International Journal of Social and Educational Innovation (IJSEIro)
Volume 10/ Issue 20/ 2023

EVALUATING UNEXPECTED ACCRUALS TO DETECT ACCOUNTING MANIPULATIONS: EVIDENCE FROM EMERGING MARKETS

Adedeji Daniel GBADEBO
Walter Sisulu University, Mthatha, South Africa
gbadebo.adedejidaniel@gmail.com

Abstract

This paper estimates and tests the power of unexpected accruals models as indicators of earnings misstatement. The models are implemented on a comprehensive sample of listed firms in Africa, with available information from 2006 to 2020. The paper aims to determine the specification-correctness as well as to confirm the most powerful of the models. The findings suggest that the models are well-specified when used on the considered firm-years. All the models are found to be powerful, although the Jones, modified Jones and adapted models are identified as most powerful on the basis of the induced expense (revenue) manipulations. At 5% level, the expense (revenue) manipulation of 6–10% accommodate at least 97% (98%) nulls' rejections for Jones, modified (Jones) and adapted models, but slightly reduced rejections ranging 95%–98%, at 1% test level. This study offers vital assessment of earnings manipulations in trying to exploit future earnings to grow stock prices.

Keywords: ***Earnings management, Unexpected accrual, Power of test;***
JEL Code: G14; G24; M41

1. Introduction

The empirical use of accruals models for the identification of systematic manipulation and earnings management (hereafter, EM) is a widespread approach in accounting research (Adeneye et al., 2023; Gbadebo et al., 2022; Adedotun et al., 2022; Mensah, 2020; Chowdhury, Mollah & Al-Farooque, 2018; Balboa et al., 2013; Ball & Shivakumar, 2006; Bartov, Gul & Tsui, 2000). The discretionary, although not a mandatory part of operating activities, represents the proportions of total accruals which quantifies the extent and direction (increase or decrease) of earnings managed that manager exercises discretions (Brennan, 2022; Malofeeva, 2018). Because by nature, accruals generally are intended to manage earnings' information, mangers understand its tractability to report losses when unable to meet profitability threshold or to report small profits when gross earnings appear insufficient to beat bonus benchmark (Gbadebo et al., 2022).

Research, since Healy (1985), uses different derivations of accrual models, including the cash flow models (Ball & Nikolaev, 2022; Dechow et al., 1998), accrual quality models (Francis et al., 2005; McNichols, 2002) and Jones-based models (Larcker & Richardson, 2004; Dechow et al., 1995; Beatty et al., 1995; Dechow, 1994; Jones, 1991) to uncover evidence of EM on financial reports of firms. Dechow (1994) shows that accruals earnings models have been tested to be greatly superior measures of performance relative to cash flow methods. They contain incremental information contents which are efficient than cash flows (Magerakis, 2022; Hong, Kim & Kwack, 2022) and exhibit higher reliable power of test (Algharaballi & Albuloushi, 2008). Dechow et al. (2012) offer that an analytical attempt to add reversal accruals in the models improve the power of tests by 40 percent due to constraint of timing-effect. Basically, only the Jones-based models and its successive modifications are models that strengthen the power of empirical tests of EM (Balboa et al., 2013; Ball & Shivakumar, 2006).

With modified specifications, several studies have performed test on the power of the alternative accrual models based on published samples from advanced economies. Dechow et al (1996) examine models and discover that the modified Jones is more powerful for testing income increasing EM. Bartov et al. (2000) suppose to use Jones and time-series modified Jones models as best detection for earnings management. Chang, Chou and Lin (2003) support the Jones model as better compare to modified-Jones. Algharaballi and Albuloushi (2008) reveal Jones approach exhibits the highest power of detecting the EM by inducing the revenue for Kuwait markets. Peasnell et al. (2000) note that cross-section models are well specified and retained relatively powerful outcome less than 10% of lagged assets in the US. The standard-Jones and the modified Jones are more powerful in unveiling bad-debt and revenue manipulations. The conclusions from these studies have been extended as foundations for empirical investigations in other regions, despite significant markets and institutional differences, including enforcement procedures, economic settings, financial regulations and others (Chijoke-Mgbame et al., 2020; Tunyi et al., 2019; Agyei-Boapeah & Machokoto, 2018). The developed economies, characterised by advanced capital markets, have capabilities to maintain robust financial reporting infrastructure and keep near accurate earnings' reports (Agyei-Boapeah & Machokoto, 2018). Testing accruals models based on Africa samples is inevitable to expand literature and the frontier of research.

The evaluation of the power of expectation accruals-based models is important for some reasons. First, extant evidence in the region reveals strong motivation for earnings manipulations (Adedotun et al., 2022), but current research remains limited to issues around determinants of EM, the influence of regulatory frameworks, and the impacts of firms' performance (Gbadebo, 2023; Adedotun et al., 2022; Agyei-Boapeah et al., 2020; Mensah, 2020). Second, the concern of practitioners on EM reflecting interests in capital market incentives vary for industrialised and other economies (Mamatzakis, Neri & Russo, 2023; Ball & Nikolaev, 2022; Chijoke-Mgbame et al., 2020; Bzeouich, Lakhal & Dammak, 2019), as such any study for African evidence represents a guide for progressing informed decision. Thirdly, research in Africa is increasingly reflecting discretionary accruals as measures of accounting quality (Adedotun et al., 2022; Mensah, 2020). Precursory study, by Gbadebo et al. (2023), reinforces evidence limited to Nigerian sample and discloses the modified Jones have the highest power capability and most suitable to detect manipulation.

This paper offers first-hand evidence on the use of cross-section estimation of the expectation accruals models based on African samples. The measures show the extent of EM by parametric estimation of accrual components of periodic earnings using derivations extracted from the financial reports. I specify and analyse five specification of standard discretionary accrual models, including the Jones, modified Jones, adapted expected accruals, lagged expected accruals and forward-looking expected accruals models. If the evidence shows that the Jones models outperforms others, then, EM relations and robustness tests would enhance when the Jones model measure is used as proxy. Otherwise, empirical evaluations base on less powerful models would certain than likely inherits inference with possible error – falsely, refuting component's true null (Teoh et al., 1998).

The paper sets two aims: (a) Because the periods considered is not lengthy but involved large number of firms, specifically 335, it is likely that the models are misspecified due to non-stationarity (Peasnell et al., 2000). Therefore, I determine the specification-correctness of the accrual's models. The test examines the extent by which, for instance, an unexpected accruals model wrongly rejects a considered null of no earnings management. According to Teoh et al. (1998), I demonstrate the sensitivity of the baseline accrual models to selected samples by simulating their firm-specific regressions. I apply 25% (1,088) observations selected (without replacement) to estimate the different accruals models for 100, 1,000, and 10,000 completed simulations. If the outcome validate that a model is not well poised to fit accruals expectations, the evidence supposes an alternative specification, including non-Jones based models, would better detect EM. (b) I evaluate the power of test measured by the probability of committing

Type 1 errors, in the use of the specific model to detect manipulations. According to Peasnell et al. (2000), I complete the power of the test by experimenting (i.e., artificially induced) 'revenue' and 'expense' manipulations on the sample to prove the economically likelihood levels of earnings management. The iteration is completed only for 10,000 completed simulations for the different accruals models. Because the samples now include to some extent EM, if there is earnings management prevalence, a powerful model dominates with more frequencies of null's rejections.

The evidence reveals that the models are all well-specified when used on the firm-years. The expense (revenue) manipulations identify that all models powerful with high rate for the null's rejection, but the 'Jones, modified Jones and adapted models', and including the lagged model for revenue manipulations, are almost equally the most powerful. Expenses (revenue) manipulations of 6–10% of lagged total assets accommodate at least 97% (98%) nulls rejections for Jones, modified Jones and adapted at 5% level. The same applies to the simulations at 1% level but with slightly reduced rejections now ranging 95%–98%. The outcome offers invaluable resource to academics, capital market stakeholders, practitioners and regulators. For instance, with the strong power indicated by the Jones model, may supposes that management may tend to maximise future earnings to increase stock prices in nearest initial public offerings. The paper is presented as follows. The section 2 discusses the expectation accruals models and section 3 the methodology, including the sampling procedures to assess the estimation and power of test. Section 4 provides results and 5 concludes.

2. Materials: Expectation Accruals Models

Accruals models remains an indispensable tool to measure accounting quality and financial performance. The accruals models are grouped into aggregated (or simple) models, which focus on total accruals, and disaggregated (or sophisticated) models, which require to split total accruals into two – the discretionary and nondiscretionary accruals. The total accrual is computed using the balance sheet method or income method (Prawitt et al., 2009; Pae, 2005; Teoh *et al*, 1998; Dechow et al., 1995; Jones, 1991). According to Hribar and Collins (2002), for each firm i in year t, the total accruals is the difference between operating profit and cash flow. Because total accrual by itself is intrinsically 'noisy', the 'unexplained' (i.e., residual) components is refer as 'discretionary' (Jones, 1991), and often interchangeably with abnormal, unexpected, or unexplained accruals (Subramanyam, 1996), and the nondiscretionary part as the normal, expected or explained accruals. The unexplained accruals are usually more variable than the explained (expected) accrual components, but less variable than the total accruals

(Subramanyam, 1996). Five discretionary accruals models - Jones, modified Jones, adapted expected accruals model, lagged expected accruals and the forward-looking expected accruals - are computed. The firm-specific expectation models are used to estimate the regression of accruals models. The larger expectation accruals suppose higher earnings management.

2.1. Jones model

The Jones (1991) assumes that the change in revenues is independent of managerial discretion. Jones (equation 1) estimates a firm-specific regression of total accruals ($TA_{i,t}$) on explicate variables associated with nondiscretionary components of earnings (change in revenues, $\Delta REV_{i,t}$, and gross-value of property, plant and equipment, $PPE_{i,t}$), for each firm i in year t. The regression estimates, $\hat{\alpha}_i' s$, is used alongside the reported earnings components to compute the Jones nondiscretionary accruals ($NDAC_{i,t}$), which is the expected (estimated) total accruals' value, whereas residuals estimates (i.e., $\hat{\varepsilon}_{1i,t} = TA_{i,t}/A_{i,t-1} - DAC_{i,t}$) is the Jones' unexpected accruals ($DACJ_{i,t}$).

$$TA_{i,t}/A_{i,t-1} = \alpha_{0,i}[1/A_{i,t-1}] + \alpha_{1,i}[\Delta REV_{i,t}/A_{i,t-1}] + \alpha_{2,i}[PPE_{i,t}/A_{i,t-1}] + \varepsilon_{1i,t} \qquad (1)$$

Where, $TA_{i,t}$ is the total accruals, and $A_{i,t-1}$ is one lagged of the total assets, i.e., the total assets in year $t-1$. A major criticism of Jones approach is that the model removes portions of managed earnings from the expected accrual, particularly, if the managers exercise real discretions over the firms' revenues.

2.2. Modified Jones model

The modified Jones, from Dechow *et al. (1995)*, notes that the Jones model misstate the expected accruals, especially, in situation with unusual firms' performance. Such misstatement makes the Jones model lack power to detect the evidence of earnings manipulation because it enforces endogeneity bias. To control such bias, Dechow *et al.* assumes that period accounts receivables are discretionary, hence inducing likely positive correlation between unexpected accruals and sales growth in current period. To correct this, he suggests to eliminate uncollected (credit) sales from revenue change The model (2) regresses the normalised $TA_{i,t}$ on ($\Delta REV_{i,t} - \Delta REC_{i,t}$) and $PPE_{i,t}$, for firm i in year t. The expected accruals and non-discretionary values (denoted, $NDACMJ_{i,t}$) are the estimates of the total accruals after obtaining $\hat{\beta}_i$'s, whilst the residuals (i.e., $\hat{\varepsilon}_{2i,t} = TA_{i,t}/A_{i,t-1} - DAC_{i,t}$) is the modified Jones' unexpected accruals ($DACMJ_{i,t}$).

$$TA_{i,t}/A_{i,t-1} = \beta_{0,i}[1/A_{i,t-1}] + \beta_{1,i}[(\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}]$$

$$+\beta_{2,i}[PPE_{i,t}/A_{i,t-1}] + \varepsilon_{2i,t} \quad (2)$$

Where $\Delta REC_{i,t}$is the accounts receivables (credit sales) in year t minus accounts receivables in year, $t-1$. As noted by Jeter and Shivakumar (1999), the model attempts to account for endogenous bias in standard Jones model, but the modification induces overestimation bias. Coulton et al. (2005) note that the assumption that credit sales result from manipulations is unproven, possibly invalid and by itself induces over-correction.

2.3. Adapted expected accruals model

The adapted expected accruals model, from Dechow, Richardson and Tuna (2003), corrects the overstatement in the modified Jones model, by making an adjustment for the expected change in net receivables. The Adapted model supposes we regresses the change uncollected sales $\Delta REC_{i,t}$ on change in revenues, $\Delta REV_{i,t}$, for firm i in year t (equation 3) and include the 'residual' part as explanatory variable to adjust the simple Jones expectation model.

$$\Delta REC_{i,t} = \kappa_0 + \kappa_1 \Delta REV_{i,t} + e_{i,t} \quad (3')$$

$$TA_{i,t}/A_{i,t-1} = \theta_{0,i}[1/A_{i,t-1}] + \theta_{1,i}[((1+\kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}]$$
$$+\theta_{2,i}[PPE_{i,t}/A_{i,t-1}] + \varepsilon_{3i,t} \quad (3)$$

κ_1 in $(3')$ has own distributions and shows the expected change in net receivable for the change in revenues. The value would normally be discretionary in the modified Jones but adds as 'nondiscretionary' in (3), since it includes the unexpected fragment (residuals) of the change in net receivable in expectation accruals (i.e., estimates of $e_{i,t}$ in $(3')$). The complete amount of the change is subtracted, whilst the expected change is added back (κ_1 multiplied by the sales- change). The regression estimates, $\hat{\theta}_i's$, is used with other earnings components to compute the model's nondiscretionary accruals ($NDACAM_{i,t}$). The residuals estimate from (3) (i.e., $\hat{\varepsilon}_{3i,t} = TA_{i,t}/A_{i,t-1} - DAC_{i,t}$) is the *Adapted model*'s unexpected accruals ($DACAM_{i,t}$).

2.4. The lagged expected accruals model

The lagged expected accrual model, according to Coulton et al. (2005), correct the misspecification of the modified Jones by simple adjustment to include the lagged value of total accruals. The intuition is that since accruals are less persistent compare to cash flows, and reverse through time, some considerable parts of accruals that explain earnings management is predictable on its own pasts (Chambers, 1999). The model incorporates the lagged of total accruals, $\mathrm{TA}_{\mathrm{i,t-i}}$, to identify for the predictable proportion.

$$TA_{i,t}/A_{i,t-1} = \delta_{0,i}[1/A_{i,t-1}] + \delta_{1,i}[((1+\kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}]$$

$$+\delta_{2,i}[PPE_{i,t}/A_{i,t-1}] \ + \delta_{3,i}[TA_{i,t-1}/A_{i,t-1}] + \ \varepsilon_{4i,t} \qquad (4)$$

The explained portion or non-discretionary accruals ($NDACLM_{i,t}$) as well as the residuals ($\hat{\varepsilon}_{4i,t} = TA_{i,t}/A_{i,t-1} - DAC_{i,t}$) of estimates, after obtaining $\hat{\delta}_i$'s, offer the expected and unexpected ($DACLM_{i,t}$) accruals to measure EM.

2.5. Forward-looking expected accruals model

The forward-looking expected accruals model, from Coulton et al. (2005), advanced the lagged model to incorporate the future revenue growth. The adjustment is made because not all inventory change is result of earnings, for instance, a write-off of obsolete inventory. Yet standard Jones model and other modifications intrinsically consider such changes as manipulations. Coulton et al. (2005) observe that this exaggerate the estimation of EM should be corrected. They include a measure of future revenue (i.e., sales) growth, $REVG_{i,t}$, to account for such accruals (McNichols, 2002).

$$TA_{i,t}/A_{i,t-1} = \rho_{0,i}[1/A_{i,t-1}] + \rho_{1,i}[((1 + \kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})/A_{i,t-1}]$$
$$+\rho_{2,i}[PPE_{i,t}/A_{i,t-1}] + \rho_{3,i}[TA_{i,t-1}/A_{i,t-1}] + \rho_{4,i}[REVG_{i,t}/A_{i,t-1}] + \varepsilon_{5i,t} \quad (5)$$

The revenue growth is computed as the change in revenue in current year (t) to the year after ($t + 1$) scaled by current revenue. The explained portion or non-discretionary accruals ($NDACFM_{i,t}$) and the residuals ($\hat{\varepsilon}_{5i,t} = TA_{i,t}/A_{i,t-1} - D\mathrm{AC}_{\mathrm{i,t}}$) of estimates, after obtaining $\hat{\rho}_i$'s, offer the expected and unexpected (denoted, $DACFM_{i,t}$) accruals to measure EM.

3. Methodology

3.1. Data and Preliminary

The accounting sample is sourced from the financial records of African listed firms for from published sources including stock exchange multi-year fact books, websites, and database of the African financial markets. The tested period is restricted to 2006–2020 window due to unavailability of some firms' information. Financial firms are not included because when testing financial firms' data, accrual testing models are inefficiently weak to examine earnings manipulations based on short term incentives (Beretka, 2019). The firms considered have at least ten (10) firm-year available data within the coverage window (Coulton et al., 2005). This restriction limits the samples to 335 firms and 4,350 firm-years satisfying the criteria with only 200 (135) firms having complete information for 15 (10) years.

As with Coulton et al. (2005), the study prefers to use the 'unexpected accruals' more regularly, in the empirical part, to describe the discretionary accruals. Each expectation accruals model (1) – (5) is estimated models cross-sectionally. Firm-specific estimation that examine EM behaviour of the accruals is required because estimating the expectation models based on time-series may lower the power of tests due to the treatment periods and overlapping estimation and (Gbadebo et al., 2023; Windisch, 2020; Jackson, 2018). More so, the cross-sectional estimations control for the structural differences amongst firms, lessen the significance of inaccurate estimations, reduce the likelihood that the accruals models' estimates are time invariants (Gbadebo et al., 2023). Peasnell et al. (2000) note that the coefficients distributions form the firm-specific estimations are more robust and specified when compare with the time-series estimation.

The models' variables are normalised by lagged of total assets to deter outliers. The estimation recovers 335 distributions of coefficients for models' estimates ($\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\theta}_i$, $\hat{\delta}_i$, $\hat{\rho}_i$) and statistics ($\overline{\mathrm{R}}^2$). The expectation accruals ($\hat{\varepsilon}_{1i,t}$, $\hat{\varepsilon}_{2i,t}$, $\hat{\varepsilon}_{3i,t}$, $\hat{\varepsilon}_{4i,t}$, $\hat{\varepsilon}_{5i,t}$) are then computed, and winsorised, trimming by 1st and 99th percentiles, to eliminate outliers from the estimates, in order to enforce the linearity assumption mandated for Jones-based models. Note that in estimating the adapted model (3), I first regress $\Delta REC_{i,t}$ on change in revenues ($\Delta REV_{i,t}$) as given by equation$(3')$. The estimation reports κ_1, a 'nondiscretionary' value, with distribution characterised by mean of 0.082 and median of 0.0056. The t-test on mean-$\kappa_1$is significant and supposes that, averagely, a-unit increase in revenue result in a 0.082 increase in net receivable. Table 1, 2 and 3, respectively, report the summary of statistics for the accrual's model components, $\overline{\mathrm{R}}^2$ of the accrual models and the expected and unexpected accruals obtained based on the specific models.

Table 1 gives statistics for the explicative components of the accrual's models. The process obtained 335 estimates, each associated to individual firm and for each components of equation (1) – (5). For the cross-section of firms, the computation indicates that the simple Jones model exhibits more components whose values are greater than zero relative to other methods. As would be expected, except for the mean of coefficients for change in revenue, both the simple Jones and modified Jones are identified closely. The average intercept coefficients, for all accrual computed method is negative and well-signed. Only the average $PPE_{i,t}$ for Jones and the lagged models appear negative, and except for the adapted model, the mean estimates of the sales unreceivable-revenue differentials is averagely positive for all models. Another information presented by the Table is that the simple Jones' model has more nonnegative discretionary accruals components ($\% \geq$), whereas the adapted model appears to identify with the least nonnegative. Some outcomes have counterintuitive coefficient signs relative to extant studies (Algharaballi & Saad Albuloushi, 2008; Chang et al., 2003).

Table 2 reveals that the Jones (Forward-looking) model has the lowest (highest) expected value of the distributions of the explanatory power ($\mathrm{E}(\overline{\mathrm{R}}_{\mathrm{i}}^{2})$), amongst the models estimated. This is not surprising because the model incorporated the most additional controlled variable included to augment the modified Jones. Relative to the lagged model, the forward-looking adds the measure of future revenue growth ($REVG_{i,t}$) adds to the model in accounting to correct for accruals and the addition would make the models further powerful (McNichols, 2002). Most estimates reveal means slightly higher than the median.

Table 3 reports shows the mean (μ) and median ($\tilde{q}_2$) values of all the expectation accruals are close to zero, although remains positive for all models. The Jones and modified Jones's expected accruals do not show significant differences in the mean and spread, both having standard deviation closely zero. The relative closeness, however, may likely be due to the winsorisation adjustment implemented to reduce outliers' influence and enforce the Jones-based linearity assumptions. The unexpected accruals are larger for the positive EM compare to the negative EM. Test at 5% level indicates significance differences in the direction and magnitudes of manipulations by the firms. There is significant difference between the average of the unexpected accruals for income-increasing ($DAC_i \geq 0$) and income-decreasing ($DAC_i < 0$) subgroups for all the model, except for the adapted, which mean difference test was not significant with p-value of 0.328 (untabulated).

Table 1: Basic statistics of the accrual's model components

Model	Components	μ	$\tilde{q}_1$	$\tilde{q}_2$	$\tilde{q}_3$	% ≥ 0
Jones	$1/A_{i,t-1}$	-0.042	0.018	0.229	1.045	55%
	$\Delta REV_{i,t}$	0.023	0.029	0.238	0.339	75%
	$PPE_{i,t}$	-0.004	0.005	0.266	1.045	20%
Modified	$1/A_{i,t-1}$	-0.041	0.007	0.227	1.028	55%
	$\Delta REV_{i,t} - \Delta REC_{i,t}$	-0.020	-0.006	0.248	1.049	63%
	$PPE_{i,t}$	0.046	0.049	0.254	0.399	21%
Adapted	$1/A_{i,t-1}$	-0.069	0.001	0.247	1.411	50%
	$((1+\kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})$	0.025	-0.007	0.253	1.407	45%
	$PPE_{i,t}$	-0.019	-0.013	0.178	0.334	12%
Lagged	$1/A_{i,t-1}$	-0.057	0.008	0.245	1.329	51%
	$((1+\kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})$	-0.013	-0.004	0.176	0.359	58%
	$PPE_{i,t}$	0.020	0.010	0.268	1.309	10%
	$TA_{i,t-1}$	-0.007	-0.031	0.218	0.375	25%
Forward	$1/A_{i,t-1}$	-0.052	0.026	0.279	1.416	50%
	$((1+\kappa_1)\Delta REV_{i,t} - \Delta REC_{i,t})$	-0.008	0.000	0.217	0.389	65%
	$PPE_{i,t}$	0.017	0.009	0.287	1.389	15%

$TA_{i,t-1}$	-0.014	-0.048	0.223	0.421	58%
$REVG_{i,t}$	-0.019	-0.001	0.242	0.429	10%

Table 1 shows associated statistics ($\mu, \tilde{q}_1, \tilde{q}_2, \tilde{q}_3$) of estimates of the explicative fragments of the five accruals models. $\mu \equiv$ mean, $\tilde{q}_1 \equiv$ 1st quartile, $\tilde{q}_2 \equiv$ median and $\tilde{q}_3 \equiv$ 3rd quartile. $\% \geq 0$ identifies the percent of the referred component greater than zero.

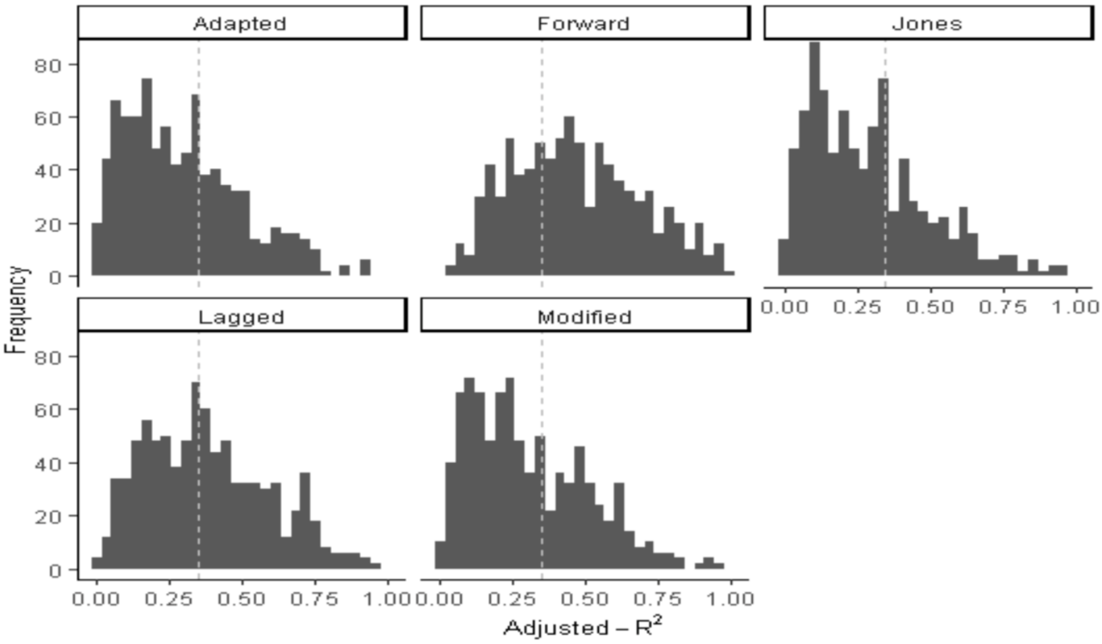


Figure 1: Distributions of $\overline{\mathrm{R}}_i^2$ from the estimations of the accrual's models
Note: Figure 1 presents the histograms of estimated $\overline{\mathrm{R}}_i^2$ for the 435 firm-year estimations for the five models
Source: Author

Table 2: Mean of Adjusted R-squared ($\overline{\mathrm{R}}_i^2$) of the distributions of the accrual models

Methods	$E(\overline{\mathrm{R}}_i^2) = \mu$
Jones	0.193
Modified	0.205
Adapted	0.251
Lagged	0.286
Forward	0.347

Table 2 shows the mean (μ) or expected value of the distribution of $\overline{\mathrm{R}}^2$ for the accrual models.

Table 3: Basic statistics of the expected and unexpected accruals

Methods	μ	σ	$\tilde{q}_2$
Jones	0.0035	0.1885	0.0497
Modified	0.0042	0.2134	0.0498
Adapted	0.0039	8.6105	-
Lagged	0.0025	3.8203	-
Forward	0.0083	2.9346	-
Jones	**-0.0148**	**0.9210**	**-0.0146**
Modified	**-0.0145**	**0.0066**	**-0.0144**
Adapted	**-0.0315**	**6.4267**	**-0.0144**
Lagged	**-0.0280**	**1.1916**	**-0.0434**
Forward	**-0.0193**	**0.4892**	**0.0228**

Table 3 shows associated statistics ($\mu, \sigma, \tilde{q}_2$) of the accruals models. $\mu \equiv$ mean, $\sigma \equiv$ standard deviation and $\tilde{q}_1 \equiv$ median. **Bold** values are for the expected accruals.

Source: Author's computed

3.2. Methods and Processes

To establish the research aims, the procedures follow two stages. The first stage conducts test for models' specification correctness to detest manipulations (Peasnell et al., 2000). The test, according to Teoh et al. (1998), verifies the sensitivity of the models to sampling, and shows the extent at which the models include Type I error – falsely refuting the null that the firm-years preclude manipulations. If the model is well-specified, regardless of sampling, the test would less likely to discard the null. Steps 1 to 4 (below) are implemented to complete the test.

1. I use an optimal rule to select 25% being 1,088 observations (without replacement) to estimate the five accruals' models (DAC_m, $m = 1$–5).
2. I create a dummy variable of the test random sample (TRD), which is coded 1 for the 1,088 selected observations in step 1 and 0 otherwise. The sampling ensures that firm-years where TRD equals 1 are unlikely characterised by EM activities.
3. I estimate the regression ($DAC_i = \pi_0 + \pi_1 TRD_i + \varepsilon_i$, i = 1 to 3,350) for the five (m) models and complete the t-test to verify the significance of $\hat{\pi}_1$. This test is completed under two hypotheses: (a) The null that unexpected accruals are greater than or equal 0 (EM $\geq$ 0) against an alternative of earnings-increasing accruals, and (b) The null that unexpected accruals are less than or equal 0 (EM $\leq$ 0), against an alternative of earnings-increasing accruals.
4. I simulate step (1) – (3) for N (=100, 1,000 and 10,000) repetitions for each expectation accruals in order to compile records of falsely rejecting $\hat{\pi}_1$. The frequencies of $\hat{\pi}_1$'s significance is recorded. For correct specification, $\hat{\pi}_1$would be significant and the null is rejected less frequently than expected in the N-simulations performed under the least probability (significance).

The second stage conduct tests to verify the models' power to recognise manipulations. The procedure, from Peasnell et al. (2000), allows inducing artificial 'revenue' and 'expense' earnings management to prove economically likelihood levels of manipulations on the selected samples without replacement. The process follows same steps (1 – 4) from the first-stage, but augments the accruals fragments with conjectured 'artificial income-increasing accruals' for the selected firm-years. The induced accruals are simulated within (0 – 10)% of lagged of total assets based on a 1% increment. The expense (revenue) inducement is realised by adding the assumed artificial expenses (revenues) manipulated to the total accruals (total sales revenue and net receivable).

After augmenting the accruals models' component for the random subsamples at which TRD_i =1, the procedure computes the induced expectation accruals. Steps (1) – (3) are iterated N (only for 10,000) times the different expectation accruals and the frequencies of the null's rejections for the repetitions is recorded. Because the samples include to some extend (e.g., induced) manipulations, an expectation accruals model with high power would, normally, more often refutes the null. If there is earnings management prevalence, a powerful model dominates with more frequencies of null's rejections. The higher the frequency of rejections a model is associated with, the more powerful it is to detect EM. This identifies the most predictive models that best recognise earnings management, and therefore considered as appropriate, efficient and best endorsed for detection of likely evidence of financial manipulation. The visualisation depicts summary of nulls' rejections (rate in %) when earnings management is induced before implementing the considered accruals models. The simulations are completed based one-tailed test at 1% and 5% significance level. The visualisation indicates the power tests for reasonable parsimonious rejections of the null. The R-codes to optimise the sampling without replacement and the Monte Carlos simulation are summarised and reported (Appendix).

4. Results

4.1. Models' specification test

Table 4 reports the simulation results of the specification-correctness test. The paper reports Type I errors, from a tailed test, for a null of non-positive EM *(alternative:* income decreasing EM) and the null of non-negative EM *(alternative:* income-increasing EM) to depict evidence for the models' specification correctness is implemented based on a-tail significance test corresponding to the considered null (Gbadebo et al., 2023; Algharaballi & Albuloushi, 2008; Peasnell et al., 2000). The repetition is conducted 100, 1,000, and 10,000 times. I approximate to nearest multiple of 0.5. For instance, 3.72 (1.25) is considered as 3.50 (1.00), and 3.84 (1.59) is considered as 4.00 (1.50) to easily aid compares with 5% (1%) level. Since the sampling ensures that firms where $TRD = 1$ may not involve in activity, the well-specified model would not exclude the null at the rate excessively greater than the 1% and 5% considered significance. The simulation for the forward-looking model has a 6% proportion of the null's rejection. This is the highest rate of null's rejections for the income decreasing EM based on

1,000 repetitions. The model is well posed since the rate does not substantially exceed the test significance of 5%. For the null that EM ≥ 0, against the alternative of earnings-decreasing, both the modified Jones and adapted models exceed the test probability level at the 100 repetitions but not substantial as well as do not exceed it for 1,000 and 10,000 repetitions. The result shows all considered models seem well-specified when used on the firm-years selections, consistent with prior evidence (Peasnell et al., 2000).

Table 4: Simulations for specification-correctness test

	H_0:→	EM ≤ 0 (%)	EM ≥ 0 (%)	EM ≤ 0 (%)	EM ≥ 0 (%)
(N)	H_1:→	Earnings ↓	Earnings ↑	Earnings ↓	Earnings ↑
	Models	5.0%	5.0%	1.0%	1.0%
100	Jones	5.00	3.00	1.00	1.00
	Modified	5.00	3.00	3.00	1.00
	Adapted	3.00	4.00	3.00	1.00
	Lagged	4.00	3.00	2.00	1.00
	Forward	4.00	3.00	1.00	1.00
1,000	Jones	5.00	5.00	1.00	2.00
	Modified	4.50	5.50	1.00	1.50
	Adapted	3.00	4.00	1.00	1.50
	Lagged	4.50	3.50	1.00	1.00
	Forward	5.00	6.00	0.00	1.00
10,000	Jones	4.50	4.00	1.00	1.00
	Modified	3.00	4.50	1.00	1.50
	Adapted	4.50	5.00	1.00	0.50
	Lagged	3.00	4.50	1.00	0.50
	Forward	4.00	4.50	1.00	1.00

Note: The frequencies of $\hat{\pi}_1$'s significance is recorded and compare with the significance level.
Earnings ↓ (↑) - means earnings-decreasing (earnings-increasing) accruals
Source: Author's computed

4.2. Models' power test

Table 4 reports results for the accruals models' power test and Figure 1 depicts the visualisations. The simulations identify the rates of null' rejections due to the artificial expense and revenue induced manipulations at significance level of 5% (Panel A) and 1% (Panel B). The test is implemented for one-tailed based on the null that the unexpected accruals are greater than or equal 0 (non-negative EM) against an alternative of earnings-increasing accruals.

Table 5: Simulation for accruals models' power test (frequency of nulls' rejections)

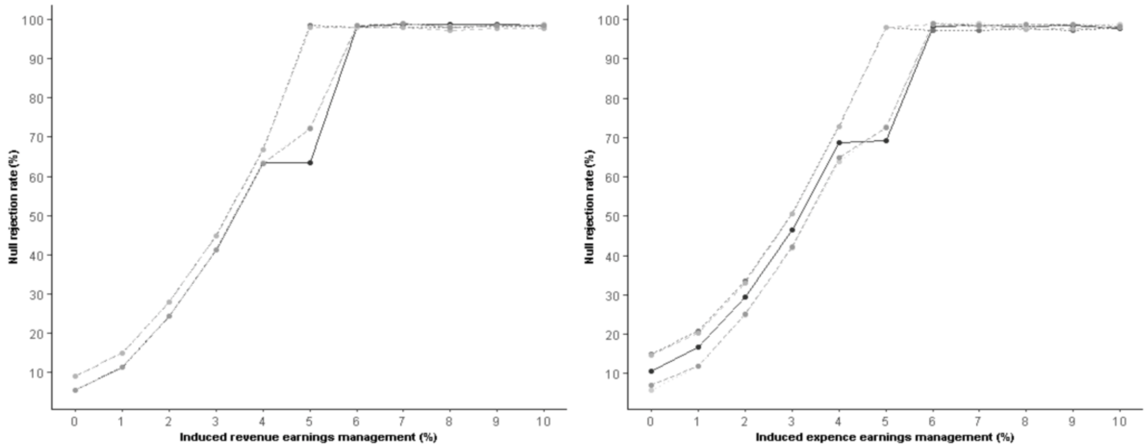
	%Induced	Jones	Modified	Adapted	Lagged	Forward
Confidence	0	04.53	05.02	05.48	06.90	05.88
Level (95%)	1	11.77	11.92	16.72	20.35	20.75
	2	25.08	24.85	29.56	33.05	33.51
	3	42.26	41.87	46.53	50.55	50.47
	4	64.95	63.72	68.72	72.67	72.79
	5	72.38	72.74	69.15	97.96	98.03
	6	98.91	98.97	98.14	98.75	97.30
	7	98.47	98.96	98.43	97.13	97.29
	8	98.38	98.16	98.26	97.40	97.68

	9	98.48	98.59	98.74	97.70	97.30
	10	98.29	98.66	98.67	98.55	98.03
	0	**04.53**	**05.02**	**05.48**	**06.90**	**05.68**
	1	**11.23**	**11.40**	**11.40**	**14.88**	**14.88**
	2	**24.22**	**24.34**	**24.34**	**27.84**	**27.84**
	3	**41.22**	**41.31**	**41.31**	**44.90**	**44.90**
	4	**63.33**	**63.45**	**63.45**	**66.91**	**66.91**
	5	**72.22**	**72.53**	**63.45**	**98.09**	**98.47**
	6	**98.43**	**98.13**	**98.36**	**98.06**	**98.06**
	7	**99.01**	**98.99**	**98.68**	**98.03**	**98.03**
	8	**98.09**	**98.30**	**98.88**	**97.27**	**98.03**
	9	**98.58**	**98.50**	**98.83**	**97.71**	**98.34**
	10	**98.48**	**98.88**	**98.51**	**97.71**	**98.34**
Confidence Level (99%)	0	02.91	03.65	04.97	05.16	05.29
	1	12.59	12.02	17.64	21.13	20.30
	2	26.04	25.94	29.47	34.28	34.07
	3	41.59	42.94	47.09	50.52	50.66
	4	64.29	64.52	70.02	72.63	73.71
	5	73.38	73.32	69.49	99.55	98.52
	6	99.14	98.78	98.97	99.50	97.21
	7	99.99	99.00	98.33	99.53	98.15
	8	98.60	98.54	99.22	99.01	97.79
	9	98.93	98.43	98.90	97.90	99.07
	10	98.89	99.35	99.77	98.51	98.80
	0	**02.91**	**03.65**	**04.97**	**05.16**	**05.29**
	1	**10.59**	**10.24**	**10.61**	**12.69**	**14.01**
	2	**22.45**	**23.86**	**22.82**	**26.49**	**26.92**
	3	**40.51**	**40.18**	**39.35**	**43.91**	**43.80**
	4	**61.61**	**62.18**	**61.42**	**64.38**	**65.40**
	5	**71.17**	**70.70**	**61.65**	**97.35**	**97.01**
	6	**96.87**	**98.27**	**96.24**	**97.27**	**96.90**
	7	**96.56**	**97.29**	**97.63**	**96.36**	**97.87**
	8	**95.90**	**97.53**	**97.93**	**94.85**	**96.59**
	9	**97.62**	**96.91**	**98.11**	**96.02**	**97.60**
	10	**97.03**	**96.93**	**97.05**	**96.96**	**97.08**

Note: Non-bold (**bold**) value is expense (revenue) induced EM. Higher frequency of rejection suggests more power to detect EM.

Source: Author's computed

Panel A: Test significance (0.05 level)



Panel B: Test significance (0.01 level**)**

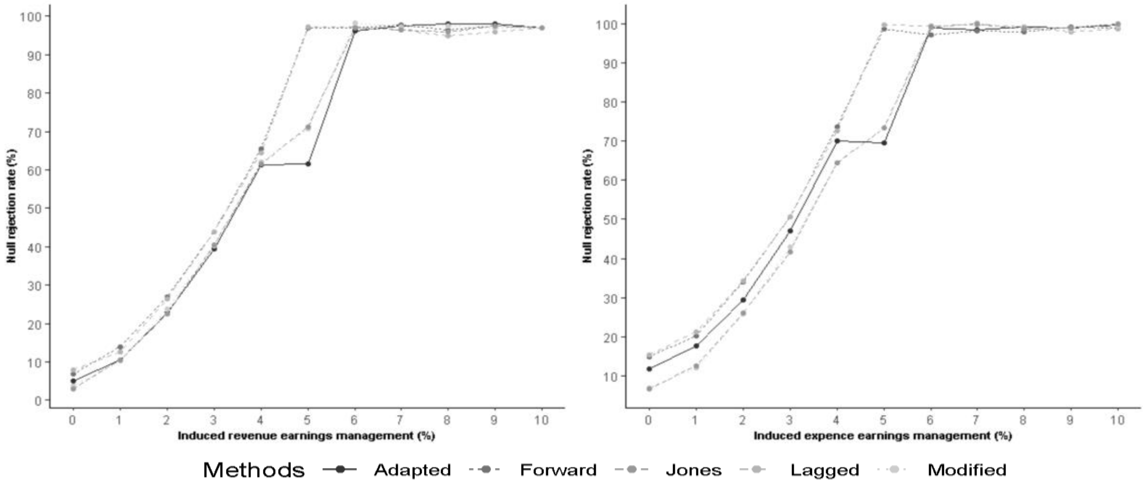


Figure 1: Simulation of power function to test earnings management of the accrual's models.
Note: The plots depict the simulation of power test. The expense manipulations' EM is applied by including the assumed 'expense (artificial) manipulation' ranging from 1% to 10% of lagged of the total assets, before estimating the models for the tested samples.

Because in the model specification correctness test, the simulations for 10,000 repetitions completely identify that all considered models are well posed the larger the iterations involved, hence, the paper reports the models' power test based on simulations for the 10,000 repetitions. The rejection rates for the 10,000 repetitions do not exceed the test significance relative to the 100, and 1,000 which exceed but not substantially. The result shows that for manipulations of about 3–5% of the lagged total assets, irrespective of the nature of manipulations (expense or revenue) implemented, the proportions of the null refutations is high, reaching up to 42–73% for Jones, modified (Jones), and adapted as well as 50–98% for forward-looking and lagged models. This becomes higher as the rate of manipulations increases, irrespective of the considered significance for the simulations. Hence, the models have high proportion of the rejection of the null of from 5–10% exercised increasing earnings management.

The results for the accruals models' simulations identify similar frequencies of the null's rejection at 1–10% of lagged total assets inducement for all accruals models. On the basis simulations due to expense manipulations to augmented the models, although all considered models are powerful with high rates of the null's rejection, but the 'Jones, modified Jones and adapted models almost equally most powerful test according to the samples. As would be seen, from the manipulations of 6–10% of lagged total assets, all models' simulations accommodate at least 97% nulls rejection in all cases with the adapted, Jones and modified, models having above 98% and highest rejections at the expense manipulations. This supposes that, the three are the most powerful model in the detection of income-increasing accruals, based on expense manipulations. The same applies to the simulations at 1% level.

Relatively, Algharaballi and Albuloushi (2008) consider four tested models to report parallel power under expense manipulation, the Jones has remains with highest power. Bartov et al. (2000) suppose use of Jones and time-series modified Jones models as best detection for earnings management. Chang, Chou and Lin (2003) support the Jones model as better, while Peasnell et al. (2000) show that three cross-sectional models are well specified and generates relatively powerful outcome less than 10% of lagged assets in the US.

The simulations of the revenues' induced models also identify all models powerful with high null's rejections. In this case, the forward-looking model identifies with the Jones, modified Jones and adapted to maintain the most powerful ability. The simulations generate the null's rejection above 98% for the revenue induced EM above 5% of lagged total assets, but below 98% for induced EM above 6% for the 'lagged expected accrual models', which is confirmed least powerful for the null' rejections based on the induced revenue at the simulation phase. The same applies to the simulations at 1% level but the null's rejections slightly reduced and range from 95% to 98% for adapted, Jones and modified models.

5. Conclusions

There is widespread interest to examine unexpected accrual models to detect accounting manipulation. Because the Jones-based models and its successive modifications strengthen the power of empirical tests of EM (Balboa et al., 2013), the paper focuses on the developed and improved methods based on this approach, and evaluate models. This study is first-hand evidence on parametric testing of accrual components of earnings from the cross-section estimation of expectation accruals models (such as Jones, modified Jones, and three expected accruals models - adapted, lagged and forward-looking) based on extracted derivations of accruals from financial reports of 335 listed firms in Africa. With the samples, the paper conducts test for models' specification correctness to detest manipulations, according to Teoh et al. (1998), as well as test to verify the models' power to recognise manipulations, suggested by Peasnell et al. (2000).

The findings suggest unexpected accrual models are well-specified when used on the firm-years. The expense (revenue) manipulations identify that all models powerful with high rate for the null's rejection, but the 'Jones, modified Jones and adapted models, and including the lagged model for revenue manipulations, are almost equally the most powerful. At 5% level, the expense (revenue) manipulations of 6–10% of lagged total assets accommodate at least 97% (98%) nulls rejections for Jones, modified Jones and adapted. The same applies to the simulations at 1% level but with slightly reduced rejections now ranging 95%–98%. The offers vital resource to academics, practitioners and regulators. The strong power identified supposes that management can exploit future earnings to increase stock prices during public offers. Although the unexpected accrual methods from modified versions the Jones (1991) have proved popular for research, some non-Jones based models as well as non-linear accruals approach have been advocated. Therefore, future studies may consider these alternatives.

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Appendix

1. # Create a dummy (trd), select 25% (i.e., 1,088) sample from the 4350 firm-years, and assign 1.
2. trd = sample (rep(c(1, 0), c(4350, 1)), 1088)
3. trd = sample(c(1,0), size = 4350, prob = c(0.25,0.75), replace = TRUE)
4. # Note: **dac1** is the column name for the unexpected accruals in the .CSV file
5. dac1.lm = lm (dac1 ~ trd) # Estimate $\mathrm{DAC_i} = \pi_0 + \pi_1 \mathrm{TRD_i} + \varepsilon_i$
6. N=10000 # N repetitions for simulation
7. p.value = numeric (N) #Define the p value
8. for (i in 1:N) {trd = sample(c(1,0), size = 4350, prob = c(0.25,0.75), replace = TRUE)
9. dac1.lm = lm(dac1~trd)
10. cor = cor.test (dac1, trd)$p.value #Obtain p-value of regression
11. p.value[[i]] = as.vector (cor.test(dac1, trd)$p.value)}
12. coef(summary (dac1.lm))[, "Pr(>|t|)"]
13. # Pull out the p-value for each one-tailed test
14. table (p.value <0.05) # @ 5% level
15. table (p.value <0.01) # @1% level