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Research Article

The Estimation and Power of Alternative Discretionary Accruals Models

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Abstract

Discretionary accruals remain decade's long measures to detect earnings management in empirical accounting research. The correctness of the specifications and test power of the information content for the models remains unexplored based on samples of most emerging market firms. Yet, country's-based researchers have increasingly used different Jones-based discretionary accruals to proxy earnings management. The paper aims to evaluate four discretionary accruals models and to decide the most appropriate one for the detection of earnings management. For the aim, we apply regression methods to estimate and evaluate four Jones-type discretionary accruals models – simple Jones, modified Jones, extended Jones cash flow model and working capital accruals – based on evidence of a final sample of 1,852 firm-year of 102 firms in Nigeria during 2001–2020. The results disclose that all models are well-specified such that the likelihood of Type I errors is minimum and below the significance level of 5%. In order to demonstrate the power of the test, the simulations completed identify that the modified Jones model is the most appropriate model to detect earnings management based on the Nigerian sample.

Keywords: Earnings Management; Discretionary Accruals; Jones Model; Modified Jones; Extended Jones Cash Flow; Working Capital Accruals

INTRODUCTION

Accounting accruals remain decades long instrument to represent the accounting quality of the performance and overall financial status of firms (Balboa et al., 2003; McNichols, 2002). Usually, managers that pursue short-term maximising incentives against long-term growth adapt accruals to manipulate their earnings. They capitalise on accruals flexibility to manage earnings downward, reporting losses when they are unable to meet profitability targets or reporting lower profits when gross earnings are insufficient to reach reference bonuses to enhance future earnings upward. Accruals management is the best channel for earnings manipulation due to their low cost and unobservability (Byzalov & Basu, 2019). The impacts of accruals are reversible due to timing effects with potential implications on future reported earnings. The manipulation of accruals, at any current period, would reverse in future (Dechow et al., 2012). Increasing earnings now through revenue overestimation (e.g., extending asset lifespan to decrease depreciation cost) would necessarily lead to future earnings decline, resulting from understating revenues.

Previous researches propose several methods to estimate accruals representing firms' performance (Dechow & Dichev, 2002; Peasnell et al., 2000; Dechow, Kothari & Watt 1998; Dechow et al., 1995; Jones, 1991). Ball and Shivakumar (2006) examine three accrual models: The cash flow model (Dechow et al., 1998), the Dechow-Dichev model (Dechow & Dichev, 2002), and the Jones-type models (Larcker & Richardson, 2004; Dechow et al., 1995; Jones, 1991). Dechow (1995) shows that accruals earnings models have been tested to be superior performance measures relative to cash flow methods. Aside, only the Jones model and its alternative modifications are widely considered in the literature to detect evidence of earnings management (Balboa et al., 2013). The models are associated with detecting the tendency for firms to manipulate earnings in pursuing short-term price incentives. They contain incremental information that exhibits higher reliability of test power (Algharaballi & Albuloushi, 2008; Teoh et al., 1998).



The estimation and power of the information content of earnings test for the different discretionary accruals models remain unexplored in Nigeria. Whereas Algharaballi and Albuloushi (2008) present the first evidence to investigate emerging economies based on the Kuwait sample, this study is the first to offer evidence for Nigeria. The study is important because there has been an increasing focus on research on the use of discretionary accruals to measure earnings management (Ozili & Outa, 2019). Yet, no paper has evaluated the power capability to proffer the most appropriate models for a sample of Nigerian firms. It provides a literature gap for the current research. This paper offers a new insight to establish if accrual models are appropriate to depict earnings manipulations in Nigeria.

We pursue two specific objectives. The first specifies and evaluates four standard discretionary accruals models to detect earnings management – the Jones model (Jones, 1991), the modified Jones (Dechow et al., 1995), the working capital accruals model (Teoh et al., 1998) and the Jones cash flow operating model (Kasznik, 1999). For a sample of 102 firms, we estimate the firm-specific linear regressions based on the specification for the particular model. We present robust evidence to show which accrual model has the highest explanatory prowess and which is adjudged most powerful. We perform specification correctness tests according to the procedure in Teoh et al. (1998). The test confirms the sensitivity of the different accrual models to the samples, evaluating the extent to which each model falsely refutes the assumption of no systematic earnings management. If evidence indicates that a particular model is incorrectly specified to fit accruals expectations, empirical research validates alternatives to detect prevalent earnings management. The second examines the test's power according to the procedure in Peasnell et al. (2000). We test the models' capability to detect earnings management by inducing pseudo-induced accruals manipulations to demonstrate the dynamics of economically plausible levels of manipulations. According to Algharaballi and Albuloushi (2008), we implement (artificially) both 'expense' and 'revenue' manipulations. We completed 1,000 simulations of 555 repeated samples (from a total of 1,852) to verify each model rate of the null's rejections for each distinct accruals manipulation. The most powerful model offers the best alternative for empirical tests for the evidence of systemic earnings management.

The outcome would be useful for auditors, regulators and the capital market. If a strong power is established, the implication is that management may tend to maximise future earnings to increase stock prices during proposals for initial public offerings. It enables a comparison based on relative firms from other emerging market studies. The remainder of the paper is structured as an underscore. Section two describes the specification of alternative discretionary accruals models. Section three discusses the method, including data construction and estimations procedures. Section four provides the results, including basic statistical descriptions and a summary of - reports earnings, total accruals, cash flows, other accruals components, alternative discretionary accruals measures, and the 102 estimates of the different discretionary accruals models. The simulations of the specification-correctness test are reported in tables, while that of the power function test is graphically depicted, following standard practice. Lastly, section five is the conclusions.

LITERATURE REVIEW

The literature presents several discretionary accruals models in different functional forms that measure earnings management. To estimate the models, we need a measure of total accruals to be identified from earnings. The total accruals can be verified from either periodic financial statements or income and cash flow statements; however, researchers mostly use financial statement accounts (Teoh et al., 1998; Dechow et al., 1995). According to Hribar and Collins (2002), for firm *i* in year *t*, total accruals, $TA_{i,t}$, is computed as the difference between operating profit, $PAT_{i,t}$, and the cash flow from operations, $CFO_{i,t}$. This method offers less complexity, provides accruals with the least possible measurement error, and captures a larger portion of managers' manipulations (Hribar & Collins, 2002).

(1)

 $TA_{i,t} = PAT_{i,t} - CFO_{i,t}$

We compare four Jones-based accruals models: the simple Jones (Jones, 1991) model, the modified Jones (Dechow et al., 1995) model, the extended Jones cash flow (Kasznik, 1999) model and working capital accrual (Teoh et al., 1998) model. For each model, all variables, including the intercept, are scaled by lagged assets to measure against heteroscedasticity.

First, *the Jones model*, from pioneered work by Jones (1991), separates asset-scaled total accruals into discretionary (unexplained) and non-discretionary (explained) components. The model is advanced on the implicit assumption that managers do not exercise discretion exercised over revenue. For firm *i* in year *t*, we regress $TA_{i,t}$ on explicative variables connected with the non-discretionary components as change in revenues and gross-value of property, plant and equipment. The regression provides estimates used to compute the non-discretionary accruals. The non-discretionary accruals ($NDACJ_{i,t}$) is the expected (estimated) value of the total accruals. After obtaining the estimates, $\hat{\alpha}_{i,i}$'s (j = 0, 1, 2) of equation (2), for each firm.

$$TA_{i,t}/A_{i,t-1} = \alpha_0[1/A_{i,t-1}] + \alpha_1[\Delta REV_{i,t}/A_{i,t-1}] + \alpha_2[PPE_{i,t}/A_{i,t-1}] + e_{1i,t}$$
(2)

$$NDACJ_{i,t} = \hat{\alpha}_0[1/A_{i,t-1}] + \hat{\alpha}_1[\Delta REV_{i,t}/A_{i,t-1}] + \hat{\alpha}_2[PPE_{i,t}/A_{i,t-1}]$$
(2)

For each firm i, $\Delta REV_{i,t}$ is change in revenues (i.e., revenues in year t minus revenues in year t - 1), $PPE_{i,t}$ is gross property, plant and equipment in year t, $A_{i,t-1}$ is the total assets in year t - 1. The estimates of the residuals (i.e., $\hat{e}_{1i,t} = TA_{i,t}/A_{i,t-1} - NDACJ_{i,t}$) is the Jones' discretionary accruals $(DACJ_{i,t})$. The discretionary accruals are a fragment of total accruals that managers exercise discretion in earnings reporting. Usually, larger discretionary accruals (in absolute terms) suppose higher earnings management in practice. One criticism of the model is that it eliminates parts of managed earnings from the discretionary accrual if managers exercise real discretion over revenue.

Second, the *modified Jones (MJ) model* from Dechow et al. (1995) improves on the limitation of the standard Jones model. Jones's principal assumption of 'no managerial discretion over revenue' introduces possible endogenous bias. Modified Jones (equation 3) attempts to control the misspecification in the simple Jones model by adjusting and removing associated changes in net receivables from changes in the revenues in other to accommodate wider evidence of earnings management (Jeter & Shivakumar, 1999). The model assumes that changes in credit sales are likely caused by manipulations of earnings. It regresses the normalised $TA_{i,t}$ on scaled ($\Delta REV_{i,t} - \Delta REC_{i,t}$) and $PPE_{i,t}$, for firm *i* in year *t*. The non-discretionary component ($NDACMJ_{i,t}$) is the estimate of the total accruals (i.e., the normalised $TA_{i,t}$), after obtaining $\hat{\beta}_{j,i}$'s (j = 0, 1, 2) of equation (3) for each firm.

$$TA_{i,t}/A_{i,t-1} = \beta_0[1/A_{i,t-1}] + \beta_1[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] + \beta_2[PPE_{i,t}/A_{i,t-1}] + e_{2i,t}$$
(3)

$$NDACMJ_{i,t} = \hat{\beta}_0[1/A_{i,t-1}] + \hat{\beta}_1[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] + \hat{\beta}_2[PPE_{i,t}/A_{i,t-1}]$$
(3')

The estimates of the residuals (i.e., $\hat{e}_{2i,t} = TA_{i,t}/A_{i,t-1} - NDACMJ_{i,t}$) is the modified Jones' discretionary accruals ($DACMJ_{i,t}$). Where $\Delta REC_{i,t}$ are the net receivables in year t minus net receivables in year t - 1, and all other variables are predetermined. As noted (Jeter & Shivakumar, 1999), MJM attempts to account for endogenous bias in the standard Jones model, but it eventually induces overestimation bias through its assumptions and modification. Coulton et al. (2005) note that the assumption that changes in receivables result from manipulations is unproven, likely invalid and may cause over-correction. In addition, such adjustment becomes only suitable in periods when real

earnings are systematically managed. Dechow et al. (1995) confirm a negative correlation between accruals and cash flows in the absence of earnings management. Third, the *Extended Jones cash flow (EJCF) model*, developed by Kasznik (1998), controls for endogenous bias from the misspecification's of the modified Jones, particularly for firms with extreme cash flows (Jeter & Shivakumar, 1999; Kasznik, 1998; Dechow et al., 1995). The model (equation 4) extended Jones cash flow by incorporating a change in periodic cash flow from operation to account for the negative correlation between operating cash flow from s and accruals. The non-discretionary component (*NDACEJCF_{i,t}*) is the estimate of the total accruals (equation 4'), after obtaining $\hat{\theta}_{j,i}$'s (j = 0, 1, 2, 3) of equation (4) for each firm.

$$TA_{i,t}/A_{i,t-1} = \theta_0[1/A_{i,t-1}] + \theta_1[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] \\ + \theta_2[PPE_{i,t}/A_{i,t-1}] + \theta_3\Delta CFO_{i,t} + e_{3i,t}$$
(4)

$$NDACEJCF_{i,t} = \hat{\theta}_0[1/A_{i,t-1}] + \hat{\theta}_1[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] \\ + \hat{\theta}_2[PPE_{i,t}/A_{i,t-1}] + \hat{\theta}_3\Delta CFO_{i,t}$$
(4')

The estimates of the residuals (i.e., $\hat{e}_{3i,t} = TA_{i,t}/A_{i,t-1} - NDACEJCF_{i,t}$) is the extended Jones cash flow' discretionary accruals ($DACEJCF_{i,t}$). And, $\Delta CFO_{i,t}$ is the change in periodic cash flow from operations between year t and year t - 1.

Four, the Working capital (WA) accruals model, proposed by Teoh et al. (1998), is a discretionary model based on WC accruals. The model is an alternative modification of the Jones model that splits total accruals into current and long-term accruals. The current accruals are changes in noncash current assets less the change in operating current liabilities. The WC accruals have both discretionary and non-discretionary parts. Algharaballi and Albuloushi (2008) note that the splitting becomes necessary because managers exercise greater discretion over current compared to long-term accruals. Hence, discretionary estimates of WC accruals ($WCA_{i,t}$) may be superior estimates than total accruals. The model regresses the normalised $WCA_{i,t}$ on scaled-changes in revenues adjusted for change in receivables ($\Delta REV_{i,t} - \Delta REC_{i,t}$) and $PPE_{i,t}$, for firm *i* in year *t*. The non-discretionary part ($NDACWC_{i,t}$) is the expected value of the WC accruals (equation 5'), after obtaining $\hat{\delta}_i$'s (j = 0, 1, 2) of equation (5), for each firm.

$$WCA_{i,t}/A_{i,t-1} = \delta_{0,i}[1/A_{i,t-1}] + \delta_{1,i}[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] + \delta_{2,i}[PPE_{i,t}/A_{i,t-1}] + e_{4i,t}$$

$$NDACWC_{i,t} = \hat{\delta}_{0,i}[1/A_{i,t-1}] + \hat{\delta}_{1,i}[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}] + \hat{\delta}_{2,i}[PPE_{i,t}/A_{i,t-1}]$$

$$(5')$$

The estimates of the residuals (i.e., $\hat{e}_{4i,t} = WCA_{i,t}/A_{i,t-1} - NDACWC_{i,t}$) is the WC accruals model' discretionary accruals ($DACWC_{i,t}$).

RESEARCH METHOD

Data

We employ earnings information for listed firms on the Nigerian Stock Exchange (NSE) for the 2001–2020 financial periods. Data used to complete the specified models are organised from the NSE and firms' consolidated sources. The sample window covered extended periods where reporting regulations permit the use of discretions in the appropriation of accounting information, according to the international framework. Appropriate proxies are adopted or computed to represent needed components not directly reported on the consolidated records (Ozili & Outa, 2019). For instance, the normalised total accruals are from equation (1), being the difference between reported profit $PAT_{i,t}$

and operations' cash flow, $CFO_{i,t}$. The total assets $(A_{i,t})$ and other accruals fragments $(REV_{i,t}, REC_{i,t}, PPE_{i,t})$ are sourced.

Prior studies that use basic descriptions of discretionary accruals to exemplify earnings management dynamics often exclude samples from financial sectors as well as over-regulated sectors (e.g., utilities firms) because their financial reporting in the sectors differs from others. In identifying the sample, we excluded 51 banks and other financial institutions from the initial sample of 162 obtained, leaving a comprehensive sample of 111 non-financial firms and 2,220 firm-year. We estimate the models cross-sectionally, subject to a minimum sample of 10 observations for individual firms (Coulton et al., 2005). In addition, we exclude nine firms due to the significant amount of unavailable information required to compute the accrual models, leaving use with 102 firms [2,040 firm-year]. We eliminated 86 missing observations for all firm-year of some included firms that exceeded the minimum requirement and could not be expunged, leading us to a sample of 1,954. These observations further reduce because we require the lag of total assets to estimate each model. For example, the 2001 total assets are considered lag for 2002, and 2019 as lag for 2020. For firms without 2001 information, we use the assets of the available lag year (e.g., 2005) to normalise the earnings components of the year after (e.g., 2006). The sample reduces by 102 to provide a final sample of 1,852 firm-year.

Procedures

The paper attempts to estimate and evaluate the power to test earnings management of four Jones-type accruals models. Following the collation of required explicate components of earnings in (1) - (5), the empirical process involves a preliminary stage and two main stages: the first conducts the model-specification correctness tests, and the second completes the model-power capability. The *preliminary-stage* requires us to perform the estimations of the coefficients of the firms-specific [(2) -(5)] regressions. We control for structural differences between firms and estimate cross-sectionally to reduce the probability of inaccurate estimations, lessen the chance that the coefficients are time invariants, and obtain estimates that are better specified and robust than the time-series counterparts (Dechow et al., 1995). Identifying the contemporaneous firm-specific differences may induce noise into the estimation process (Peasnell et al., 2000). We estimate the regressions for each firm-year combination for the separate models and obtain 102 distributions of estimates for each of the models' coefficients $(\hat{\alpha}_i, \hat{\beta}_i, \hat{\theta}_i, \hat{\delta}_i)$, as well as the distributions of first-order tests ($\overline{\mathbb{R}}^2$, F) information, and compute the discretionary accruals (i.e., residual estimates $\hat{e}_{1i,t}$, $\hat{e}_{2i,t}$, $\hat{e}_{3i,t}$, and $\hat{e}_{4i,t}$, denoted as $DACJ_{i,t}$, DACMJ_{i,t} DACEJCF_{i,t} and, DACWC_{i,t}) for all models. Because the Jones-based models are typically linear, the linearity assumption is enforced by either excluding (using a median interquartile range of residual plots) or trimming (using winsorisation) all extreme values and outliers from the different samples of the discretionary accruals. Since 'excluding' makes us loose observations, we prefer to winsorise the first (1st) and penultimate (99th) percentiles before we complete the specificationcorrectness and power function test evaluations.

The *first-stage* requires us to establish the specification-correctness of the models to detest systemic earnings management (Peasnell et al., 2000). We verify if the models estimated at the preliminary-stage correctly capture the fitted discretionary accruals, otherwise, empirical research would be better performed on validated alternatives, including a non-Jones based, approach. We perform a model specification test according to Teoh et al. (1998). The test evaluates the extent to which each model likely contains Type I error (falsely refuting the null of no systematic earnings management) against the alternative hypothesis. The test confirms the sensitivity of the specified model to the samplings. The procedure requires randomly selecting some samples from the firm-year and performing a *t*-test on the estimated coefficient based on each selected sample. The test null follows that since the selected observations are random, we do not expect to find evidence of earnings management in the ergodic realisations. Therefore, if the model is well-specified, a significant test on

the slope estimates would fail to reject the null. The stage involves four steps (a) – (d):

- (a) Following an optimal sampling-rule and applying 30% (555) observations arbitrarily selected (without replacement) from the (preliminary stage) computed discretionary accruals, which in a general context, we denote different fitted value, *m*, computed discretionary accruals, $DAC_{m,i}$ (for, m = 1 to 4), *m* been the four Jones-type models estimated.
- (b) Generate a binary variable denoted TSD_i (test sample dummy) and coded 1 for 555 selected observations in (a) and 0 for the rest 1,297 samples. (See additional R-code materials to generate sampling without replacement and experiment with Monte Carlos simulations).
- (c) Estimate the regression (equation 6) for each measure of accruals computed, and perform a *t*-test whether $\hat{\gamma}_1$ (i.e., the estimate of TSD_i) is significantly different from zero. Under a one-tail test at a 5% level, we conduct the *t* tests for two cases of alternative hypotheses, each verifying existence of either income-increasing (negative earnings management) or income-decreasing (positive earnings management) of the particular accruals model.

$$DAC_i = \gamma_0 + \gamma_1 TSD_i + \varepsilon_i \tag{6}$$

(d) Repeat steps (a) – (c) 1,000 times for the different, *m*, computed discretionary accruals, $DAC_{m,i}$ (for, m = 1 to 4).

For a well-specified model, $\hat{\gamma}_1$ would normally be statistically insignificant and null of no earnings management (i.e., $\gamma_1 = 0$) should not be refuted more than often anticipated in the 1,000 simulations completed under the least possible significance (or probability level) specified.

The *second-stage* requires us to verify the firm-specific accruals models' power (or ability) to identify earnings management. We demonstrate the dynamics of economically plausible manipulation levels by completing tests that experimentally induced ranges of income-increasing earnings management on the randomly selected samples (where $TSD_i = 1$) in step (a) of first-stage. The procedures follow similar steps described in the first-stage. In this context, to execute step (a), we involve the preliminary-stage to augment the required model's accruals fragments with the 'artificially induced income-increasing accruals' for the arbitrarily selected firms. The induced income-increasing accruals are computed as (0 - 100)% of the lagged total assets, $A_{i,t-1}$, subject to a 20% increment on each new experimentation for the same accruals model for different manipulation types (Peasnell et al., 2000).

Consistent with Algharaballi and Albuloushi (2008), we implement two distinct types of accruals manipulations. The first 'expense manipulation' is implemented by adding the assumed (artificial) expenses manipulated to the total accruals, $TA_{i,t-1}$ (for models 1-3) or to the total working capital accruals, WCA_{i,t-1} (for model 4). The second 'revenue manipulation' is implemented by adding the artificial value of revenues manipulated to the total sales revenue and net receivable (Peasnell et al., 2000). After augmenting the required accruals models component for the $TSD_i = 1$ subsample, we follow the procedure in the preliminary stage to compute the induced discretionary accruals, $DAC_{m,i}$ (for, m = 1 to 4). We simulate with only five ranges (20%, 40%, 60%, 80%, 100%) of firms first lagged total assets for the *m*-different models. Steps (a) – (c) are repeated 1,000 times for each *m*-different discretionary accruals. We compile the null rejection frequencies for the repetitions of each accruals model. The test is benchmarked at a 5% level [one-tailed], record and visibly report the nulls rejection rates. Since the selected samples now contain a 'certain' level of earnings manipulations, one would normally expect a model with high power to more often reject the null (that $\gamma_1 = 0$). In a simulated experiment under the endemic existence of earnings management activities, a powerful model would dominate with higher frequencies of the null's rejection. The higher rejection regularities a model is associated with, the more powerful the model is assumed to detect prevalent manipulations.

FINDINGS AND DISCUSSION

Table 1 reports statistical information on all variables: profits, total accruals, working capital accruals and explicative components of the accruals. Panel A reports basic statistics for the full sample (N=1,852), whereas Panel B and Panel C reports a basic description for the case where $PAT_i \ge 0$, having N=1,343 ($PAT_i < 0$, N=509). Each fragment of the accruals model, including the intercept $[1/A_{i,t-1}]$ is normalised, ensuring only standardised regression estimates, already controlled for heteroscedasticity, are produced. Likely due to the sample design and selection criteria, the description slightly favours profitable firms. The non-negative profit constitutes 73% of the total sample. The total and working capital accruals are small but averagely positive. All explicative accruals components disclose positive mean and median, with most medium values lesser than the corresponding average. The mean difference (via Welch) tests indicate that profit, total and working capital accruals are significantly different for profits ($PAT_i \ge 0$) and losses ($PAT_i < 0$) reporting firms. A significant difference is reported for total and working capital accruals for the two subsamples. We find significant differences across the profits and losses reporting firm's subsamples for the control variables. Other than the intercept and ΔREV_i , the Welch tests indicate significant difference in the means of both groups.

Variables	μ	med	σ	μ	med	σ	μ	med	σ	Mean (μ) Difference
	Panel A		-	Panel		-	Panel		-	Welch Tests
	Full samp	le (N=1,8	852)		$\geq 0, N=2$	1,343		< 0, N	= 509	p-value
Earnings				i		,	i			L
0						0.1	-	-	0.1	
PAT _i	0.21	0.10	0.16	0.13	0.11	0	0.06	0.10	5	(0.000)
Accruals										
						0.3			0.2	
TA_i	0.14	0.03	0.35	0.08	0.04	5	0.28	0.23	4	(0.000)
						0.1			0.1	
WCA_i	0.05	0.01	0.14	0.05	0.02	3	0.05	0.02	9	(0.041)
Explicative	fragments	of accruz	uls mode	ale						
Explicative	inaginentis	of acci ua		.15		0.0			0.0	
$1/A_{i,t-1}$	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.5240
7 6,6 1						1.1			1.0	
ΔREV_i	0.21	0.08	1.14	0.20	0.08	6	0.23	0.07	5	0.0971
ΔREV_i						1.2	-	-	0.4	
$-\Delta REC_i$	-0.19	0.07	1.14	0.21	0.07	5	0.29	0.15	0	(0.011)
						1.7			1.2	
PPE _i	0.41	0.27	1.64	0.41	0.26	3	0.45	0.34	0	(0.008)
						0.3			0.1	
CFO _i	0.11	0.08	0.31	0.11	0.08	3	0.12	0.10	8	(0.000)

Table 1. Descriptive information of 'earnings, accruals and accruals components'

Source: @Authors (2022)

Table 1 shows basic statistical (N, μ , *med*, σ) of the annual assets-scaled net profits (*PAT_i*), accruals (*TA_i*, *WCA_i*) and the various discretionary accruals model fragments from 2001–2020. N \equiv Number of observations, $\mu \equiv$ Mean, *med* \equiv Median, $\sigma \equiv$ Standard deviation. The firms showing net profit earnings (*PAT_i* \geq 0, N=1,343) is about 73% of the total sample. All accruals fragments identify positive mean and median, with most medium values lesser than the associated average.

The Welch t-test verifies the null that the difference in mean for the $PAT_i \ge 0$ and $PAT_i < 0$ subgroups, is 0. The reported *p*-value (in parenthesis) offers the least likelihood to wrongly refute the

null, and it indicates significance at either 1% or 5% level (2-tailed), for both subgroups. The results show significant differences across the profits and losses firms for the control variables. Other than the intercept and ΔREV_i , the Welch tests indicate significant differences in the means of both groups.

Table 2 Descriptions in formation and for time to all of differences discover the second se

Accrual Comp.	Coef.	μ	μ_{se}	σ	\widetilde{q}_1	med	\widetilde{q}_3	$\widetilde{\mu}_3$	$\widetilde{\mu}_4$	% ≥ 0
Simple Jones:										
$TA_{i,t}/A_{i,t-1} = \alpha_{0,i}[$	$1/A_{i,t-1}$]	$+ \alpha_{1,i} [\Delta R]$	$EV_{i,t}/A_{i,t-}$	$_{1}] + \alpha_{2,i}[PI$	$PE_{i,t}/A_{i,t-}$	$[-1] + e_{1i,t}$				
$1/A_{i,t-1}$	$\hat{\alpha}_0$	0.237	0.242	2.448	-0.432	-0.020	0.340	-5.619	40.596	85
$\Delta REV_{i,t}$	$\hat{\alpha}_1$	0.006	0.029	0.295	-0.161	-0.011	0.162	1.903	9.755	60
PPE _{i,t}	$\hat{\alpha}_2$	-0.213	0.243	2.455	-0.339	-0.023	0.430	5.433	38.786	15
	$\overline{\mathbb{R}}^2$	0.265	0.016	0.165	0.071	0.150	0.301	1.063	0.308	
	F	2.782	0.219	2.209	0.411	0.940	2.302	2.485	7.381	
Modified Jones										
$TA_{i,t}/A_{i,t-1} = \beta_{0,i}[$		$+ \beta_{1,i} [(\Delta I)$	$REV_{i,t} - \Delta$	$REC_{i,t})/A_{i,t}$	$[-1] + \beta_{2,i}$	$[PPE_{i,t}/A]$	$A_{i,t-1}] + e_2$	2 <i>i</i> ,t		
$1/A_{i,t-1}$	\hat{eta}_0	0.267	0.227	2.297	-0.429	-0.030	0.255	-5.502	36.154	80
$\Delta REV_{i,t} - \Delta REC_{i,t}$	\hat{eta}_1	0.017	0.027	0.269	-0.154	0.009	0.144	0.078	1.852	60
PPE _{i,t}	\hat{eta}_2	-0.211	0.229	2.313	-0.307	-0.006	0.406	5.471	35.651	15
	$\overline{\mathbb{R}}^2$	0.281	0.018	0.186	0.081	0.149	0.313	1.219	1.335	
	F	3.031	1.146	11.570	0.468	0.935	2.425	9.240	87.533	
Extended Jones Cas $TA_{i,t}/A_{i,t-1} = \theta_{0,i}$	$1/A_{i,t-1}]$									
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$	0.226	0.190	1.920	-0.180	-0.022	0.111	-4.755	32.568	80
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_1}$	0.226 -0.004	0.190 0.021	1.920 0.209	-0.180 -0.089	-0.022 0.011	0.111 0.100	-4.755 0.249	32.568 1.460	45
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$	0.226 -0.004 -0.223	0.190 0.021 0.188	1.920 0.209 1.898	-0.180 -0.089 -0.141	-0.022 0.011 0.005	0.111 0.100 0.155	-4.755 0.249 4.788	32.568 1.460 33.512	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\hat{\theta}_3}$	0.226 -0.004 -0.223 -0.676	0.190 0.021 0.188 0.031	1.9200.2091.8980.311	-0.180 -0.089 -0.141 -0.929	-0.022 0.011 0.005 -0.743	0.111 0.100 0.155 -0.495	-4.755 0.249 4.788 0.855	32.568 1.460 33.512 0.078	45
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$	0.226 -0.004 -0.223 -0.676 0.620	0.190 0.021 0.188 0.031 0.028	1.9200.2091.8980.3110.284	-0.180 -0.089 -0.141 -0.929 0.351	-0.022 0.011 0.005 -0.743 0.702	0.111 0.100 0.155 -0.495 0.866	-4.755 0.249 4.788 0.855 -0.408	32.568 1.460 33.512 0.078 -1.213	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$	$\frac{1/A_{i,t-1}]}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\hat{\theta}_3}$	0.226 -0.004 -0.223 -0.676	0.190 0.021 0.188 0.031	1.9200.2091.8980.311	-0.180 -0.089 -0.141 -0.929	-0.022 0.011 0.005 -0.743	0.111 0.100 0.155 -0.495	-4.755 0.249 4.788 0.855	32.568 1.460 33.512 0.078	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ Working Capital Ac	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$ F cruals:	0.226 -0.004 -0.223 -0.676 0.620 56.297	0.190 0.021 0.188 0.031 0.028 20.820	1.920 0.209 1.898 0.311 0.284 210.270	-0.180 -0.089 -0.141 -0.929 0.351 2.026	-0.022 0.011 0.005 -0.743 0.702 8.846	0.111 0.100 0.155 -0.495 0.866 24.226	-4.755 0.249 4.788 0.855 -0.408 7.229	32.568 1.460 33.512 0.078 -1.213	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ $Working Capital Ac$ $WCA_{i,t}/A_{i,t-1} = \delta_{0}$	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$ F cruals: $p_i[1/A_{i,t-1}]$	$\begin{array}{c} 0.226\\ -0.004\\ -0.223\\ -0.676\\ 0.620\\ \hline 56.297\\ \end{array}$	0.190 0.021 0.188 0.031 0.028 20.820	$\begin{array}{c} 1.920\\ 0.209\\ 1.898\\ 0.311\\ 0.284\\ 210.270\\ \end{array}$	-0.180 -0.089 -0.141 -0.929 0.351 2.026	-0.022 0.011 0.005 -0.743 0.702 8.846	0.111 0.100 0.155 -0.495 0.866 24.226	-4.755 0.249 4.788 0.855 -0.408 7.229	32.568 1.460 33.512 0.078 -1.213	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ $Working Capital Ac$ $WCA_{i,t}/A_{i,t-1} = \delta_{0}$ $1/A_{i,t-1}$	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$ F cruals: $\frac{1}{b_i} \frac{1}{A_{i,t-1}}$ $\frac{\delta_0}{\delta_0}$	$\begin{array}{c} 0.226 \\ -0.004 \\ -0.223 \\ -0.676 \\ 0.620 \\ \hline 56.297 \\ \end{array}$	0.190 0.021 0.188 0.031 0.028 20.820	1.920 0.209 1.898 0.311 0.284 210.270	-0.180 -0.089 -0.141 -0.929 0.351 2.026	-0.022 0.011 0.005 -0.743 0.702 8.846	0.111 0.100 0.155 -0.495 0.866 24.226	-4.755 0.249 4.788 0.855 -0.408 7.229	32.568 1.460 33.512 0.078 -1.213	45 10
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ $Working Capital Ac$ $WCA_{i,t}/A_{i,t-1} = \delta_{0}$	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$ F cruals: $\frac{1}{\hat{\lambda}_1} (1/A_{i,t-1})$ $\frac{\hat{\delta}_0}{\hat{\delta}_1}$	$\begin{array}{c} 0.226\\ -0.004\\ -0.223\\ -0.676\\ 0.620\\ \hline 56.297\\ \end{array}$	0.190 0.021 0.188 0.031 0.028 20.820	$\begin{array}{c} 1.920\\ 0.209\\ 1.898\\ 0.311\\ 0.284\\ 210.270\\ \end{array}$	$\begin{array}{c} -0.180\\ -0.089\\ -0.141\\ -0.929\\ 0.351\\ 2.026\\ \end{array}$	-0.022 0.011 0.005 -0.743 0.702 8.846	$\begin{array}{c} 0.111\\ 0.100\\ 0.155\\ -0.495\\ 0.866\\ 24.226\\ \end{array}$	-4.755 0.249 4.788 0.855 -0.408 7.229 $e_{4i,t}$	32.568 1.460 33.512 0.078 -1.213 59.146	45 10 15
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ $Working Capital Ac$ $WCA_{i,t}/A_{i,t-1} = \delta_{0}$ $1/A_{i,t-1}$	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_2}{\hat{\theta}_3}$ $\overline{\mathbb{R}^2}$ F cruals: $\frac{1}{\delta_0}$ $\frac{\hat{\delta}_1}{\hat{\delta}_2}$	$\begin{array}{c} 0.226 \\ -0.004 \\ -0.223 \\ -0.676 \\ 0.620 \\ \hline 56.297 \\ \end{array}$	0.190 0.021 0.188 0.031 0.028 20.820 Δ <i>REV_{i,t}</i> - 0.193	1.920 0.209 1.898 0.311 0.284 210.270 ΔREC _{i,t})/A 1.951	$\begin{array}{c} -0.180\\ -0.089\\ -0.141\\ -0.929\\ 0.351\\ 2.026\\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ $	-0.022 0.011 0.005 -0.743 0.702 8.846 5 _{2,i} [PPE _{i,t} 0.038	$\begin{array}{c} 0.111\\ 0.100\\ 0.155\\ -0.495\\ 0.866\\ 24.226\\ \end{array}$ $/A_{i,t-1}] + \\ 0.330\\ \end{array}$	-4.755 0.249 4.788 0.855 -0.408 7.229 $e_{4i,t}$ 3.006	32.568 1.460 33.512 0.078 -1.213 59.146 26.896	45 10 15
$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$ $PPE_{i,t}$ $CFO_{i,t}$ $Working Capital Ac$ $WCA_{i,t}/A_{i,t-1} = \delta_{0}$ $1/A_{i,t-1}$ $\Delta REV_{i,t} - \Delta REC_{i,t}$	$\frac{1/A_{i,t-1}}{\hat{\theta}_0}$ $\frac{\hat{\theta}_1}{\hat{\theta}_2}$ $\frac{\hat{\theta}_3}{\bar{R}^2}$ F cruals: $\frac{1}{\hat{\lambda}_1} (1/A_{i,t-1})$ $\frac{\hat{\delta}_0}{\hat{\delta}_1}$	$\begin{array}{c} 0.226\\ -0.004\\ -0.223\\ -0.676\\ 0.620\\ \overline{56.297}\\ 1]+\delta_{1,i}[(\\ 0.130\\ 0.049\\ \end{array}$	$\begin{array}{c} 0.190\\ 0.021\\ 0.188\\ 0.031\\ 0.028\\ 20.820\\ \hline\\ \Delta REV_{i,t}-\\ 0.193\\ 0.028\\ \end{array}$	$\begin{array}{c} 1.920\\ 0.209\\ 1.898\\ 0.311\\ 0.284\\ 210.270\\ \hline\\ \Delta REC_{i,t})/A\\ 1.951\\ 0.284 \end{array}$	$\begin{array}{c} -0.180\\ -0.089\\ -0.141\\ -0.929\\ 0.351\\ 2.026\\ \hline \\ \\ \hline \\ \\ -0.361\\ -0.103\\ \end{array}$	-0.022 0.011 0.005 -0.743 0.702 8.846 5.2, <i>i</i> [<i>PPE</i> _{<i>i</i>,<i>t</i>} 0.038 0.010	$\begin{array}{c} 0.111\\ 0.100\\ 0.155\\ -0.495\\ 0.866\\ 24.226\\ \hline\\ /A_{i,t-1}] +\\ 0.330\\ 0.206\\ \end{array}$	$\begin{array}{c} -4.755\\ 0.249\\ 4.788\\ 0.855\\ -0.408\\ 7.229\\ \hline\\ e_{4i,t}\\ 3.006\\ 0.574\\ \end{array}$	32.568 1.460 33.512 0.078 -1.213 59.146 26.896 0.774	45 10 15 85 55

Table 2 shows the distribution characteristics $(\mu, \mu_{se}, \sigma, \tilde{q}_1, med, \tilde{q}_3, \tilde{\mu}_3, \tilde{\mu}_4)$ for 102 coefficient estimates of each explicative fragment as well as the means of the first order tests statistics (\mathbb{R}^2, F) of the four different accruals models (2) – (5), based on the NSE sample, during (2001–2020). $\mathbb{R}^2 \equiv$ Coefficient of determination, $F \equiv$ F-statistics, $\mu \equiv Mean$, $med \equiv$ Median, $\tilde{q}_1 \equiv$ 1st (lower) quartile value, $\tilde{p}_3 \equiv$ 3rd (upper) quartile value, $\mu_{se} \equiv$ Standard error of the mean, $\sigma \equiv$ Standard deviation, $\tilde{\mu}_3 \equiv$ Skewness and $\tilde{\mu}_4 \equiv$ For empirical simplicity, Kurtosis, %≥0 indicates the percentage of the specific estimated coefficient ≥0, which is approximated in the nearest multiple of 5. The coefficients are obtained based on the cross-sectional version, which offers better specified and robust estimates than the time-series counterparts (Dechow et al., 1995).

The result shows that a greater amount of the average of the coefficients are well-signed – rightly positive for mean estimates of $\Delta REV_{i,t}$ or $\Delta REV_{i,t} - \Delta REC_{i,t}$, but negative for most mean estimates of the $PPE_{i,t}$. The normalised intercept is averagely positive for all four models. The mean estimate of the change in revenues (i.e., $\hat{\alpha}_1$, for the simple Jones) and the mean estimate of change in receivables and change in the revenue's differentials (i.e., $\hat{\beta}_1$ and $\hat{\delta}_1$, for modified Jones and WC accruals) is positive but only negative (i.e., $\hat{\theta}_1 = -0.014$) for the Extended Jones CF. The average of the $PPE_{i,t}$ estimates are negative for all models and the lowest ($\hat{\delta}_2 = -0.255$) for the WC accruals. The explanatory power for the working capital accruals driven by its fragments is highest at 62%, whereas only an average of 20-28% is accounted for by the total accruals models.

Table 2 reports statistical information on the models' parameters estimated with linear regressions. The results summarise the 102 different estimates of the coefficients of the profitearnings portions associated with the particular accruals model. The mean estimates show that all four models are significant for the F-test. The smallest mean of the F statistics is 1.803, which is significant at 5%, and others are highly significant. It indicates that the linear relationship between the total or working capital accrual measures (i.e., the dependent variable) and the independent variables does not occur by chance. The variability of the total accruals explained by its fragments ranges around 20-28% average, whereas 62% of the working capital accruals is driven by the explicative components. The extended Jones CF, non-surprising, has the highest explanatory power due to the additional controlled variable (i.e., firms' cash flow) incorporated to augment the modified Jones. Such an addition makes the models more powerful. Generally, except for the mean of estimates for the change in revenue (which differed by both representation and computation for the Jones and modified Jones), as expected, both Jones and modified Jones do not identify substantial differences. The greater amount of the average of the coefficients is well-signed – rightly positive for mean estimates of $V_{i,t}$ or $\Delta REV_{i,t} - \Delta REC_{i,t}$, but negative for most mean estimates of the *PPE*_{i,t}.

The normalised intercept is averagely positive for all four models. The mean estimate of the change in revenues (i.e., $\hat{\alpha}_1$, for the simple Jones) and the mean estimate of change in receivables and change in the revenues differentials (i.e., $\hat{\beta}_1$ and $\hat{\delta}_1$, for modified Jones and WC accruals) is positive but only negative (i.e., $\hat{\theta}_1 = -0.014$) for the Extended Jones CF. The average of the $PPE_{i,t}$ estimates are negative for all models, and the lowest ($\hat{\delta}_2 = -0.255$) for the WC accruals. The mean of the parameter estimates of the $CFO_{i,t}$, in the Extended Jones, CF is negative and consistent with Algharaballi and Albuloushi (2008). Although most estimates identify means higher than the median, we could not establish sufficient evidence that the difference is significant for the majority of the model's estimates.

Table 3 reports *statistical information on alternative accruals measures*. Descriptive statistics clarify the mean, standard deviation, median and percentiles. Both mean and median values of all the discretionary accruals measures are close to zero, although still positive for Jones and Modified Jones but negative for the other two accruals types. Not surprising the extended Jones CF discretionary accruals is negatively high (-0.31), likely the result of the large influence of the majority of the negative estimates of the *CFO*_{*i*,*t*} components. About 75% of the WC discretionary accruals are negative (% < 0), while larger (55 – 70) percent for others are non-negative (% \geq 0).

Discretionary				%							Mean
Accruals	μ	med	σ	≥ 0	μ	med	σ	μ	med	σ	Diff.
$DAC_{i,t}: \hat{e}_{ji}$	Panel	A: Full sa	ample		Panel	B: DAC	$C_i \ge 0$	Panel	C: DAC _i	< 0	p-value
$DACJ_i(\hat{e}_{1i})$	0.02	0.00	0.32	69.5	0.18	0.07	0.15	-0.25	-0.20	0.09	(0.001)
$DACMJ_i(\hat{e}_{2i})$	0.02	0.00	0.31	61.2	0.26	0.07	0.13	-0.21	-0.20	0.08	(0.000)

Table 3. Descriptive information of the alternative discretionary accruals measures

Discretionary				%							Mean
Accruals	μ	med	σ	≥ 0	μ	med	σ	μ	med	σ	Diff.
$DACEJCF_i(\hat{e}_{3i})$	-0.31	0.01	0.16	55.3	0.15	0.03	0.10	-0.49	-0.18	0.15	(0.104)
$DACWC_i$ (\hat{e}_{4i})	-0.09	-0.04	0.23	24.8	0.00	0.04	0.13	-0.11	-0.04	0.19	(0.000)

Source: @Authors (2022)

Table 3 shows basic statistics (μ , med, σ) of the fitted alternative discretionary accruals during (2001–2020). $\mu \equiv$ Mean, med \equiv Median, $\sigma \equiv$ Standard deviation. Mean Diff.: Mean (μ) difference (Welch-t) tests. The test verifies the null that the difference in mean is 0, for the $DAC_i \ge 0$ (income-increasing or negative earnings management) and $DAC_i < 0$ (income-decreasing or positive earnings management) subgroups of the particular accruals model. The reported *p*-value (in parenthesis) offers the least likelihood to wrongly refute the null, and it indicates significance at either 1% or 5% level (2-tailed), except for the extended Jones CF. DAC_i mean difference between the two subsamples.

Both Jones and modified Jones do not identify substantial differences in the mean (0.02), median (0.00) and even standard deviation, which shows a close spread, likely due to winsorisation adjustment completed to lesson outliers' influence. We recover a significant difference between the mean of the discretionary accruals for $DAC_i \ge 0$ (income-increasing) and $DAC_i < 0$ (income-decreasing) subgroups of particular accruals model, except for the extended Jones CF mean difference of the two subsamples, $DACEJCF_i$ (*p*-value = 0.104). Discretionary accruals are significantly larger for positive earnings management than negative earnings management, at least at the 5% significant level. It supposes substantial differences in the magnitudes and directions of systematic manipulations across those firms.

Table 4 presents the Pearson ordinary correlation coefficients $(r_{x_1x_2})$ for profits, accruals (Total and WC), and other accruals models fragments variables pairs assumed as, x_i and x_j having n-set $[(x_{1,1}, x_{2,1}), x_{1,2}, x_{2,2}), \dots, (x_{1,n}, x_{2,n})]$ with $r_{x_1x_2} = \sum_i^n (x_{1,t} - \bar{x}_1)(x_{2,t} - \bar{x}_2) \left[\sqrt{(x_{1,t} - \bar{x}_1)^2} \sqrt{(x_{2,t} - \bar{x}_2)^2} \right]^{-1}$. Panel A [B] of Table 4 presents the correlations for full samples (subsamples based on $PAT_i \ge 0$ (lower diagonal correlations estimates) and $PAT_i < 0$ (upper diagonal correlations estimates). The **Bold** figures disclose statistical significance using probability, p|t| = 0, at 1% or 5% levels only. The variables exhibit varying degree of association across the full samples and the subsamples. The remainder of the control and discretionary fragment variables exhibit correlation variations across both the small-profits and small-losses subsamples.

Table 4 presents the *Pearson correlation coefficients* of profits, accruals (Total and WC) and accruals models' fragments variables. Unlike the firm-specific adopted for the estimations of each accruals model (in Table 2), we estimate the correlation coefficients based on the pooled cross-sectional of the associated firms' data for profits, total and working capital accruals, as well as explicative accruals components, according to Dechow et al. (1995). Panel A is the correlations for the entire sample, which shows that the discretionary accruals are very highly correlated with each other, but slightly less correlated with specific fragments of the accruals earnings. For instance, the $DACJ_i$ is highly positive associated with $DACMJ_i$ and TA_i . Panel B represents correlations based on earnings subsamples for small profits, i.e., $PAT_i \ge 0$ (figures below principal diagonals) and small losses, i.e., $PAT_i < 0$ (figures above principal diagonals). The correlation is stronger and more significant for variables of the $PAT_i \ge 0$ relatives to those of the $PAT_i < 0$ subsamples. The remainder of the control and discretionary fragment variables exhibit some correlation variations across both the small-profits and small-losses subsamples, as expected, which indicates systematic differences across earnings management objectives based on magnitude, purposes and directions.

					Table 4.	Pearson co	rrelation coef	ficients				
	PAT _i	CFO_i	TA_i	WCA_i	DACJ _i	DACMJ _i	DACEJCF _i	DACWC _i	$1/A_{i-1}$	ΔREV_i	$\Delta REV_i - \Delta REC_i$	PPE _i
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Full sar	nple correla	tion coefficie	ents									
[1]	1											
[2]	-0.013	1										
[3]	0.469	-0.889	1									
[4]	-0.035	0.010	-0.024	1								
[5]	0.469	-0.889	1.000	-0.024	1							
[6]	0.470	-0.888	0.999	-0.024	0.999	1						
[7]	1.000	0.000	0.458	-0.035	0.457	0.458	1					
[8]	-0.035	0.009	-0.024	1.000	-0.024	-0.024	-0.035	1				
[9]	-0.023	0.004	-0.014	-0.019	0.000	0.000	0.000	0.000	1			
[10]	-0.020	-0.002	-0.008	0.014	0.000	-0.008	-0.021	0.013	-0.029	1		
[11]	0.002	0.053	-0.046	0.005	-0.046	0.000	0.000	0.000	-0.005	0.011	1	
[12]	-0.020	-0.004	-0.006	-0.015	0.000	0.000	0.000	0.000	0.760	0.002	-0.001	1
Panel B	8: Correlation	n coefficients	s for $PAT_i \ge$	0 (lower dia	igonal) and P	$PAT_i < 0 $ (up	per diagonal)					
[1]	1	-0.005	0.655	-0.062	0.655	0.655	1.000	-0.063	-0.081	-0.006	-0.010	-0.037
[2]	0.008	1	-0.759	-0.045	-0.759	-0.758	0.004	-0.044	0.080	0.040	0.030	-0.004
[3]	0.284	-0.956	1	-0.007	1.000	1.000	0.648	-0.008	-0.114	-0.034	-0.029	-0.021
[4]	-0.034	0.021	-0.030	1	-0.005	-0.005	-0.063	1.000	0.024	0.078	0.051	-0.033
[5]	0.284	-0.956	1.000	-0.030	1	1.000	0.648	-0.006	-0.099	-0.023	-0.031	-0.030
[6]	0.282	-0.955	0.999	-0.030	0.999	1	0.648	-0.006	-0.100	-0.036	-0.007	-0.028
[7]	0.999	0.031	0.262	-0.035	0.262	0.261	1	-0.063	-0.070	-0.006	-0.011	-0.031
[8]	-0.034	0.020	-0.029	1.000	-0.030	-0.030	-0.033	1	0.031	0.078	0.049	-0.031
[9]	0.001	-0.002	0.002	-0.029	0.017	0.017	0.040	-0.006	1	-0.050	-0.045	0.190
[10]	-0.023	-0.007	0.000	-0.006	0.008	0.000	-0.024	-0.007	-0.028	1	-0.070	-0.035
[11]	-0.045	0.055	-0.066	0.001	-0.066	-0.015	-0.049	-0.005	-0.002	0.018	1	0.032
[12]	-0.012	-0.004	0.000	-0.012	0.008	0.008	0.023	0.007	0.809	0.007	-0.002	1

Table 4. Pearson correlation coefficients

Source: @Authors (2022)

	Tuble 5. Regularities of the har	
	H_0 : No earnings management, EM =	H_0 : No earnings management, EM =
	0	0
Discr.	H_1 : $PAT_{i,t}$ decreasing accruals,	H_1 : $PAT_{i,t}$ increasing accruals ($EM <$
Accruals	(EM > 0)	0)
Simple Jones	4.20	4.24
Modified Jones	2.85	4.10
Extended Jones		
CF	3.54	3.30
WC accruals	3.49	4.65

Table 5. Regularities of the null's rejection

Source: @Authors (2022)

Table 5 reveals the proportions (%) of the null' rejection based on the one-tailed test for both $PAT_{i,t}$ decreasing accruals (EM > 0) and $PAT_{i,t}$ increasing accruals (EM < 0). Under the null of no earnings management (EM = 0), the simulations for the four particular models are completed using a sample of 555 (one-third of the total sampling observations of 1852) at a 5% significance level. The simulations are iterated 1,000 times based on optimal sampling rules.

Table 5 reports the results of the *simulation tests for models specification*. We perform a model specification test according to Teoh et al. (1998), using (6) and one-tailed t-statistics of wrongly rejecting the estimates (γ_1) of the test sample dummy (TSD_i) . According to prior studies (Algharaballi & Albuloushi, 2008; Peasnell et al., 2000), we complete two different tests for the null and compute the likelihood rate of possible Type I errors (i.e., the proportion of true null's rejections) based on one-tailed tests. The first is under the null of no existence of systematic earnings management (i.e., average discretionary accruals equal to zero), with an alternative of the existence of income-decreasing accruals (evidence of positive earnings management). The second has the same null but a different alternative of the existence of income-increasing accruals (i.e., presence of negative earnings management). If any equations (2) - (5) are well-specified, the data, irrespective of sample and resampling, would be less likely to reject the null at the 5% significant level accommodated for the test. The simulations disclose that for all the models, the percentage of the null's rejection is close to the test levels, indicative that all tested models are rightly specified as applied to the Nigerian firm-years samples. This finding is consistent with prior research (Algharaballi & Albuloushi, 2008; Peasnell et al., 2000). Finally, we verify the most powerful model (s) for empirical testing of earnings management. We completed the models' power simulations test for the four models, using a one-tailed test at a 5% level. Figure 1 and 2 visually depicts the simulation of power functions to test for Expenses and Revenue induced manipulation' earnings management. Both display the graphical summary of nulls' rejections when we implement the manipulation before we compute the different accruals models by adding the assumed amount of 'expenses (artificial) manipulation' at levels ranging from 20% to 100% of lagged total assets, $TA_{i,t-1}$, (at an interval of 20%). Under the null of no existence of systematic earnings management, we simulate only the alternative of income-increasing accruals.

Figure 1 depicts the simulation of power function to test the expense manipulations' earnings management, using the discretionary accruals models. We implement the expense manipulations by adding the assumed amount of expense (artificial) manipulation ranging from 20% to 100% of lagged of total assets (at intervals of 20%), before we complete the different accruals models. We complete the simulations using one tailed tests level of 5%.

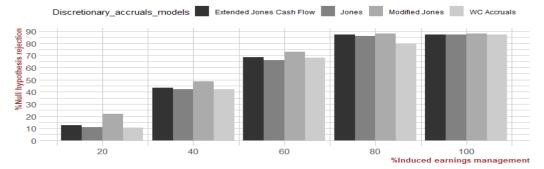
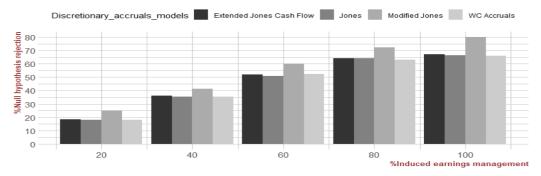
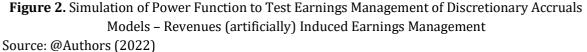


Figure 1. Simulation of Power Function to Test Earnings Management of Discretionary Accruals Models – Expenses (artificially) Induced Earnings Management Source: @Authors (2022)

Figure 2 depicts the simulation of power function to test the revenues manipulation earnings management, using the discretionary accruals models. We implement the expense manipulations by adding the assumed amount of revenue (artificial) manipulation ranging from 20% to 100% of lagged of total assets (at intervals of 20%), before we complete the different accruals models. We complete the simulations using one tailed tests level of 5%.





Both plots show that all models indicate relatively powerful tests for plausible parsimonious levels of accruals management. For the four different discretionary accrual models, the proportion of null rejections is approximately 35–50%, even for moderate accruals manipulations on 40% of lagged total assets, contingent on the type of accruals manipulation implemented and the particular accrual model functional. All models have a high percentage of the null (of no earnings management)'s rejection at 5% levels, from 20–100% experimental exercised increasing manipulation.

The simulations of the expense-augmented accruals models (Figure 1) indicate that the Modified Jones model produces the most powerful tests. The results identify similar regularities of the null's rejection at 20–100% of the lagged total assets artificial inducement for the Jones, Extended Jones CF and WC accruals models. Only the Modified Jones evidently have a different as well as the highest rejections at each stage of the expense experimented manipulation, except at the 100% inducement exercise, where all four models report similar levels of null rejections. It supposes that, of all the models, the Modified Jones is the most powerful model in the detection of expenses augmented income-increasing accruals.

The simulations of the revenues' augmented accruals models (Figure 2) indicate that the

Modified Jones maintains the most powerful capability. The simulations generate the null's rejection around 50–80% for revenue-induced manipulations at 60–100% of lagged total assets. Amidst the tested models, Modified Jones identifies the greatest null rejection at every simulation stage. The result shows that the Extended Jones CF power test reports rejections consistently below the Modified Jones but has the higher null rejection among the other three models. Algharaballi and Albuloushi (2008) show for Kuwait that the four models record similar power under expense manipulation, but the simple Jones has the highest power.

CONCLUSIONS

Empirical literature recognises the use of accounting accruals as a proxy for accounting quality to measure performance, financial status and plausible evidence of earnings manipulations. Research on the use of discretionary accruals to detect earnings management of Nigerian firms is increasing (Ozili & Outa, 2019). Yet, evaluating the correct specification and power of the test for the accruals model remains non-tested for Nigeria samples. This paper analyses four accruals models' specifications and power capability on a comprehensive sample of listed non-financial firms in Nigeria. Our objective is to decide the most appropriate one for detecting earnings management. For the aims, we use firm-specific estimations, and complete simulations to evaluate the alternative accruals functions. The result indicates that the different models are correctly specified and fitted for the samples, consistent with extant studies. In addition, we found that the Modified Jones has the highest power of test capability when both expense and revenue manipulation are simulated to establish the model that best detect evidence of earnings management. The implication of this finding is that the modified Jones model is the most appropriate model to detect earnings management based on the Nigerian sample. The findings can be useful, when combined with other firm characteristics (Cadot et al., 2020; Kusumawardhani, & Murdianingrum, 2022; Adedokun et al., 2022) to show their impact on earnings management.

LIMITATION & FURTHER RESEARCH

In sum, we establish quantitation information on accruals models' estimation and power dynamics. The research is conducted under a number of limitations. First, the study focuses only on the Jones-type models to detect the evidence of earnings management. Second, the models consider being of linear regression specifications. If linearity in accrual models is tested miss-specified for emerging market data, certainly the inferences on earnings management based on the use of a linear estimation become questionable and probably invalid (Ball & Shivakumar, 2006). The paper suggests the following for future studies. First, future research may consider the appropriateness of non-Jones-based models, such as the Cash Flow, Dechow-Dichev and Performance Matched Discretionary models (Kothari et al., 2005). Future research may examine whether the nonlinear may generate a better accruals estimation and power measure than the conventional linear model.

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