mizik and Roychowdhury, 2016; Lawson and Wang, 2016). In her famous study, Jones (1991) developed a firm-specific time-series model to separate accruals into the non-discretionary component and the discretionary component, and since then various modifications of the Jones model have emerged to improve the estimation of discretionary accruals. In particular, DeFond and Jiambalvo (1994) estimated Jones model in a cross-sectional setting, which has become an extensively-adopted approach because it does not require long time-series data for individual firms and thus is not subject to survival bias.

Notwithstanding their popularity in earnings management/quality research, the traditional cross-sectional accrual models are prone to a specific type of measurement error arising from the assumption that all firms in an industry have the same accrual-generating process. Dopuch, Seethamraju, Mashruwala and Zach (2012) challenged this homogeneity assumption by empirically examining several accrual determinants including (a) receivable turnover, (b) payable turnover, (c) inventory turnover, and (d) profit margin. They find that firms in industries with higher variations in these accrual determinants have larger absolute discretionary accruals, thus providing evidence on the measurement error inherent in the traditional cross-sectional accrual models. To address this issue and reduce the measurement error in estimating discretionary accruals, this paper suggests an alternative approach (referred to as the "cycle approach") that explicitly considers the heterogeneity of firms' accrual-generating process based on operating cycles. In so doing, this paper contributes to the literature by improving the estimation of discretionary accruals and reducing the likelihood of improper inferences made from biased estimation results.

The proposed cycle approach features a two-step implementation of discretionary accruals estimation. The first step measures the within-industry variation of firms' operating cycles, which captures the heterogeneity of accrual generating process in a given industry. The second step then applies those operating cycle variations to the estimation of discretionary accruals by allowing the regression coefficients on a key accrual determinant, i.e., sales changes, to differ across firms with varied operating cycles. Applying this approach to four commonly-used cross-sectional accrual models: Jones model, modified Jones model, performance-matched Jones model and performance-matched modified Jones model, the paper shows that the absolute values of discretionary accruals are consistently smaller than those estimated using the traditional approach without the cycle adjustment, especially in industries where firms have more heterogeneous accrual generating process, as measured by operating cycles. This finding indicates a reduction in measurement error from the model estimation perspective. To demonstrate the usefulness of the new approach, the paper further tests and finds that cycle-adjusted discretionary accruals, versus unadjusted discretionary accruals, exhibit a stronger explanatory power for earnings management as proxied by the SEC Accounting and Auditing Enforcement Releases (AAER). Together, these empirical findings support the notion that the cycle approach improves the estimation of discretionary accruals from both internal (i.e., reduced measurement error) and external (i.e., enhanced prediction of earnings management) perspectives.

The paper proceeds as follows. Section 2 reviews the accrual models in the literature. Section 3 develops the new accrual model estimation approach. Section 4 discusses data and samples. Section 5 reports the measurement errors of cycle-adjusted discretionary accruals and unadjusted discretionary accruals. Section 6 presents the empirical results of explanatory power test of various discretionary accrual estimates using AAER as an external measure of earnings management. Section 7 concludes.

RELATED LITERATURE

A vast body of accounting research examines accruals, and the pervasiveness of accruals-based research in the accounting literature is intuitive given that accruals are the primary mechanism that makes financial statements useful (Larson, Sloan, and Giedt 2018). The efforts made by accounting researchers to distinguish non-discretionary and discretionary accruals date back to Healy (1985) and DeAngelo (1986). Healy (1985) assumed that non-discretionary accruals follow a mean-reverting process and used the mean of total accruals scaled by lagged total assets from the estimation period as the measure of non-discretionary accruals. Regarded as a special case of Healy's model, DeAngelo (1986) assumed a random walk process for non-discretionary accruals and measured them as accruals of the last year (t-1). In both models, the discretionary accruals are the difference between the total accruals and non-discretionary accruals. However, neither model considers the effect of changes in a firm's economic conditions on its non-discretionary accruals.

Distinct from Healy (1985) and DeAngelo (1986), Jones (1991) developed an accrual model in which a firm's total accruals were regressed on changes in sales from year t-1 to year t and the gross property, plant and equipment (PP&E), thus explicitly controlling the effect of changing economic conditions, i.e., sales and depreciation of tangible assets, on non-discretionary accruals. Jones model (1991) was estimated using a time-series firm-specific regression. First, the regression coefficients were estimated during the estimation period. And the estimated coefficients were used to calculate the non-discretionary accruals of the event period. Discretionary accruals were measured by regression residuals since they indicate the portion of total accruals that cannot be explained by changes in sales and PP&E. Specifically, the following regression is estimated:

Jones Model (1991)

$$\frac{ACC_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{\Delta SALE_{it}}{TA_{it-1}} + \alpha_3 \frac{PPE_{it}}{TA_{it-1}} + \varepsilon_{it} \qquad (1)$$

where ACC_{it} denotes the total accruals of firm i at the end of year t; TA_{it-1} denotes the firm's total assets at the end of year t-1; $\Delta SALE_{it}$ is sales in year t less sales in year t-1; PPE_{it} is gross property, plant at the end of year t, and equipment.

Later, Dechow, Sloan and Sweeney (1995) developed a modified version of Jones model (1991) and showed that the modified Jones model exhibited increased power in detecting earnings management. Specifically, the modified Jones model assumed all the credit sales in the event period result from earnings management and adjust change in sales is for the change in receivables. The following regression model is estimated:

Modified Jones Model (1995)

$$\frac{ACC_{it}}{TA_{it-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{it-1}} + \alpha_2 \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} + \alpha_3 \frac{PPE_{it}}{TA_{it-1}} + \varepsilon_{it} \qquad (2)$$

where ΔAR_{it} denotes changes in net receivables from year t-1 to year t, and other variables are the same as defined in Equation 1.

While the original Jones model was implemented in a time-series setting, DeFond and Jiambalvo (1994) estimated the Jones model in a cross-sectional setting. Specifically, the accrual model was estimated separately for each group of firms in the same 2-digit Standard Industrial Classification (SIC) industry every year, and the residuals of the regression are considered as discretionary accruals. Since the cross-sectional model did not require a sufficient long time series of observations to estimate the regression coefficients, it became widely adopted in accounting research. The discretionary accruals estimated cross-sectionally using the Jones model (i.e., Equation 1) and modified Jones model (i.e., Equation 2) are referred to in the paper as *DA_J* and *DA_MJ*, respectively.

Another important improvement to accrual models subsequent to the modified Jones model was developed by Kothari, Leone and Wasley (2005). Dechow, Sloan and Sweeny (1995) argued that discretionary accrual estimates tend to over-reject the null hypothesis of no earnings management when applied to samples of firms with extreme performance. To reduce the measurement error caused by extreme performance, Kothari et al. (2005) used a control sample design and developed the performance-matched accrual model. Specifically, the performance-matched discretionary accrual model adjusted a firm's estimated discretionary accruals by subtracting the corresponding discretionary accruals of a firm matched based on industry and current year's return on assets. Their results suggest that performance-matched discretionary accrual is the best specified discretionary accrual measure and can reduce the likelihood of invalid inference. In this study, the performance-matched discretionary accruals estimated using the Jones and modified Jones models are referred to as *DA_JP* and *DA_MJP*, respectively.

Despite their popularity and improvements, cross-sectional accrual models are subject to another source of measurement error, as identified by Dopuch, Seethamraju, Mashruwala and Zach (2012). In particular, Dopuch et al. (2012) argued that an important assumption of accrual models is that firms estimated in the same regression model have homogeneous accrual generating process. Traditional cross-sectional accrual models are estimated for firms with common 2-digit SIC industry codes. However, they found that the assumption of homogenous accrual process is violated in industries where firms' accrual determinants are highly dispersed. They also showed that firms in industries with high variations in accrual determinants are likely to have large absolute value of discretionary accruals, i.e., large measurement error. To address this particular source of measurement error, this paper proposes an alternative approach under which firms' operating cycles are explicitly considered when estimating accruals. The cycle approach, to be the described in detail below, is developed to help further reduce the measurement error in accrual estimations and enhance the power of using discretionary accruals to detect earnings management.

DEVELOPMENT OF "THE CYCLE APPROACH"

The proposed cycle approach builds on a theoretical framework provided by Dechow, Kothari, and Watts (1998) for the determination of non-discretionary working capital accruals (hereafter the DKW model). In the DKW model, working capital accruals are expressed as $[\alpha + (1-\pi)\gamma_1 - \beta(1-\pi)] \times \Delta SALE_t + \varepsilon_t$, where $\Delta SALE_t$ is changes in sales from year t-1 to t; α is inverse of accounts receivable turnover; γ_1 is inverse of inventory turnover; β is inverse of accounts payable turnover and π is profit margin. The term, $[\alpha + (1-\pi)\gamma_1 - \beta(1-\pi)]$, essentially measures a firm's expected operating cycle expressed as a fraction of a year. As such, working capital accrual is primarily a function of the product of a firm's expected operating cycle and its changes in sales.

Applied to empirical models, the DKW framework suggests that the coefficient of changes in sales should reflect a firm's expected operating cycle. Thus, in estimating non-discretionary accruals, an accrual model should allow the coefficient on changes in sales to differ between firms with different expected operating cycles. Without proper adjustment for firms' operating cycles, as Dopuch et al. (2012) pointed out, large measurement errors in discretionary accruals could result from the estimation of the traditional "unadjusted" approach. The implementation of the cycle approach is detailed below.

First, a firm's operating cycle (*CYL*) is calculated as the number of days in receivable (*AR*), plus the number of days in inventory (*INV*), and minus the number of days in payable (*AP*). Specifically, the operating cycle is computed as follows:

$$CYL_{it} = \frac{365}{Receivable\ Turnover} + \frac{365}{Inventory\ Turnover} - \frac{365}{Payable\ Turnover} = \frac{365}{\frac{SALES_{it}}{(AVG\_AR_{it})}} + \frac{365}{\frac{COGS_{it}}{(AVG\_INV_{it})}} - \frac{365}{\frac{COGS_{it}}{(AVG\_AP_{it})}} \quad (3)$$

As stated above, the subscripts i and t denote the firm and the year, respectively. $SALES_{it}$ is firm i's net sales revenue of year t and $COGS_{it}$ is cost of goods sold. AVG_AR_{it} is the average of accounts receivable of year t. AVG_INV_{it} is the average of inventory of year t and AVG_AP_{it} is the average of accounts payable of year t. All three average variables are calculated as the average of the balance at the beginning of year t and the balance at the end of year t.

Next, the expected operating cycle of a firm in year t ($EXPCYL_{it}$) is measured as the average operating cycle for the previous three years, from year t-3 to year t-1, to mitigate the impact of temporary shocks affecting operating cycles.

$$EXPCYL_{it} = \frac{CYL_{it-1} + CYL_{it-2} + CYL_{it-3}}{3} \quad (4)$$

Based on the length of expected operating cycles, all sample firms are then partitioned into five quintiles each year. Finally, to allow the coefficient of changes in sales to be different for firms with different expected operating cycle, four indicator variables (QT2 to QT5) of the operating cycle quintiles are added to the cross-sectional Jones model as follows:

$$\frac{ACC_{it}}{TA_{it-1}} = \beta_0 + \beta_1\frac{1}{TA_{it-1}} + \beta_2 QT2_{it} + \beta_3 QT3_{it} + \beta_4 QT4_{it} + \beta_5 QT5_{it} + \beta_6\frac{\Delta SALE_{it}}{TA_{it-1}} + \beta_7\frac{\Delta SALE_{it}}{TA_{it-1}} \times QT2_{it} + \beta_8\frac{\Delta SALE_{it}}{TA_{it-1}} \times QT3_{it} + \beta_9\frac{\Delta SALE_{it}}{TA_{it-1}} \times QT4_{it} + \beta_{10}\frac{\Delta SALE_{it}}{TA_{it-1}} \times QT5_{it} + \beta_{11}\frac{PPE_{it}}{TA_{it-1}} + \varepsilon_{it} \quad (5)$$

Similarly, the following expanded version of cross-sectional modified Jones model is estimated.

$$\frac{ACC_{it}}{TA_{it-1}} = \beta_0 + \beta_1 \frac{1}{TA_{it-1}} + \beta_2 QT2_{it} + \beta_3 QT3_{it} + \beta_4 QT4_{it} + \beta_5 QT5_{it} + \beta_6 \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} + \beta_7 \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} \times QT2_{it} + \beta_8 \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} \times QT3_{it} + \beta_9 \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} \times QT4_{it} + \beta_{10} \frac{\Delta SALE_{it} - \Delta AR_{it}}{TA_{it-1}} \times QT5_{it} + \beta_{11} \frac{PPE_{it}}{TA_{it-1}} + \varepsilon_{it} \quad (6)$$

Equations (5) and (6) are estimated for each 2-digit SIC industry every year. The regression residuals are referred to as the cycle-adjusted discretionary accruals and denoted as *DA_JC* and *DA_MJC*, respectively. The performance-matched discretionary accruals of Equations (5) and (6) are calculated by matching each test sample with a control sample based on return on assets and industry membership. Specifically, the performance-matched discretionary accrual adjusts a firm's estimated discretionary accrual by subtracting the corresponding discretionary accrual of a firm matched on the basis of 2-digit SIC industry and current year's return on assets. The performance-matched discretionary accruals estimated using cycle-adjusted Jones model and cycle-adjusted modified Jones model are denoted as *DA_JPC* and *DA_MJPC*, respectively.

The four cycle-adjusted discretionary accruals, estimated as described above, are then tested against their counterparts, i.e., the unadjusted discretionary accruals estimated using the traditional cross-sectional model (*DA_J, DA_MJ, DA_JP,* and *DA_MJP*), to examine the reduction in measurement error and the ability to detect earnings management.

DATA AND SAMPLE

Data come from the following two sources. First, the annual financial statement data are collected from the Compustat-North America database. Second, the Accounting and Auditing Enforcement Releases (AAERs) data come from the SEC releases. The sample contains all firms, except those in the financial service industries (i.e., SIC codes 6000-6999), with available data to calculate accruals and operating cycles. The sample period is from 1988 to 2015, as the cash flow data required to calculate accruals only became available since 1988. Using the statement of cash flow approach, this paper calculates accruals as earnings minus cash flows. This approach is selected over the balance sheet approach since the latter measures accruals with significant measurement errors leading to invalid inferences (Hribar and Collins, 2002).

Several filters are applied to the construction of the final test sample. First, to obtain meaningful regression results, observations in any 2-digit SIC industry with less than 25 firms in a given year are excluded from the analysis. Second, to mitigate any undue influence of outliers, firm-years with beginning-of-year stock price less than \$5 and beginning-of-year total assets less than \$3 million are excluded. Finally, following prior literature (e.g., Kothari et al., 2005), all variables in estimating accrual models and all control variables in the firm-level analysis are winsorized at the 1st and 99th percentiles each year. The final sample consists of 77,307 firm-year observations. For industry-level analysis, discretionary accruals are averaged for each 2-digit SIC industry every year, resulting in a test sample of 1,029 industry-year observations.

REDUCTION IN MEASUREMENT ERROR (INDUSTRY-LEVEL ANALYSIS)

To examine the usefulness of the proposed alternative approach to accruals estimation, the paper conducts two formal tests to compare the cycle-adjusted discretionary accruals against the unadjusted discretionary accruals. The first test examines whether the cycle approach reduces the measurement error in the estimated discretionary accruals, as the key rationale behind developing the cycle approach is to address potential heterogeneity of the accrual generating process of firms in the same industry (Dopuch et al., 2012).

According to the DKW model discussed above, a firm's accrual generating process hinges on its expected operating cycle. Based on previous discussion, an industry composed of firms exhibiting more (less) dispersed expected operating cycles would have a more (less) heterogeneous accrual generating process and suffer from greater (less) measurement errors in discretionary accruals estimated using the traditional, i.e., unadjusted, cross-sectional approach. To show this, the standard deviation of firms' expected operating cycles for each industry is calculated every year to measure the level of heterogeneity of accrual generating process in that industry year (denoted as *IND_HETERO*), and the industry-averages of unsigned (i.e., the absolute value of) discretionary accruals are calculated for all of the four accrual models: the Jones model, the modified Jones model, the performance-matched Jones model, and the performance-matched modified Jones model, using both the unadjusted approach (denoted as *ABS_DA_J, ABS_DA_MJ, ABS_DA_JP and ABS_DA_MJP*, respectively) and the cycle approach (denoted as *ABS_DA_JC, ABS_DA_MJC, ABS_DA_JPC and ABS_DA_MJPC*, respectively). As in the literature, the absolute value of discretionary accruals captures the magnitude of measurement error contained in each measure.

Panel A of Table 1 (Appendix) reports the descriptive statistics of all the industry-level variables. In Panel B the Pearson (Spearman) correlation coefficients are reported below (above) the main diagonal. IND_HETERO_{jt} measures the level of industry heterogeneity of industry j in year t. IND_SIZE_{jt}, which measures the industry size, is defined as the number of firms in industry j in year t. Several important observations can be made here. First, as shown in Panel B of Table 1 (Appendix), the unsigned discretionary accruals estimated under the unadjusted approach (i.e., *ABS_DA_J, ABS_DA_MJ, ABS_DA_JP,* and *ABS_DA_MJP*) are all positively correlated with industry heterogeneity (*IND_HETERO*), which is consistent with Dopuch et al. (2012)'s argument that the measurement error is larger in industries where firms' accrual generating process is more heterogeneous. Second, as reported in Panel A of Table 1 (Appendix), the measurement errors of estimated discretionary accruals (i.e., the magnitudes of their absolute values) are smaller if estimated using the cycle approach versus the unadjusted approach. For example, the mean measurement error in the cycle-adjusted Performance-matched Jones model (*ABS_DA_JPC*) is 0.080, lower than the mean error of 0.086 in the unadjusted Performance-matched Jones model (*ABS_DA_J*). Third, all the unsigned discretionary accruals are positively correlated with industry size (*IND_SIZE*), suggesting that industry size is a potential factor to control for when evaluating the performance of cycle-adjusted discretionary accruals.

Collectively, these descriptive statistics and correlations show that the cycle approach, which takes into consideration a firm's expected operating cycle when estimating accruals, reduces the magnitude of regression residuals (measurement errors). However, it is noteworthy to discuss two caveats/cautions. First, the cycle approach appears to mitigate but not eliminates the measurement error arising from heterogeneity in firms' accrual-generating process. This can be seen from the positive correlations between cycle-adjusted discretionary accruals and industry heterogeneity. Second, one could argue that the magnitude of estimated residuals by construct would decrease as the number of explanatory variables increase in a regression, which provides an alternative explanation to the findings discussed above. The main industry-level analysis discussed below helps rule out this alternative explanation.

To formally test whether the cycle approach reduces the measurement error in accrual estimations, the means of absolute discretionary accruals estimated using the cycle approach and their counterparts estimated by the traditional industry approach are compared for subsamples based on the level of heterogeneity. Specifically, an industry's heterogeneity is considered to be low (high) if the *IND_HETERO* for that industry is lower (higher) than sample median in a given year. Also, as mentioned above, since Panel B of Table 1 shows *IND_SIZE* is positively related to the absolute values of discretionary accruals, the industries are partitioned into four size groups each year to control for the effects of *IND_SIZE* on absolute discretionary accruals. Specifically, the value of industry size rank is set to 1 to 4 if *IND_SIZE* is less than or equal to 50, between 51 and 100, between 101 and 150, and greater than 150, respectively.

Table 2 (Appendix) reports the main results of this industry-level analysis. Panel A (Panel B) reports the results for cycle-adjusted versus unadjusted discretionary accruals estimated using the performance-matched Jones model (performance-matched modified Jones model). Since the performance-matched discretionary accruals are calculated as the difference in estimated discretionary accruals between a test firm and its control firm, using them to test reductions in measurement error will not be subject to the problem mentioned above, i.e., automatic reductions in estimated residuals due to an increased number of explanatory variables in a regression. As shown in Panel A of Table 2 (Appendix), the differences in regression residuals between cycle-adjusted and unadjusted discretionary accruals (*DIFF*, defined as *ABS_DA_JP* minus *ABS_DA_JPC*), are consistently positive across all columns and statistically significant in most of the columns. Similar patterns are observed in Panel B of Table 2 (Appendix), further corroborating results shown in Panel A. Taken together, these findings show that the measurement errors are smaller when the cycle approach, as compared to the traditional approach, is used to estimate discretionary accruals. Furthermore, the reductions in measurement error appear to be greater in industries of high heterogeneity of accrual-generating process versus those of low heterogeneity (i.e., the values of *DIFF* are greater in high versus low heterogeneity subsamples in all but one industry size group). This suggests that the cycle approach's advantage in reducing the measurement error of discretionary accruals is more pronounced in industries where firms are more heterogeneous.

Lastly, Panel C and Panel D report results from the Jones model and the modified Jones model, respectively. Consistent with the results from Panels A and B, the difference variable, *DIFF*, continues to be positive and statistically significant in all low/high heterogeneity subsamples across four industry size groups. These results, albeit not immune to the aforementioned alternative explanation, nonetheless provide a consistent message with respect to the usefulness of cycle-based adjustments when estimating discretionary accruals.

DETECTING EARNINGS MANAGEMENT (FIRM-LEVEL ANALYSIS)

While the first test, as discussed above, shows that the cycle approach helps reduce measurement errors in estimating discretionary accruals, it is important to demonstrate that the cycle adjustments also add value to one of the main uses of discretionary accruals, i.e., detection of earnings management. To this end, the paper employs Accounting and Auditing Enforcement Releases (AAERs) released by SEC to test whether cycle-adjusted discretionary accruals, as compared to their unadjusted counterparts, have better ability to explain/detect earnings management. AAERs are a common external indicator of earnings misstatement used in the literature (Dechow, Ge and Schrand, 2010; Karpoff, Koester, Lee and Martin, 2017; Shi, Sun and Zhang, 2018), and the main advantage of using AAERs is that researchers can have high level of confidence that SEC has identified earnings-manipulating firms (Dechow, Ge, Larson and Sloan, 2011). In other words, firms subject to AAERs are likely to have earnings misstatement, which implies low earnings quality.

To conduct this test, the following Logit regression models are estimated at the firm level to compare the explanatory power of discretionary accruals estimated by the cycle approach versus that of discretionary accruals estimated by the traditional approach.

$$AAER_{it} = \beta_0 + \beta_1 DA_{it} + \beta_2 MV_{it} + \beta_3 BM_{it} + \beta_4 LEV_{it} + \beta_5 INCOME_{G_{it}} \\ + \beta_6 BUB_{it} + \beta_7 SOX_{it} + \beta_8 FCR_{it} + \varepsilon_{it} \quad (7)$$

$$AAER_{it} = \beta_0 + \beta_1 DA\_CYL_{it} + \beta_2 MV_{it} + \beta_3 BM_{it} + \beta_4 LEV_{it} + \beta_5 INCOME_{G_{it}} \\ + \beta_6 BUB_{it} + \beta_7 SOX_{it} + \beta_8 FCR_{it} + \varepsilon_{it} \quad (8)$$

$$AAER_{it} = \beta_0 + \beta_1 DA_{it} + \beta_2 DA\_CYL_{it} + \beta_3 MV_{it} + \beta_4 BM_{it} \\ + \beta_5 LEV_{it} + \beta_6 INCOME\_G_{it} + \beta_7 BUB_{it} + \beta_8 SOX_{it} + \beta_9 FCR_{it} + \varepsilon_{it} \quad (9)$$

$AAER_{it}$ is an indicator variable set to one if firm *i* is subject to an SEC enforcement (AAER) in year *t*, and zero otherwise. DA_{it} is a continuous variable of firm-level discretionary accruals estimated using the traditional approach for (1) the performance-matched Jones model (*DA_JP*), (2) the performance-matched modified Jones model (*DA_MJP*), (3) the Jones model (*DA_J*), and (4) the modified Jones model (*DA_MJ*). On the other hand, DA_CYL_{it} is a continuous variable of cycle-adjusted discretionary accruals, also estimated using the four accrual models (i.e., *DA_JPC*, *DA_MJPC*, *DA_JC*, and *DA_MJC*).

MV_{it} is the market value of equity (in billions); BM_{it} is the book-to-market ratio, calculated as the book value of equity divided by the market value of equity. LEV_{it} is leverage, calculated as long-term debt divided by total equity. $INCOME\_G_{it}$ is income growth, calculated as income before extraordinary items of year t minus income before extraordinary items of year t-1, scaled by total assets at the beginning of year t. MV_{it}, BM_{it}, LEV_{it} and $INCOME\_G_{it}$ are included as control variables to capture the potential effects of firm size, growth potential, capital structure and earnings growth on the likelihood of firms receiving an SEC's enforcement action. BUB_{it} is an indicator variable capturing the stock market bubble in early 2000s and set to one for firm observations in 2001 or 2002, and zero otherwise. SOX_{it} is an indicator variable capturing the effect of Sarbanes-Oxley Act and set to one if the observation is after 2002 and zero otherwise. Finally, FCR_{it} is an indicator variable capturing the 2008 financial crisis and set to one for observations between 2007 and 2009 and zero otherwise.

Equations (7) and (8) estimate the association between AAER and discretionary accruals estimated using the traditional approach and the cycle approach, respectively. A positive and significant coefficient on discretionary accruals, β_1, would suggest that discretionary accruals can be used to detect earnings management as measured by AAER. To test the relative performance of cycle-adjusted discretionary accruals versus unadjusted discretionary accruals, both variables are included in the AAER regression, i.e., Equation (9), which allows the coefficient on *DA*, β_1, to be directly compared to that on *DA_CYL*, β_2, to identify which estimate have better ability in detecting earnings management.

Another important difference between this test and the previous measurement error test is that signed discretionary accruals are used in the earnings management analysis. This is because positive and negative discretionary accruals have different implications in the setting of earnings misstatement. Large positive discretionary accruals indicate overstatement of earnings, which is more likely to be subject to SEC enforcement actions than understatement represented by negative discretionary accruals. As evidence, less than four percent of enforcement actions in the AAER sample are due to understatement (32 out of 809 firm years). Therefore, it is appropriate to use the signed measure to test the ability of discretionary accruals to detect earnings management. Further, to avoid the undue influence of understatements on the test results, the 32 understatement observations are excluded from the analysis.

Table 3 (Appendix) reports the descriptive statistics of variables used in the firm-level analysis. The sample consists of 77,328 firm-year observations spanning the period 1988 to 2015. As shown in Table 3 (Appendix), AAERs represent low-incidence events, as the sample mean of *AAER* is 0.009 indicating less than 1% of the observations are SEC enforcement actions. As such, an AAER can be considered as a case of egregious earnings management.

Table 4 (Appendix) presents the Logit regression results from estimating Equations (7) to (9) using the 77,328 firm-year observations and two subsample tests based on low and high industry heterogeneity. Similar to the organization of Table 2, Panel A (Panel B) of Table 4 (Appendix) reports the estimation results for the performance-matched Jones model (the performance-matched modified Jones model), and Panels C and D present the results for the Jones and the modified Jones models, respectively.

As reported in the first column of Panel A, the coefficient on *DA_JP*, i.e., unadjusted discretionary accruals estimated using the performance-matched Jones model, is positive but not statistically significant (Z-stat = 0.93). By contrast, the coefficient on *DA_JPC*, i.e., cycle-adjusted discretionary accruals is positive and statistically significant at the 5 percent level (Z-stat = 2.05), suggesting that firms having higher cycle-adjusted discretionary accruals are more likely to be subject to an AAER. Turning to Column 3 of Panel A where *DA_JP* and *DA_JPC* are both included in the same regression, the results indicate that coefficient on *DA_JPC* is still positive and significant at the 5 percent significance level (Z-stat = 2.05) while the coefficient on *DA_JP* becomes negative (which is likely caused by a high level of linear correlation between the *DA_JP* and *DA_JPC*). Together, these findings show that discretionary accruals estimated by the cycle approach have greater power of detecting/explaining SEC's enforcement actions than discretionary accruals estimated using the unadjusted approach. In terms of the subsample tests, as shown in Columns 4 and 5 of Panel A, the superior ability of cycle-adjusted discretionary accruals in detecting earnings management is more pronounced in industries with higher accrual-generating heterogeneity.

Panels B, C, and D of Table 4 (Appendix) report the Logit regression results when discretionary accruals are estimated using the performance-matched modified Jones model, the Jones model and the modified Jones model, respectively. The empirical results are similar to those shown in Panel A. Most importantly, the coefficients on cycle-adjusted accruals variables (i.e., *DA_CYL*), when unadjusted accruals variables are also included in the model, are consistently positive and significant at 10 percent significance level or above across all three panels. By contrast, the coefficients on unadjusted discretionary accruals variables (i.e., *DA*) all become negative in these estimations. These findings provide additional evidence that cycle-adjusted discretionary accruals are superior to unadjusted discretionary accruals in the detection of the most egregious cases of earnings management, i.e., SEC AAERs.

In sum, the regression results of Table 4 (Appendix) consistently suggest that the discretionary accruals estimated using the cycle approach have superior ability in detecting earnings misstatement, as indicated by SEC's enforcement releases. These findings also provide the external validity of the new estimation approach proposed by the paper. Further, combined with the results shown in the industry-level analysis, the results suggest that the cycle approach can effectively reduce the noise contained in discretionary accruals estimated using the unadjusted approach and leads to more accurate and reliable references.

CONCLUSION

Building on prior literature, this study proposes an alternative approach to the estimation of discretionary accruals. Explicitly considering firm's operating cycles, the cycle approach aims to help reduce measurement errors contained in discretionary accruals estimation caused by an unrealistic assumption imposed by commonly-used cross-sectional accrual models, i.e., all firms in an industry have the same accrual generating process (Dopuch et al., 2012). Using an industry-level analysis and controlling for industry size effect, the paper shows that cycle-adjusted discretionary accruals, as compared to unadjusted discretionary accruals estimated using the traditional approach, have a lower level of measurement errors. Further, the reduction in measurement errors appears to be more pronounced in industries where firms are more heterogeneous. Next, using a firm-level analysis, the paper assesses whether the discretionary accruals estimated by the cycle approach can lead to more reliable and accurate references. Using AAER as the proxy for egregious cases of earnings management, the paper finds that cycle-adjusted discretionary accruals are superior, versus unadjusted discretionary accruals, in detecting AAERs. Together, these findings demonstrate both internal and external validity of the proposed cycle approach as well as provide direct evidence on its usefulness in a highly relevant setting, i.e., detection of earnings management.

This paper contributes to the ever-growing literature on accrual models by proposing a theory-based and easily-implementable approach to improving the estimation of discretionary accruals. The cycle approach effectively reduces the measurement error caused by heterogeneous accrual generating process within an industry (Dopuch et al., 2012). Researchers should consider using the cycle-adjusted approach when estimating discretionary accruals to mitigate the undue influences of measurement errors and achieve more reliable inferences. Future research can also extend the analysis to other earnings management or related settings and further examine the applicability of the cycle approach.

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APPENDIX

Table 1 Summary statistics: industry-level variables

Panel A: Descriptive statistics

Panel A presents the descriptive statistics of 1,029 industry-year observations from year 1988 to 2015. $ABS\_DA\_JP_{jt}$, $ABS\_DA\_MJP_{jt}$, $ABS\_DA\_J_{jt}$ and $ABS\_DA\_MJ_{jt}$ are the absolute value of discretionary accruals of industry j in year t estimated using the traditional performance-matched Jones model, performance-matched modified Jones model, Jones model and modified Jones model, respectively. $ABS\_DA\_JPC_{jt}$, $ABS\_DA\_MJPC_{jt}$, $ABS\_DA\_JC_{jt}$ and $ABS\_DA\_MJC_{jt}$ are their cycle-adjusted counterparts, i.e., the absolute values of discretionary accruals from the aforementioned four discretionary accrual models estimated using the cycle approach. IND_HETERO_{jt} is the variance of firms' expected operating cycle of industry j in year t. IND_SIZE_{jt} is the number of firms of industry j in year t.

Variable		Mean	Std. Dev.	Quartile1	Median	Quartile3
Measurement error proxy variables:	$ABS\_DA\_JP_{jt}$	0.086	0.039	0.060	0.079	0.103
	$ABS\_DA\_MJP_{jt}$	0.086	0.039	0.060	0.078	0.103
	$ABS\_DA\_J_{jt}$	0.065	0.030	0.047	0.060	0.079
	$ABS\_DA\_MJ_{jt}$	0.066	0.030	0.047	0.060	0.080
	$ABS\_DA\_JPC_{jt}$	0.080	0.038	0.054	0.075	0.099
	$ABS\_DA\_MJPC_{jt}$	0.081	0.039	0.055	0.075	0.101
	$ABS\_DA\_JC_{jt}$	0.060	0.030	0.041	0.055	0.073
	$ABS\_DA\_MJC_{jt}$	0.061	0.030	0.041	0.055	0.075
Other variables:	IND_HETERO_{jt}	64.46	27.66	44.57	61.25	79.95
	IND_SIZE_{jt}	110.01	114.10	40.00	61.00	118.00
	Observations	1,029				

Panel B: Pearson and Spearman correlations

Panel B presents the Pearson correlation (below the main diagonal) and Spearman correlation (above the main diagonal) of 1,029 industry-year observations. All reported correlation coefficients are significant at 5% significance level or better.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
$ABS\_DA\_JP_{jt}$ *(1)*	-	0.99	0.92	0.92	0.95	0.94	0.89	0.89	0.48	0.33
$ABS\_DA\_MJP_{jt}$ *(2)*	0.99	-	0.91	0.92	0.94	0.94	0.89	0.89	0.48	0.33
$ABS\_DA\_J_{jt}$ *(3)*	0.92	0.91	-	0.99	0.92	0.91	0.96	0.96	0.50	0.32
$ABS\_DA\_MJ_{jt}$ *(4)*	0.92	0.92	0.99	-	0.92	0.91	0.96	0.96	0.50	0.32
$ABS\_DA\_JPC_{jt}$ *(5)*	0.95	0.95	0.92	0.92	-	0.99	0.93	0.93	0.49	0.42
$ABS\_DA\_MJPC_{jt}$ *(6)*	0.95	0.95	0.91	0.91	0.99	-	0.92	0.93	0.49	0.42
$ABS\_DA\_JC_{jt}$ *(7)*	0.89	0.88	0.97	0.97	0.95	0.94	-	0.99	0.50	0.44
$ABS\_DA\_MJC_{jt}$ *(8)*	0.89	0.89	0.97	0.97	0.94	0.94	0.99	-	0.50	0.44
IND_HETERO_{jt} *(9)*	0.40	0.39	0.41	0.41	0.40	0.39	0.40	0.40	-	0.33
IND_SIZE_{jt} *(10)*	0.28	0.28	0.30	0.29	0.35	0.34	0.37	0.37	0.34	-

Table 2 Industry-level analysis: measurement error test

Table 2 reports the means of unsigned (i.e., the absolute value of) cycle-adjusted versus unadjusted discretionary accruals estimated using performance-matched Jones model (Panel A), performance-matched modified Jones model (Panel B), Jones model (Panel C) and modified Jones model (Panel D). The means of unsigned discretionary accruals are reported for subsamples partitioned by the level of (1) heterogeneity and (2) industry size. Heterogeneity is considered low (high) if IND_HETERO_{jt} for that industry is lower (higher) than sample median in a given year. The value of industry size rank is set to 1 to 4 if IND_SIZE_{jt} is no more than 50, between 51 and 100, between 101 and 150, and greater than 150, respectively. *Diff* is defined as the absolute value of unadjusted discretionary accruals minus their cycle-adjusted counterparts.

Panel A: Performance-matched Jones model

Industry size rank	1 (small)		2		3		4 (large)	
Heterogeneity	Low	High	Low	High	Low	High	Low	High
ABS_DA_JP (1)	0.0653	0.0964	0.0826	0.0946	0.0897	0.0880	0.0727	0.1050
ABS_DA_JPC (2)	0.0569	0.0858	0.0782	0.0914	0.0885	0.0860	0.0723	0.1037
Diff = (1) - (2)	0.0084	0.0106	0.0044	0.0033	0.0012	0.0020	0.0004	0.0013
t-value	(13.23)	(6.24)	(5.04)	(3.16)	(1.12)	(2.21)	(0.81)	(5.08)

Panel B: Performance-matched modified Jones model

Industry size rank	1 (small)		2		3		4 (large)	
Heterogeneity	Low	High	Low	High	Low	High	Low	High
ABS_DA_JP (1)	0.0656	0.0963	0.0825	0.0948	0.0902	0.0884	0.0731	0.1052
ABS_DA_JPC (2)	0.0576	0.0861	0.0791	0.0920	0.0889	0.0867	0.0730	0.1042
Diff = (1) - (2)	0.0080	0.0102	0.0034	0.0029	0.0013	0.0017	0.0001	0.0010
t-value	(12.33)	(5.71)	(3.55)	(2.68)	(1.06)	(1.87)	(0.32)	(3.93)

Panel C: Jones model

Industry size rank	1 (small)		2		3		4 (large)	
Heterogeneity	Low	High	Low	High	Low	High	Low	High
ABS_DA_JP (1)	0.0496	0.0720	0.0633	0.0739	0.0693	0.0644	0.0555	0.0811
ABS_DA_JPC (2)	0.0420	0.0608	0.0594	0.0690	0.0673	0.0623	0.0544	0.0791
Diff = (1) - (2)	0.0076	0.0113	0.0039	0.0049	0.0021	0.0020	0.0010	0.0020
t-value	(19.07)	(12.97)	(10.97)	(9.17)	(4.42)	(5.37)	(5.21)	(11.70)

Panel D: Modified Jones model

Industry size rank	1 (small)		2		3		4 (large)	
Heterogeneity	Low	High	Low	High	Low	High	Low	High
ABS_DA_JP (1)	0.0499	0.0728	0.0637	0.0746	0.0697	0.0647	0.0559	0.0817
ABS_DA_JPC (2)	0.0424	0.0614	0.0602	0.0700	0.0679	0.0628	0.0550	0.0799
Diff = (1) - (2)	0.0076	0.0114	0.0035	0.0046	0.0018	0.0019	0.0009	0.0018
t-value	(18.38)	(12.97)	(8.96)	(8.17)	(3.19)	(5.35)	(4.31)	(10.62)

Table 3 Descriptive statistics: firm-level variables

Table 3 presents the descriptive statistics of 77,328 firm-year observations from year 1988 to 2015. DA_JP_{it}, DA_MJP_{it}, DA_J_{it} and DA_MJ_{it} are discretionary accruals of firm i in year t estimated using the traditional performance-matched Jones model, performance-matched modified Jones model, Jones model and modified Jones model, respectively. DA_JPC_{it}, DA_MJPC_{it}, DA_JC_{it} and DA_MJC_{it} are their cycle-adjusted counterparts, i.e., discretionary accruals of the aforementioned four discretionary accrual models estimated using the cycle approach. $AAER_{it}$ is an indicator variable set to one if firm *i* is subject to an SEC enforcement (AAER) in year *t*, and zero otherwise. MV_{it} is the market value of equity (in billions). BM_{it} is the book-to-market ratio, calculated as the book value of equity divided by the market value of equity. LEV_{it} is leverage, calculated as long-term debt divided by total equity. $INCOME\_G_{it}$ is income growth, calculated as income before extraordinary items of year t minus income before extraordinary items of year t-1, scaled by total assets at the beginning of year t. BUB_{it} is an indicator variable capturing the stock market bubble in early 2000s and set to one for firm observations in 2001 or 2002, and zero otherwise. SOX_{it} is an indicator variable capturing the effect of Sarbanes-Oxley Act and set to one if the observation is after 2002 and zero otherwise. FCR_{it} is an indicator variable capturing the 2008 financial crisis and set to one for observations between 2007 and 2009 and zero otherwise.

Variable	Mean	Std. Dev.	Quartile1	Median	Quartile3
DA_JP_{it}	-0.003	0.171	-0.059	-0.002	0.053
DA_MJP_{it}	-0.003	0.171	-0.059	-0.002	0.053
DA_J_{it}	0.004	0.120	-0.030	0.009	0.046
DA_MJ_{it}	0.005	0.121	-0.030	0.009	0.047
DA_JPC_{it}	-0.003	0.167	-0.059	-0.002	0.053
DA_MJPC_{it}	-0.003	0.168	-0.059	-0.002	0.053
DA_JC_{it}	0.003	0.116	-0.031	0.007	0.045
DA_MJC_{it}	0.004	0.117	-0.031	0.007	0.045
$AAER_{it}$	0.009	0.094	0.000	0.000	0.000
MV_{it}	4.100	12.532	0.125	0.510	2.205
BM_{it}	0.608	0.546	0.296	0.491	0.762
$LEVERAGE_{it}$	0.180	0.172	0.011	0.150	0.292
$INCOME\_G_{it}$	-0.003	0.112	-0.025	0.005	0.029
BUB_{it}	0.076	0.265	0.000	0.000	0.000
SOX_{it}	0.433	0.496	0.000	0.000	1.000
FCR_{it}	0.103	0.304	0.000	0.000	0.000
Observations	77,328				

Table 4 Firm-level analysis: detecting earnings management

Table 4 reports the Logit regression results of equation (7) to (9) using performance-matched Jones model (Panel A), performance-matched modified Jones model (Panel B), Jones model (Panel C) and modified Jones model (Panel D). The same period is 1988 to 2005. In each panel, columns (1) to (3) report the parameter estimates of equation (7) to (9) respectively using the full sample, i.e., 77,328 firm-year observations. Column (4) and (5) report the parameter estimates of equation (9) using subsamples based on the level of industry heterogeneity. In parentheses are Z-statistics computed based on standard errors clustered by firm. ***, ** and * indicates that the coefficient is statistically different from 0 at the 1%, 5% and 10% level, respectively.

Panel A: Performance-matched Jones model

	Dependent Variable = $AAER_{it}$				
	Full Sample Test			Sub-sample Test	
				Low Heterogeneity	High Heterogeneity
	(1)	(2)	(3)	(4)	(5)
DA_JP_{it}	0.129		-1.328*	0.003	-1.664**
	(0.93)		(-1.79)	(0.00)	(-2.03)
DA_JPC_{it}		0.197**	1.529**	0.915	1.841**
		(2.05)	(2.05)	(0.51)	(2.25)
MV_{it}	0.013***	0.013***	0.013***	0.012*	0.013***
	(4.27)	(4.27)	(4.27)	(1.92)	(4.10)
BM_{it}	-0.450***	-0.450***	-0.446***	-0.476*	-0.382***
	(-3.44)	(-3.44)	(-3.42)	(-1.75)	(-2.66)
$LEVERAGE_{it}$	0.020	0.023	0.029	0.737	0.023
	(0.06)	(0.06)	(0.08)	(1.25)	(0.06)
$INCOME\_G_{it}$	-0.068	-0.062	-0.060	-1.086	0.078
	(-0.20)	(-0.19)	(-0.18)	(-1.06)	(0.24)
BUB_{it}	1.061***	1.062***	1.061***	1.157***	1.005***
	(10.29)	(10.30)	(10.29)	(3.97)	(9.10)
SOX_{it}	-0.557***	-0.556***	-0.554***	-0.711**	-0.515***
	(-3.96)	(-3.96)	(-3.95)	(-2.16)	(-3.41)
FCR_{it}	-0.374*	-0.374*	-0.375*	-0.531	-0.285
	(-1.73)	(-1.73)	(-1.73)	(-0.94)	(-1.17)
Constant	-4.462***	-4.463***	-4.470***	-4.950***	-4.386***
	(-32.85)	(-32.83)	(-33.03)	(-17.95)	(-29.99)
Observations	77,328	77,328	77,328	23,897	53,431
Pseudo R^2	0.032	0.032	0.033	0.037	0.030

Panel B: Performance-matched modified Jones model

	Dependent Variable = $AAER_{it}$				
	Full Sample Test			Sub-sample Test	
				Low Heterogeneity	High Heterogeneity
	(1)	(2)	(3)	(4)	(5)
DA_MJP_{it}	0.161		-1.106	-0.176	-1.396*
	(1.39)		(-1.57)	(-0.11)	(-1.68)
DA_MJPC_{it}		0.206**	1.300*	0.963	1.571*
		(2.22)	(1.86)	(0.58)	(1.92)
MV_{it}	0.013***	0.013***	0.013***	0.012*	0.013***
	(4.27)	(4.27)	(4.27)	(1.92)	(4.10)
BM_{it}	-0.450***	-0.450***	-0.446***	-0.472*	-0.383***
	(-3.44)	(-3.43)	(-3.42)	(-1.75)	(-2.66)
$LEVERAGE_{it}$	0.021	0.023	0.025	0.733	0.018
	(0.06)	(0.06)	(0.07)	(1.25)	(0.05)
$INCOME\_G_{it}$	-0.067	-0.062	-0.065	-1.092	0.073
	(-0.20)	(-0.19)	(-0.20)	(-1.07)	(0.22)
BUB_{it}	1.061***	1.062***	1.061***	1.155***	1.005***
	(10.29)	(10.30)	(10.29)	(3.97)	(9.10)
SOX_{it}	-0.557***	-0.556***	-0.555***	-0.711**	-0.516***
	(-3.96)	(-3.96)	(-3.95)	(-2.16)	(-3.41)
FCR_{it}	-0.374*	-0.374*	-0.375*	-0.531	-0.285
	(-1.73)	(-1.73)	(-1.73)	(-0.94)	(-1.17)
Constant	-4.462***	-4.463***	-4.469***	-4.951***	-4.383***
	(-32.83)	(-32.83)	(-33.02)	(-18.01)	(-29.96)
Observations	77,328	77,328	77,328	23,897	53,431
Pseudo R^2	0.032	0.032	0.033	0.037	0.030

Panel C: Jones model

	Dependent Variable = $AAER_{it}$				
	Full Sample Test			Sub-sample Test	
				Low Heterogeneity	High Heterogeneity
	(1)	(2)	(3)	(4)	(5)
DA_J_{it}	0.738**		-1.246	1.486	-1.792
	(2.19)		(-1.12)	(0.61)	(-1.58)
DA_JC_{it}		0.868***	2.078*	0.479	2.502**
		(2.67)	(1.93)	(0.20)	(2.27)
MV_{it}	0.013***	0.013***	0.013***	0.012*	0.013***
	(4.25)	(4.25)	(4.25)	(1.94)	(4.08)
BM_{it}	-0.467***	-0.466***	-0.461***	-0.498*	-0.396***
	(-3.51)	(-3.51)	(-3.50)	(-1.80)	(-2.72)
$LEVERAGE_{it}$	0.035	0.040	0.043	0.773	0.036
	(0.10)	(0.11)	(0.12)	(1.31)	(0.09)
$INCOME\_G_{it}$	-0.391	-0.432	-0.378	-1.876*	-0.168
	(-0.97)	(-1.10)	(-0.98)	(-1.73)	(-0.43)
BUB_{it}	1.057***	1.057***	1.058***	1.157***	1.002***
	(10.21)	(10.21)	(10.21)	(3.98)	(9.02)
SOX_{it}	-0.552***	-0.551***	-0.551***	-0.706**	-0.511***
	(-3.93)	(-3.93)	(-3.93)	(-2.14)	(-3.39)
FCR_{it}	-0.381*	-0.381*	-0.380*	-0.539	-0.290
	(-1.76)	(-1.76)	(-1.76)	(-0.96)	(-1.20)
Constant	-4.464***	-4.466***	-4.470***	-4.963***	-4.385***
	(-32.56)	(-32.62)	(-32.89)	(-17.77)	(-29.90)
Observations	77,328	77,328	77,328	23,897	53,431
Pseudo R^2	0.033	0.033	0.034	0.039	0.031

Panel D: Modified Jones model

	Dependent Variable = $AAER_{it}$				
	Full Sample Test			Sub-sample Test	
				Low Heterogeneity	High Heterogeneity
	(1)	(2)	(3)	(4)	(5)
DA_MJ$_{it}$	0.840**		-1.135	0.500	-1.601
	(2.57)		(-1.20)	(0.26)	(-1.45)
DA_MJC$_{it}$		0.953***	2.051**	1.603	2.388**
		(2.87)	(2.26)	(0.85)	(2.24)
MV$_{it}$	0.013***	0.013***	0.013***	0.012*	0.013***
	(4.26)	(4.26)	(4.27)	(1.95)	(4.09)
BM$_{it}$	-0.466***	-0.465***	-0.459***	-0.489*	-0.396***
	(-3.51)	(-3.50)	(-3.49)	(-1.79)	(-2.72)
LEVERAGE$_{it}$	0.039	0.044	0.045	0.782	0.035
	(0.11)	(0.12)	(0.12)	(1.33)	(0.09)
INCOME_G$_{it}$	-0.461	-0.496	-0.452	-1.900*	-0.237
	(-1.14)	(-1.25)	(-1.15)	(-1.80)	(-0.60)
BUB$_{it}$	1.057***	1.057***	1.057***	1.157***	1.002***
	(10.21)	(10.20)	(10.21)	(3.98)	(9.02)
SOX$_{it}$	-0.550***	-0.549***	-0.549***	-0.703**	-0.510***
	(-3.92)	(-3.91)	(-3.91)	(-2.13)	(-3.37)
FCR$_{it}$	-0.382*	-0.383*	-0.381*	-0.540	-0.292
	(-1.77)	(-1.77)	(-1.77)	(-0.96)	(-1.20)
Constant	-4.468***	-4.471***	-4.474***	-4.975***	-4.387***
	(-32.53)	(-32.63)	(-32.87)	(-17.85)	(-29.84)
Observations	77,328	77,328	77,328	23,897	53,431
Pseudo R^2	0.033	0.034	0.034	0.039	0.031